# IWISH - Intelligent Workflow optimization and Intuitive System interaction in Healthcare

# DELIVERABLE D 1.1

## Use case descriptions and clinical State of the Art analysis

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## HISTORY

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## Deliverable review procedure:

- **2 weeks before due date**: deliverable owner sends deliverable –approved by WP leader– to Project Manager
- **Upfront** PM assigns a co-reviewer from the PMT group to cross check the deliverable
- **1 week before due date**: co-reviewer provides input to deliverable owner
- **Due date:** deliverable owner sends the final version of the deliverable to PM and co-reviewer

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# 1 Introduction

## 1.1 Aim of the activity

The goal of this document is to provide a description for the selected clinical areas which are; interventional cardiology (Cathlabs) and surgery (operating rooms) and the selected uses cases. The selected use cases are: UC1: Workflow monitoring and analysis to improve Operation Room efficiency during gynaecology and liver oncology, UC2: Efficiency improvement in the catheterization laboratory for cardiac procedures, UC3: Improve Hospital and Operation Room efficiency and workflow optimization for kidney transplantation, and haemorrhoid, UC4: Intelligent Resource Allocation in Operating Rooms.

The clinical area descriptions and the use cases form the basis for the general description of the current workflow, current challenges and opportunities. Then detailed state-of-the-art analysis will be performed to identify key innovation areas and how the clinical use cases will be improved. The documents form the basis for the requirements to be defined in Task 1.2 and will be used as reference in prototype development, piloting and evaluation.

The descriptions are based on open literature and the knowledge provided by the clinical partners in the project. Each of the targeted clinical areas is described in a standardized way. In the first section, a short introduction is given that provides the background & context of the clinical area. The second section describes the clinical state of the art and the third section reviews the current process flows with its bottlenecks and inefficacies.

## 1.2 Contributors

| Use case | Section | Authors |
|---|---|---|
| 1 | Workflow monitoring and analysis to improve Operation Room efficiency during gynaecology and liver oncology | LUMC, New Compliance |
| 2 | Efficiency improvement in the catheterization laboratory for cardiac procedures | TUD, Philips |
| 3 | Improve Hospital and Operation Room efficiency and workflow optimization for kidney transplantation and haemorrhoid | Mia Technology, ARD group |
| 4 | Intelligent Resource Allocation in Operating Rooms. | Workforce Optimizer |
| | Overall editor | LUMC |

## 1.3 Glossary

| | |
|---|---|
| AI | Artificial Intelligence |
| CAS | Context Aware System |
| Cath lab | Cardiac catheterization Laboratory |
| GDPR | General Data Protection Regulation |
| HIS | Hospital Information System |
| OR | Operating Room |
| MIS | Minimally Invasive Surgery |
| RFID | Radio Frequency Identification |
| RGB | Red/Green/Blue (camera) |
| RMSE | Root mean squared error |
| RTLS | Real-Time Location System |
| SP | Surgical process |
| SPM | Surgical Process Model |
| SW | Surgical workflow |
| SWA | Surgical workflow analysis |

# 2 Clinical areas

## 2.1 (UC1) Workflow monitoring and analysis to improve Operation Room efficiency during gynaecology and liver oncology

### 2.1.1 Introduction

Hospitals are continuously under pressure in terms of costs, time and patients to be treated. This is caused by the ageing population, the increased amount of possible treatments and the high costs of healthcare at the OR (Dexter, 2003). A significant part of the costs of a hospital is comprised of the costs of the OR department. Therefore, these departments are always looking for ways to improve in order to reduce these costs.

The planning and workflow is at the base of the processes at the OR. Inefficiencies are present in every process, also in the planning and workflow of a hospital. An example is the delay of the start of clinical procedures at the OR. The frequency of delayed starts for surgeries in Dutch academic hospitals is reported to range between 54% and 74% with mean absolute delays ranging from 16 to 36 minutes (van Veen-Berkx, 2016). By taking the average costs per minute of OR time, the possible savings can be estimated. The average costs for one minute of OR time at a Dutch hospital are about 20 euros. This number contains all cost, both fixed and variable. Using this number, we can make a rough estimate for possible cost savings. When only 5 minutes are saved during all procedures on a 20 rooms big department, the total amount of yearly savings can add up to 1 million dollars per medical institution (of 20 rooms) per year. This is calculated by considering an average of 2 procedures per OR per day and a total of 260 days of full OR use. These numbers cannot be used as a direct guideline for possible savings; these costs are an average for all types of surgery and can differ between hospitals. However, it does offer an indication for the possible effect of time savings and the scale of the financial benefit.

An analysis method is essential to find inefficiencies in processes and to measure the effect of improvements (Joerger, 2017). Adding to that, Bardram et al (2010) wrote: "accurate knowledge about the progress of an operation is essential for coordination in an OR suite on a large hospital, which again has significant impact on efficiency". Hospitals do have software that is used for management of data for operating procedures. However, these systems often rely on manual data, and manual input is prone to human error. Next to that, it is labour intensive. The more data to be collected, the more time it takes for medical personnel at the OR. It is evident, that there is a need for automated and unbiased data collection about surgical state and progress. This data can be used for interoperative and retrospective analysis (Garbev, 2015).

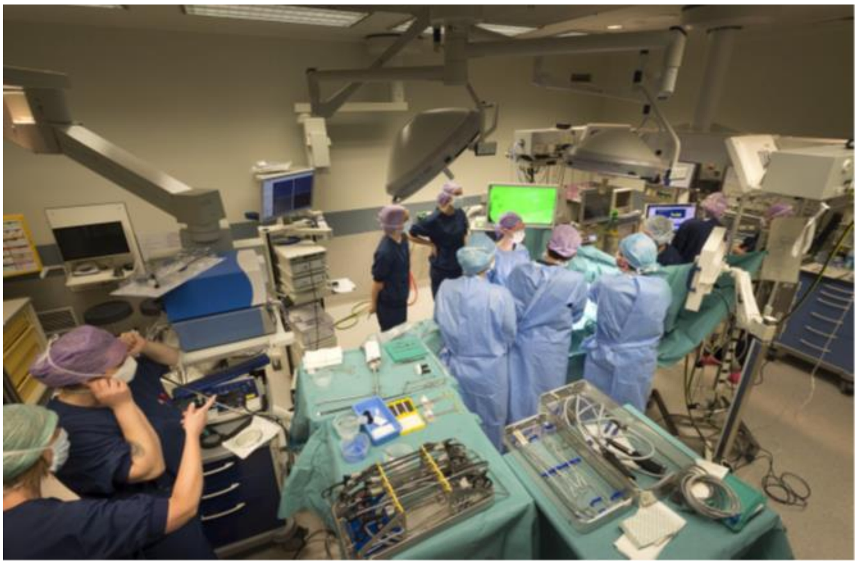

*Figure 1: An example of an OR at the LUMC. Surgical procedures have become more complex, more tools and equipment are used. Processes change and inefficiencies sneak in easily.*

Improvements can come from a Context Aware System (CAS) in the OR. This system will understand the context of a surgical procedure, but such a system will rely on action or phase recognition. This type of system can provide assistance to a surgeon in the form of providing information that is relevant during different phases of a surgical procedure. Surgeon distraction causes safety issues (Padoy, 2015). Adding a quote of Katic et al.: "The rise of intra-operative information threatens to outpace our abilities to process it. Context-aware systems, filtering information to automatically adapt to the current needs of the surgeon, are necessary". Next to that, communication and teamwork problems are reported to account for 52% of all disruptions in a surgical procedure (Wiegmann, 2007). A CAS could aid in tackling these issues. Collecting all information at the OR in combination with surgical context awareness can aid in dynamic scheduling. This enables not only the improvement of procedures but can also bene t the efficiency at a department wide level.

### 2.1.2 State-of-the-art analysis

The analysis of surgical processes and their progress, by recognising different activities or phases, has been the subject of many research projects. Different approaches have been investigated to tackle this problem. Below a brief overview will be given of methods that have been used in research.

Surgical tool tracking:

The tracking of tools and instruments forms a significant part in the field of surgical process analysis. Different techniques have been used to derive information about instrument use. Optical markers have been used in research for tool tracking. This required medical tools to be equipped with these markers to be detected (Zhang, 2017). Lesser-known techniques such as ultrasound have been used as well. Objects or humans can be tracked with an ultrasound system when they are equipped with a beacon. This technique can image the three-dimensional position of the ultrasound marker (Stoll, 2005). Analysing solely the activation of an electrosurgical device proved to provide enough information to estimate the remaining surgery time (Guédon, 2015). Using only the binary use data picking instruments from the surgical table proved to be sufficient for the detecting of seven labels that are related to surgical workflow (Bouarfa, 2009).

The work of Bardram et al (2011), used a Real-Time Location System (RTLS) to recognise seven phases in a surgical procedure. The RTLS system functioned by having personnel wearing RFID tags. These tags were used to determine their location based on triangulation of these tags. The instruments were equipped with RFID tags as well to detect their usage. This system is able to recognise seven procedural phases for a laparoscopic appendectomy with the recognition accuracy ranging from 0.5 to 1.0, with an average of 0.77 for all phases together.

Video recordings:

Next to tool tracking with the use of sensors, a combination of video recordings and object detection algorithms are also used to track tools for surgical activity analysis. In this case, algorithms detect the different tools that are used. During Minimally Invasive Surgery (MIS), the surgeon performs a surgical procedure using small incisions instead of a large opening. A camera is used to present a view of the abdominal cavity. Recording video is inherent to this type of procedures. Next to that, the recordings present a condensed environment with a limited set of variables. Together, this has pushed the development of automatic video analysis in MIS procedures. This technique is also applied to cardiac and retinal surgery (Zhao, 2019).
Human movement in the OR is used as a source of information for tracking surgical progress as well. A combination of RTLS for human movement and RFID for instruments showed good results. But without the data of instrument usage, the video data did not provide a good score (van Veen-Berkx, 2016). This is caused by measurements not being precise enough. It must be noted that this research dates from 2011 and technology has developed significantly. In more recent research, using video data for surgical phase recognition did seem to provide good results. A recognition rate of 70.82% is reported. Adding the information of an RTLS system, the performance is increased to 78.81% (Nara, 2017).
The detection and analysis of human trajectories within the OR is also interesting for surgical activity recognition. Activities are directly related to movement. However, the amount of research on this topic is limited. An area that does start to generate more attention is Human Pose Estimation. It has taken benefit from the development of Computer Vision algorithms (Toshev, 2014). This technique is also applied to the complex environments of ORs (Srivastav, 2018). Instead of relying on sensors installed in the OR equipped to humans, the data of human poses are generated from a distance, see Figure 2. Without influencing the process. The scores for the accuracy range from 73.70% for the average of all body parts to a maximum score of 97.90% of single body parts.

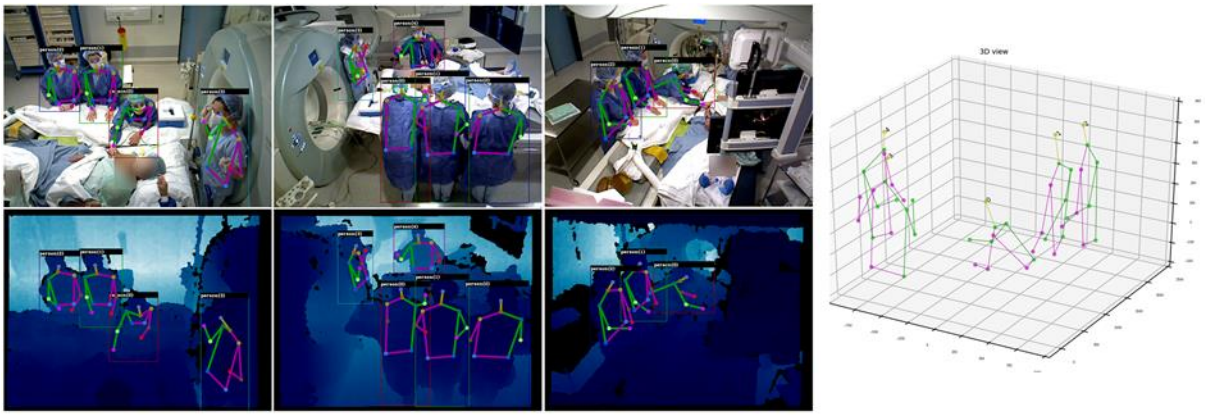

*Figure 2: This image shows the areas defined for the MVOR video data. Cameras 3 is used, because it has the best overview. The areas are left and right of the bed, for persons directly performing the surgical activities. An area above the scanner is to detect personnel when scans are made. The area outside the surgical area and below the bed is where nurses are mostly active and where other activities take place that are not directly related to surgery.*

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## 2.2 (UC2) Efficiency improvement in the catherization laboratory for cardiac procedures

### 2.2.1 Introduction

With the expected increase of the prevalence of cardiovascular disease in the upcoming years, the demand of the catheterization interventions will also rise. By 2035, more than 45.1% in the US population is predicted to have some form of cardiovascular disease (Benjamin, 2018). The growing volumes and health care costs will put a strain on hospitals and health care providers, as more individuals need to be treated with the same resources. Therefore, there is a growing necessity to optimize the efficiency in cath labs.

**Surgical process modelling and workflow analysis for catheterization intervention**
To enable optimization of efficiency, a complete overview is needed of the clinical workflow. Current approaches in literature are mostly focused on the OR optimization, where the mapping of clinical procedures is mainly described using so called surgical process models (SPM) and surgical workflow analysis (SWA). The term “surgical process” (SP) is defined as “a set of one or more linked procedures or activities that collectively realize a surgical objective within the context of an organizational structure defining functional roles and relationships”, whereas SPM is considered “a simplified pattern of a SP that reflects a predefined subset of interest of the SP in a formal or semi-formal representation” (Neumuth, 2009; Neumuth, 2017). A “surgical workflow” is defined as the automation of SPM (Lalys, 2014; Padov, 2010). SPM and SW allow for detection of adverse effects in a procedure, thereby aiding in decision-making, evaluation of skills and improving patient safety and optimizing procedure time.

### 2.2.2 State of the art analysis

Modeling SW is a multi-step process where several aspects must be taken into account. The first step in determining SW is to accurately describe the surgical steps and its level of abstraction for structured data according to different levels of granularity. A procedure is composed of phases, tasks, activities and motions (Lo, 2003). A phase is, by definition, the type of events occurring during the procedure, whereas tasks are defined as “the sequence of activities used to achieve a surgical objective”. An activity is a physical task and a motion is a “surgical task involving only one hand trajectory but with no semantics”. In addition, there is a need for a common ontology for SPM for facilitating the description of the procedure and application of SPM into different surgical disciplines. The chosen ontology and thereby granularity levels form the basis for the mathematical formalization of the process.

Data acquisition
The next step is collecting the necessary data for building the model. The level of granularity determines the complexity of the model: studies may choose to record the entire procedure, or the phases, tasks and motions respectively, or a combination. In addition, one or more actors of the procedure can be studied (e.g. the medical staff that has an impact on the procedure). The time of acquisition can also vary: data can be acquired either pre-operatively, intra-operatively, post-operatively or perioperatively (combination of the three phases) depending on the study goals.
Regarding acquisition methods, two approaches are known: observer-based (manual) and sensor-based (automatic). When an observer-based method is used a human

observer uses either offline recording material (e.g. videos from the procedure) or online recording. Sensor-based acquisition targets extracting information from the procedure and to recognize activities or events. This approach is mostly applied in studies tracking tools (Neumuth, 2012; Padoy, 2008) or operator(s) (Nara, 2009). Some sensors used are motion tracking systems (Ahmadi, 2009), Radio Frequency Identification (RFID) tags (Neumuth, 2013), electromagnetic (EM) sensors (Meißner, 2014), and infrared thermal cameras (Unger, 2014). Other sources such as audio recording (Suzuki, 2012) of the sounds associated with the activation and deactivation of instruments and other apparatus are also used to provide information about the advancements of the procedure.

Both approaches present significant advantages and drawbacks. Observer-based approaches allow for recording of finer details of interventions but are inherently prone to human error. In addition, manual annotation is time consuming and requires an expert surgeon for recording. In sensor-based methods, often alterations are needed in the used medical devices or protocols, which may disturb the natural flow of the interventions. Methods such as video- and image-based analysis can acquire information without disrupting the environment and the flow.

Several studies have provided methods for automatic or semi-automatic data-acquisition which have been tested in variety of clinical interventions. Rather than designing sole algorithms for data processing, other studies focused on inventing specific software for the entire multi-step process of workflow generation.

For generation of process models, different approaches are used mainly implementing statistical models such as Dynamic Time Warping (DTW) (Forestier, 2015; Blum, 2010), Convolution Neural Networks (Al Haij, 2017), Decision trees and its extension Random Forest (RF) (Forestier, 2015), Gaussian mixture multivariate autoregressive (GMMAR) models (Al Haij, 2017), Hidden Markov Models (HMM) (Loukas, 2013), Support Vector Machines (SVM) (Blum, 2008) and latent Dirichlet allocation (LDA) (Primus, 2016). These methods all have their advantages and disadvantages (Tran, 2017) and are thereby chosen depending on the purpose of the study.

Workflow monitoring in cath labs

In the literature, workflow monitoring is mainly applied in the OR and catheterization interventions have only been studied in one article. This study (Hisey, 2018) validates the workflow detection method for a training system (Central Line Tutor) for providing trainees with real-time feedback while learning the procedure of central venous catheterization on one hand. Other studies examined implementing workflow monitoring for management purposes for interventions, and progression and prediction of the surgical phase during a laparoscopic hysterectomy case, based on a random-forest model (Meeuwsen et al. 2019)

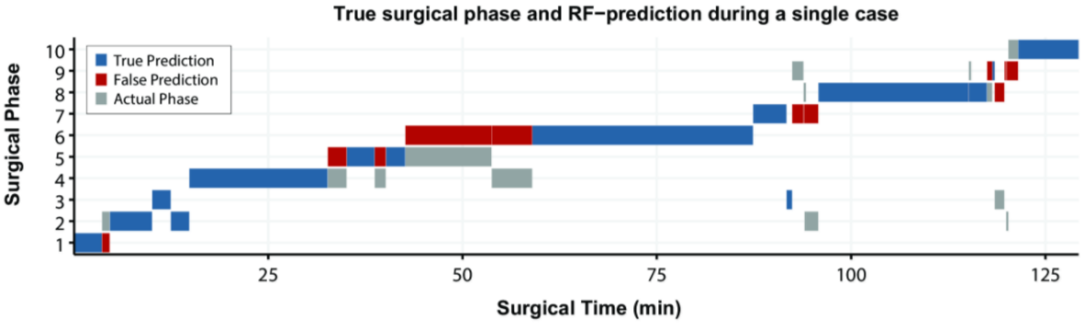


*Figure 3: Visual representation of surgical phase predictions (red, blue) vs actual phase (grey).*

So far approaches mainly focus on specific aspects of the workflow such as detection of the intervention phase and intervention time predictions. For phase recognition at the OR, mostly instrument tracking data has delivered promising results (Meeuwsen, 2018). Franke et al. (2012) proposed an automated model using generalized surgical models (gSPM) for time and resource management in the OR. The process representation is based on Markov Chain Theory, where a partition into intervention phases, tasks and detailed information on the activities is supported. A next study of Franke et al. (2013) focused on low-level activities for the prediction of intervention times, introducing a time prediction algorithm. Although the model managed to predict the remaining procedure time with great accuracy, optimization of this method is necessary to reduce the missed steps in the interventions. Qi et al. (2006) a surgical management information system driven by workflow. This system is semi-automated as no real-time monitoring occurs. Instead, this model creates a predefined task list tailored to a specific surgery, which users need to execute. Based on this information, the duration of the task is recorded.

Although these studies are mostly applied in the OR, insight can be gained into the process of data acquisition and generation of the model for extension to cath labs. For the cath lab approaches that include staff activity and motion, hand motion, spatiotemporal features of staff trajectory or a combination of action, instrument and anatomical structures seem to be viable. Recognition of visual features can also be employed to carry out phase recognition tasks.

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## 2.3 (UC3) Improve Hospital and Operation Room efficiency and workflow optimization for kidney transplantation, and haemorrhoid

### 2.3.1 State of the art analysis

Privacy of data is the main aspect for Ethics and decision-making in an AI system and requires efficient mapping of the relevant inputs and the output decision. Surgical operations incorporate a significant amount of sensitive patient data and a decision-making process should clearly define the stakeholders, facts, goals, values and norms (Rudzicz, 2020).

It is a fact that the intraoperative videos have a positive impact on the performance of practicing surgeons, considering the larger medical audience it reaches and acts as an alternative to live training (Saun 2019). However legal constraints allow fewer cases to be examined.

The Turkish use case focuses on the capturing of intraoperative videos for kidney, gall bladder and haemorrhoid cases and each procedure carries significant data when combined with the information obtained from the Hospital Information System (HIS) including MR images, patient pre-operative data and the status of medical equipment. Obtaining data from medical devices is troubles process for 3rd party applications but determinant data can be obtained for the start and end of procedures. Video analytics for the usage of these equipment and tracking them is an alternative approach for the cases of inaccessibility via data ports. There are several approaches to these analytics including pixel-based approach, block-based approach, neural network approach and Gaussian Mixture Model (GMM) but trained models for the operation type exclusive will be necessary to determine the procedures effectively (Olatunji, 2019).

Cross-view tracking with geometric affinity is a salient approach for operating rooms where across viewing cameras detect the 2D joints of the area and estimate the 3D poses. Enhancing of this approach enable the multi-view tracking for the 3D pose estimation (Chen, 2020).

Natural Language Processing (NLP) carries highly valuable information that can be obtained from audio recordings of intra-operative procedures as well as text analysis. Examples show the significance of identifying the pre-operative risk factors or post-operative follow-up recommendations from the advanced NLP algorithms. Most common model is Google's BERT (Bidirectional Encoder Representations from Transformers) which was introduced in 2019. Its "self-attention" mechanism provides higher accuracy by giving context to each word and relate it to its neighbours (Anteby, 2021). Incorporation of this model in the Turkish use case, especially kidney operations will provide a key role in the start and end timestamps of the main surgery processes.

It is a common desire for developers to obtain as much as valuable data from various sources and evaluate the usability for their solution. However legal structure is a key factor that significantly shape the desired architectures and data flow. The Turkish use case requires processing of personal data of the patients as well as surgery professionals in order to enable an efficient AI based operation efficiency solution. Therefore, data privacy and protection is a major concern for this use-case. The Turkish government has released the Personal Data Protection Law (No: 6698) (Turkish Republic Personal Data Protection Law, 2016) in 2016. Article 3-b clearly states the anonymization of personal data so that the personal information cannot be used to identify a person directly or indirectly by combining with other information. Similarly, The General Data Protection Regulation of EU (2016/679 (GDPR, 2016) has entered into force on 24 May 2016 and applies since 25 May 2018. Recital 26 defines this issue as “data rendered anonymous in such a way that the data subject is not or no longer identifiable”. Therefore, data protection and accountability principles must be fulfilled:

- Lawfulness, fairness and transparency: All data processing modules to be lawful, fair and transparent to the data subject
- Purpose limitation: Collection and processing the data for only necessary purposes specified in Turkish use case
- Data minimization: Similar to the purpose limitation, the collection of data for the target domains and use cases will only contain the absolutely necessary information.
- Accuracy: The personal data will be kept accurate and up to date.
- Storage limitation: The personally identifying data will be only be stored as long as the necessary requirements of Turkish Use case
- Integrity and confidentiality: Security, integrity and confidentiality of the processing.
- Accountability: Authorized ‘data controllers’ will ensure the accountability of GDPR compliance with all these principles.

The legal frame forces AI solution developers to a predilection of either data anonymization or incorporating synthetic data. Deloitte has drawn attention to this matter and recommended a data anonymization process in its paper ‘Preserving Privacy in Artificial Intelligence Applications through Anonymization of Sensitive Data’ by defining the requirements, identifying personal directly identifiable information, determining the potential quasi-identifiers and finally identifying sensitive attributes in order to start the anonymization process (Deloittte, 2022).

Video imaging is under the scope of European Data Protection Board Guidelines 3/2019 on processing of personal data through video devices. (European Data Protection Board, 2020). The guidelines clearly force the CCTV solution manufactures to disband conventional architectures and incorporate stringent and preventive designs. The Turkish use-case requires a mobile surveillance solution with an end-to-end encryption of the camera and network video recorder (NVR) for the data and stream. Furthermore, the operation images are required to be pixelated so that the patient and the medical professionals are not directly identifiable. The Access to the images will only be valid via the mobile imaging platform with four-eyes-principle and time limited Access.

### 2.3.2 Literature

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## 2.4 (UC4) Intelligent Resource Allocation in Operating Rooms

Due to a lack of funding, the clinical centre SingHealth will not be able to participate and contribute to Use Case 4 in the IWISH project. Project partner Workforce Optimizer in Singapore has received test data from a Singaporean hospital, and plans to develop a mock-up training data set based on these test data which will be used to develop their procedure scheduling application. The data consists of multiple relevant interventions in an operating theatre in the hospital. In addition to the abovementioned Use Case 4 plan, the consortium will investigate other opportunities to enrich Use Case 4 with relevant clinical data.

# 3 Conclusions

This document has given an overview of the description for the selected clinical areas and their state of the art. From the descriptions, it is clear that there are still quite some challenges and opportunities to improve the workflow.

Important for the workflow improvement is the automatic collection of data. It has been described that manually collecting data is labour intensive and error prone. Therefore, the process of data collection which is the input for the workflow optimization software, should be as automatic as possible.

In the past, different approaches using tags or other devices have been tried to track people and equipment. Disadvantage is that additional devices have to be attached to equipment or people have to wear tags. Important is that the data acquisition should not interfere with the normal way of working.
In the first three use case, video analysis is mentioned as good alternative to acquire data. Since the introduction of deep learning techniques, the automatic analysis of video streams has become feasible, but still improvement in the recognition is necessary.
With the introduction of the video in the OR or Cathlab, the privacy of personal and patients should be taken into account.