The Role of Internet of Things and Digital Twin in Healthcare Digitalization Process

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Abstract. Among all the work and organization contests, hospitals represent one of the most complex systems and are difficult to manage because unpredictable or highly variable elements coexist in daily routine. In fact, variability plays a key role in the healthcare sector. Operating Rooms (OR) are one of the most crucial environments in the hospital and the way they are run affects many other processes. Medical staff has to note down the various times that represent all the states that the patient has to undergo to successfully conclude the surgery. These procedures are normally made either at the end of the shift or anytime the staff can find some free time. Undeniably, this may lead to human mistakes and inaccuracies. The authors described the application of tools and methodologies borrowed from Industry 4.0 (IoT, Digital Twin, Decision Support System (DSS), Data Mining and System Dynamics) in order to explore better and, possibly improve, the efficiency of ORs. During an 18 days period in June 2018, real time data acquisition was performed in 30 surgeries in an Italian hospital by an independent observer not involved in the patient treatment while the patient's care providers (anesthesiologists, surgeons, nurses) were unaware of the activity of the observer. The authors demonstrated, through ANOVA analysis, that the use of Internet of Things is a powerful instrument for real time data caption and for avoiding artificial variability.

Keywords: Data Mining · Decision Support System (DSS) · Digital Twin · Healthcare · Hospital · Industry 4.0 · Internet of Things (IoT) · Real time · System Dynamics

1 Introduction

Among all the work and organization contests, hospitals represent one of the most complex systems and are difficult to manage because unpredictable or highly variable elements coexist in daily routine [1, 2].

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In fact, variability plays a key role in the healthcare sector [3]: it occurs in the hospital in different forms such as clinical variability, flow variability and professional variability [3]. In addition, the mission of the hospital is to provide healthcare and activities focused on diseases control, pain relief, diagnostic activities etc. and, for this reason, often the patient's data entry are not in real time. As a direct consequence, a gap between the real and registered data occurs, besides, these latter are the ones usually used for performance analysis. The evolving technology provides new instruments to detect data in real time.

Operating Rooms (OR) are one of the most crucial environments in the hospital and the way they are ruled affects many other processes such as bed assignment, surgery waiting lists, staff recruitment and so forth [4]. For this reason, optimizing and improving the OR efficiency is one of the most recurring themes in many scientific fields like engineering, medicine, economics and management. Some of the main issues which underlies mistakes and wastes of time are those related to repetitive and manual tasks [5].

Indeed, these activities are frequent in the OR, in fact, medical staff has to note down the various times that represent all the states that the patient has to undergo to successfully conclude the surgery. These procedures are normally made either at the end of the shift or anytime the staff can find some free time. Undeniably, this may lead to human mistakes and inaccuracies [5].

In the following chapter, the authors will describe the possible application of tools and methodologies borrowed from Industry 4.0 (IoT, Digital Twin, Decision Support System (DSS), data mining, system dynamics) in order to explore better and, possibly, improve the efficiency of ORs.

2 Material and Methods

2.1 Terms and Definition

The IEEE Community defines the IoT as: "… a selfconfiguring and adaptive system consisting of networks of sensors and smart objects whose purpose is to interconnect "all" things, including every day and industrial objects, in such a way as to make them intelligent, programmable and more capable of interacting with humans" [6].

The concept of Digital Twin has been introduced in 2002 by Professor Michael Grieves at University of Michigan. He defines Digital Twin as: "the Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin" [7].

One of the first contextualization and definition of DSS was provided by Sprangue back in 1980. He said that: "The concepts involved in DSS were first articulated in the early '70's by Michael S. Scott Morton under the term "management decision systems"… A few firms and scholars began to develop and research DSS, which became characterized as interactive computer-based systems, which help decision makers utilize data and models to solve unstructured problems" [8].

The authors defined Data Mining as "the science of extracting useful knowledge from such huge data repositories." or "[…] the science of extracting useful knowledge from such huge data repositories." Furthermore, they affirm that Data Mining is "a broad field that combines techniques from different areas in computer science and statistics" [9].

The authors pointed out that: "system dynamics involves the ability to represent and assess the dynamic complexity of the behavior that arises from the interaction of a system's agents over time both textually and graphically. Plus, it is also a set of synergistic analytic skills used to improve the capability of identifying and understanding systems, predicting their behaviors, and devising modifications to them in order to produce desired effects. These skills work together as a system" [10].

2.2 Literature Selection

In the literature, IoT applications in the healthcare sector can be found with a particular focus on the Operating Room [11]. IoT can be used with different aims in OR such as to improve the technical skills of the young orthopaedics [12], for anhestesia data caption [13] or for govern the drugs along with the supply chain and for the patient safety in the OR [14]. Gomes C et al. reported a new Decision Support System supported by Data Mining and Simulation tecniques for the surgery in a Portuguese hospital which aims to help the staff to manage the patients' scheduling and resource allocation processes [15]. All of these fields converge in Industry 4.0. A literature review on Healthcare 4.0 has been carried out [16]. C. Patrone et al showed an interesting application of IoT in a smart post-hospitalization for older people [17].

2.3 Case Study

As previously stated, a possible difference between the real time of an event and the corresponding registered one may differ, even significantly, affecting any inference on the data themselves. This bias can be highlighted, for example, coupling data registration on medical records during the surgical process in the OR with a real time acquisition using IoT.

The case study introduced consists of a real time data driven Digital Twin (DT) modeled in System Dynamics and enabled by IoT buttons. This type of buttons is small, easy to use and, once pressed, it sends a per-programmed message through a network to a server. In the setting here described, two different AWS (Amazon Web Service) IoT buttons are used and once pressed, they record treatment time and then transmit it to a database used for data visualization and analysis. Furthermore, they become the input data of a System Dynamics model which outlines the operation flow.

During an 18 days period in June 2018, real time data acquisition was performed in 30 surgeries in an Italian hospital by an independent observer not involved in the patient treatment while the patient's care providers (anesthesiologists, surgeons, nurses) were unaware of the activity of the observer. The following two types of routine elective surgeries have been considered:

– *ordinary surgery:* pre-booked and scheduled in the ordinary surgery activity and admitted to the ward;

– *day surgery:* pre booked and scheduled in the ordinary surgery activity without admission to the ward, here after the anesthesia recovery, the patient is ready to go home within two days.

Before surgery, the patients are submitted to a pre-surgery visit. Here, they are classified as ordinary or day surgery, according to the type the treatment they need. This is a pivotal decision since it is related to the type of operation and to the availability of hospital beds.

Nine instants describe the patient pathway, corresponding to a punctual time (HH:MM):

- T0-patient gets into the Block of Operating Rooms (BOR)
- T1-patient gets into the OR
- T2-anesthesia infused, patient ready for surgery
- T3-skin incision
- T4-skin suture
- T5-end of anesthesia
- T6-exit from the OR
- T7-exit from the BOR
- T8-OR is available for next surgery

For each instant an external observer, a student, pushed the button. The device is connected to Wi-Fi and it directly collects the data in a database implemented in Excel.

Several methods are available for comparing the two data sets in order to demonstrate the effectiveness of this new approach. The easiest one is to calculate the difference between the time Tn collected with IoT buttons and the same time Tn collected without the IoT button. For statistical analysis, two-way Analysis of Variance (ANOVA) was performed. Table 1 demonstrates the results of two-way ANOVA.

2.4 Digital Twin

A Digital Twin has been created with Powersim produced by Powersim Software AS, this model is continuous and it has been created using a System Dynamics approach. It reproduces the patient's event-chain starting from their arrival in the OR to their exit. This model exploits a top-down approach where each state represents one of the nine states (T1-T9) and it depends on the previous state. Therefore, once the time of the previous event has been completed, the flow is enabled and the patient can move to the next state. The change of a state is triggered by a condition that allows the patient's flow across the arrows from one state to another.

Data collected from the buttons are stored in a database that are used to feed the Digital Twin which simulates surgery processes. Thanks to this system, knowing the expected waiting time and the probability to be operated in an established time becomes possible. This is useful both for patients who will be able to know how long they will have to wait for their surgeries, and even for nurses and surgeons who will be able to schedule a better and leaner operation planning.

Table 1. Two – Way ANOVA results

	Times	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6	Y_i
T_1–T0	**IoT**	0.90	17.22	6.13	28.10	0.10	16.00	68.45
	Manual	8.00	0.00	0.00	50.00	7.00	6.00	71.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 139.45
		SSTratt	0.54	1	0.54	0.0025	4.96	
		SSE	2152.38	10	215.24			
		SST	2152.92	11		**SIGNIFICANT**		
T_2–T_1	**IoT**	2.95	36.32	0.13	55.88	1.90	53.00	150.18
	Manual	26.00	10.00	10.00	11.00	17.00	49.00	123.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 273.18
		SSTratt	61.58	1	61.58	1.74E−27	4.96	
		SSE	3.53E+29	10	3.53E+28			
		SST	3.53E+29	11		**SIGNIFICANT**		
T_3–T_2	**IoT**	51.83	28.70	45.88	1.08	3.73	8.00	139.23
	Manual	23.00	33.00	10.00	4.00	17.00	10.00	97.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 236.23
		SSTratt	148.64	1	148.64	1.04E−06	4.96	
		SSE	1.424E+09	10	1.42E+08			
		SST	1.424E+09	11		**SIGNIFICANT**		
T_4–T_3	**IoT**	23.10	1.40	1.13	25.62	10.02	18.00	79.27
	Manual	19.00	32.0	34.00	25.00	30.00	15.00	155.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 234.27
		SSTratt	477.96	1	477.96	4.50E−33	4.96	
		SSE	1.062E+36	10	1.06E+35			
		SST	1.06E+36	11		**SIGNIFICANT**		
T_5–T_4	**IoT**	1.70	3.72	3.08	10.27	60.23	2.00	60.75
	Manual	0.00	5.00	6.00	0.00	1.00	1.00	53.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 113.35

(*continued*)

Table 1. (*continued*)

	Times	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5	Patient 6	Y_i
		SSTratt	12.58	1	12.58	9.55E−06	4.96	
		SSE	1.32E+07	10	1.32E+06			
		SST	1.32E+07	11		**SIGNIFICANT**		
T_6–T_5	**IoT**	15.13	6.20	34.70	1.95	2.72	6.00	66.70
	Manual	8.00	0.00	5.00	16.00	9.00	7.00	45.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 111.70
		SSTratt	39.24	1	39.24	6.93E−07	4.96	
		SSE	1.62E+05	10	1.62E+04			
		SST	1.63E+05	11		**SIGNIFICANT**		
T_7–T_6	**IoT**	12.47	12.53	9.33	14.30	3.12	9.00	60.75
	Manual	11.00	20.00	5.00	0.00	8.00	9.00	53.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	Y = 145.30
		SSTratt	4.50	1	4.50	6.93E−07	4.96	
		SSE	6.50E+07	10	6.50E+06			
		SST	6.50E+07	11		**SIGNIFICANT**		
T_8–T_7	**IoT**	13.13	19.05	12.80	8.02	15.30	8.00	76.30
	Manual	9.00	10.00	15.00	14.00	10.00	11.00	69.00
			SS	**DoF**	**MS**	$\mathbf{F_0}$	$\mathbf{F_{tab}}$	
		SSTratt	4.44	1	4.44	4.93E−18	4.96	
		SSE	9.02E+18	10	9.01E+17			
		SST	9.02E+18	11		**SIGNIFICANT**		

3 Discussion

The healthcare sector is affected by natural and artificial variability [3]. The natural variability is random and it is the result of the intrinsic element of health care delivery. An example of natural variability is that every patient is different than the other because of age, co-morbidities, response to therapy and so on. The artificial variability is not random and it is usually linked with defects or with wrong decisions made by the organization. An example of artificial variability made by Litvak [3]: is “the unfamiliarity with a new technology can be eliminated through education and certification”. In other words, manager can focus on the topic and eliminate the artificial variability whereas the natural variability can only be observed and measured.

These general principles are well shown in the table where ANOVA analysis reports through SSE a high level of noise. A limitation of the study is due to the sample size and to the surgical operations selected: a single surgical specialty has been selected (orthopedics) and not a single type of surgery (i.e. hip replacement).

The need to explore tools that allow clinicians to better schedule the surgical activity avoiding the artificial variability influence is still under explored. For example, Gomes et al. used the DSS to optimize surgery schedules and to measure their quality in order to reduce the waiting lists [15].

More recently Karakra et al. used the definition of Digital Twin in the healthcare sector. In detail, they used IoT Devices for real time data caption [18].

This data feed the Discrete Event Simulation model implemented through FlexSim, produced by FlexSim Software Products, Inc. The system implemented by the authors simulates the efficiency of the services according to which the decision maker can adapt the activities schedule (labs, diagnostic procedures, etc.). More details about the use of Digital Twin in healthcare can be found in [19] and [20].

Starting from this background the authors decided to evolve the use of real time simulation developing a tool daily available for the decision maker in surgeries. This implies the possibility to obtain a suggestion from the model to a better allocation of the resources. For example, the model could be able to predict, based on a datawarehouse of similar surgeries, the expected time of the end of the surgical act (T4) so that the decision maker is able to optimize how to procede according to the total time available for surgery in a single day. Better use of available resource is the direct consequence.

4 Conclusion

The authors strongly believe, according to Litvak, that to measure processes avoiding artificial variability is a key point for improvement. The use of Internet of Things is a powerful instrument to perceive this goal as shown in this work.

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