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REVIEW ARTICLE

Surgical process modelling strategies: which method to choose for determining workflow?

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ABSTRACT

The vital role of surgeries in healthcare requires a constant attention to improvement. Surgical process modelling is an innovative and rather recently introduced approach for tackling the issues in today's complex surgeries. This modelling field is very challenging and still under development, therefore, it is not always clear which modelling strategy would best fit the needs in which situations. The aim of this study was to provide a guide for matching the choice of modelling strategies for determining surgical workflows. In this work, the concepts associated with surgical process modelling are described, aiming to clarify them and to promote their use in future studies. The relationship of these concepts and the possible combinations of the suitable approaches for modelling strategies are elaborated and the criteria for opting for the proper modelling strategy are discussed.

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Introduction

Improvement of the surgical and interventional procedures for treatment of different diseases is a worldwide constant goal of various researchers with different expertise. As a result of the introduction of advanced technologies and tools, treatment procedures have become more and more complex, involving complex logistics, much technology, and large teams. Furthermore, procedures are also highly dependent on various factors, such as: the surgeon's skills and preferences and patient-specific properties, including patient health condition and clinical history, as well as type, location, number and size of the treatment areas. These variations make each surgical procedure unique, which adds to the inherent complexity of surgeries and consequently to their improvement.

Due to surgical uniqueness and complexities, attempts for improvement of surgical procedures by development of e.g., artificial intelligence (AI), new devices, etc., and enhancement of surgical team skills might be inefficient or remain unused in clinical practice as it is difficult to find the true bottlenecks and parameters for improvement. As a part of these developments, in recent years employment of Artificial Intelligence (AI) in the operating rooms has attracted attention. AI is a challenging field that has the potential to improve surgical procedures, either via surgeon feedback or by automating technical tasks in the operating room. In both cases, machine learning (ML) can aid to make highly reliable decisions in real time, and to perform tasks by surgeon properly. Data are the foundation for ML; however, the complexity of surgical treatments makes interpretation and management of the huge amount of data difficult. Dividing a surgical procedure into a sequence of identifiable and meaningful tasks aids improvement of different aspects of ML, including data acquisition, data storage, data analysis, etc.

The concern of finding the structural coherence of complex surgical procedures and obtaining profound qualitative and quantitative understanding of the relations between different surgical procedures has resulted in the start of methodical analyses of surgical procedures in 2001 [1]. Since then, surgical process models have increasingly been studied to grasp an understanding of various procedures and to attempt improving their efficiency, efficacy or quality. Different methods of AI can greatly benefit modelling of surgical procedures. These

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methods, including ML, artificial neural networks, computer vision and natural language processing, are used to establish surgical workflows and to build surgical process models, as was shown in [2,3]. Such methods can automate and increase accuracy of different steps of data acquisition, analysis and modelling for a reliable process modelling. They also provide input for human designers to clearly visualize workflows, making easy-to-interpret models and visualizing relations and patterns between extensive sets of actions and decisions. So far, different studies have aimed at the investigation of employing surgical procedure models for various purposes, such as surgeon skills evaluation and training [4–8], analysing clinical team workload [9,10] optimization of operating room (OR) management [11–13], introduction of new technologies [14–16], predicting next surgical task [17,18], and predicting surgery duration [19,20].

Two previous review papers [21,22] cover the relevant concepts of surgical process modelling. However, due to the complexity of the field, the dependencies between these concepts and the criteria for selection of the most suitable modelling strategy are not clear. The aim of this paper is to provide a guide on how to select the best strategy for modelling surgical procedures. Therefore, we will provide essential details of different modelling concepts that should be considered when attempting to conduct surgical process analyses. Moreover, a new classification of the possible combinations of the involved concepts in surgical process modelling is provided to show how the selections depend on each other. Finally, an application of the modelling strategies in a clinical study demonstrates how the presented concepts can be used in real studies.

Methods

A literature search was carried out in Scopus [www.scopus.com]. Keywords and their synonyms and alternative spellings were included in the search by using Boolean operators and wildcard characters. The search query used to search titles and abstracts was: ((*surg** OR *therap** OR *"operating room"*) AND (*"workflow analysis"* OR *"process model*"* OR *"workflow model*"* OR *"hierarchical decomposition*"*)) OR "*surgical ontology*". As some terminologies are common between different fields or have different meanings, the articles with terms 'animal' and 'surge' were excluded. The search included articles written in English and conference proceedings between January 2000 and 1st August 2018.

Inclusion criteria were defined to limit to studies that focused on any attempt aiding to extract the sequential pattern of surgical tasks in the operating room. The inclusion criteria were used to select the publications first based on their title and then on their abstracts. Extra sources were added from the references of the selected publications (backward snowballing). Moreover, relevant publications from the same authors were also considered as extra sources. As a result, a total of 168 publications were selected. Because of the limited number of references allowed by the journal, only the most relevant references were selected per presented concept as examples of groups of references with similar focus/approach. Figure 1 shows the result of the literature selection procedure.

Modelling strategies

A surgical procedure can be defined as a set of sequential and parallel activities, executed by clinical and technical team members with different expertise, through preparing and using equipment and tools with the ultimate goal of high-quality treatment of a patient without complications. In 2001, MacKenzie et al. [1] for the first time described a surgical procedure as a sequence of steps: a workflow. Later, various researchers worked on modelling surgical procedures, resulting in the introduction of new modelling

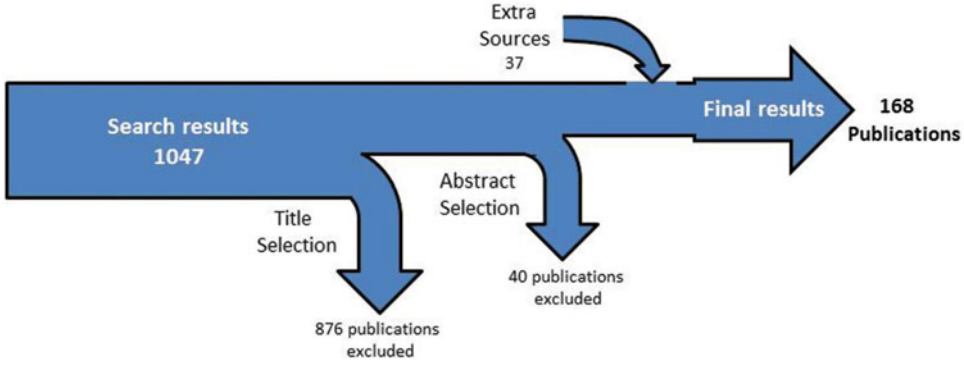

Figure 1. Literature selection procedure and results.

strategies, each with its own specifications, advantages and limitations. These modelling strategies are characterized each by their own granularity levels, data acquisition methods, modelling approaches, model representation, modularity design and generalization. An ontology, proper terminology, and definitions for surgical process models, facilitate the comprehension of models that assist the analysis.

Ontologies, which are explicit and formal descriptions of all the entities of the procedure, largely benefit managing information involved in surgery. These unique ontologies can be used to assign semantics to data, establish easy-to-interpret models, share information between possible developed software and different studies. Bridging the gap between the field of ontology and surgical process models led to the introduction of different surgical ontologies, e.g., [23,24]. Ontologies reduce the complexity of modelling and increase model usability and efficiency. The urgency and usefulness of sharable, easy-to-interpret and easy-to-update surgical process models has recently attracted particular attention from the expertise in the field to reach a standard and comprehensive ontology in surgical process models [25].

Due to the diversity of modelling strategies, numerous combinations can be used for the procedure analysis. Which combination should be used depends directly on the purpose of the study to be conducted. In the rest of the paper, we refer to different modelling strategies (granularity levels, data acquisition, model representation, etc.) as different *concepts*. Each concept has different characteristics (manual and computer-based in data acquisition or top-down and bottom-up in modelling approach) and we refer to these as *aspects* of a concept. Aspects can contain different *methods*, such as observation in manual data acquisition or workflow diagrams in numeric model representation.

There are five concepts that need be considered when choosing a workflow modelling approach. These concepts are interconnected and selection of one might affect the choices left for the others. In Table 1, the involved concepts are defined, their different aspects are listed, and contributing factors for selection of the proper aspects are proposed. These concepts are further discussed in the following sub-sections.

Granularity level

The description of a procedure can be done at different levels of detail and abstraction: granularity levels. The concept of granularity levels for description of a surgical procedure was first used by MacKenzie et al. [1]. They referred to it as a hierarchal decomposition of a surgical procedure and defined the different levels of granularity (from low to high) as 'procedure', 'step', 'substep', 'task', 'subtask' and 'motion'. Note that more details result in higher granularity levels or lower levels of abstraction and vice versa. Lalys & Jannin defined different granularity levels as 'procedure', 'phase', 'step', 'activity', 'motion' and 'low-level information' [22]. Other terminologies are also used for different levels of granularity such as surgical episode [26], surgical deed [27], gesture [28], high-level task [2], low-level task [19], etc. Regardless of the specific terminology used for the different

Table 1. Modelling strategies concepts, definitions and dependencies.

Concept	Definition Aspects	Criteria and dependencies
A. Granularity level	• Description of the procedure at different levels of detail/abstraction. • Low to high	• Purpose of study • Data acquisition
B. Data acquisition	• Acquiring data of surgical procedure for modelling and analysis. • Manual/Computer-based	• Purpose of study • Granularity level • Modelling approach • Benefits and drawbacks • Available equipment and recourses
C. Model representation	• Representation method of modelling surgical procedure • Descriptive/Numeric	• Purpose of study • Data acquisition • Benefits and drawbacks
D. Modelling approach	• Direction of modelling (from low to high granularity levels or vice-versa) • Top-down/Bottom-Up	• Data acquisition • Granularity levels • Benefits and drawbacks
E. Generalization	• Surgical procedure analysis and generalizing the model.	• Purpose of study • Similarity metrics • Statistical analysis • Data mining and data warehousing

granularity levels, there are two factors that determine which granularity levels should best be chosen:

Purpose of the study: The level of granularity depends on the aim of study. For example, if evaluation of the performance of an improved surgical instrument for manipulating specific tissue in a surgical procedure is the aim, a high level of granularity is needed. In case the aim of study is to analyse the effect of the same instrument on the outcome of the entire procedure, less granularity is needed. Lalys and Jannin, in their review paper, defined a phase as 'a major type of event occurring in the surgery'. However, a major event in a surgery depends on the aim of the study and may be rather subject to preference. If the study aim is to acquire the data at two levels of granularity (e.g., pre-, and post-surgical phases and activities within these phases), one can define the granularity levels as phase and sub-phase, respectively. Therefore, the number of granularity levels is rather arbitrary and depends on how detailed the granularity levels are defined.

Data acquisition: Not all data acquisition methods provide the possibility to achieve all granularity levels. For example if the data acquisition method is based on interviews with a clinical team, only very low granularity levels can be achieved.

The determination of the required granularity levels is a primary step in modelling strategies. If the granularity level is defined properly at the start of modelling, the effort for the remaining steps of modelling decreases tremendously, making the data acquisition and modelling process more efficient.

Data acquisition

Data acquisition of the surgical procedure model can be done manually or computer-based. With manual data acquisition, the data are acquired through observation, available documentation, interviews with experts and literature study. Workflow observations of surgical processes can be done either online, e.g., [1,7,15] or offline, e.g., [1,15,29]. In online observation, the observer is present in the OR to record the data and any related information. Online observation has several advantages, including better insight into ergonomics in the OR and the interaction between clinical team members. However, due to large amounts of data and parallel activities in the OR, comprehensive manual online data recording is sometimes impossible and the likelihood of human error in recording the data is high. Offline observation through video recordings of the OR aids to overcome the online observation limitations, but at the cost of losing interaction of the observer with the clinical team. Observation supporting systems have been developed in order to improve the accuracy and completeness of both offline and online observations, e.g., [30,31]. Observations in the OR cannot always provide the required low-level data. Furthermore, these usually lack complete data of the treatment procedure on the patient's organ. In the case of, e.g., laparoscopic surgery, there is usually access to the laparoscopic video data, which is a rich source of data with high granularity.

Patient and procedure data documented by the clinical staff as part of their routine can be very valuable in surgical procedure modelling studies, in particular for the collection of preoperative and postoperative data. Interviews with clinical experts, e.g., [15,32] and literature studies particularly provide information for qualitative analysis of the surgical procedure. Figure 2 shows the different methods of manual data acquisition and the corresponding benefits and downsides.

Computer-based technologies were introduced to automate data acquisition and eliminate human error. Different types of sensors and image processing techniques have been used for data acquisition and tracking of different entities in the OR, e.g., [30–38]. The main purpose of using tracking systems is to detect the presence, absence or movements of clinical staff or/and instruments during the operation. The tracking can be done in the OR, e.g., [33,34] or by processing of the videos, e.g., [35–37]. Recently, other approaches have emerged, such as an approach based on the combination of video processing and instruments weight [38,39]. However, the computer-based approaches are not free of pitfalls and limitations either, due to the complexities of the field of surgical process modelling. The first challenge here is that flawless identification of a specific task in the surgical procedure based on a signal can be a limiting factor, i.e., the purpose of using an instrument might not be clear based on the acquired signal. For example, a sensor can detect the usage of an electrical surgical knife; however, it does not identify whether it is used to cut the lesion or to dissect the fat. Several researchers are focusing on this challenge and try to recognize the related tasks from microscopic, endoscopic and laparoscopic videos, e.g., [40–43].

The second corresponding challenge is the development of reliable sensors and tracking systems. The two major tracking systems, optical [44] and

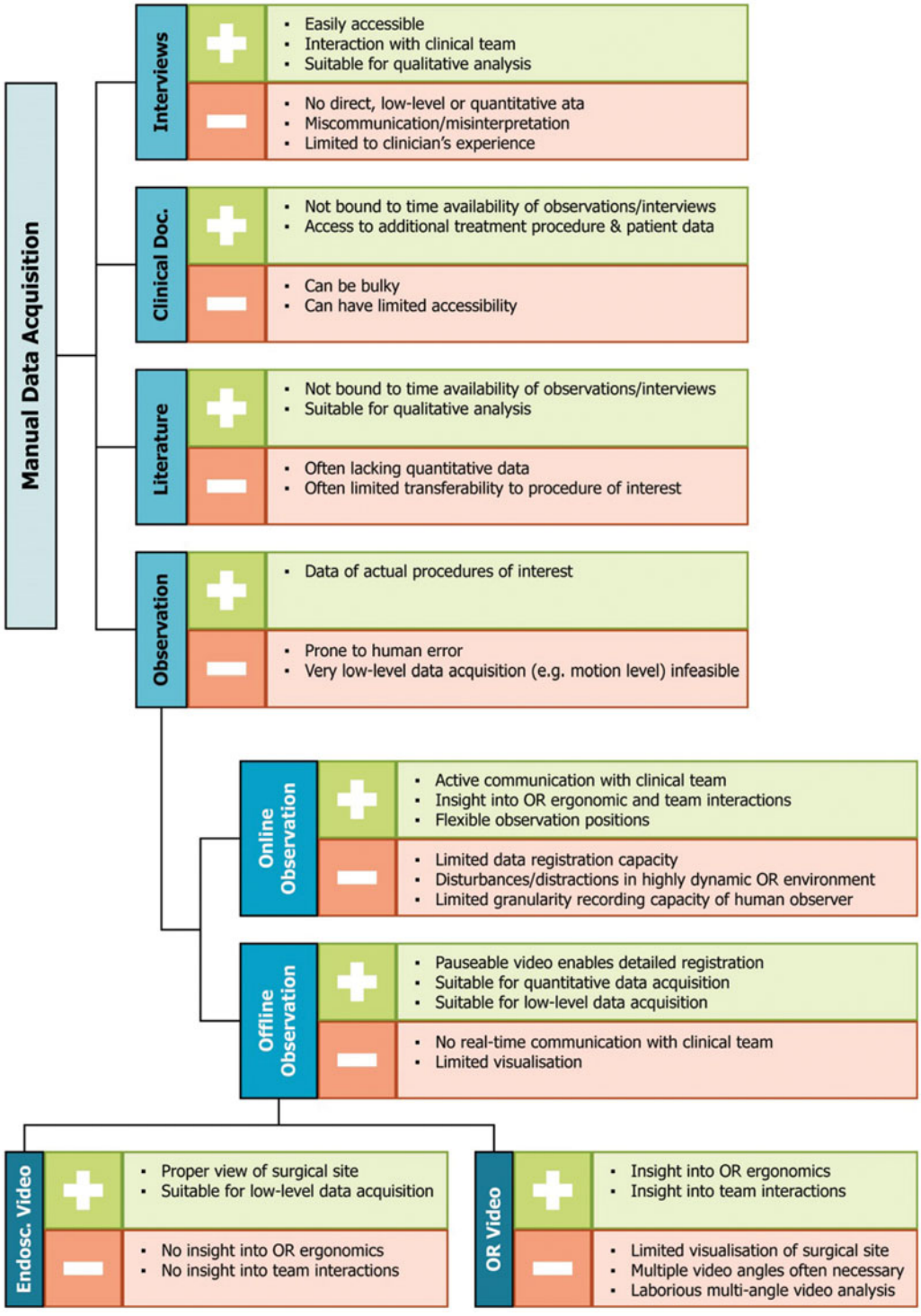

Figure 2. Different methods of manual data acquisition and the corresponding benefits (indicated with '+') and drawbacks (indicated with '−').

electromagnetic [45], each have their own drawbacks and weaknesses. In optical tracking systems, tracking markers must be attached to rigid targets and should always be visible to the tracking system. Therefore, it is difficult to track soft tissues and flexible instruments. Furthermore, these tracking systems do not function if the view is obstructed when the marker is inside the body or when the surgeon's hand or the clinical team block the view [44,45]. Electromagnetic tracking systems do not suffer from these problems, but their performance deteriorates in the vicinity of metal objects [45]. Apart from tracking systems, useful information may be obtained from several other types of sensors that can be used to monitor patients,

Table 2. Benefits and drawbacks of manual and computer-based data acquisition technologies.

	Benefits	Drawbacks
Manual	• Less initial effort for data acquisition (No need to set-up computer-based acquisition systems). • Easier data interpretation. • Acquisition from different sources other than OR (interview, literature study, etc.). • Interactions with clinical team in the OR.	• Time consuming data acquisition. • Not possible to acquire very low-level data (e.g. at the motion level). • Possibility of human error.
Computer-based	• Possibility of acquiring very low-level data. • Precise data acquisition. • Automate data acquisition.	• Time consuming and complex data interpretation. • Possible error in data recording. • Possible error in data interpretation. • Time consuming setting up computer-based acquisition systems. • Usually physical object attached to the tools, clinical team or patient.

e.g., [46] or record OR audio and video, e.g., [47]. The advantages and disadvantages of the discussed manual and computer-based technologies are summarized in Table 1.

Acquiring a comprehensive and solid data set is a crucial step in surgical procedure modelling. An error in the data affects the whole modelled procedure and the underlying analysis. Thus, the selection of proper data acquisition methods is a challenging and crucial step when setting up a clinical workflow study. The choice of data acquisition method highly depends on four aspects:

Purpose of the study: Depending on the purpose of the study the questions of '**Who What Which Where When**' are answered to aid proper data acquisition. An example is given to clarify the concept. If evaluation of the performance of an enhanced sealing device for resection of parenchyma is the aim, the performance might be gauged by measuring 1) the total time spent on performing the required resection, and 2) the amount of bleeding to be suctioned by the surgeon. For the time registration, the required data are determined as follows: **Who**: Not important, **What**: Resection time (cut, suction and coagulation), **Which**: Sealing device, **Where**: Parenchyma, **When**: From when resection starts until ends. For the bleeding amount the questions are answered as follows: **Who**: Surgeon, **What**: Suction, **Which**: Sealing device, **Where**: Parenchyma, **When**: During the total duration of suction.

Granularity level: Data acquisition and granularity levels are interconnected. Data acquisition is done based on how detailed the granularity is defined and to which level the data is required. For example, if a level of granularity as high as recording the spatial motion of a surgical instrument is required, manual data acquisition is not an option.

Modelling approach: The choice of modelling approach can affect the choice of data acquisition methods, e.g., if a top-down approach is used, only manual data acquisitions are likely to be suitable.

Benefits and drawback of the available methods: See Figure 1 and Table 2.

Model representation

The way a description of a surgical process model is represented largely determines how and how easily the results can be interpreted and used for further work. Model representations can be categorized as descriptive or as numerical. In **descriptive representations**, the behaviour of a system is described using plain text as a list of encountered activities, e.g., [2,20,48], surgical milestones, e.g., [49], etc. In **numeric representation** the behaviour of a system is modelled using numbers, mathematical relations or programming languages. Any type of formal (e.g., Petri net, CSP), e.g., [50] and semiformal (e.g., XML, UML,) e.g., [14,27,51] languages, business process languages (e.g., BPMN, BPEL), e.g., [52], workflow diagrams e.g., [15,53] and workflow modelling language (e.g., YAWL), e.g., [54] is categorized as a numeric representation. The choice of model representation depends on:

Purpose of the study: Purpose of study determines how and to what extent qualitative or quantitative analysis of the surgical procedure is required. As each model representation provides different possibilities for analysis, the proper model representation should be selected in line with the purpose of the study.

Data acquisition method: Numeric representations can be based on both manual and computer-based data acquisition, whereas descriptive representations are usually based on manual data acquisition.

Benefits and drawbacks of different model representations: Descriptive representations are usually easier to comprehend and more easily accessible, but they often need to be accompanied by numeric representations for further analysis. The relations between the entities in a workflow are not fully provided in the descriptive representations. On the other hand,

numeric representations provide the detailed relations between entities and provide the means for simulations and qualitative analyses, but at the cost of reduced flexibility and great initial efforts.

Modelling approach

There are two main approaches for modelling surgical procedures: top-down and bottom-up [21]. Top-down modelling (applied by, e.g., [15,53]) starts from the highest abstraction level (with lowest granularity) and works down to the lowest abstraction level (with highest granularity). An overview of the entire procedure will first be formulated and the details of the procedure are modelled in increasingly higher levels of granularity, following the desired granularity levels. Bottom-up modelling (applied by, e.g., [2,19,40,43,55,56]) starts from the lowest abstraction level (highest granularity) and then up. Low-level data (e.g., from computer-based technologies) is used to extract meaningful data at the desired granularity level. Much like the selection criteria for the aspects discussed above, the selection of a modelling approach depends on:

Data acquisition method: Data acquisition methods differ for top-down and bottom-up approaches. The top-down approach relies on manual data acquisition, whereas the bottom-up approach can receive data both from manual and computer-based technologies. A top-down approach is usually based primarily on manual data acquisition, because computer-based technologies often acquire data primarily at the highest granularity level. In the bottom-up approach, transferring low abstraction level data to high abstraction level information requires conceptual information about the procedure.

Granularity level: Selection of the modelling strategy might be preferred to bottom-up approaches, when modelling requires data at very high granularity level (e.g., biomechanical properties of the tissue). Such low-level information is usually obtained from computer-based data acquisition [22].

Benefits and drawbacks: The top-down approach brings understanding of the entire procedure at a high level of abstraction, which reduces the likelihood of inaccurate identification of the lower abstraction activities. However, as the low-level data are initially not modelled, the high level tasks might be identified or described inaccurately due to a lack of profound insight into the procedure. The bottom-up approach has the advantage of having a higher resolution in the data gathered at the lowest abstraction and can therefore be more precise. Yet, because in a bottom-up approach a global overview of the procedure is not established at first hand, identifying the high-level tasks from very low-level information is usually complex and the results might not accurately resemble reality. In top-down approaches, the designer skills and possession of a good overview of the procedure are of great importance to properly break the procedure into meaningful components [21]. However, in the bottom-up approach conceptual information about the procedure is sufficient to start the modelling based on the acquired data and selected model representation principles.

Generalization

Each treatment is a unique procedure. In order to develop a generic model that describes a surgical procedure with all its variations, acquiring data from sufficient individual procedures with one or more similar characteristics is necessary. The observation results from individual procedures are combined into a generic model. Depending on the aim of the study, the level of generalization of the model may vary. The heterogeneity of the data collected directly affects generalizability of the resulting model. If the purpose of the study is the analysis of the procedure model of a general treatment method composed of broad ranges of techniques, the data set should contain sufficiently many registrations of sufficiently many differently executed techniques within the procedure to reliably capture all its variations. Furthermore, the patient condition heterogeneity influences the generality of the procedure model; if all patient conditions are similar, the model establishment is most probably biased. Apart from heterogeneity of data, the way the model is analysed also defines the level of generality. Analysis of the model can be aimed at covering either all the events or only the most probable events in the same population of the treatment procedures.

After determining the sequence of activities and modelling each individual procedure, either descriptive or quantitative, through a top-down or a bottom-up approach, the generalization of the procedures can be done by merging the sets of individual models. For merging sets of procedures, similarity metrics need to be taken into account. Neumuth et. al. suggested granularity similarity, content similarity, temporal similarity, transitional similarity, and transition frequency similarity as possible similarity metrics [57]. Statistical analysis can be employed for merging of the individual models when the modelling language supports the quantitative analysis. In statistical

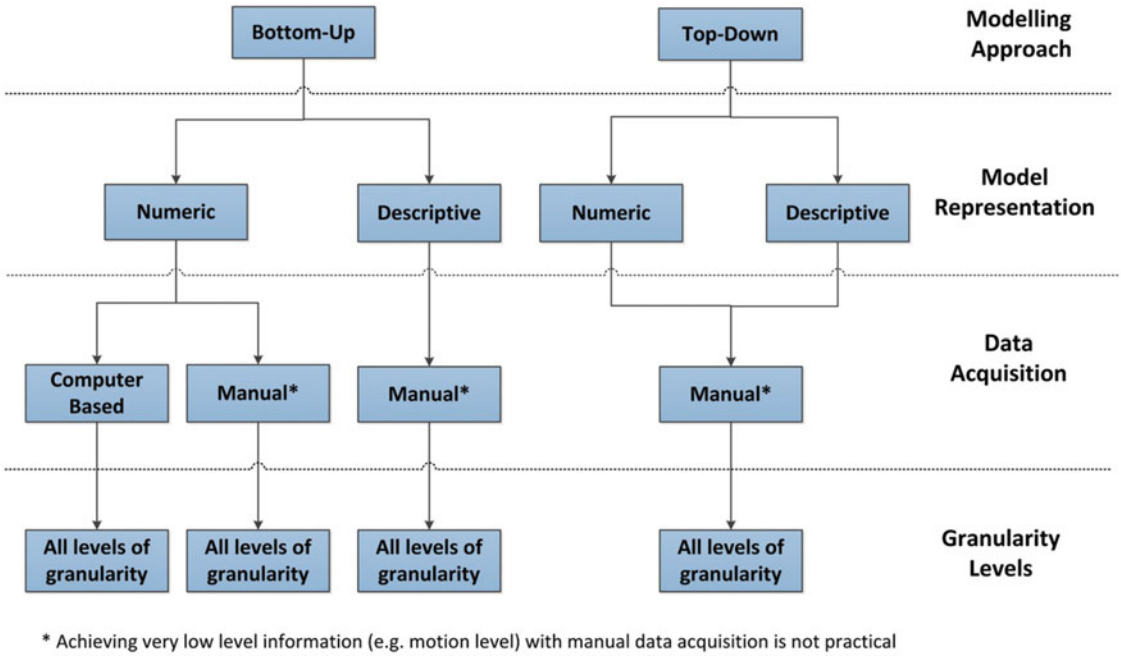

Figure 3. Chains of modelling strategies and their compatible aspects.

analysis the intermittent events can be filtered out or be considered as an event with low probability and the most frequent events forms the backbone of the general process model [21,56]. Depending on how big the dataset is, data mining and data warehousing techniques may aid the establishment of the generic surgical procedure model [58,59].

Figure 3 is a compact guide for designers of or researchers on surgical process models and demonstrates what aspects of the modelling strategies concepts are compatible with each other and shows how categories of these concepts are related to each other. Depending on the purpose of study and the available resources, the designer can select one of the possible chains of modelling strategies proposed in Figure 3.

Modular design

In order to propose a structured model of a surgical procedure and increase the usability and efficiency of such a model, designing it in a modular way can offer great benefits. In a modular design, a system is composed of components (modules) with specific functionalities. Each module can work independently and interacts with the other modules in the system. Although application of modular design in the development and analysis of a surgical procedure requires great initial design effort, it brings several advantages, such as:

- Data acquisition of the desired part of the model is facilitated as each module can be treated separately. In case of observation several observers can work in parallel, while each observer is responsible for one or a few modules for data acquisition. This decreases the workload per person, which results in higher-quality data acquisition.
- Analysis of the desired part of the model becomes more efficient as each part of the surgical workflow can be modelled with minimal dependency on the other parts. Thus, analysis can easier be focused on individual modules without missing relevant information.
- Modules can be used in the description of several types of surgeries when they share the same goal in parts of their procedures.
- When using the surgical process model as a basis to improve the surgical procedure, several designers can work in parallel, each responsible for the improved design of one or a few modules.
- Updates and changes in the model (because of future technology advancements, etc.) can be easily implemented as the designer only needs to adapt the specific modules or add new modules to the surgical process model.
- Testing and error detection are easier because the modules can be treated as black boxes or isolated sub-systems.

Validation and verification

Any developed surgical workflow model should be verified and validated. Although verification and

validation are sometimes interchanged, these are in fact two different concepts. Verification confirms that the model is developed *right*, i.e. it confirms that the developed model reflects the real procedure in clinical practice. On the other hand, validation confirms that the *right* model is developed i.e. it confirms that the developed model suits the purpose of the study and analysis.

The datasets for verification and validation may be obtained from different sources, such as computer simulations, phantoms, simulated OR procedures and real OR data. The data from computer simulations, phantoms and simulated OR procedures provide flexibility at the cost of only delivering artificial data. Data from real OR procedures are more difficult to obtain and less flexible, but are the data closest to reality.

Qualitative and quantitative approaches can be used for verification and validation. How and to what extent qualitative and quantitative verification and validation are to be carried out may depend on the properties of the developed model. For example, assume that a surgical workflow model is developed which covers an entire treatment procedure and offers the order of the steps in a surgery. Then, a qualitative approach can be used to confirm that all datasets fit the path options offered by the established workflow. Next, a quantitative approach would be applied to confirm that the sum of the individual durations of all workflow elements encountered during a procedure equals the total procedure time [15].

Example of modelling strategies applied in practice

To show how to use the presented concepts in a real situation, we discuss an envisioned clinical study on evaluation of AI in the operating room. The laparoscopic procedure is to be performed in a novel hybrid OR containing a robotic system that supports the task of insertion of trocars. The OR is equipped with a navigation platform consisting of a planning software that assists the surgeon by suggesting suitable locations for trocar insertion. This platform uses machine learning to compare the data of patient conditions with data-sets from previous surgeries to be able to suggest more accurate locations. We would like to analyse the performance of this novel system, evaluate its benefit over conventional manual trocar placement and determine how we can efficiently improve the system for clinical use. The locations of the incisions for the trocars should be planned depending on the target organ, where the tumour is located in the organ and other limitations, such as patient physical condition and clinical history. It is important that clinicians can be easily involved for validation of the workflow and in the decision-making for further improvement of the technology in the system or the workflow for using the system. In order to analyse the effect of this system on the procedure, several research questions should be answered, and some of them quantitatively:

Q1 - How does the system affect the outcome of laparoscopic surgery?

Q2 - Does the system benefit insertion of trocars? If so, to what extent?

Q3 - Which activities in performing trocar insertion are affected by this system? How large is the effect?

Q4 - Are there any effects of this system on other actions in the procedure? If so, in which actions and to what extent?

Q5 - Can usage of system be improved to achieve better outcome of the procedure? Which actions are useful to be improved? How those actions are optimised? And how much is the effect of the improvement on the procedure?

These questions may individually require different modelling strategies, as described next.

A) Granularity level: For each of the research questions stated above, the optimal granularity may vary:

A1 - As the effect of the system on the entire procedure is needed, the granularity level is defined very low, at the level of the entire procedure.

A2 - Purpose of the study is evaluation of the outcome of insertion of trocars when the system is in use. Therefore, insertion of trocars can be treated as a black box step composed of several activities sharing the same goal, but with only its end result being of importance. Therefore, an 'inserting trocars' step is defined, and the granularity level is chosen at the step level.

A3 - The robotic system and navigation platform affect the physical activities and planning involved with insertion of trocars. In order to determine the influenced activities and the extent of influence, a more detailed granularity level than in 1 and 2 is required. If the effect of using robotic arms in performing the tasks on the biomechanical properties of the tissue is required, a very high granularity level is selected. If the impact of using the system on the duration of planning is needed, a lower granularity level is sufficient.

A4 - Depending on how abstract all actions are defined in the procedure, different granularity levels (very high until entire procedure) could be suitable. However, in its broadest formulation, a very high

Figure 4. Granularity levels used in the study, from lowest level to highest level, from left to right, respectively.

granularity level is required, with maximum detail and knowledge of all detailed actions and decisions in this procedure.

A5 - The system can be improved either through technical developments or by improving the flow of the system usage during the procedure in clinical practice. Different granularity levels can be determined in analysing which actions can be improved, how and how much. Furthermore, the analysis of the effects of the improvement on the system can be done on all activities in the procedure (as discussed in A4), or only focuses on the set of activities for inserting trocars (like in A2 and A3).

Based on the arguments above, the granularity levels which we would choose in this study are shown in Figure 4.

B) Data acquisition: Data acquisition is dictated by the aim of the study, available resources and the benefits and drawbacks of each method. In this study, data acquisition can be selected as computer-based or manual. However, as manual data acquisition is more readily available and the required granularity level is reachable by manual data acquisition as well, we opt for manual data collection.

C) Model representation: For the quantitative analysis of the workflow, numeric modelling is required. Workflow diagrams can be used for a numeric representation. Workflow diagrams are flexible, the relations between the actions are provided and the model is more understandable for involved experts with different backgrounds (e.g., medical doctors and engineers). Modelling the relationships between different entities of the procedure, which is provided in the workflow diagrams, is a point of great use in such a study. These relationships aid analysis of the system improvement by performing simulations to enhance the flow of usage of the system and its development. When the relationships are modelled, supervised machine learning can also be efficiently done by the navigation system for data collection and data analysis.

D) Modelling approach: As the required granularity level is not very high and we are looking at a specific task (inserting the trocars), it is more natural to first set the boundaries for the inserting trocars step and from there work down in the levels of abstraction: top-down approach.

E) Generalization: Based on the defined granularity levels, selected model representation principles and modeling approach (A, C and D), and the data acquired by the selected data acquisition methods (B), each of the entitled procedures are analysed. In generalization, the individual procedures can be analysed and then combined into a generic model. However, in the top-down approach as the procedure is mostly formulated based on overview of the designer, that is not mandatory to model individual procedures to establish the generic model. Based on the similarity metrics, the model representation principles and the defined granularity levels, the generalization process is specified. In this study as the aim is to anaylse the effect of the system on the procedure, infrequent tasks are useful to be considered in generalization process.

So far, the proper modeling strategies are selected. The data acquired from the selected data acqusition method and proper analysis are used to establish surgical process models. In this show-case, we acquired data from Oslo Unversity Hospital, Norway (OUH) and Erasmus Medical Center (Erasmus MC), The Netherlands, to establish the workflow of laparascopic liver surgery, see Figure 5.

In this study, verification and validation both can be done based on data and/or by interviewing experts. However, verification and validation should be taken care of differently:

Verification: The clinical team experience and the data from different sources (e.g., real procedures, phantom or simulations) will aid in verifying that the model resembles the clinical performance. Depending on the granularity levels and the entities definitions, the data should be acquired and registered for each and every entity of the procedure to be used for quantitative and qualitative verification.

Validation: Validation confirms that the developed model suits the purpose of the study and analysis. Answering the questions 1 to 5 above requires being able of quantitatively analysis of the modelled procedure and the possible corresponding simulations. The entire logic of the modelling can be tested and validated by data from different resources or generated artificial data for different entities of the procedure. In contrast to verification, in validation the data may not be necessary for all entities when the same logics are used for the model. Validation can be done by

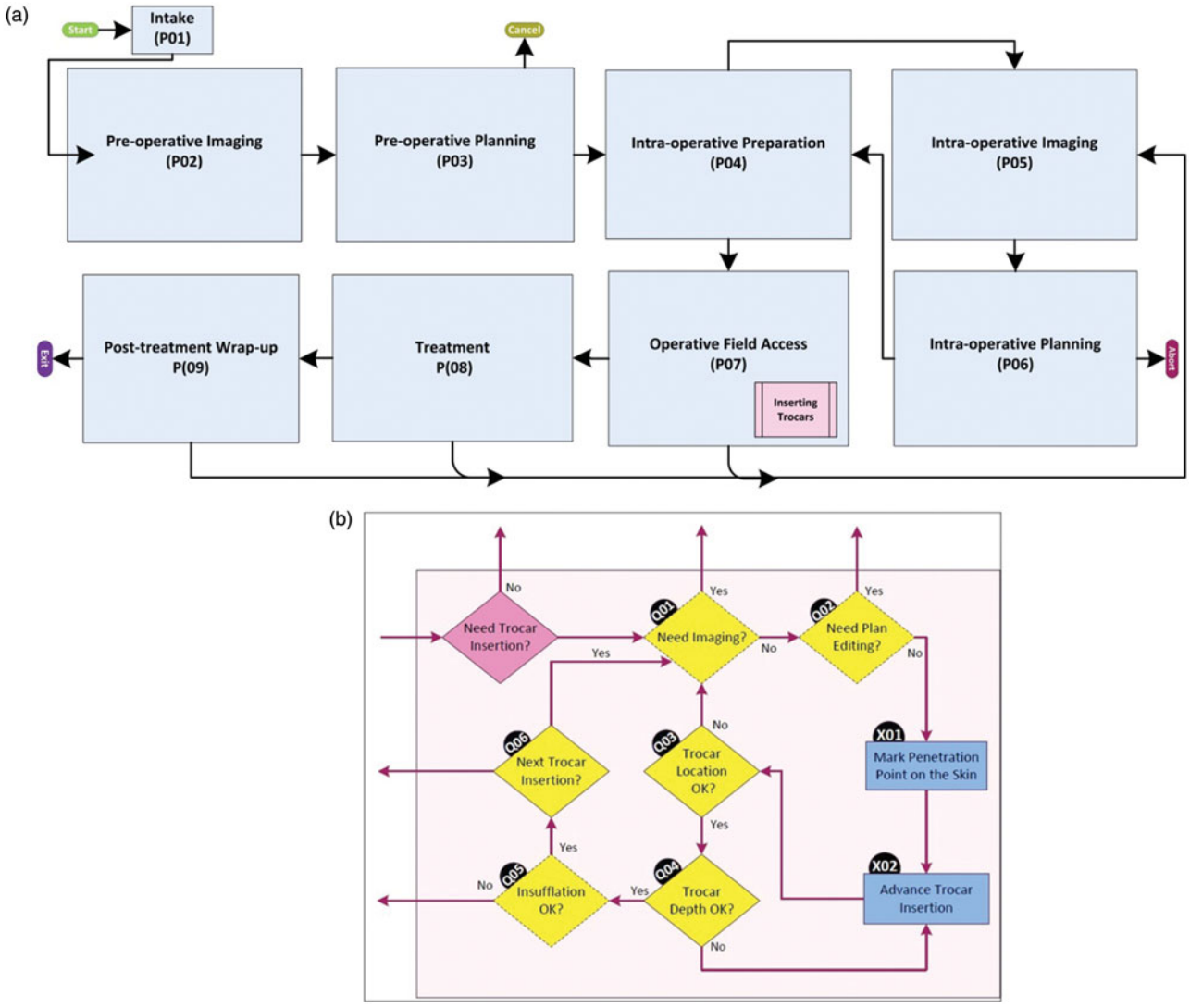

Figure 5. Workflow diagram of the laparoscopic surgery (a) at phase level and (b) at activity level for the "inserting trocars". The data was obtained from online and offline observations in OUH and Erasmus MC.

experienced researchers in the field of surgical process modelling.

Discussion

The aim of this review-based guide was to aid selecting the proper modelling strategies depending on the purpose of analysis and the surgical procedures to be studied. Different relevant concepts in surgical modelling strategies and the criteria for selecting the most suitable modelling strategies for a study were described. For each of the involved concepts, the benefits and drawbacks, and dependencies of the aspects in different concepts to each other were explained in a step-wise manner (Table 2).

The current study was limited to process modelling in the surgical field, whereas workflow modelling approaches in other fields may very well offer valuable additions. Furthermore, employing AI in surgical process modelling was discussed, however how to employ AI in the field of analysis of surgical procedures should be investigated in more detail. However, within the bounds and limitations of this study it was shown that the selections of the proposed aspects in modelling approach are independent of choices in model representation (Figure 4). Top-down and bottom-up approaches can both use descriptive and numeric representations and vice-versa. On the other hand, selection of a modelling approach and model representation can depend on the data acquisition (and vice-versa); e.g., computer-based data acquisition normally works with bottom-up modelling [22] and numeric representation, and top-down approaches and descriptive representation can normally work with the data from manual acquisition methods. Different granularity levels can be acquired from

different combinations of concepts. However, there are limitations: e.g. using a manual approach is mostly not very practical in combination with high granularity levels.

The presented benefits and drawbacks of different methods for data acquisition shown in Figure 2 and Table 2 can be used during workflow study design for proper selection of combinations of modelling approaches and model representations. Overall, selection of the proper modelling strategy is primarily dictated by the aim of the study and the available resources. However, the concepts are interconnected and the selection of one aspect affects the selection of the others. Being aware of the benefits and drawbacks of each aspect can aid selection of the most suitable modelling strategy for satisfying the aim of the modelling study.

Conclusion

Surgical process modelling is an innovative approach to establish a firm base for analysis of various aspects of surgical procedures and paves the way for further optimization and improvement of the procedures. Surgical process modelling allows for evaluating the introduction of new technologies and tools prior to the actual development and is beneficial in optimization of the treatment planning and treatment performance in the operating room. This potentially saves considerable cost and effort compared to trial and error development. Therefore, surgical process modelling can potentially aid development of technologies and tools to satisfy the requirements of actual usage experience in the clinical practice.

Concepts underlying surgical procedure modelling were discussed and different modelling strategies clarified. The advantages and disadvantages of these strategies and their corresponding methods were discussed. The criteria of selecting and using the most suitable modelling strategy were explained and clarified through examples. The purpose of a study largely determines the selection of the most suitable modelling strategy.

AI benefits surgical process modelling and also can benefit from surgical process models. In this study we provided an example of how the required analysis for surgical process modelling could be done and discussed how evaluation of AI in the operating room can be performed by employing surgical process modelling concepts.

We discussed how the selection of modelling strategies can be aided by applying the provided criteria. Applying modularity may facilitate and improve the efficiency of surgical process modelling studies and subsequent updates and analyses. Combinations of top-down and bottom-up approaches for establishing a surgical process model allows taking advantage of the strengths of both modelling approaches. Similarly, different data acquisition methods could be combined to overcome their individual limitations, achieving a solid, accurate and efficient data base. Overall, the current review illuminates the importance of surgical process modelling for improving different aspects of treatment procedures and provides an overview of various modelling strategies that can be used to establish surgical process models.

Declaration of interest

No potential conflict of interest was reported by the authors.

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