# SurgicalDataOS

A Professional Knowledge Representation Platform for Collaborative Surgical Intelligence

*From Surgical Video to Structured, Validated Surgical Knowledge*

White Paper

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## Abstract

Surgical expertise is generated continuously but remains largely implicit in clinical practice, operative video, and traditional teaching. Video preserves visual activity but does not fully represent observations, interpretations, decisions, actions, or outcomes. SurgicalDataOS is proposed as a professional surgical knowledge platform that converts operative video into structured, reviewable, and reusable Knowledge Objects. Surgeons contribute video, artificial intelligence proposes initial annotations, and surgeons review, correct, and enrich the resulting representation. The validated output can support surgical education, peer learning, research, expert knowledge preservation, and future computational applications.

## Executive Summary

- Surgical procedures generate information involving observation, interpretation, decision, action, and evaluation. Operative video captures only part of this information.
- SurgicalDataOS converts video into structured Knowledge Objects through an AI-assisted, surgeon-validated workflow.
- The resulting resources can be used for teaching, peer learning, research, knowledge preservation, and future computational systems.
- The platform is intended for a professional network of surgeons, educators, researchers, trainees, and institutions.
- The current demonstrator illustrates the core video-to-Knowledge Object concept.

## 1. Introduction: The Unrepresented Knowledge of Surgery

Surgery is a knowledge-intensive activity involving perception, interpretation, decision-making, execution, and evaluation.

Much of this expertise remains implicit and is rarely captured in a structured and reusable form. Operative video preserves anatomy, instruments, tissue interaction, procedural sequence, and visible outcomes. It does not fully preserve recognition, rationale, perceived risk, or the relationship between an action and its intended result(1–3).

Existing video-analysis systems identify visible features, but visible labels do not necessarily represent surgical knowledge. A clinically meaningful representation must connect observations with interpretations, decisions, actions, and outcomes.

SurgicalDataOS provides a framework through which operative video can be converted into structured surgical knowledge, with AI assisting capture and the surgeon providing validation.

The utility of a computational surgical system depends not only on its algorithms, but also on the adequacy of its knowledge representation.

In this white paper, surgical knowledge means structured information about a surgical situation, including what is observed, how it is interpreted, what decision follows, what action is taken, and what result or subsequent state is produced. Surgical state means the clinically relevant condition of the operative situation at a given point in time, including anatomy, tissue configuration, procedural context, operative objective, and other factors that influence the next action.

## 2. The SurgicalDataOS Vision

SurgicalDataOS is designed to convert operative video into structured surgical knowledge.

A surgeon uploads a procedure or selected video segment. AI proposes relevant annotations and Knowledge Objects. The surgeon reviews, corrects, and enriches them. The validated result becomes a structured, searchable, and reusable resource for teaching, peer learning, research, and future computational applications.

The platform is intended to support a professional network of surgeons, educators, researchers, trainees, and institutions. Contributions may be attributed to verified professionals, reviewed by peers, and linked to procedures, techniques, outcomes, and evidence.

SurgicalDataOS does not seek to impose a single canonical surgical technique. It is designed to preserve different approaches while recording their context, reasoning, actions, and outcomes.

The current website demonstrates the core concept. A complete platform would require professional verification, secure data management, AI-assisted annotation, surgeon review, peer validation, governance, and educational access.

## 3. From Surgical Video to Structured Knowledge

SurgicalDataOS uses operative video as the primary source for creating structured surgical knowledge.

The process consists of four stages:

- Video contribution: A surgeon uploads a complete procedure or selected operative segment.
- AI-assisted annotation: AI identifies relevant procedural events and proposes structured annotations.
- Surgeon review: The contributing surgeon reviews, corrects, and supplements the proposed annotations.
- Knowledge Object creation: The validated information is organized into Knowledge Objects that can be searched, viewed, compared, taught, and reused(4).

The resulting resource retains the original video while adding a structured layer describing clinically meaningful events and their relationships(5–9).

Annotation is the act of assigning labels, attributes, or time-linked descriptions to source data. Knowledge representation is the larger structured arrangement of those descriptions, their provenance, and their relationships so that the resulting information can be interpreted, queried, compared, and reused. In SurgicalDataOS, annotation is therefore a means of constructing a knowledge representation, not a synonym for the representation itself.

## 4. AI-Assisted, Surgeon-Validated Knowledge Capture

AI performs the initial analysis and organization of operative video. Its output is treated as a proposal rather than a final clinical interpretation(10,11).

The surgeon reviews proposed Knowledge Objects, corrects inaccuracies, adds missing context, and confirms their clinical meaning.

AI detects, organizes, and proposes; the surgeon interprets, validates, and enriches; SurgicalDataOS stores and presents the resulting knowledge.

The objective is to combine the scalability of AI with the contextual accuracy of surgical expertise(12,13).

## 5. The Knowledge Object

A Knowledge Object (KO) is the basic unit of structured knowledge in SurgicalDataOS.

It represents a clinically meaningful surgical event or transition, connecting what is observed with its interpretation, decision, action, and outcome.

A Knowledge Object may include:

- Video reference
- Procedure phase and stage
- Observation
- Interpretation
- Decision
- Action
- Event
- Outcome
- Knowledge Extract

Not every Knowledge Object will contain all elements with equal certainty. Some information may be directly visible, inferred from the sequence, or supplied by the surgeon.

The Knowledge Object represents a meaningful unit of surgical knowledge rather than merely a frame, instrument movement, or isolated video label(14–16).

## 6. Structure of Surgical Knowledge

SurgicalDataOS organizes each Knowledge Object around six essential elements:

Context → Observation → Interpretation → Decision → Action → Outcome

Context is the relevant procedural, anatomical, or situational setting. Observation is what is seen or detected. Interpretation is the meaning assigned to the observation. Decision is the selected response or strategy. Action is the operative step performed. Outcome is the immediate result or subsequent state.

These elements may be explicitly documented, inferred from video, or confirmed by the surgeon. Their relationships are as important as the individual fields(4,14). The operational schema may also include Procedure Phase, Procedure Stage, Event, Video Time, and Knowledge Extract.

6.1 Relationships between Knowledge Objects

Knowledge Objects are not intended to function as isolated records. They are connected through explicit relationships that preserve the structure of a surgical episode, the evolution of surgical state, and the reasoning linking one clinically meaningful event to another.

The principal relationships may include:

• Temporal relationship: identifies the order, overlap, duration, or temporal proximity between Knowledge Objects.

• Causal or consequential relationship: records when one event, observation, or decision contributes to, produces, or explains a subsequent event or outcome.

• State-transition relationship: connects the operative state before an action with the state produced after it, allowing an outcome to become the observation for a subsequent Knowledge Object.

• Hierarchical or compositional relationship: links broader procedural phases and stages to constituent events, actions, or sub-events.

• Dependency relationship: records when a decision or action depends on a preceding observation, interpretation, anatomical condition, technical constraint, or operative objective.

• Alternative-strategy relationship: links different clinically valid decisions or actions that may arise from the same surgical state, together with their indications, assumptions, and outcomes.

• Corrective or revision relationship: preserves the connection between an initial AI-generated or surgeon-authored object and a later correction, clarification, or enrichment without erasing provenance.

• Evidence or provenance relationship: links a Knowledge Object to its source video segment, contributing surgeon, reviewer, supporting reference, or other basis for the represented claim.

These relationships can be represented as a directed graph in which Knowledge Objects are nodes and the relationships between them are typed edges. The graph need not prescribe a single surgical pathway; it can represent branching decisions, recurring observations, alternative techniques, and feedback from outcomes into subsequent interpretation. This relational layer is what allows SurgicalDataOS to support sequence reconstruction, technique comparison, explanation, traceability, and future computational use beyond simple annotation lookup.

## 7. Representing Surgical Events

A Knowledge Object should be created when a meaningful change occurs in the surgical situation or operative intent.

A new object is appropriate when the surgeon's operative objective changes, a distinct surgical event becomes observable, and the new state is semantically independent of the preceding state.

During cataract surgery, examples may include positioning the nucleus for a planned chop, initiating a vertical chop, propagation of the fracture, and separation and removal of a nuclear fragment.

For example, the initiation of a vertical chop is an Event because it identifies an operative occurrence or transition. The resulting nuclear fracture, stability of the remaining nucleus, or unintended extension of a crack is recorded as an Outcome because it describes the state produced by that event. An Event identifies what happened; an Outcome records what resulted. In practice, an event may have several immediate or delayed outcomes, and an outcome may become the observation that informs a subsequent Knowledge Object.

Minor instrument movements, tremor, drift, or continuous adjustments within the same operative intention do not necessarily require separate Knowledge Objects.

The aim is to represent clinically meaningful transitions rather than every movement in the video.

## 8. Representational Sufficiency

The usefulness of a computational system depends not only on algorithmic sophistication, but also on the adequacy of the knowledge it receives.

A representation is task-relatively sufficient when it preserves the elements and relationships necessary to support the intended task, such as recognizing an event, explaining an action, comparing techniques, supporting education, assisting decisions, or training a computational system.

A representation recording only instruments, anatomy, or movement may be adequate for visual-recognition tasks but insufficient for tasks requiring interpretation, intent, rationale, or outcome.

Representational sufficiency is not absolute. It depends on the task, available information, and required level of detail.

Accordingly, representational sufficiency should be treated as a task-specific design and evaluation claim, not as a universal property of a dataset or platform. A representation may be sufficient for reconstructing procedural sequence while remaining insufficient for explaining intention, identifying perceived risk, or supporting a decision-making task. Sufficiency must therefore be assessed against a defined task, information requirement, and acceptable level of uncertainty.

## 9. Collaborative Surgical Knowledge Creation

SurgicalDataOS supports the progressive development of surgical knowledge through contribution, review, and reuse.

A Knowledge Object may initially be created by the operating surgeon and subsequently examined by other qualified users. Comments, interpretations, references, or alternative approaches may be linked without altering the original provenance.

The platform can therefore support surgeon-authored knowledge, peer discussion and validation, technique comparison, evidence-linked interpretation, educational adaptation, and institutional or research collections.

The original video and authorship remain identifiable, while subsequent contributions are recorded as additions, revisions, or alternative interpretations.

This structure also permits more than one clinically valid strategy to be represented without forcing them into a single normative pathway. Alternative decisions can be linked to the same surgical state, provided that their indications, assumptions, and outcomes are recorded. Such alternatives should be treated as attributable interpretations or strategy branches rather than as errors merely because they differ from the original contributor's approach.

## 10. Applications

The structured knowledge generated by SurgicalDataOS may support:

- Surgical education
- Peer learning
- Research into decisions, techniques, workflows, and outcomes
- Preservation of expert knowledge
- Simulation
- AI development
- Institutional learning

These applications depend on the quality, completeness, validation, and governance of the underlying knowledge(17–19).

The proposed distinction is not that surgical data science, workflow analysis, knowledge graphs, or educational repositories have previously lacked structure. Rather, SurgicalDataOS seeks to connect these established directions through a common unit that links observable surgical events to interpretation, decision, action, and outcome. Its intended contribution is therefore the integration and explicit representation of the cognitive-clinical relationships that are often left implicit in predominantly visual, procedural, or motion-based datasets(1–9,14–19).

## 11. Scope and Future Development

SurgicalDataOS is currently a conceptual and technical demonstrator for converting operative video into structured surgical knowledge.

A production platform would require further development in AI annotation and validation, secure data handling, patient privacy, professional identity verification, Knowledge Object standards, interoperability, peer review, governance, educational interfaces, research access, and evaluation.

For robotics and other advanced computational applications, the proposed representation should be understood as a possible knowledge substrate for research into task segmentation, decision support, shared autonomy, and evaluation of surgical behaviour. It does not, by itself, establish robotic competence, autonomous control, or regulatory readiness. Those capabilities would require independent technical, clinical, safety, and validation evidence.

The framework does not claim to capture every dimension of surgical expertise. Intention, uncertainty, rationale, and intraoperative judgment may require surgeon input beyond what can be inferred from video alone.

In particular, the cognitive elements—especially Interpretation and Decision—require dedicated elicitation and inter-rater evaluation. They should not be treated as empirically validated merely because phase, step, instrument, or skill annotations have established agreement measures in prior work. Future studies should examine cognitive-object agreement, provenance quality, hindsight bias, downstream usefulness, and performance against clearly specified tasks.

SurgicalDataOS should be understood as an evolving framework rather than a completed or comprehensive model of surgery.

## 12. Conclusion

Surgical expertise contains observations, interpretations, decisions, actions, and outcomes that are only partially preserved in operative video.

SurgicalDataOS proposes a practical framework for converting this experience into structured Knowledge Objects through AI-assisted annotation and surgeon validation.

Its immediate purpose is to create more useful resources for surgical teaching, peer learning, research, and knowledge preservation. Its longer-term potential lies in making structured surgical knowledge available to computational systems.

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