Internet of Things and Artificial Intelligence for Perioperative Tracking Patients: Towards a New Model for an Operating Rooms

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Research Article

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Abstract

Operating rooms management is a critical point in healthcare organizations; inefficient scheduling and allocation of human and physical resources are often present. This study aims to automatically collect data from a real surgical scenario to develop an integrated technological-organizational model that optimizes the operating block resources.Each patient is real-time tracked and located by wearing a bracelet sensor with a unique identifier. Exploiting indoor localization, the software architecture is able to collect the time spent in every steps inside the surgical block. The preliminary results are promising, making the study feasible and functional. Times automatically recorded are much more precise than those collected by humans and reported in the organization's information system. In addition, Machine Learning can exploit the historical data collection to predict the surgery time required for each patient according to the patient’s specific profile. This approach will make it possible to plan short and long-term strategies optimizing the available resources.

Background

Operating Rooms (ORs) are responsible for large amounts of profits and costs [1]. About 60% of all hospitalized patients are treated in the OR [2]. Surgical scheduling is a key process in the perioperative organization; it begins by analyzing a list of daily cases and their expected duration. If cases consistently run longer, OR over-utilization will result in costly overtime pay and staff dissatisfaction. On the other hand, if actual case times are shorter than expected, OR under-utilization will be converted into staff idle time, which is associated with up to 60% higher costs [3]. Case duration prediction is usually demanded by the surgeon, who reserves a time slot. With this method, it has been proven that surgeons underestimate case duration up to 42% of the time and overestimate it 32% of the time [4]. Another common approach is to use the electronic health record (HER) to calculate case duration based on historical data for a given procedure. HER has a higher accuracy [5], but available EHRs only generate case durations for the average patient and do not take into account the patient’s specific profile (e.g. age, sex, body mass index, allergies, comorbidities, etc.). The rise of Big Data offers novel possibilities for patient-targeted predictions by exploiting Machine Learning (ML) and Deep Learning (DL) techniques. In particular, supervised learning techniques are able to identify latent patterns among large quantities of data by training the model to minimize a loss function between the actual output and the desired (supervised) one. The model is afterward able to generalize on unseen cases that belong to the same data distribution. For this reason, ML is also gathering attention in the medicine field for both clinical and organizational purposes notwithstanding we are still in the early phase of this scenario with several challenges to deal with [6–9]. The main issue to exploit ML is providing accurate and noise-absent samples to the model, which is critical when historical data are collected by human processes. In light of this, the aim of our research project is to develop an integrated technological-organizational model capable of exploiting data deriving from ORs to optimize the management and organization of the whole operating block. To achieve such a result, we have first developed an IoT architecture that is able to collect real data to minimize the presence of errors or noise in data in order to maximize the ML performances. After that, we will proceed to develop an optimal scheduler for surgical procedures able to integrate clinical/anamnestic information, data deriving from the analysis of surgical timing, and time spent in the Recovery Room (RR) able to optimize the organization.

Methods

Our research work is a prospective, single-center, interventional study. The study was approved by the Local Ethics Committee (protocol nr. 1284/2020/OSS/AOUPR, Comitato Etico Unico per l'Area Vasta Emilia Nord; NCT05106621, https://clinicaltrials.gov/). Patientes were routinely asked to consent to the use of anonymized aggregate data for research purposes as part of the intake process, as customary at our institution. We checked for expressed consent in patients' medical records; additionally, we attempted to contact survivors to discharge to confirmtheir consent to the use of clinical data for the present study. The project is divided into three phases (Fig. 1):

1. Internet of Things (IoT) for data collection and patients enrolment

2. Machine Learning for time prediction
3. Optimization with discrete-events simulation

In the first phase, we developed an IoT architecture to perform indoor localization of patients in ORs and in Recovery Room (RR). Patients are required to join the study by submitting an informed consent form. If they agree, they are provided with a personal sensor (Bluetooth Low Energy BLE beacon tag) when entering the operating block entrance or in the ward. Tags are detected by Raspberry-Pi devices (detector) that are located in the environment of interest. Detectors communicate with a private Locale Area Network (LAN) in order to manage our data flow and to provide additional security levels. Moreover, in this section we describe the components and our solution for monitoring patients' movements inside the

surgical block. We realized a client-server architecture that provides the communication between the sensor modules and the server in our system. The whole IOT system has several parts that are listed below.

Bluetooth Low Energy (BLE) beacons

BLE is a wireless technology that is widely used when we talk about the Internet of Things (IoT). BLE technology operates on two main channels: advertising and data. For our purposes, we decided to use only the advertising channel in order to detect beacons when they are near to our sensors. For this reason, we adopted the iBeacon protocol from Apple. The iBeacon protocol identifies beacons with a triplet of UUID, major, and minor.

For this prototype we used the BlueUp beacon with 800ms of advertisement time. Each beacon has a unique ID, associated with the patient. The beacon is assigned to each patient and is worn on a noninvasive part of the body. The beacon is worn by patients as a bracelet thanks to a wrist band. Being affixed to the patient's wrist is the best compromise between comfort and signal efficiency.

Sensor Modules

As a sensor module, we used a Raspberry Pi 4 device, running the Raspian OS 64 bit version. The sensor module continually scans for BLE advertisements, checking them against a list of pre-registered beacons provided by the central server. Using a list makes us able to ignore non-registered beacons, saving bandwidth and processing resources. The sensors autoconfigure themselves. They can be rebooted or shutdown at any time. When the sensors receive a beacon advertisement, they append the package received and its timestamp into a json and forward the information to the central server over a Transmission Control Protocol (TCP).

We estimate the patient's presence inside a specific room in the compartment using the residence time within the range of action of the sensor. Every sensor has its own residence time and a tunable threshold of signal sensitivity. This last parameter can increase or decrease the sensor's range of action. If the beacon remains for a certain amount of time in the action range of a sensor, the beacon is marked as entered into the roomFƒƒ.

Central Server

The central server indexes and collects the data coming from the sensor modules. that has the following duties: a) storing records coming from each detector in a MongoDB database; b) coordinating the distributed solution and message exchange using a publish-subscribe mechanism based on MQTT and finally, it exposes a web server that is used as a unique interface between the software architecture and the hospital operators. The central server hosts the eclipse mosquitto based MQTT broker. When it receives the packets from the sensors, it determines whether the beacon is in the room where the sensor is located. Our implementation of the beacon server used a Python-based service and exploited the MongoDB database to store the various detections. The data format is shown in (Table 1**).** The central server also has the duty to send information to the edge modules, regarding the list of pre-registered beacons, the identity of the sensor itself, and a time-synchronization message.

Table 1

Table 1
Data stored by the server, for each sensor, when an entry is recorded in the database

Fields	Description
uuid	Beacon universally unique identifier
minor	Contains the unique beacon id
macAddress	Beacon MAC Address
timestamp	First detection timestamp
last_detection	Last detection timestamp (continuously updated)
flag	Boolean value that id true specifies that the patient is currently in that specific room
identification_code	Unique number assigned to a specific patient

Client Interface

The client interface, hosted by the central server, offers several functionalities. The first one regarding enrollment. The patient enrollment is made by an operator when the patient enters the operating block to have surgery. The enrollment is performed using a tablet device that communicates with the web app, and by providing the necessary information (Fig. 2). The system also provides a graphic interface able to monitor in real-time the various movements of patients (Fig. 1).

Implementation and case study

We schematized a generic path a patient could be subject to inside the operating block (Fig. 3). Furthermore, we drew up a data collection procedure that must be respected to gather the information accurately (Fig. 4) (Fig. 5).

In addition, if the patient agrees to participate in the study we collect:

- data about surgical procedures;
- personal and anamnestic data;
- data from Recovery Room;
- data regarding hospital stay (e.g. Intensive Care Unite (ICU) admission).

Personal data are extracted from the information systems of the Ospedale Maggiore of Parma using pseudo-anonymization techniques

The prototype of the IOT architecture described and illustrated previously was installed successfully in the surgical block and is still functional. We collected data from more than 100 patients. It is possible to see in (Table 2) the final output illustration that we obtain when we combine the data from various sensors and reconstruct the patient's path.

Table 2

Table 2
Table showing the patient’s path owithin the operating compartment with the relative timestamps and time spent in the every rooms

Beacon ID	Identification Code	Room	Timestamp	Last Detection	total_time
3287	PR-0170	Entrance	2022-05-24 07:47:31.988000	2022-05-24 07:51:18.086000	00:03:46.098000
3287	PR-0170	Corridor	2022-05-24 07:51:50.639000	2022-05-24 07:53:03.557329	00:01:12.918329
3287	PR-0170	Operating Room	2022-05-24 07:54:52.586975	2022-05-24 10:59:05.650000	03:04:13.063025
3287	PR-0170	Recovery Room	2022-05-24 11:00:08.795296	2022-05-24 12:54:34.885000	01:54:26.089704
3287	PR-0170	Entrance	2022-05-24 12:54:44.533703	2022-05-24 12:57:04.107000	00:02:19.573297

The second step will involve the application of ML and Deep Learning algorithms to study the feasibility of predicting surgical procedure time by providing the patient’s features and the surgery ones as input. Since a lack of public datasets or similar approaches in scientific literature, we are currently performing a feature selection task among more than 50 variables, to identify which features can maximize the prediction accuracy in terms of Root-Mean-Squared Error (RMSE) of the surgery time. Several ML approaches can be possible since the task of intra-operative time prediction can be modeled in different ways. Since the total time in the Operating block is composed of the sum of the time spent in the OR and the one in the RR, this prediction task can be modeled using two different ML models or a unique one that tries to estimate directly the total time. Moreover, depending on the dataset size Tree-based ensemble models (e.g., Gradient Boosting, XGBoost) could better suit the task. On the other hand, the complexity of the task and the non-linear dependency of several features within the target variable of the time required may require the use of Deep Neural Networks. On one hand, Deep Learning requires a larger data collection but at the same time, it would be possible to exploit its ability to perform Representation learning of the input, requiring less feature engineering.

Once ML is trained to predict the surgery time, we will proceed to step three, which is the use of simulation models of discrete events. In these models, an "event" is an instantaneous occurrence that involves a change in the value of at least one of the system variables. The basic idea of the simulation model will be to evaluate some key performance indexes of the ORs in the current scenario (AS-IS analysis) and then to reproduce new scheduling logic for surgical interventions that allows those indexes to be improved (TO BE reengineering), with an evaluation of the benefits achieved.

Discussion

The use of AI, and in particular ML, is expanding in every area, including healthcare. Many results are now available about the excellent predictive capabilities of these new tools in medicine. Thanks to their use, intelligent tools useful to support healthcare professionals in daily practice will be increasingly available. Their possible exploitation in the health organization is no exception. Liu et al. showed as ML is superior to logistic regression for risk estimation, in the context of hospital performance assessment. Furthermore, similar applications can be found in the context of forecasting healthcare costs, risk of readmission, and hospitalization.[14–17]

The study by Luo et al [18] is also very interesting; ML models are applied with the intent of estimating the risk of cancellation of an operating session, with the negative impact that this entails both in terms of costs and on waiting lists and therefore also translates into delayed access of the patient to surgery [17, 18] Moreover, a novel approach has been presented by Abbou et al.[35]. The authors used data from the electronic hospital register (EHR) from December 2009 to May 2020 for a total of 297,480 interventions from two public hospitals in Israel in this study. They use pre-operative data to predict the duration of the surgery, including: patient clinical data, experience of surgeons, patient nationality, results of analyzes carried out before the operation, etc. They compare the predictions between a naive model and a ML model (Xgboost), comparing various metrics. The Authors deduced that the use of Big Data can certainly be useful for predicting the duration of interventions in the operating room and that ML model performs better than the their naive model.

However, in order to be able to apply these models, it is essential to obtain data with quality and precision. Currently, recording times and patient movements within the surgical block are often made manually by various operators involved and subsequently reported in computer systems. However, this detection method is often partial and most not in real-time. Having the possibility of a direct recording, with the minimum human interference, could allow instead to increase the quality of the dataset and therefore obtain more precise results.[19–21] Furthermore, having a system equipped with the ability to independently record the patient's movements, could be able, in addition to reducing the error rate, to lighten the workload of the operators themselves and indirectly reduce the changeover times between the different patients. [17,21–25] Nevertheless, building a tracking system inside a hospital is not a simple task. Not all hospitals are equipped with the highest technology available. Some are small in size and therefore do not have sufficient resources available to make organizational systems high-tech. Others, despite being larger in size, have old structures in which it is not always easy to implement new technologies. Therefore, we decided to look for a solution that suits our needs, and that could be economical, did not require an expensive infrastructure to rely on, and that could be achievable in most situations.

To understand which technologies were the best for our use case, we decided to analyze several options and constraints. The main constraints encountered were:

- ease of installation
- tracking devices’ battery life

- tracking devices' reuse and cleaning

Considering these major constraints, we analyzed and considered several technologies. The first one we analyzed was RFID, unfortunately, this technology provided for cumbersome structures for tracking and the range of action was limited, which could have brought discomfort to the members of the medical staff. Moreover, the RFID devices' battery life was not enough for our case study. After that, we analyzed UWB, discarded due to the low autonomy that the devices reach. Finally, we decided to adopt BLE tracking devices.

BLE fitted our use case. The detectors are small and easy to install, the devices' range of action is very wide and the tracking devices' battery life can last even a few months. Furthermore, our use case does not involve tracking of healthcare personnel, but only patients.

Building a tracking system using BLE also has economic advantages; it does not burden the hospital budgets and is cost-effective. For all the reasons mentioned above, it was decided to use this technology excluding others. The architecture presented in this way can trace the movements of patients within the OR. Data obtained will form a dataset that can be used to perform ML tasks. By combining the tracking data with those of clinical assessment, it will be possible to create an algorithm capable of predicting the duration of a specific surgical intervention.

The IoT architecture developed in this study will be useful to collect real data about the patients flow in the surgical department. But having solid data and predictions about OR occupancy is still not enough. It is then necessary to create organizational systems capable of using that information. Not being able to transform these results into intelligent tools that can be used in daily practice has been recognized in fact as one of the major limitations that currently hinder the use of these technologies in medicine[26]. To overcome these limits, a simulation model will be developed for reproducing the patients' flow. This model, feed with high quality data, will be used to determine the best scheduling logic, in order to optimize the usage of resources in the ORs. A preliminary testing phase was performed using randomly generated patients' data, in the attempt to check the model effectiveness in reproducing the system, as well as to embody alternative scheduling logics and performance indexes. Results, both in terms of the model capability to reproduce the current system and in evaluating its performance, are promising and, at the same time, highlight potential for improvement in the efficiency of the surgery department, which is the ultimate aim of the project. In a more advanced phase of the research, the simulation and scheduling logics will be supported by the availability of accurate predictions, enabled by a ML model. In general terms, it is expected that an accurate evaluation of the patient's flow (based on real data) and a reliable prediction of the surgery cases (based on the ML model) will make it possible to define an optimized planning of surgical procedures, decreasing, consequently, the unused times of the ORs and hopefully, increasing the number of surgical interventions in a day. This is an innovative aspect of the whole project; indeed, although ML, simulation and scheduling have been applied in healthcare environment, their combined usage opens new ways for process improvement. This approach, thanks to its consistent predictive performance over various forecast intervals, can positively influence the choices of healthcare personnel in the short term and obviously long-term strategic planning[27].

Conclusions

Surgery has a great impact on the health economy; thus the optimal management of the resources destined for the ORs becomes crucial. Considering Literature and our preliminary results, it, therefore, seems possible to assume that the application of AI models in the context of the ORs organization, associated with a patient indoor traceability system, is not only feasible but could also lead to a more targeted organization (Fig. 6**)**[28, 29].

Declarations

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Ethics approval: The study was approved by the Local Ethics Committee (protocol nr. 1284/2020/OSS/AOUPR, Comitato Etico Unico per l'Area Vasta Emilia Nord; NCT05106621, https://clinicaltrials.gov/).

AUTHORS CONTRIBUTIONS: All authors contributed to the study conception and design. Eleonora Bottani, Valentina Bellini, Monica Mordonini, Michelangelo Craca, Elena Bignami prepared figures. Eleonora Bottani, Valentina Bellini, Mattia Pellegrino, Monica Mordonini, Gianfranco Lombardo, Beatrice Franchi prepared tables. All authors reviewed the manuscript.

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Figures

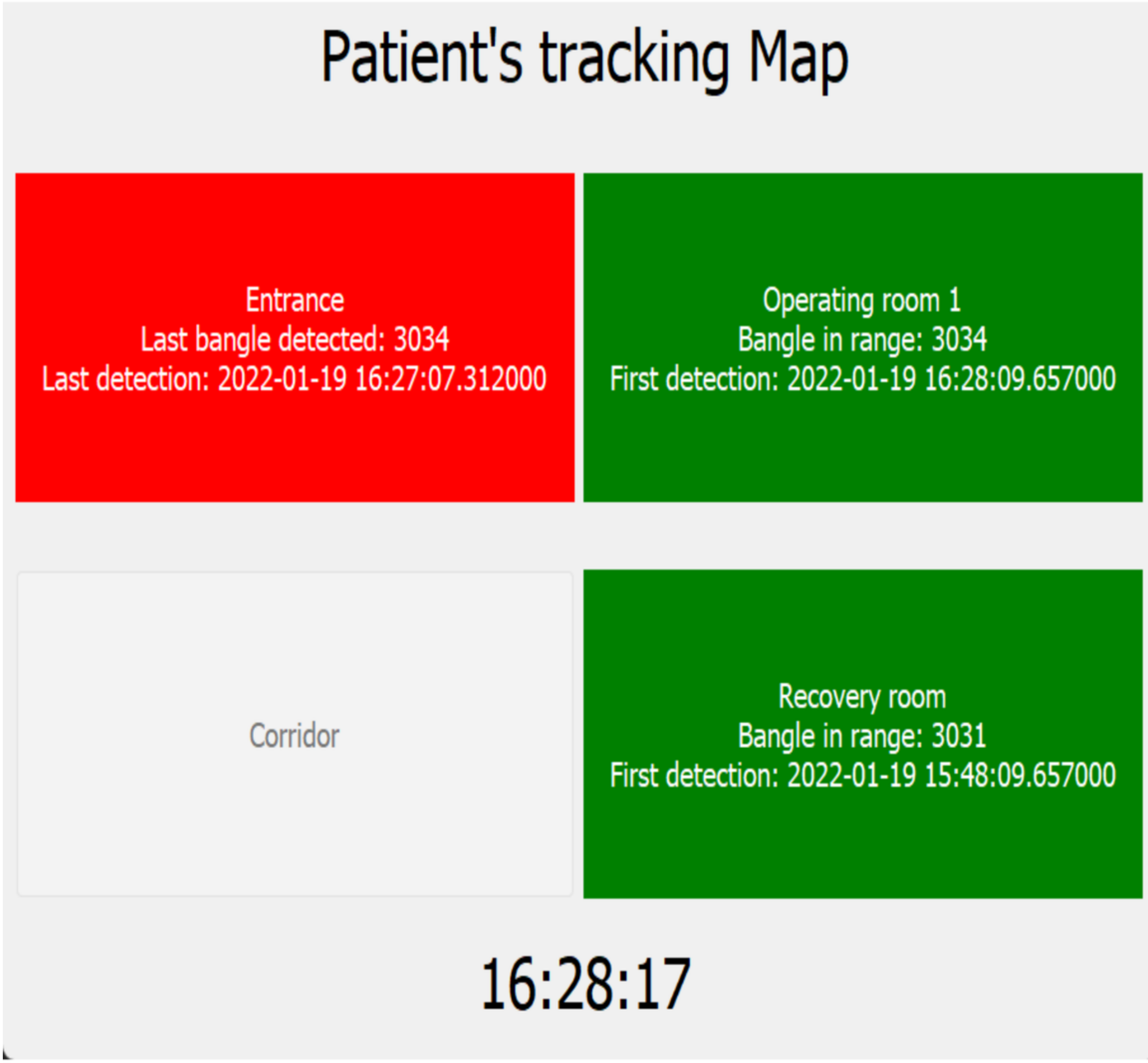

Figure.1

Figure 1

Home page of the web application responsible for the bangle-patient association

Figure.2

Figure 2

Graphic interface for monitoring the patients’ movements inside the operating compartment. A green color of the cell means that the patient is near the sensor that is associated with a specific room or place. If instead the color of the cell is red, it means that no tracking device has been detected for some time. Finally, if the cell is gray, it means that we do not have tracking data for that place.

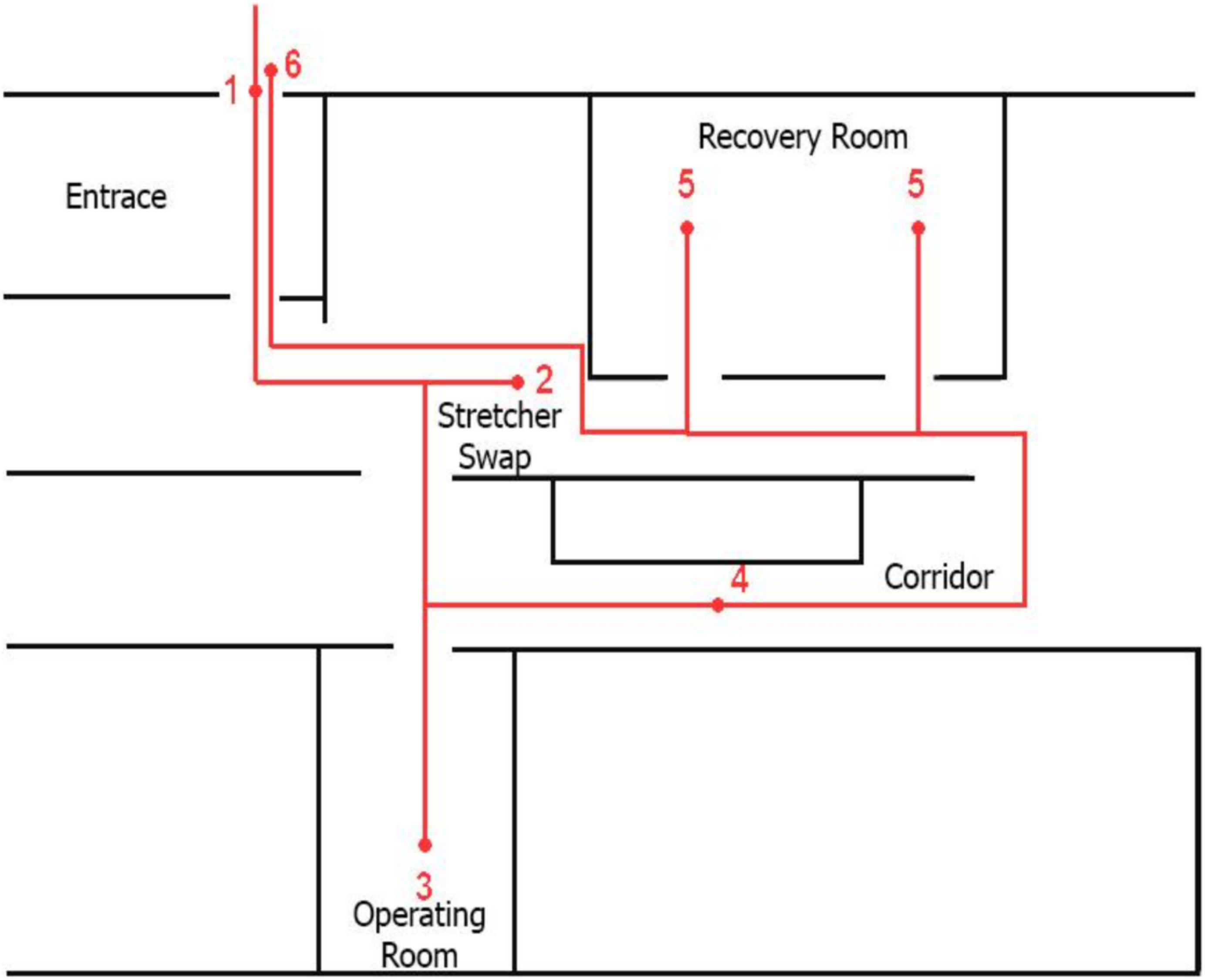

Figure.3

Figure 3

Patient's generic path illustration within operating block. A generic patient accesses the operating compartment from tracking point (**1**). After, the patient is placed on another stretcher, and an operator assigns to him/her a bangle and takes care of the relative association (number **2**); then, the patient goes to the assigned OR, for example, point number **3**. Once the surgical procedure ends, the patient is transferred to the Recovery Room (point **5**) where he/she is monitored after the procedure. The patient can then either exit the operating block from point **6** or can return in OR in case of acute surgical complications. Moreover, during these activities, the patient could remain idle at an unspecified point in the corridor, represented by point number **4**

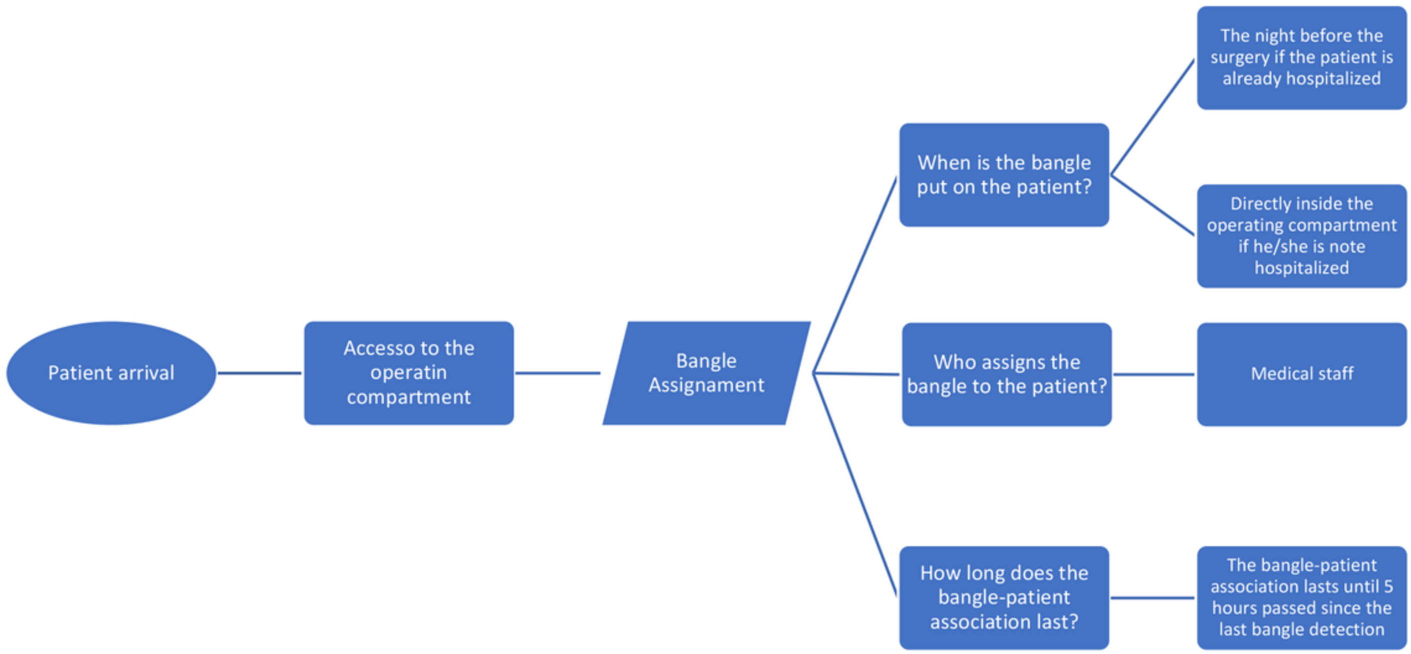

Figure.4

Figure 4

easy identification of the patient, in the operating compartment, through the association with a tag and a code

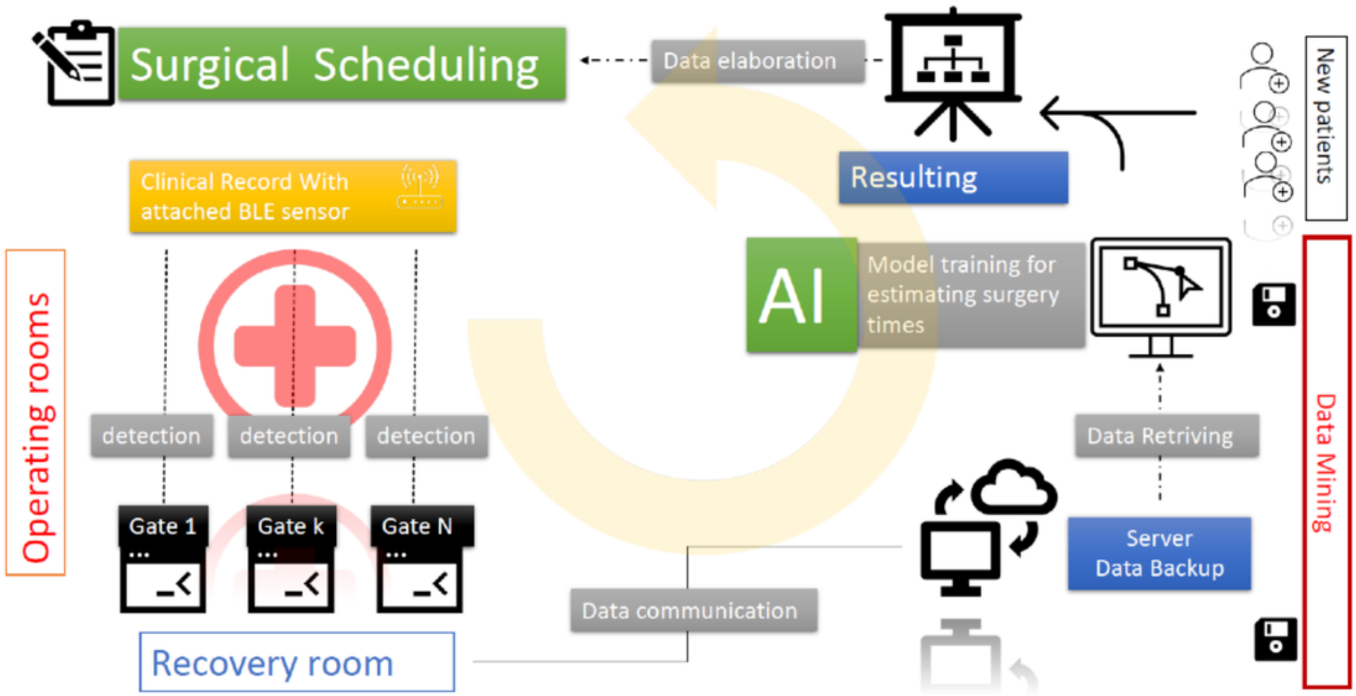

Figure.5

Figure 5

Logical scheme of the indoor patient tracking system, data storage and dataset analysis using Machine Learning models. Data security will be ensured by different levels of protection at several steps

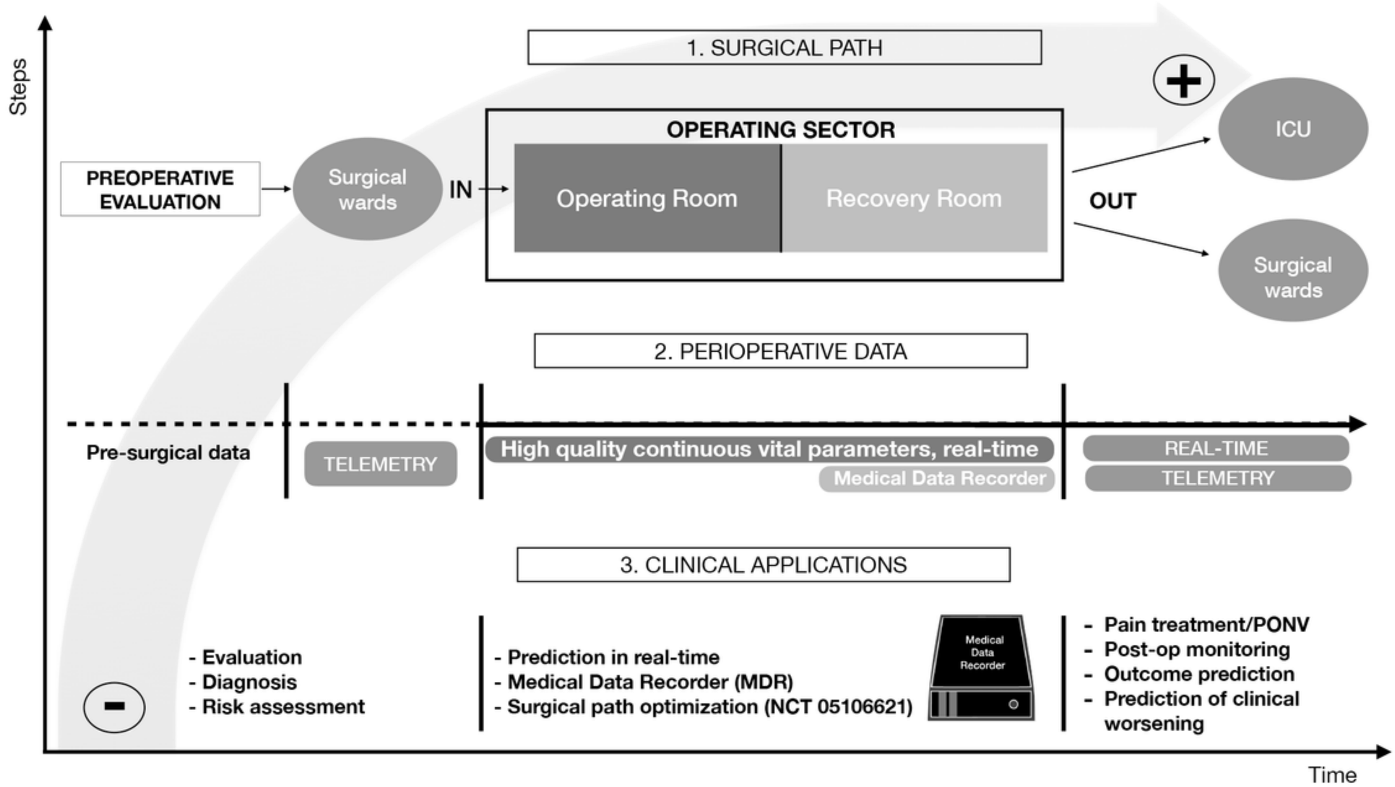

Figure.6

Figure 6

use of artificial intelligence in the operating sector for a more targeted organization of resources