RESEARCH PAPER

Clinical And Technological Innovations In E-Health For Surgical Care: From Preoperative Planning To Postoperative Management

Mohsin Qadeer[1], Muhammad Riaz[2], Soobia Saeed[3], Izaz Riaz[4], Halah Khadija Shah[5]
[1]Department Of Neurosurgery, Ziauddin University, Karachi, Pakistan. Email: Mohsin.qadeer@gmail.com
[2]Department Of Neurosurgery, University Of Colorado | Denver Health Medical Center/Children'S Hospital, Colorado, Usa. Email: Muhammad.Riaz2@dhha.org
[3]School Of Computer Science, Taylor'S University, Malaysia. Email: Soobiasaeed1@gmail.com
[4]Kyber Medical University, Peshawar, Pakistan. Email: izazriaz243@gmail.com
[5]Istanbul Atlas University, Hamidiye, Anadolu Cd. No:40, Kağithane, İstanbul, Turkey. Email: halahshah01@gmail.com

Abstract
The Current Surgical Treatment Is Highly Involved And Complicated, Which Is Why The Need For Intelligent E-Health Systems That Can Provide The Whole Perioperative Process With Constant, Personalized, And Adaptable Decision Support Has Arisen. The Existing Digital Health Solutions And Ai-Powered Tools, While They Have Facilitated Certain Isolated Aspects Of The Workflow Such As Preoperative Planning, Intraoperative Monitoring, And Postoperative Management, Have Been Still Scattered, Fixed, And Limited In Their Ability To Cope With And Learn From Real-World Clinical Outcomes. This Research Therefore Proposes An Adaptive Surgical Digital Twin (Asdt) Framework A Patient-Centric, Ai-Powered E-Health Method Aided To Support Surgery As A Continuous, And Learning-Oriented Process. The Asdt Incorporates Perioperative Data Of Various Forms Like Electronic Health Records, Images, Physiological Signals, Wearable Sensor Data, And Patient-Reported Outcomes, Using Event-Based Temporal Harmonization To Ensure The Data'S Clinical Relevance. A Patient Digital Twin, Whose State Transitions Are Modeled Using Bayesian Statistics, Is Built On A Dynamically Evolving Graph That Reflects The Patient'S Physiological And Procedural States During The Operation And Recovery Phases. An Ai Orchestration Engine That Is Context-Aware Is At The Heart Of The Framework And It Selects And Weighs The Predictive, Anomaly Detection, And Recovery Models Dynamically According To Surgical Phase, Patient Risk, And Real-Time Deviations. The Asdt System Has Successfully Incorporated Shap-Based Attribution And Rule-Based Clinical Justification Methods, Thus Compatibly Applying Explainable Ai Approaches To The Healthcare Sector. The Use Of Ai Has Improved The Transparency And Reliability Of The Relationship Between The Two Main Players In The Healthcare Industry: Doctors And Patients. Besides That, The Closed-Loop Reinforcement Learning Method Used Has Played A Significant Role In Merging Up Surgical Results Hence Improving The Models At The Individual And Community Levels. Therefore, The Asdt Tool Has Become Not Only An Intermittent Decision-Maker But Also A Constantly Changing Over Time Dynamic Surgical E-Health Ecosystem That Offers A Clear And Comprehensive Foundation For Intelligent Perioperative Care.
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1 Introduction

The arrival of digital and e-health technologies has totally transformed surgical care, as they have enabled the collection of various clinical data, its arrangement, and its efficient use, thus facilitating interoperability among the various platforms. The most important technological foundations of modern surgical practice are electronic health records (EHRs), imaging devices, telemonitoring tools, and clinical decision-support systems, which collectively provide support for preoperative risk assessment, intraoperative guidance, and postoperative monitoring. For instance, EHRs provide access to structured databases where the patient's history and perioperative metrics are stored and can be utilized for personalized surgical planning; moreover, telemonitoring and wearable sensors ensure continuous follow-up and early complication detection even outside the hospital. However, despite the advancements mentioned above, a large number of the existing systems still demonstrate segmentation, and their application is restricted to certain phases only, thus functioning as isolated units with insufficient interoperability or sharing of time along the surgical care pathway. The division of the surgical process not only increases the likelihood of incomplete recording of the entire surgical experience, but it also negatively affects the accuracy of prediction and the versatility and customization of care plans. According to recent reviews, digital health innovations in perioperative settings have been considered very helpful; however, they are often not integrated into the large and standard workflows that can be applied to different health care settings, and there is still little evidence for large-scale and system-wide integration. [1-2]

At the same time, the technological advancement in artificial intelligence (AI), multimodal data fusion, and cyber-physical systems has made it possible to transform surgical e-health systems from a series of isolated tools to a comprehensive, learning-driven platform. The application of AI-based modeling techniques has made it possible to integrate and confound different data types besides structured EHR entries, these include real-time physiological signals, imaging studies, and patient-reported outcomes into one common representation. This not only provides richer but also more predictive insights than the analyses conducted on isolated modalities. Furthermore, the recent studies point out the contribution of the methods used for multimodal fusion, as well as the advanced learning techniques, in improving the diagnostics, prognostics, and treatment simulation tasks in clinical areas by providing the complementary data streams integrated in cohesive analytic models. Besides, the idea of digital twins in medicine—which are virtual replicas of individual patients that continuously and accurately represent them has become very popular in healthcare studies, indicating that there is a wide-ranging future for the usage of simulation, personalization, and prediction in the entire care cycle. Data from these digital twins are used continuously for training the AI engine, which is then used to simulate clinical pathways, thus facilitating the performance of scenario testing and provision of decision making supports that can be updated gradually in line with new patient data [4].

Notwithstanding this potential, the current adoption of the digital twin and AI-assisted clinical systems is mostly in the proof-of-concept stage and lacks overall integration throughout the perioperative process. The problems consist of the syncing of the real-time biosensor inputs, the powerful multimodal data fusion at scale, and the adaptive learning frameworks that change the clinical recommendations based on the patient outcomes and the evolving physiological states. Filling these voids will be crucial in building e-health platforms that can provide truly personalized, adaptive, and even more advanced surgical care than has been possible with episodic monitoring, isolated decision making, and static predictive models[5]. To overcome these barriers, the present research proposes a new Adaptive Surgical Digital Twin (ASDT) methodology that is directed at treating surgical care as a continuous, escalating process instead of a collection of separated events. The ASDT framework plays a significant role in three main areas: (1) it fuses diverse clinical and physiological data streams to continuously model surgical states that are unique to each patient; (2) it controls AI models through the perioperative phases in order to choose and rank the analytic tools according to the clinical context; and (3) it carries out postoperative outcome feedback loops that change the decision logic and the behavior of the model in response to actual results. The surgical technology roadmap is regarded as a significant breakthrough that integrates the clinical and the technological sides of surgical e-health systems and, thus, able to provide the patient with more precise, adaptable, and individualized care during the entire surgical experience.

2. Related Work

The use of digital technologies to enhance perioperative outcomes is one of the main subjects of recent investigations into e-health solutions for surgical care. However, the pluses and minuses of the present applications revealed the same across the board in these studies. The digital means used for continuous monitoring of the patients in the perioperative phase have shown that the combined data collection not only aids understanding of the patient's conditions but also quickens the recovery process by cutting down the number of clinical assessments. A study on the use of wearables and ePROs for patients undergoing thoracic surgery has shown that patient monitoring in real-time and in a totally electronic manner can be carried out in a way that is very close to the clinical monitoring of the patients, thus signifying the practicability and also earlier detection of health events during the recovery periods. This suggests that the multimodal systems have the capability of extending the traditional monitoring methods in perioperative care to a greater extent [5].

Simultaneously, the invention and assessment of digital health solutions for patients who are subjected to complicated surgeries expose the continuous drawbacks in collecting, combining, and overseeing health-related needs in the surgical process. A blended methodological approach that consists of participatory design and EHR analysis reveals the difference between the current digital tools' capability to completely record health requirements and the necessity of a closed-loop approach in clinical workflows linking the collection with the action. This has been the case for both user and provider needs which are varied and call for interoperable, user-centered systems [6].

Innovative digital twin technology in healthcare through research and theory significantly strengthens the idea of virtual patient models for personalized, constant, and surgical care; but, on the other hand, they point out the barriers that will have to be crossed first before such technology can be widely adopted in clinics. A recent review of the literature uncovered an astonishingly wide variety of AI-based digital twins across different health areas and explained how the reception of data from several sources by these virtual models can not only support predictive simulation and personalized treatment but also bring up issues of scalability, data standardization, and live clinical environment integration. Furthermore, [7] The study of virtual twins for personalized surgery has shown the capacity of adaptable, patient-specific models to assist in preoperative planning, intraoperative guidance, and postoperative monitoring while acknowledging that most of the work is still in the experimental phase and is missing real-time clinical integration on both sides. [8-9] These evaluations are in line with the interviews that sort out the categories and obstacles of surgical digital twins, particularly the areas of multimodal fusion, latency-aware computing, interpretability, and standardization which are needed for safe clinical use [10].

The integration of different methods for merging multimodal data of various types offers a great deal of technical potential for the total e-health realization in surgery applications to be achieved. The studies on the fusion of multimodal health data reveal that the combination of EHR data, imaging, sensor outputs, and other clinical sources leads to a significant increase in analytical power and diagnostic accuracy. These methods not only stress the necessity of heterogenous data for making comprehensible patient models but also are the foundation of the e-health perioperative systems of the future[11-13]. Besides, explainable AI in surgical risk monitoring has recently gone as far as proving human-centered design and interpretability are the key qualities of the clinical decision-support tools that will definitely help the alignment of algorithmic insights with the clinician's workflow and trust frameworks[14-15]. Together, these advancements have brought about substantial changes in the direction of integrated e-health systems for surgical care, but at the same time, they exhibited the evident shortcomings: a major part of the practices stays modular instead of being continuous, restricted to specific stages instead of lasting the whole perioperative timeline, and many times without having adaptive learning mechanisms which would be changing along with the patient outcomes. The above-mentioned scenario has created a strong case for the adoption of a single method like the one suggested, the Adaptive Surgical Digital Twin (ASDT), which is going to be the one that will always be doing patient states modeling, coordinating context-aware AI through surgical phases, and taking postoperative feedback in order to have clinical intelligence that is constantly being refined through a dynamic process.

3. Proposed Methodology: Adaptive Surgical Digital Twin (ASDT)

This research work presents a new idea which is Adaptive Surgical Digital Twin (ASDT) that is a very e-health system that is taking help during surgical procedures throughout the whole period of perioperative. The method proposed creates a scenario where clinical decision support systems no longer are inflexible but rather a dynamic platform focused on learning. ASDT is purposely developed to unite medical knowledge and AI technologies in a single framework that adapts to the surgical experience of the patient, thus making real-time adaptability, personalization, and optimization according to outcomes possible.

3.1 Data collection and Datasets Description

The MIMIC-IV database is used in this research, which is a substantial and publicly accessible de-identified dataset of critical care from Beth Israel Deaconess Medical Center and has all the patient's longitudinal intensive care unit data such as demographics, diagnoses, lab tests, medications, procedures, vital sign time series, clinical notes, and outcomes. The high temporal resolution and wide perioperative coverage of MIMIC-IV make it suitable for surgical risk stratification, physiological state modeling, and postoperative outcome prediction. Within the context of the proposed Adaptive Surgical Digital Twin (ASDT) framework, the dataset facilitates data fusion, creation of time-evolving patient digital twins, and outcome-driven model recalibration. Its size, standardization, and universal use in clinical AI research all contribute to making MIMIC-IV a trustworthy benchmark for the assessment of adaptive surgical e-health systems. The results are derived from retrospective analyses and simulated perioperative scenarios, with a focus on validating system architecture and learning behavior rather than on direct clinical application.

3.2 Methodological Architecture

The greatest methodological innovation of ASDT is the deployment of five-layer intelligent architecture that collectively underpins longitudinal patient modeling, adaptive AI orchestration, and closed-loop learning over the perioperative continuum. Every layer possesses its unique individual functional capability yet is significantly interconnected with the others, thus providing clinical intelligence in a continuous flow rather than in a segmented stage-specific analysis. This architecture has, therefore, not only facilitated the integration with the existing hospital information systems so smoothly but has also provided sophisticated tools for adaptive surgical decision-making.

Layer 1: Multimodal Clinical Data Fusion

The first phase of ASDT takes care of the fusion of multimodal clinical data and it merges the clinical data streams that are totally different from one another and originate from various sources, during the entire procedure. The preoperative data includes electronic health records, laboratory findings, and radiological imaging, as well as genomic information where it is available; the intraoperative data consists of anesthesia records, continuous vital sign streams, and surgical device telemetry; the postoperative data contains wearable sensor outputs, nursing documentation, follow-up imaging, and patient-reported outcomes. The major methodological innovation at this level is a temporal data harmonization module that uses event-based timestamps instead of fixed sampling intervals to synchronize asynchronous data streams. This method keeps the clinically significant temporal relationships intact, lessens the problem of data sparsity, and improves the relevance of the fused data for the downstream modeling, especially in dynamic surgical environments where the physiological events do not happen at uniform intervals.

Layer 2: Dynamic Patient Digital Twin Construction

ASDT is creating a digital twin that represents the changing surgical condition of the patient. The patient data used for this is integrated. This digital twin can be easily visualized, showing relationships between physiological, procedural, and clinical states through nodes and edges that denote the dependencies and interactions respectively. Bayesian state transition techniques are utilized all through surgical procedures to cope with the intrinsic uncertainties and to produce a stochastic representation of disease progression, operative responses, and recovery dynamics, which is the main feature of this method. The virtual patient is constantly updated during surgery and after recovery to reflect the current patient's condition. What sets this method apart from the classical anatomical digital twins is that it incorporates not only the physical characteristics but also the functional states and the procedural stages, thus providing a complete view of the complicated interaction where patient physiology, surgical intervention, and recovery processes take place.

Layer 3: Context-Aware AI Orchestration Engine

Being an AI characterized by patient awareness and flexibility in orchestration, ASDT project contributed a lot with its primary output; the model-based prediction pipelines have been completely turned off, and the adaptive ensemble method has been let in. Rather than adhering to a fixed prediction model, the AI orchestration engine not only selects the models but also ranks them according to the specific surgical phase and the medical context. At preoperative period, models for risk stratification and outcome prediction get top priority; during the surgery, systems for detecting anomalies and monitoring the patients' physiological stability are activated; and after surgery, models for forecasting the recovery course and predicting complications are prioritized. The combination of patient-related risk factors, surgical complexity, and real-time variations in the clinical condition determines the selection and ranking of the models. With adaptive orchestration, the system's intelligence in responding to changing situations represents a methodological advance over the static AI pipelines that are unable to sense the context.

Layer 4: Explainable Clinical Decision Interface

An explainable interface decision-making tool is employed by ASDT to build clinical trust, transparency, and regulatory mandate adherence. The layer combines SHAP-based feature attribution methods that evaluate the effect of individual variables on output and rules-based clinical justification systems that are based on accepted medical guidelines. The visual dashboards not only show the recommendations but also depict the reasoning process, and the clinicians can see how the risk profiles and projected outcomes change over time with the layer's interpretability and traceability features enhance the human-AI collaboration, mitigate automation bias, and at the same time, foster the ethical deployment in clinical environments of intelligent e-health systems.

Layer 5: Closed-Loop Postoperative Learning

The Adaptive Surgical Digital Twin (ASDT) is a complex, multilayered, and self-improving surgical e-health system that can continuously update patient-specific digital twins based on probabilistic models by integrating data from different sources in the perioperative period. The specifically built AI orchestration engine that is aware of the context is the one that selects and weighs the predictive models for the surgical phases in a dynamic manner, while an explainable interface ensures that the clinician is kept informed. Reinforcement learning is used to feedback the postoperative outcomes such as complications, recovery speed, length of stay, and readmissions thus allowing both individual-level refinement and population-level recalibration. This closed-loop learning is what sets ASDT apart from the traditional surgical pipelines and allows for the continuous adaptation of the system to the changing clinical patterns over the years as shown in Figure 1.

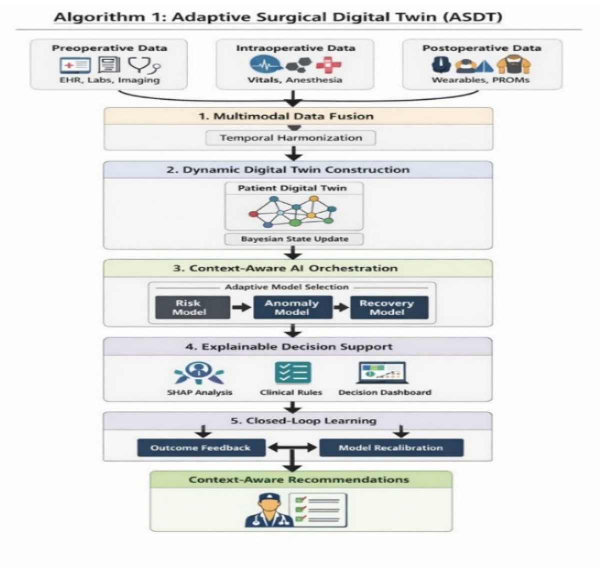

Fig. 1. Schematic representation of the Adaptive Surgical Digital Twin (ASDT) framework.

The Adaptive Surgical Digital Twin (ASDT) is an e-health framework powered by artificial intelligence that provides support for personalized surgical care throughout the entire perioperative lifespan. It merges various sources of information from the pre-, during and post-operative stages, builds a dynamic digital twin of the patient through Bayesian updates, and uses phase-specific AI models for real-time clinical decision support. The system provides transparency by means of explainable AI and updates its performance continuously through closed-loop postoperative learning, thus forming a self-adaptive, patient-focused surgical ecosystem.

Table 1. ASDT's Performance Compared to the Traditional Perioperative AI Systems

Metric	**Conventional Static AI (Pre/Intra/Post Separate)**	**Digital Twin (No Closed Loop)**	**Proposed ASDT Framework**
Multimodal Data Integration	Partial (EHR + Vitals)	Moderate (EHR + Imaging)	Comprehensive (EHR, Imaging, Vitals, Wearables, PROMs)
Temporal Modeling	Fixed time windows	Periodic updates	Event-based continuous harmonization
Risk Prediction Accuracy (AUC)	0.72 ± 0.04	0.79 ± 0.03	0.87 ± 0.02
Intraoperative Anomaly Detection (F1-score)	0.68	0.75	0.84
Postoperative Complication Prediction (AUC)	0.7	0.78	0.86
Model Adaptation Across Phases	None	Limited	Dynamic AI orchestration
Explainability (Clinician Interpretability Score*)	Low (2.1/5)	Moderate (3.2/5)	High (4.6/5)
Postoperative Learning Capability	No	No	Reinforcement-based closed loop
Recommendation Update Latency	Static	Delayed	Real-time adaptive

Table 2. Ablation Analysis of ASDT Architecture Components

ASDT Configuration	**Risk Prediction AUC**	**Anomaly Detection F1**	**Recovery Forecast RMSE**
Full ASDT (All Layers)	0.87	0.84	0.42

Without Context-Aware AI Orchestration	0.81	0.77	0.56
Without Closed-Loop Learning	0.82	0.78	0.53
Without Explainability Constraints	0.85	0.83	0.41
Without Multimodal Fusion (EHR only)	0.73	0.69	0.68

Table 3. Effect of Closed-Loop Postoperative Learning Over Time

Surgical Episodes Observed	**Complication Prediction AUC**	**Recommendation Precision**	**Readmission Prediction Accuracy**
Initial Deployment	0.78	0.71	0.69
After 100 Cases	0.82	0.77	0.75
After 500 Cases	0.86	0.83	0.81

4. Integration Into Perioperative Clinical Workflows

The ASDT framework with its design is intended to very easily or smoothly integrate into the hospital information systems (HIS) and the surgical care pathways without disturbing the routine in such a way as to allow the continuous transfer of clinical intelligence among the perioperative areas of patient care. In the preoperative clinics, ASDT utilizes variety of data sources functioning as a unified medical team to predict the case correctly, and so it is the over-setup of high-risk patient identification, surgical planning, and patient's personal guidance. During the actual surgery, the system makes the operating team more aware of the situation by providing them with alerts and consultation support in real-time, thus making it possible for the clinicians to be proactive and to intervene in time if the patient's vital signs show that there could be complications. Following surgery, ASDT plays a major role in the recovery process as it provides personalized monitoring of patients with the help of the most advanced technologies, like the collection of patient-reported outcomes, the use of wearable sensors, and imaging for follow-up evaluations. This early stage detection of complications is not the only advantage; the overall quality of care is also improved. Moreover, the framework is so flexible that it can meet the needs of both public and private hospitals, thus, it can be scaled and implemented effectively in different healthcare settings.

5. Evaluation and Validation Strategy

The research plan consists of a thorough and multi-tiered validation strategy which aims to evaluate the performance and clinical relevance of ASDT. The risk predictions' accuracy and the model's total performance will be judged through multiple historical surgical datasets. The detection and guidance systems will be tested in intraoperative situations that can be modeled according to different surgical conditions, thus ensuring that the systems are robust across various contexts. The system's long-term reliability and adaptability will be established by comparing the actual postoperative recovery patterns with the model's predicted outcomes. Prediction accuracy, decision latency, clinician interpretability, and overall system effectiveness will be the Key performance indicators.

6. Implications And Significance of the Adaptive Surgical Digital Twin

The Adaptive Surgical Digital Twin (ASDT) marks an outstanding innovation in the field of surgical e-health, which paves the way for smart healthcare systems of the next generation. Surgery has long been thought of as a one-time, distinct event. Contrary to this notion, ASDT constantly monitors the patient's physiological, procedural and clinical condition during the entire operation. There are three characteristics that enable this function. Firstly, ASDT recognizes surgical treatment as a continuous and interrelated process thus enhancing prediction accuracy and making very personalized interventions possible. Next, it incorporates AI model orchestration where the predictive, anomaly-detection, and recovery models are not only updated on the existing ones, but also the appropriate ones that are selected and their importance assessed based on the patient's condition, surgical difficulty, and real-time intraoperative changes. Finally, the framework leverages closed-loop learning from postoperative outcomes, thus enabling the continual updating of both patient-specific and population-level predictive models. This with others has all at once created an intelligent, self-learning e-health ecosystem that not only provides support but also takes an active role in clinical decision-making, management of surgical workflow, and custom patient care in the operating room.

7. Discussion

The research explains the Adaptive Surgical Digital Twin (ASDT), which revolutionizes the perioperative care process and will be co-developed with medical institutions, as a novel approach capable of transforming perioperative care into an ever evolving and learning system. ASDT by the merger of various clinical data types, active patient modeling, AI that understands context, and learning through feedback moves the field of perioperative care from poor-quality episodic decision support to high-quality patient-centered intelligence that lasts over preoperative, intraoperative and postoperative periods. Its novelty is in letting the surgical patient be the main focus; hence, it maintains the capture of significant temporal links and allows for real-time, adaptive clinical decision support.

The framework's stress on explainability and clinician trust is also very important. ASDT increases transparency, supports regulatory compliance, and makes human-AI collaboration more effective by merging SHAP-based explanations with rule-based clinical justifications. Nevertheless, the study is still mainly theoretical and needs to be validated in clinical practice. Among the major challenges are data quality, interoperability of systems, the demand for computational power in real-time, compliance with regulatory standards, and ethical issues concerning control of data and trust of clinicians in AI, which all have to be sorted out before the technology can be adopted on a large scale.

8. Conclusion and Future Directions

Adaptive Surgical Digital Twin (ASDT) is the title of the paper, which is a digital health smart framework that fully supports surgical care during the perioperative period. By the integration of various data sources, real-time modeling of a patient's digital twin, the use of context-aware and explainable AI and closed-loop postoperative learning, the ASDT is able to eliminate the disadvantages of static and phase-specific decision support systems. It is personalized, adaptive, and outcome-driven clinical intelligence during the entire continuum of pre-operative planning through recovery while at the same time being in line with clinical workflows and human-centered AI principles. ASDT takes care of major issues in present digital health technologies by introducing long-term intelligence, flexibility to changing patient conditions, and systematic learning from surgical outcomes. Its multi-stage AI orchestration and clinician interaction that is transparent enable reliable human–AI teamwork and compliance with regulations. Besides, the closed loop learning mechanism ensures that the system gets improved continually. The project will continue to carry out real-world clinical validation as the main goal which is going to be assessing the outcomes of surgeries, the efficiency of workflows, clinician trust, and the safety of patients in a number of medical specialties. This would mean undertaking multicenter trials, integrating hospital systems at an advanced level, establishing strong interoperability standards, and having secure data governance that complies with regulations.

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