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DOCTORAL THESIS

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# Interactive Process Mining Techniques to Co-create Interactive Process Indicators to Evaluate and Characterize the Clinical Practice in Emergency Departments

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# *Abstract*

According to the World Health Organization, life expectancy has increased by six years in the last two decades. This has led to an increase in chronic diseases among the population. Consequently, health systems have been forced to look for preventive measures and improvement of care processes to guarantee sustainability. Key factors for this improvement are safety, efficacy, efficiency, patient-centred care, timeliness, and equity, all of which pursue to minimize risks and provide optimal care. Likewise, Emergency Services face significant challenges due to the high demand to which they are subjected, which results in saturated Emergency Departments and errors that can lead to adverse events. Therefore, improving patient safety is crucial to obtain better care in the Emergency Department. Paradigms such as Value-Based Healthcare advocate measuring the Quality of Care, optimizing the allocation of resources, and achieving better results through continuous improvement being the traditional performance indicators, those that have played a crucial role in this process by aligning activities and objectives, providing information on the patient's experiences and their state of health, as well as contributing to the evaluation of performance, clinical efficacy and quality improvement. However, these indicators may present limitations due to their abstract nature and the complexity of the data. Therefore, the key indicators may not fully represent the complexity of these processes. Furthermore, adapting these indicators to continuous changes can be challenging, making it difficult to understand the systems. Techniques such as Artificial Intelligence can offer valuable information when processing large data sets, which are particularly interesting in the health sector. In this way, Process Mining, an emerging paradigm gaining popularity in several domains, including health, offers the opportunity to analyze and improve processes, contributing to alleviating the crisis that health systems face today. This doctoral thesis presents a new way to measure the value of the emergency process with interactive process indicators based on Process Mining techniques as a solution to issues not covered by traditional measurement techniques or new technologies such as Artificial Intelligence. In addition, this thesis proposes a novel method to measure the Quality of Care in addition to understanding the stroke care process in Emergency Services. This approach offers a more dynamic and interactive way of analyzing healthcare processes, which allows for a better understanding and measuring of the value chain, which helps identify specificities in the emergency care process and thus discover the behaviour of the stroke disease process. Finally, this thesis presents an application based on Process Mining to support this method, designed and implemented for this purpose.

# *Resumen*

Según la Organización Mundial de la Salud, la esperanza de vida ha aumentado en seis años en las últimas dos décadas. Esto ha llevado a un aumento de las enfermedades crónicas entre la población. Como consecuencia, los sistemas de salud se han visto obligados a buscar medidas preventivas y de mejora de los procesos de atención para garantizar su sostenibilidad. Factores clave para esta mejora son la seguridad, la eficacia, la eficiencia, la atención centrada en el paciente, la puntualidad y la equidad, los cuales buscan minimizar riesgos y brindar una atención óptima. Asimismo, los Servicios de Urgencias se enfrentan a grandes desafíos debido a la alta demanda a la que están sometidos, lo que resulta en Servicios de Urgencias saturados y errores que pueden derivar en eventos adversos. Por lo tanto, mejorar la seguridad del paciente es crucial para obtener una mejor atención en el Servicio de Urgencias. Paradigmas como el Cuidado de la Salud Basado en el Valor abogan por medir la calidad de la atención, optimizar la asignación de recursos y lograr mejores resultados a través de una mejora continua. Siendo los indicadores de rendimiento tradicionales los que han desempeñado un papel crucial en este proceso, al alinear actividades y objetivos, brindar información sobre las experiencias del paciente y su estado de salud, así como contribuir en la evaluación del rendimiento, la eficacia clínica y la mejora de la calidad. Sin embargo, estos indicadores pueden presentar limitaciones debido a su naturaleza abstracta y la propia complejidad de los datos. Por lo tanto, es posible que el uso de indicadores clave no represente en su totalidad la complejidad de estos procesos. Además, la adaptación de estos indicadores a continuos cambios puede ser un desafío, lo que dificulta la comprensión de los sistemas. Técnicas como la Inteligencia Artificial pueden ofrecer una información valiosa al procesar grandes conjuntos de datos, que son de especialmente interés en el sector de la salud. De esta forma, la Minería de Procesos, un paradigma emergente y que está ganando popularidad en varios dominios incluido salud, ofrece la oportunidad de analizar y mejorar los procesos, contribuyendo a aliviar la crisis a la que se enfrentan los sistemas de salud hoy en día. Esta tesis doctoral introduce nuevos indicadores de proceso basados en técnicas de Minería de Procesos para el proceso de urgencias como solución a cuestiones no cubiertas por las técnicas de medición tradicionales o nuevas tecnologías como la Inteligencia Artificial. Además, esta tesis presenta un método novedoso para medir la Calidad de la Atención, así como comprender el proceso de atención del ictus en los Servicios de Urgencias. Este enfoque ofrece una forma más dinámica e interactiva de analizar los procesos de atención de la salud, lo que permite un mejor entendimiento, además de medir la cadena de valor, lo que ayuda a identificar especificidades en el proceso de atención en urgencias y así descubrir el comportamiento del proceso de la enfermedad de ictus. Por último, en esta tesis se presenta una aplicación basada en Minería de Procesos para soportar este método diseñada e implementada para tal fin.

# *Resum*

Segons l'Organització Mundial de la Salut, l'esperança de vida ha augmentat en sis anys en les últimes dues dècades. Això ha portat a un augment de les malalties cròniques entre la població. Com a conseqüència, els sistemes de salut s'han vist obligats a buscar mesures preventives i de millora dels processos d'atenció per a garantir la seua sostenibilitat. Factors clau per a aquesta millora són la seguretat, l'eficàcia, l'eficiència, l'atenció centrada en el pacient, la puntualitat i l'equitat, els quals busquen minimitzar riscos i brindar una atenció òptima. Així mateix, els Serveis d'Urgències s'enfronten a grans desafiaments a causa de l'alta demanda a la qual estan sotmesos, la qual cosa resulta en Serveis d'Urgències saturats i errors que poden derivar en esdeveniments adversos. Per tant, millorar la seguretat del pacient és crucial per a obtindre una millor atenció en el Servei d'Urgències. Paradigmes com la Cura de la Salut Basat en el Valor advoquen per mesurar la qualitat de l'atenció, optimitzar l'assignació de recursos i aconseguir millors resultats a través d'una millora contínua. Sent els indicadors de rendiment tradicionals els que han exercit un paper crucial en aquest procés, en alinear activitats i objectius, brindar informació sobre les experiències del pacient i el seu estat de salut, així com contribuir en l'avaluació del rendiment, l'eficàcia clínica i la millora de la qualitat. No obstant això, aquests indicadors poden presentar limitacions a causa de la seua naturalesa abstracta i a la pròpia complexitat de les dades. Per tant, és possible que els indicadors clau no representen íntegrament la complexitat d'aquests processos. A més, l'adaptació d'aquests indicadors a canvis continus pot ser un desafiament, la qual cosa dificulta la comprensió dels sistemes. Tècniques com la Intel·ligència Artificial poden oferir una informació valuosa en processar grans conjunts de dades, que són d'especialment interés en el sector de la salut. D'aquesta manera, la Mineria de Processos, un paradigma emergent i que està guanyant popularitat en diversos dominis inclòs salut, ofereix l'oportunitat d'analitzar i millorar els processos, contribuint a alleujar la crisi a la qual s'enfronten els sistemes de salut hui dia. Aquesta tesi doctoral introdueix nous indicadors de procés basats en tècniques de Mineria de Processos per al procés d'urgències com a solució a qüestions no cobertes per les tècniques de mesurament tradicionals o noves tecnologies com la Intel·ligència Artificial. A més, aquesta tesi presenta un mètode nou per a mesurar la Qualitat de l'Atenció, així com comprendre el procés d'atenció del ictus en els Serveis d'Urgències. Aquest enfocament ofereix una forma més dinàmica i interactiva d'analitzar els processos d'atenció de la salut, la qual cosa permet un millor enteniment, a més de mesurar la cadena de valor, la qual cosa ajuda a identificar especificitats en el procés d'atenció en urgències i així descobrir el comportament del procés de la malaltia de ictus. Finalment, en aquesta tesi es presenta una aplicació basada en Mineria de Processos per a suportar aquest mètode dissenyada i implementada per a tal fi.

# Contents

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# List of Abbreviations

| | |
|---|---|
| **AI** | **A**rtificial **I**ntelligence |
| **CQI** | **C**ontinuous **Q**uality **I**mprovement |
| **CROM** | **C**linical-**R**eported **O**utcome **M**easure |
| **EBM** | **E**vidence-**B**ased **M**edicine |
| **ED** | **E**mergency **D**epartment |
| **HCP** | **H**ealth**c**are **P**rofessional |
| **HIS** | **H**ealth **I**nformation **S**ystem |
| **ICHOM** | **I**nternational **C**onsortium for **H**ealthcare **O**utcomes **M**easurement |
| **IHI** | **I**nstitute for **H**ealthcare **I**mprovement |
| **IOM** | **I**nstitute **o**f **M**edicine |
| **IPI** | **I**nteractive **P**rocess **I**ndicator |
| **IPM** | **I**nteractive **P**rocess **M**ining |
| **IT** | **I**nformation **T**echnology |
| **KPI** | **K**ey **P**erformance **I**ndicator |
| **LSS** | **L**ean **S**ix **S**igma |
| **MTS** | **M**anchester **T**riage **S**tandard |
| **OECD** | **O**rganization for **E**conomic **C**o-operation and **D**evelopment |
| **PALIA** | **P**arallel **A**ctivity **L**og **I**nference **A**lgorithm |
| **PREM** | **P**atient-**R**eported **E**xperience **M**easure |
| **PROM** | **P**atient-**R**eported **O**utcome **M**easure |
| **QoC** | **Q**uality **o**f **C**are |
| **RQ** | **R**esearch **Q**uestion |
| **Runner** | Interactive Process Mining **Runner** |
| **TPA** | **T**imed **P**arallel **A**utomaton |
| **VBHC** | **V**alue-**B**ased **H**ealth**c**are |
| **WHO** | **W**orld **H**ealth **O**rganization |

# Part I

# Background

# Chapter 1

# Introduction

## 1.1. Introducing quality in healthcare

In ancient times, Hippocrates established the principle of *non-maleficence* as the basis for modern medicine as it is known today, where clinicians still follow this oath of *"do not harm"*. He was the first to highlight the importance of applying good practices to promote patients' health[1]. Still, it was not until the early 90's[2] when standardization emerged in the health care field as Evidence-Based Medicine (EBM) to help in caring for patients. For years, the EBM promoted extracting the knowledge from existing evidence and taking advantage of the experience of health professionals[3, 4].

EBM brought the evidence found over the years to daily practice. In general terms, it contributed to improving clinical effectiveness, the traceability of care processes, reducing risks and disseminating best practices and standards, helping to judge whether a treatment was good. Nevertheless, this did not mean that this attention was of quality. The United States began a movement emphasizing deficiencies in health systems and the need to evaluate health care quality [5]. Although EBM tried to contribute to this quality, the reality was that these clinical protocols and standards didn't reflect patient factors. Clinical protocols contemplated general conclusions extracted from the studies realized and did not consider specificities of the patient, such as pluripathologies or comorbidities[6, 7].

Besides, the design of clinical protocols was a tedious task based on subjective analysis and consensus of the health experts, which may bring to erroneous interpretations of the real protocol[8]. Thereby the high level of variation in the patient outcomes suggested that standard protocols needed to be tailored following individuals' needs as well as to determine if interventions were effective, being introduced at this point the concept of Quality of Care (QoC)[9, 10].

## 1.2. Defining quality of care

Over the years, there have been attempts to define QoC[11, 12], but was the definition provided by the Institute of Medicine (IOM)[1] in 1990 (*"Quality of Care is the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge"*[13]), the one recognized by the World Health Organization (WHO)[14]. Several years after,

[1]The IOM became the National Academy of Medicine in 2015

members of the *National Research Council* and the *Agency for Health Care Policy and Research* of the United States realized an analysis of the necessities behind the QoC for a real change. The study stressed the need to offer different types of services to achieve better outcomes with a beneficial impact on patient health and family satisfaction from the individual and general overview. This work reinforced the idea that the search for quality care is not a task isolated in time. Alternatively, it is a continuous improvement process which should pay attention to outcomes and processes over time, and where all health professionals involved in the care should have access to new health care knowledge generated (good or bad and the outcomes resulted) for better coordination among team members[15]. These statements were the forefather of what resulted in the work *"The err is human: Building a safer health system"*[16], used as principal conductor of the book *"Crossing the Quality Chasm: A New Health System for the 21st Century"*[17], published by the IOM in 2001. This book was a call for action to improve the healthcare delivery system as a whole by introducing the six dimensions (safe, effective, efficient, timeliness, patient-centred, equitable) in which healthcare systems function.

Furthermore, patient safety is perhaps one of the most critical dimensions for patients and relatives, reflected in these reports [16, 17], as well as in other countries worldwide. But patient safety is also the basis of good health service along with reducing unfavourable results [18]. The IOM defines Patient Safety as *"the prevention of harm to patients"* where the most used definition is the *adverse event*, *"an incident which resulted in harm to a patient"*[19]. According to WHO, *adverse events* are one of the world's ten leading causes of morbidity and mortality, translating into up to 15% of total expenditure in hospitals of the Organization for Economic Co-operation and Development (OECD) countries. Besides, in high-income countries, it is estimated that one of each ten patients is injured while receiving care, being almost 50% of this harm provoked by adverse events preventable[20, 21].

## 1.3. Emergency departments idiosyncrasy

One of the most critical services where quality is crucial is Emergency Department (ED). ED is one of the services that more pressure suffers in a hospital, which offers 24-hour emergency care to patients who need urgent medical attention. In the last years, the number of visits to ED has increased considerably[22]. Only in Spain has passed from 26,97 million emergencies in 2014, through 28,22 million in 2015 to 29,4 million in 2017. In the last report provided by the Spanish Ministry of Health, the number of emergencies treated in 2019 in specialized care is about 30,37 million[23], with 7,3 queries per inhabitant, has the seventh-highest frequentation of the 22 EU countries that are members of the OECD[24]. This increase in the number of visits adversely affects patient outcomes[25] and raises health care costs, emerging questions about the QoC in ED[26, 27]. One of the reasons for this increase is the change in the profile of the citizens, who suffer from a significant prevalence of chronic diseases, being reflected in the patients that visit EDs [28, 29]. Due to ageing and comorbidity, more complex patients require much more laborious attention and care[30], increasing the number of ED patients, but also the visits of patients motivated by non-urgent problems that result in an unappropriated use of ED that could be potentially be cared for in primary care[31, 32]. These two factors are considered critical, contributing to

ED crowding as well as the difficulty in accessing a bed for hospitalization for those critical patients[33], which leads to patients remaining in the ED[34, 35, 36].

## 1.4. Measuring healthcare quality in emergency departments

Health systems' cost is considerable worldwide, but patient harm is a global health burden too. Preventing much harm to patients is possible, representing a noteworthy reduction in invested healthcare resources [37]. Especially nowadays, after the COVID-19 pandemic, mainly in ED, and the high demand for the resources that still remain, there is a need to offer value-based care to make sustainable health systems. If value improves, all stakeholders involved in the care are benefited, as well as the health care systems sustainability. In this regard, QoC defined how health care should be, even though there was a need to measure this quality in order to balance resources invested and care offered. Initiatives such as Value-Based Healthcare (VBHC) proposed by Michael Porter and Elizabeth Teisberg in 2006, considered the value as the better health outcomes obtained with the least possible resources[38], something in line with IOM's six dimensions. With patients in the centre, the objective is to identify patients' everyday needs of concrete medical conditions (e.g. stroke) through the measurement of health outcomes and costs, not under individual units or specialities, which provides limited information, instead, about the entire cycle of care offered to patients[39]. It also settled the basis of what the Institute for Healthcare Improvement (IHI) presented one year later: The Triple Aim, a broader approach to improving the whole population's health beyond hospitals and primary care, being its main objectives to provide: 1) better care of the population, 2) better health of the individuals at 3) lower costs [40, 39].

Supporting a top-down approach (figure 1.1), the VBHC paradigm proposes an outcome measure hierarchy divided into three different levels and organized by dimensions, being an outcome considered as any result that affects a patient's health.

As the outcomes of the first level are resolved, those of the following ones take on importance. It is, for stroke patients, surviving is the priority, but as long as this is over, their concern is focused, as far as possible, on recovering their previous physical condition (second dimension) and keeping it over time (third dimension).

It is possible through a continuous improvement process where starting from the patient's initial condition, process and health indicators (e.g. Key Performance Indicators defined in the literature) are quantified in order to determine the QoC in terms of safety, effectiveness, efficiency, timeliness, and equitably provided as well as the costs invested on patients and other aspects of the health organizations (see figure 1.2). It will directly influence the health indicators (Clinical-Reported Outcomes Measures - CROMS) that act as predictors of outcomes (e.g. blood pressure measures of people suffering from hypertension may suffer heart failure). Furthermore, by reducing adverse events, inefficiency and ineffectively of treatment is reduced and speed up recovery, contributing to improving patient outcomes (PROMS) and patient satisfaction with the care experience (PREMS) that consequently affect the patient compliance with the treatment, impacting all together in the final health outcomes[41].

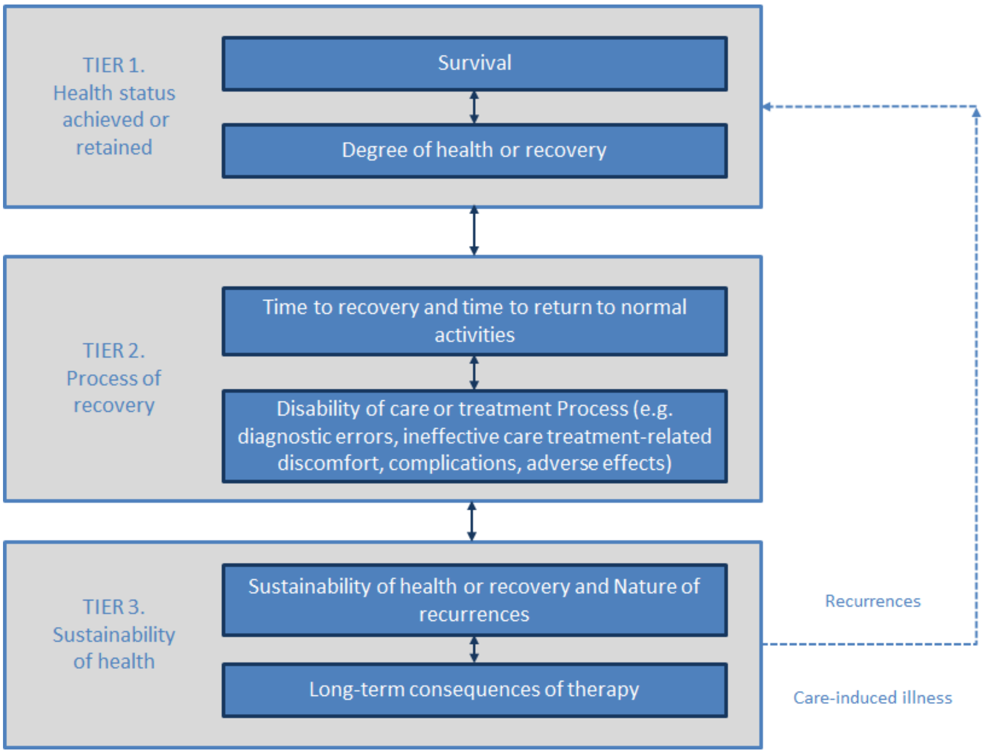


FIGURE 1.1: VBHC approach division into levels and dimensions (based on figure "The Outcome Measures Hierarchy"[41])

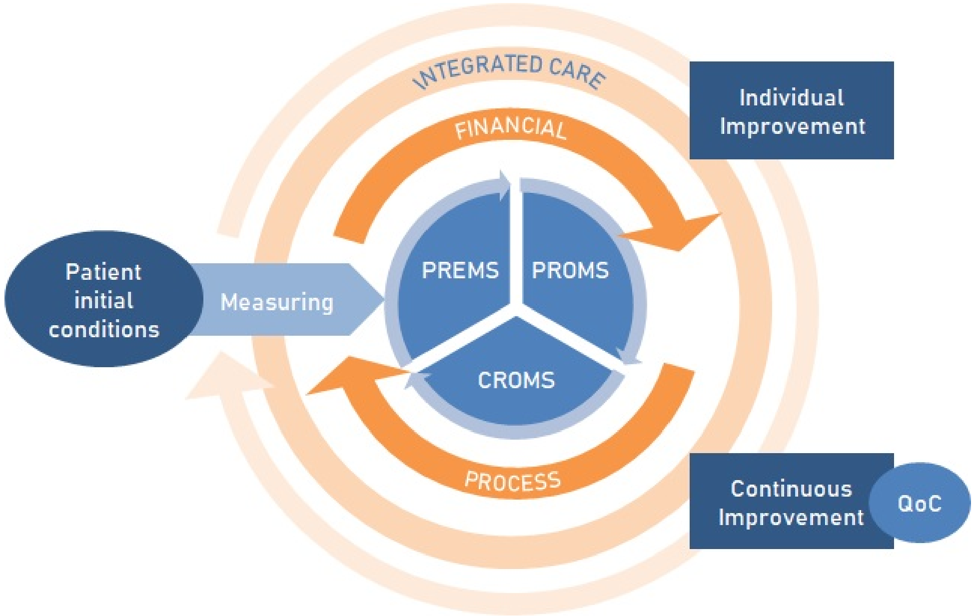


FIGURE 1.2: Life cycle for measuring value

## 1.5. Pursuing continuous quality improvement in emergency departments

The pursuit for value in healthcare goes through offering care of quality. With the patient in the centre, actions that aim to eliminate avoidable harm to health also contribute to increasing the effectiveness of treatments and the efficiency of processes. But, health care processes are inherently complex, this fact emphasizes the need to apply principles of quality management methods for improving health care services and patient health outcomes since as much complexity they have, the more room for improvement there is [16, 42].

There are world plenty of Continuous Quality Improvement (CQI) techniques to identify inefficiencies, ineffective care and preventable errors to make the changes that will lead to better patient health outcomes[43, 44]. Additionally, these methodologies can contribute to achieving the vision of quality and safety. CQI requires knowledge about the behaviour of systems and processes, but most important is to understand the variability of health care processes[45] to determine when and how to make process improvements. For example, in the ED, reducing the time to attention would contribute to speeding up the recovery of stroke patients. Thus, these tools can be used to identify the need for process improvement, decide on what improvements are needed, measure the impact of those changes and assess what further improvements are needed[46]. To this end, CQI uses statistical techniques in the form of Key Performance Indicators (KPI) to understand variability [47, 48, 49].

KPIs have been used traditionally to help organizations align their activities and objectives, track progress, and increase visibility on essential matters,[50] showing trends for the macro levels[43]. Quality indicators play a role in highlighting issues, such as long waiting times. Though they may not provide all the details, they contribute to understanding patients' perspectives on their health and care experiences. In EDs, KPIs are very helpful in measuring the QoC. Some examples are the Length of Stay (LoS), estimates the time that the patient spends in the ED[25], defining the gold standard for a reasonable quality of the service offered, or revisits that are considered adverse events because the patient returns to the service due to a lack of complete stabilization of the health status of the patient[51, 52].

As said, KPIs are used to monitor progress, quantify benefits, and identify areas needing attention. They align employees towards common goals, but their implementation in healthcare is often limited and abstract, relying on a single number[53, 54]. Implementing quality indicators requires significant time, effort, and resources, leading to challenges in consensus-building and dealing with complex healthcare data[55, 56]. Lack of involvement from all team members can result in negotiations over general goals instead of measuring real benefits, leading to frustration and poor results[57, 58]. Additionally, KPIs measure change over time, but they are often disconnected from data systems, hindering the identification of long-term problems and root causes. Analyzing KPI data requires specific skills, and KPIs must be dynamic to adapt to continuous organizational changes[59, 53]. A successful approach involves combining top-down and bottom-up perspectives from stakeholders[57]. While KPIs provide quantitative information, they may not pinpoint the causes of performance variance, limiting the understanding of evaluated systems and hindering the assessment of hidden problems and potential process improvements[60].

In addition, KPIs do not have a natural way to represent process behaviours. Instead, they are often based on averages rather than understanding actual variation in processes[15, 61, 62], which would be adequate if the data do not fluctuate much around it, but due to the complexity and variability of clinical data, this does not usually happen[63].

On the other hand, tools such as process maps, commonly used in project management, can describe processes and ensure that all steps are carried out in the proper sequence. A process map is created with information provided by team members and can help them to clarify what they know about their environment and determine what they need to be improved[64]. However, team members need to agree on a common understanding of how the current process works with an accurate and shared vision. Moreover, in many cases, this work is done manually, where reaching a consensus among the different stakeholders involved becomes a time-consuming task[63]. Then, the use of technology presents great opportunities in collecting and analyzing healthcare data for converting it into information and knowledge, being best to use data-driven systems that provide Healthcare Professionals (HCPs) with objective perception about the process[43].

## 1.6. From knowledge-based to data-driven analysis in healthcare

For creating valuable indicators beyond KPIs, instead of fully trusting in the subjective perception of human experts and providing a partial view of reality, it is necessary to provide objective and holistic frameworks that offer a view of the whole process. Currently, the amount of data collected and stored digitally is enormous and can be used to increase objectivity by creating models using Artificial Intelligence (AI) techniques. As a result, the science in data analytics is advancing rapidly so organizations can use this knowledge and continue improving[65, 66]. However, even with current advances, in many cases, there is an impediment to the use of AI-based systems, which is that they often lack transparency, a concept known as a *Black Box*. These systems allow compelling conclusions, but they cannot be explained, being something of vital importance in the health field[67], even though the potential of data-driven systems to lead to better outcomes is possible in many scenarios, and VBHC and CQI can benefit from it by supporting the decision-making process[68].

In this framework, Process Mining[69] is an emerging discipline providing comprehensive tools to support process improvement. Since Process Mining appeared, many dedicated Process Mining applications have been released, both commercial and academic, providing new means to improve processes in various application domains. Process discovery, conformance checking, or enhancement are techniques widely supported by these tools. Some examples of well-known Process Mining applications are ProM[70], Celonis and Disco[71]. Where ProM provides hundreds of plugins, offering the possibility of extending its functionality and developing new ones, the complexity of the tool may overwhelm medical end users. Instead, applications such as Celonis and Disco offer a better user experience while focusing on data extraction, performance analysis, and scalability[69].

Process Mining techniques are widely used in different business areas, despite the potential of Process Mining, its adoption in the health domain is not so extended beyond some case studies in a research context[72, 73]. Healthcare processes are highly complex. HCPs act according to their knowledge and experience and need to deal with specific patient situations, deviating from defined guidelines and resulting in processes with a high degree of variation.

According to Process Mining Community[74, 75], it is desirable the creation of tools, methodologies and algorithms that approach the Process Mining paradigm for HCPs. *Interactive Process Mining* methodology (IPM)[76] is based on special multi-disciplinary sessions called *Interactive Process Mining Data Rodeos* (Data Rodeos) for co-creating tailored processes that can support a better understanding of the process in HCPs' daily practices. However, to keep the successful implementation of *IPM*, it is crucial to have the support of an interoperable, customizable, expandable and easy-to-use application. Within *IPM*, the concept of KPI acquires a new perspective, incorporating the process information. In this paradigm, the indicators referring to the behaviour of the process are Interactive Process Indicators (IPIs). *IPIs* are not numbers but are measurable and comparable process models. For example, the *IPI* allows for analysis of the process in more detail. Starting from the visual model, it can be identified the patients that revisit the hospital and analyze the profile of those patients in order to make decisions. Instead, the KPIs only offer a number. These are the result of *Data Rodeos* and co-created by experts in Process Mining and HCPs.

This work has analyzed the power of *IPIs* to represent, measure and study EDs. This analysis has been made from a general perspective as well as particularized in a time-dependent disease such as stroke. In addition, it has been designed a new toolkit named *PMApp*, specially intended to support the start-up of *Data Rodeos* to enable the application of the *Interactive Process Mining* methodology in real scenarios and then to facilitate its acceptance by HCPs in their daily practice.

## 1.7. Hypothesis, research questions and objectives in brief

This research aims to enhance the characterization of ED processes by introducing *IPIs* as a novel approach. The hypothesis to be validated suggests that *Interactive Process Mining*, through the co-creation of *IPIs*, can offer both qualitative and quantitative insights into daily ED practices and effectively measure the value chain within them. To address this hypothesis, specific Research Questions (RQs) have been formulated.

In line with this, in this work, it has been considered the feasibility of utilizing *IPIs* to depict ED processes by consolidating KPI data broadly to assess the value chain within disease-specific processes in the ED and to create an application supporting collaborative *IPI* development for iterative and interactive analysis of care processes in daily clinical practice.

Similarly, the main aim of this work is, on one hand, to show how *Interactive Process Mining* techniques can measure, characterize, and support the analysis and optimization of EDs and, on the other hand, develop an *IPI* entailed creating a tool to offer a distinct perspective from conventional KPIs in EDs. This *IPI* should continuously provide insights that are easy to navigate and comprehend within the broader context of ED care processes, ultimately enhancing the HCPs' understanding of process behaviour.

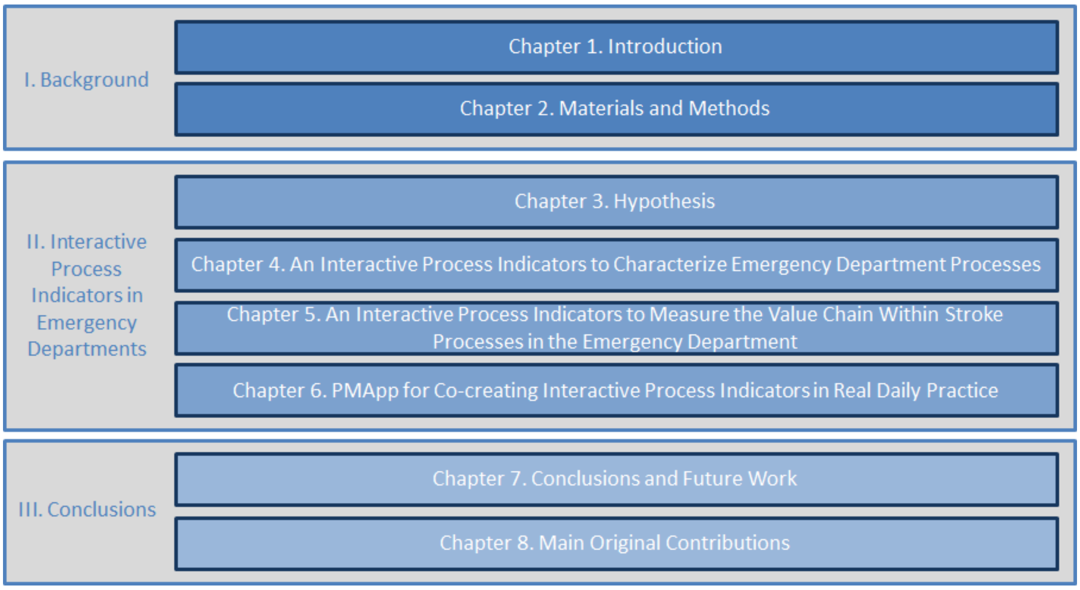


FIGURE 1.3: Structure of the thesis

Additionally, the examination of time-dependent stroke care processes in the ED, using the general *IPI*, has been conducted in line with the principles of VBHC to pinpoint specific characteristics and optimize the process. Furthermore, the creation of a Process Mining application tailored for HCPs has been essential to address the challenges encountered within healthcare systems. This application is adaptable, seamlessly integrated with existing health organization systems, ensures data quality, offers customization options, and presents a user-friendly interface.

In summary, this doctoral thesis seeks to leverage *Interactive Process Mining* techniques to co-create *IPIs* for EDs. The key objectives include showing the effectiveness of *IPIs* in characterizing ED processes, measuring the value chain comprehensively, and designing an adaptable Process Mining-based application to support these efforts in real-world healthcare environments.

## 1.8. Structure

Figure 1.3 presents the overall structure of the document. Chapter 1 introduces the main challenges and motivation behind the work proposed in this thesis. Chapter 2 describes what resources have been used to realize the work in this thesis. Chapter 3 introduces the main hypothesis of the work, the RQs, and the research objectives. Chapter 4 presents general *IPIs* characterizing the ED of a hospital as an alternative to the traditional KPIs. Chapter 5 presents an *IPI* for the stroke illness in the ED, demonstrating that *IPIs* can also contribute to understanding specific processes according to VBHC. Chapter 6 introduces the *PMApp* toolkit as a means to customize dashboards in the co-creation of *IPIs*. Chapter 7 states how the work has committed the RQ and the objective together with its main conclusion and introduces possible future work. Finally, Chapter 8 presents the main original contributions of the present work done by the author.

# Chapter 2

# Materials and Methods

As introduced in Chapter 1, safety is a crucial aspect of the Quality of Care (QoC), especially in Emergency Departments (EDs) that suffer from high demand. Adverse events resulting from errors can lead to significant financial costs at a national level, necessitating a focus on reducing errors and improving the reliability of healthcare systems through systems redesign. About this, Donabedian[77] highlighted the significance of resources, care processes, and their impact on patient and population health in understanding the QoC. In this regard, continuous improvement theories, such as Lean Six Sigma (LSS) or Plan-Do-Study-Act (PDSA), are paramount in healthcare to prevent and reduce errors and patient harm. Learning from mistakes is essential for building trustworthy health systems and prioritizing patient safety. Traditional Key Performance Indicators (KPIs) align daily activities and objectives and provide valuable insights into patient experiences and health status, contributing to performance assessment, clinical effectiveness, and quality improvement in healthcare. Nonetheless, KPIs have a limited and abstract nature, and due to the complexity of healthcare data, they pose challenges such as their adaptation to continuous change to facilitate a better understanding of evaluated systems. Thus, using KPIs may limit the representation of care processes. Still, Process Mining (PM) techniques have proven valuable in healthcare, enabling organizations to analyze processes, identify issues, and find solutions. However, data quality, process variability, and understandability challenges have been highlighted. Despite these challenges, PM has continued to be used in various healthcare use cases. A specific approach known as *Interactive Process Mining* (IPM) has been proposed to address the limitations of traditional KPIs and offers a dynamic alternative for measuring and optimizing ED processes. This paradigm involves Healthcare Professionals (HCPs) in the process learning method, allowing co-creation and comprehension of care processes, leading to *Interactive Process Indicators* (IPIs), which provide a continuous, interactive, and understandable representation of care processes compared to classical indicators, enabling HCPs to understand better and measure the characteristics and evolution of the processes.

## 2.1. Understanding the quality of care for bringing better outcomes

Within the QoC, safety is one of the main pillars since harm is what patients care most about[18]. In caring for a patient, there are interventions in which an error can be made, the most common are during diagnosis and treatment. Diagnostic errors

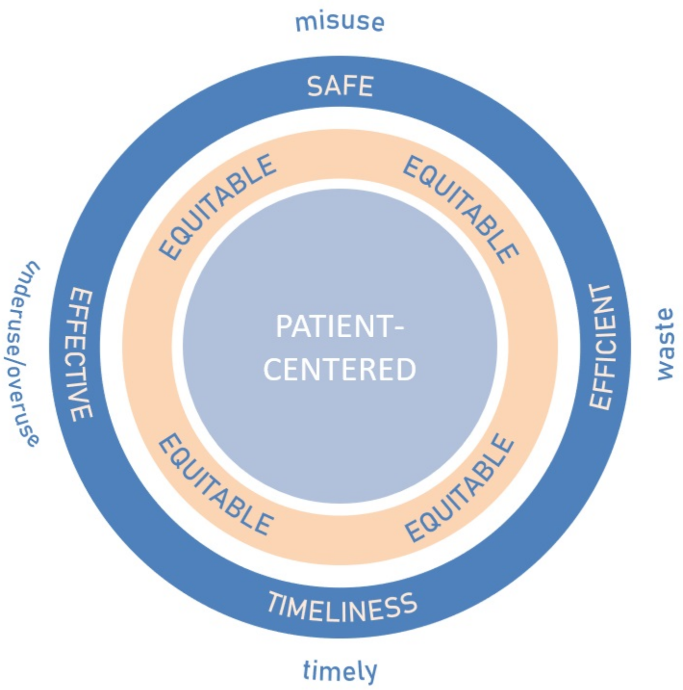


FIGURE 2.1: Quality of Care dimensions and related issues provoking adverse events

can be defined as a diagnosis that is missed, wrong, or delayed due to defects in the health care system[78, 79, 80]. For example, in the case of diagnostic errors, it may occur due to receiving the diagnosis late or not doing the appropriate tests. In the case of treatment errors, they can happen when following a specific medical procedure or administering a medication dosage. These errors could occur due to, for example, a failure in communication between different actors in the value chain, when the doctor does not explain well the instructions to follow at home, or the lack of data or knowledge regarding the illness or experience by professionals[81, 78]. But not all errors result in harm, and when it occurs, it is considered an adverse event, one of the leading causes of morbidity and mortality in the world[20]. The detection of adverse effects can significantly contribute to measuring the quality of the service offered and improving it. In addition, poor-quality care is associated with damage because it can cause direct harm, and care deficiencies can provoke adverse events, something that can be prevented[77, 18]. In terms of additional treatments and extra days in the hospital, adverse events may not be significant for a patient. Still, it translated to financial costs at a national level[18] suppose a considerable expense, being around a 15% of total expenditure in hospitals of countries belonging to the Organization for Economic Co-operation and Development (OECD), something of particular relevance in the sustainability of health systems[20, 82]. Thus, avoiding only adverse events is not enough. Instead, any error must be reduced in pursuit of high reliability of all the elements that make up the health system by redesigning systems in terms of procedures, technology, etc.[83, 84, 82].

According to Donabedian[85] aspects such as material and human resources, how the process of care is provided and received, and their effects on the health status of patients and populations are fundamental elements to understanding that quality depends on the relationship between many components[77] like the safety that emerges from the interaction of many elements in the health system, so it is not enough to try to eliminate errors and possible preventable adverse events but rather to seek reliable health systems that reduce the chances of error to the maximum[77, 12, 86], taking into account all the QoC dimensions[87, 17, 88] (see figure 2.1):

- **Safe**, providing health care that minimizes patient harm. Avoiding misuse of treatments that may provoke complications that could have been avoided, for example, giving an antibiotic to a patient with a known penicillin allergy or performing a surgery that was not appropriate.
- **Effective**, delivering health care based on the evidence to improve health outcomes of individuals and society. Avoiding underuse, which refers to that health care service was not provided and it would have been beneficial for the patient, for example, not giving the corresponding dose to control a hypertension crisis of a patient and overuse, when the benefits obtained by the patient are less than the injuries it may provoke, for example, giving to a child a medication only indicated for adults.
- **Efficient**, maximizing the resources in health care. Avoiding wastes, for example, of laboratory supplies because of an excess of tests during diagnosis or patient transportation to the RX room far from the ED.
- **Timeliness**, delivering health care that is timely and geographically reasonable. Avoiding waiting times that may affect the health status of the patient, for example, it is critical the time to treatment in patients with stroke as it may affect the recovery of the patient and the consequences derived from the illness.
- **Patient-centered**, delivering health care which takes into account the preferences of individuals and culture. Considering the patient's preferences, needs and values, for example, when a mother can select between a less invasive treatment, but it will take longer in time or surgery treatment. She chooses the latter option because she has two small children and can not visit the hospital so often to receive treatment.
- **Equitable**, delivering health care that does not vary in quality because of personal characteristics such as gender, race, ethnicity or socioeconomic status. To offer the same care opportunities regardless of personal characteristics, for example, to provide care for a young and an older patient suffering from the same condition.

Thus, continuous improvement theories play an important role in preventing and reducing errors and harm to patients while providing healthcare and learning from mistakes and adverse events towards trustworthy health systems[79, 18].

## 2.2. Continuous quality improvement theories in healthcare

QoC analysis should be focused on measuring the performance of care processes at all levels to act and implement changes, becoming the basis of the Continuous

Quality Improvement (QCI), which definition is: *"Continuous Quality Improvement is a structured organizational process for involving personnel in planning and executing a continuous flow of improvements to provide quality health care that meets or exceeds expectations"*[43]. Health organizations should support this culture of continuous improvement since errors can be reduced by system improvements, even never being entirely eliminated. These improvements lose efficacy over time, and new fixes are necessary to solve new mistakes[89], which is directly related to clinical efficiency, contributing to the safety culture[90]. Promoting a safety culture in health organizations helps guide HCPs toward assuring that those changes introduced meet optimal health outcomes over time[91, 92]. The adoption of process-based approaches aids the identification of these inefficiencies, ineffective care and preventable errors[93, 94, 95, 80].

The prevalent quality improvement (QI) techniques frequently employed in healthcare encompass the PDSA cycle, Six Sigma principles, and Lean strategies[44].

The PDSA cycle is a widely used method for rapid cycle improvement in healthcare[96, 97], is an iterative problem-solving model used for improving processes by carrying out changes[98]. The framework comprises three key questions to address before experimenting with an improvement concept, along with a procedure for evaluating change proposals.

- *What are we trying to accomplish?* (The aims statement).
- *How will we know if the change is an improvement?* (The measures of success to use)
- *What changes can we make that will result in improvement?* (The change concepts to be tested).

Furthermore, as with any change, it is necessary to define a team as champions to test the changes on a small scale before being adopted by the whole organization. It may contribute to reducing barriers to change. Then it involves a continuous, four-step process (see figure 2.2):

- In the **Plan** phase, improvement ideas are detailed, tasks assigned, and expectations confirmed with the team. Measures of improvement are selected. Questions such as *Who? What? Where? When?* are answered in this phase
- The **Do** phase involves implementing the plan and documenting any deviations (defects) as well as beginning the analysis of the data.
- The **Study** phase analyzes the results and identifies what went right, what went wrong, and what changes are needed for the next cycle, summarizing what was learned.
- In the **Act** phase, decide whether the change can be implemented or not. Those lessons learned, then, are incorporated into the next cycle.

On the other side, Lean main target is to eliminate waste by addressing specific problems in the whole process (and organization), being a cross-cutting approach[99]. The first step is the selection of the objective. Then, continuing with the identification

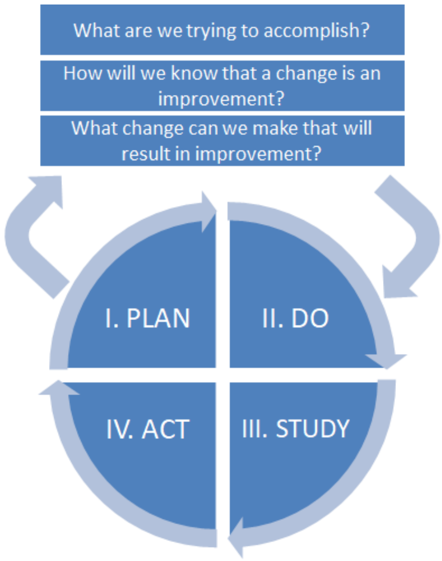


FIGURE 2.2: Plan-Do-Study-Act methodology (based on figure "Model for improvement"[96]

of the value-added activities, non-value-added activities (but needed) that are necessary and those that are avoidable to create the products and services in response to customer needs that are reflected in the Value Stream Mapping, a high-level visual representation of processes that are used as qualitative analysis tool[100], being in the healthcare domain, the value added to patients[101].

In the following figure 2.3[1], can be seen the seven wastes considered in healthcare[100]:

- **Motion** refers to an excessive movement of people such as walking around, for example, medical staff wasting time going from one floor to another.
- **Transport** refers to the physical movement of patients and materials, such as when a patient is moved from room to room or medical equipment moving around.
- **Waiting**, the waste caused by the time wasted waiting for the next process step, for example, when a patient is in the ED waiting to be attended by a doctor.
- In the case of **Over-processing**, it refers to doing more activities than needed to complete a task, for example, unnecessary diagnostic tests.
- **Inventory**, is due to medicines or materials stored up, where for example, it is easy to find forgotten medications whose expiration date has passed in the storehouse.

[1]These icons are available at https://www.flaticon.com. Hospital free icon designed by joalfa. Wheelchair free icon designed by Tanah Basah. CT Scan free icon designed by surang. Forbidden free icon designed by prettycons. Clockwise, Footsteps, Pills free icons designed by Freepik.


FIGURE 2.3: Wastes defined by Lean in healthcare

- **Defects** are considered the consequences of medical errors, for example, dollars wasted in a treatment that did not result well or loss of years because of an incorrect medication quantity.
- Finally, **Overproduction** is when waste is caused by doing more than is required, for example, unnecessary diagnostic tests or medications, hiding other wastes, requiring more time to process the returned medicines[102].

Another of these strategies is Six Sigma[103], which seeks to reduce variation of a concrete process from a proposed standard contributing to reducing errors[104, 105, 106]. This follows a data-driven decision-making philosophy through a five stages approach: **D**efine, **M**easure, **A**nalyze, **Improve**, and **C**ontrol known as **DMAIC**.

- **Define** the problem. It should consider the voices of the customer, process and organization. Process and the details are represented by process mapping, cause-effect analysis tools, and Statistical Process Control (SPC). This widely used technique can help identify if process changes have the expected effect by representing statistical significance with control charts[107].
- **Measure** the baseline. At this stage, an important issue is the selection of critical-to-quality characteristics (CTQs), which must be identified quantitatively and the corresponding KPIs identified for each specific problem[108]. This latter represents, for example, waiting times, or costs of medical errors, determining how well the process is performing compared to others and the gaps for improvement. CTQs are the key measurable indicators of a service that establish standards or specifications to satisfy patients' requirements. CTQs are similar to KPIs. Some CTQs are shared, whereas others are indicators useful to measure the evolution of the changes and KPIs to quantify the desired result[109].
- **Analyze** the root causes that are producing issues,
- **Improve** by designing potential solutions, assessing impact and evaluating risks,

- **Control** the changes derived from the developed solutions, verify benefits and document new procedures[98, 110].

Both approaches have the same objective, to provide quality. Where Six Sigma mainly focuses on operational aspects, Lean emphasizes strategic aspects to understand value[111]. Their combination resulted in LSS[112], where Lean does not need a deep understanding of the organization while facilitating the identification of critical areas and Six Sigma techniques can drive the required improvements. The alignment of both strategies helps to keep direction and focus within healthcare, to provide care of quality and value to patients, promoting a sustainable approach to organizational change and process improvement[113, 114].

The selection of a particular methodology relies on the specific characteristics of the improvement initiative. Across these methodologies, it is possible to encounter comparable techniques and tools[115, 44, 116].

## 2.3. Prioritizing and tracking healthcare improvements

KPIs are traditional measures used for years. Performance measures should help the organization align daily activities and objectives, help people see progress, and increase visibility on what matters objectively, empowering organization staff[50]. Quality indicators stress problems, for example, long waiting times. Although they do not provide sufficient information to identify where issues are, they contribute to this purpose and other aspects under the patients' perspective of their health and experiences whilst receiving care[117]. In line with this, Patient-Reported Outcomes Measures (PROMS)[118, 119] can contribute to measuring the QoC. PROMS measure people's satisfaction with their care by the use of validated questionnaires and can relate to generic aspects of their health status, such as level of impairment, disability, and health-quality of life, where examples of well-known measure tools are EuroQOL-5 Dimension Questionnaire (EQ-5D) to measure health status and quality of life[120, 121] or Short Form 36-Question Health Survey (SF-36) health survey to measure the wellbeing[122, 123], or disease-specific, such as the modified Rankin Scale (mRS) for estimating the level of disability of stroke patients[124, 125], National Institute of Health Stroke Scale (NIHSS) focused on measuring the stroke severity[126]. PROMS measure clinical effectiveness and safety, contributing to performance appraisal and quality improvement to maximize value[118, 119]. Other measures contributing to counting the QoC are Patient Reported Experience Measures (PREMS)[127, 128], which objective is to gather information on patients' experience of the received care. An example of a measure questionnaire is the Consultation and Relational Empathy (CARE)[129] or the Picker Patient Experience questionnaire[130]. Hence, PROMS and PREMS provide information about physical, emotional, and functional wellbeing[131]. PROMS and PREMS have considerable potential in identifying strengths and weaknesses of health care delivery relevant to HCPs[132], being an indicator of quality, but not a direct measure for it[133].

Additionally, QoC refers to the standard of healthcare, but it requires measurement to balance resource allocation and the care provided. The approach proposed by Michael Porter and Elizabeth Teisberg in 2006 defines value as achieving improved health outcomes using the least possible resources[38], aligning with the six dimensions outlined by the Institute of Medicine (IOM). Placing patients at the core aims to identify their specific medical needs in everyday situations, such as stroke, by measuring health outcomes through PROMS, PREMS and other measures and costs comprehensively, rather than focusing solely on individual units or specialities[39]. In this regard, the parents of the Value-Based Healthcare (VBHC)[38, 39] initiative founded the International Consortium of Health Outcomes Measures (ICHOM)[134, 135] non-profit organization that was focused on the definition of Standard Sets for medical conditions to provide value to patients. Resulting in a better manner of organizing outcomes indicators mainly focused on aspects that matter to patients, such as survival, acute complications and long-time quality of life, following the three dimensions model proposed by VBHC[41] and introduced in Chapter 1. So that, PROMS and PREMS have considerable potential in identifying strengths and weaknesses of health care delivery relevant to HCPS[132], being an indicator of quality, but not a direct measure for it[133].

Besides, apart from the mentioned above and according to Mainz et al.[117], quality is multidimensional and requires many different measures that can be classified on *rate-based* to measure events that occur with some frequency, for example, the percentage of patients starting triage in less than 10 minutes should be greater than 95%. Other measures are the *sentinels* indicators to identify undesirable events, for example, errors in the identification of patients, errors in the administration of drugs or various therapies that severely affect the patient's clinical situation. Furthermore, Mainz et al.[117] aligned these indicators with the Donadebian assessment approach[85, 136, 137], being related to:

- **Structure** indicators measure how prepared the organization is to provide care in terms of organizational structure and equipment and how efficient it is with respect to the outcomes and process indicators obtained. They can be classified into material resources, which refers to facilities, financing and equipment (e.g. inpatient floor beds), and human resources, which refers to staff and their qualification, including the training provided (e.g. the number of nurses). And organizational structure in terms of policies and procedures (e.g. nurses/bed ratio). These indicators can contribute to measuring the *efficiency* of the care offered concerning the outcomes and process indicators obtained, identifying different wastes, for example, the cost of the total stay of a patient in the ED.

- **Process** indicators measure how the organization provides care in terms of steps of how the clinical pathway is delivered, which usually are closely linked to the outcomes' indicators, for example, when a blood test is performed on the patient, or patients pending of being transferred to their destination service who remain in the Emergency Service. It is calculated as the percentage obtained by dividing the total number of patients admitted pending transfer by the number of observation beds. Thus, process indicators are helpful to rate *efficiency, effectiveness, and timeliness* of the care provided.

- **Outcome** indicators measure the results of that care by describing how the delivered care affects the health status of the patients (Clinical-Reported Outcomes Measures - CROMS) but also may include other aspects such as the satisfaction of the patient with the care received (PROMS and PREMS). There are *intermediate* indicators that are useful to measure CROMS by reflecting changes in the health status of the patient that can affect concrete outcomes, being evidence-based. For example, the LDL cholesterol level below the standard 100 mg/dl level can indicate a potential improvement in the risk of myocardial infarction. Intermediate indicators can contribute to quantifying outcome indicators that can be described as:

- *Death* is the most undesirable outcome considered the most serious adverse event[19].
- *Disease* as symptoms (e.g. fever), physical signs (e.g. shakes), or laboratory abnormalities (e.g. iron deficiency) in the form of CROMS.
- *Discomfort* as symptoms such as pain, nausea, or dyspnea. PROMS can contribute to reporting the patient's physical well-being, for example, the Visual Analogue Scale, to estimate the pain suffered by the patient[138].
- *Disability* unable to do usual activities at home, work, or leisure. PROMS provides the quality of life and functional well-being, such as the Modified Rankin Scale (mRS) that measures the disability of the stroke suffered[124, 125].
- *Dissatisfaction* as an emotional reaction to disease and its care (e.g. anger), where PROMS and PREMS are collected to provide the emotional well-being and experience of the patient concerning the care received, for example, the Hospital Anxiety and Depression Scale to measure the mental health of the patient[139].

There are different degrees of adverse events that can be detected in outcomes, going from *None* through *Moderate* (those that need treatment but do not interfere in the daily life of the patient) to *Severe* (those that need more serious interventions, provoking potentially disabling results), which can affect to the satisfaction and experience of the patients[140, 141], or even death. Thus, outcome indicators contribute to measuring how *patient-centred, safe and equitable* is the care given.

- In addition, it is essential for the analysis to consider **Social Determinants** that affect health outcomes, which may be demographic and psychosocial characteristics (e.g. gender, age), lifestyle factors (e.g. smoking, physical activity), the severity of the illness, which can be collected by using PROMS, and comorbidities. It can contribute to looking into specific groups of patients to enable to relate indicators with desirable outcomes[117].

Hence, KPIs goals are to monitor progress, show real benefits easily quantified or underline those parts that require more attention. It also helps to keep aligned the employees towards the same target, ensuring everybody works in the same direction. Nevertheless, although KPIs have been used to measure the QoC as well as VBHC (figure 2.4), this vision is usually narrow and abstract because they concentrate a lot of information in a single number, failing to reflect the outcomes mentioned above for a better analysis[53, 54]. Therefore, the implementation of quality indicators

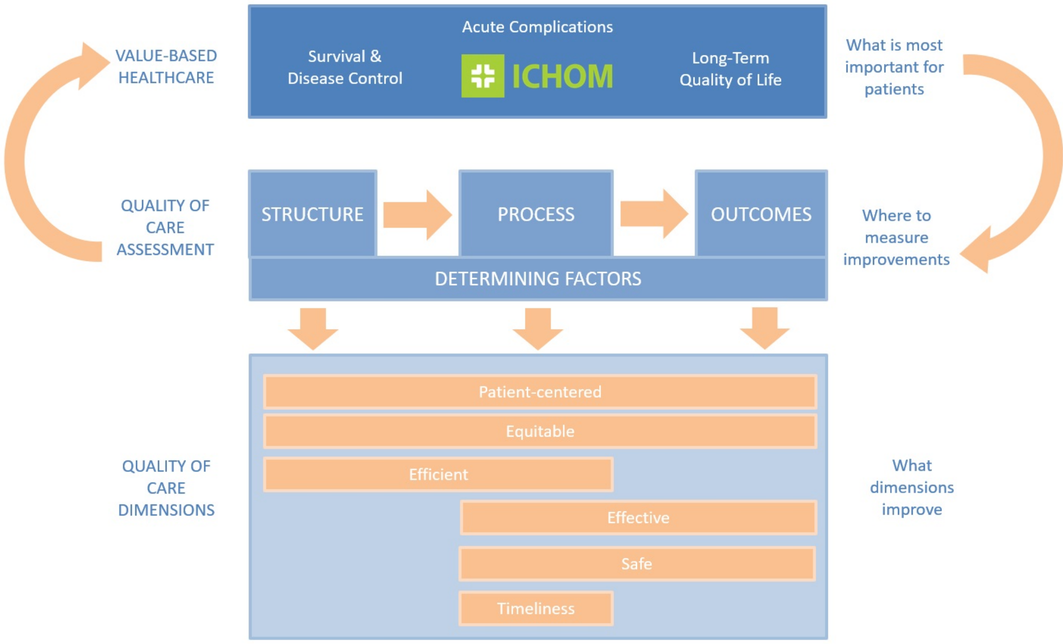


FIGURE 2.4: From Value-Based Healthcare to Quality of Care

needs time, effort and resources that, in many cases, are not available[55, 56], which demands the creation of a very strong consensus and assumptions about the process behaviour because of the high complexity of health care data[63]. And although the implementation may be articulated, many times, this process does not involve all team members, which can turn into negotiations about general goals rather than measuring the real benefit for the stakeholders, deriving on long processes[142, 53] where professionals get frustrated and lose interest with poor results[57, 58].

Similarly, KPIs measures change over time, but usually, they are not connected to a data system that facilitates the identification of longer-term problems using performance measures and root causes in the results[59, 53], as well as requiring appropriate skills to analyze data. For that reason, KPIs need to be dynamic to reflect the organization's evolution and to learn how to cope with continuous change to be successful[143], besides being defined and maintained following a top-down and bottom-up approach, combining the knowledge of the process and the overview of the stakeholders[57]. Consequently, KPIs offer quantitative information, from which it is difficult to pinpoint causes of performance variance, which prevents a better understanding of the evaluated systems, being unable to assess hidden problems and reveal additional process improvement possibilities[60].

## 2.4. Data-driven strategies to decision-making: what makes the difference?

Thus, using KPIs limits the ability to represent care processes generally. In this respect, science in data analysis is advancing to allow organizations to transform data into knowledge to help them achieve their goals[66], making available very powerful

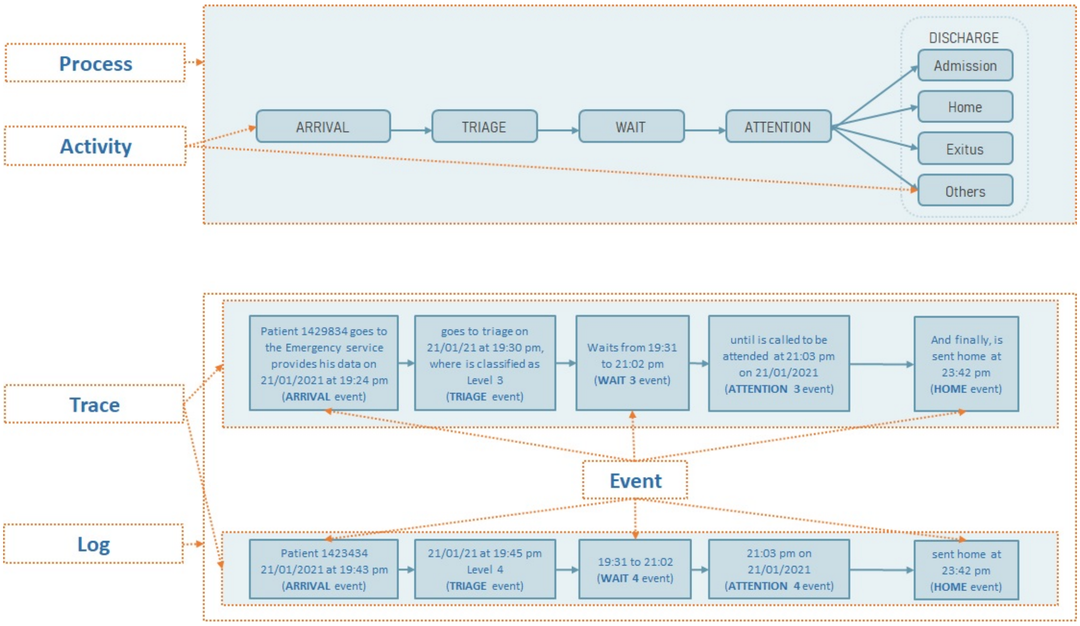


FIGURE 2.5: Process Mining basic concepts

information[144]. However, even with current advances, technical challenges hamper the use of systems based on Big Data at a certain level, for example, fragmentation of the data in silos and the lack of interoperability[145]. Apart from these main issues, others are highly relevant in healthcare, which in many cases, would involve reexamining assumptions and identifying possible bugs and erroneous data at the different phases of their calculation, particularly a challenge due to their complexity[146]. Still, this lack of clarity, a concept known as a *Black Box*, does not allow explaining what is happening behind the scene, something of utmost importance in healthcare[67, 68].

In this line, Process Mining[147], a data-driven research field, focuses on analyzing processes. As figure 2.5 presents, a *process* is composed of activities, an *activity* is the conceptual description of an event associated with a process, and an *event* refers to an activity at a point in time. Moreover, at least the following characteristics should be recorded for each event: identification (Id), which can refer to, for example, a resource, episode, or patient. This depends on the type of analysis to be done when the event occurred (timestamp) and the label (activity name) associated with the activity used to represent the events. A *trace* is a sequence of events, and a log is a collection of traces. Additionally, other attributes can complete the *Event Log* information, for example, the patient's age or gender.

Process Mining techniques enable organizations to analyze processes, determine problems, and identify possible solutions. The methods used for this purpose are *Process Discovery* that can produce a model from an event log. Thus, real processes will be represented, which tend to differ from handmade described process models because real processes have much more variability. *Process Conformance* can compare the model discovered with another event log of the same process. For example, those EDs following the Manchester Triage Standard (MTS)[148] can be compared with the actual data and see how much it differed from the Gold Standard. *Process Enhancement* where the idea is to extend the model discovered by providing information available in the event *Log* in a manner that enriches the process[69].

Although the usefulness of Process Mining in healthcare has been proved, the first studies underlined some issues that needed to be tackled, being the most emphasized issue the data quality, for example, missing or incorrect event data[149, 150, 151]. In the case of the ED, when a patient arrives and needs immediate attention, the clinical staff attend to him and then, after their stabilization, introduces partially administrative data because they do not remember the exact time when the patient was attended to or that information is simply not introduced into the system.

The other known problem is the *Spaghetti Effect*[147, 152], which is associated with high variability of the processes, especially in healthcare where less structured processes are possible. This results in the reduction of the understandability and readability of the model, not providing the knowledge expected of HCPs and other experts. These matters are of special relevance since the techniques available at that time were not mature enough, were tedious, or led to discarding relevant information for the analysis, which in healthcare is of utmost importance. Furthermore, the necessity to deal with outliers cases can hamper the understanding of the model and its interpretation[153]. In addition, it was identified the need to offer a high granularity as well as user-friendly software based on Process Mining for non-experts[154, 151]. Thus, a relatively novel method known as *IPM*[155] can suppose a solution to this problem.

## 2.5. Interactive process mining

*IPM* is a paradigm incorporating HCPs in the process learning method. *IPM* promotes not only discovering the process but also co-created it in collaboration with the HCPs to let them comprehend their daily practice, ensuring the usefulness, trustability, and in consequence, the acceptance and adoption of the characterization of the process. Processes discovered by *IPM* techniques can be used as process indicators representing the reality of an HCP in a more continuous, interactive and understandable way than classical indicators. Aligned with this, *IPIs* are defined, which are *"process representations that can be used to understand or measure the characteristics or intensity of one fact or even to evaluate its evolution"*[156].

*IPIs* are navigable models that present the real process resulting from applying different Process Mining techniques. Besides, *IPIs* include high and low-level data of the process modelled combined with domain knowledge in the form of KPIs[50]. For example, in EDs, an *IPI* can include KPIs in an integrated manner for measuring the QoC or VBHC, such as the length of stay[157, 158] or the number of patients that are hyperfrequenters[159]. Where KPIs enable to identify where the problems are (for example, stays longer than 4 hours are counterproductive against patient outcomes[158]), the depicted model provides navigability and flexibility when analyzing the process, allowing to answer open questions until identifying root causes. This combination gives the *IPI* an advantage over alone KPIs, inviting deeper research. This process is iterative, and it is possible to make new co-creation sessions (*Interactive Process Data Rodeos* or Data Rodeos) that lead to new improvement paths and to apply the necessary changes that can later be measured to estimate their viability. *IPM* is a framework where HCPs play a central role throughout the process of comprehension

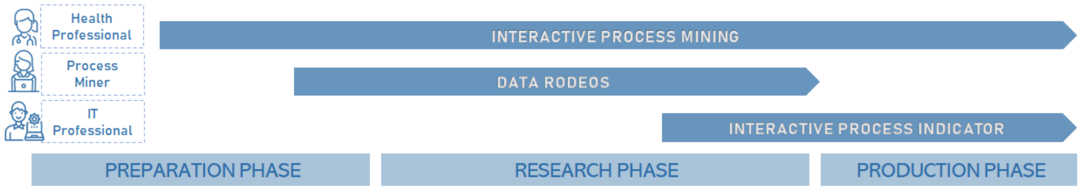


FIGURE 2.6: Interactive Process Mining paradigm

and defining an *IPI*. This indicator can be calculated using the data present in the system along with Data Rodeos.

The concept of Data Rodeo is essential in *IPM* methodology, being its main objective to build the *IPI*[155]. A Data Rodeo is defined as *"a highly coupled multidisciplinary interactive data analysis aimed at building process indicators that allow understanding, quantifying and qualifying processes and their changes in an objective, comprehensive and exploratory way"*[160]. Data Rodeo is intended for iteratively curating data, co-creating a process indicator, analyzing and validating it by the HCPs and training them in acquiring the necessary skills to extract the maximum profit of the *IPI*. Data Rodeos are performed by *Interactive Process Miners* (Process Miners) in collaboration with HCPs and Information Technology (IT) experts of hospitals, conforming a multidisciplinary team to build the *IPIs*.

The above-described method corresponds to the three phases of the *IPM* methodology (see figure 2.6). The *Preparation phase*, where the central objective is to achieve synergy among the multidisciplinary team members and specify the research matters, and the *Research phase*, where Data Rodeos are carried out until deciding the *IPI*, to be finally analyzed in the *Production phase*[155].

Initial hypotheses are defined in the phase of *Preparation*. In many cases, this task involves carrying out a bibliographic review to define indicators that help to analyze the questions posed and identify the necessary data sources to be resolved. This work is done by a multidisciplinary team composed of at least one or more HCPs who are experts in the field, a Process Miner, and IT professionals. A first Data Rodeo between a Process Miner and at least an HCP may be done at this stage. If it is the first time that the Process Miner has worked on that specific domain, it is of paramount importance to understand the process and the purpose of the analysis. The HCPs should be able to explain the main process and particularities they would like to research and represent them as a workflow, which aim is to capture the various ways resources are represented and utilized in the workflow. Examples of these resources may be equipment, hospital areas such as an operating room, an episode (for example, of EDs), a risk (for example, of increasing the probability of suffering obesity) or a patient journey (for example, a stroke patient). Furthermore, it is interesting to involve an IT professional to solve questions such as *"Is that information available in the Hospital Information System?"* or *"Where can it be found?"* but also to make them understand the kind of data needed (resourceID, activity name, and start timestamp, being end timestamp desirable but not mandatory)[69] and the format in which it is needed. Once the data is available for the Process Miner, it is time to start with the Data Rodeos to look for the best views that answer HCPs' questions.

In the phase of *Research*, Data Rodeos are co-creation sessions where the multidisciplinary team defines *IPIs*. In this phase, information regarding the process is used in relation to each of the steps (Events) that make it up. For example, in EDs, these steps would be *arrival*, *triage*, *waiting time*, *attention*, and *discharge*. The represented process is combined with further complementary data, such as KPIs (examples are the length of stay or the number of deaths), to discover care circuits, inefficiencies, bottlenecks, etc., analyze differences, or any information that helps to improve the care offered through a reduction in adverse events, improvement in the effectiveness and efficiency of the use of resources, a drop of waiting times, among others.

Once the *IPI* has been defined and validated, the phase of *Production* starts, and the multidisciplinary team corrects and states new questions to investigate and discover the fundamental causes of the problems being identified, giving rise to changes, which can, in turn, be measured and evaluated by the team in new Data Rodeos. Depending on the objectives can have different approaches: *Research*, where HCPs exploit the *IPI* to find scientific evidence; *Concrete Improvement*, where the multidisciplinary team analyzes the *IPI* to identify problems and their root causes. The HCPs will then be able to propose changes that can be measured and valued by the team, or *Continuous Improvement*, where experts in continuous process improvement can be part of the multidisciplinary team to generate the *IPI* to formulate changes. This process is iterative, and it is possible to make new Data Rodeos that lead to new improvement paths and apply the necessary changes that can later be measured to estimate their validity. CQI approaches are mainly focused on process improvement. Methodologies such as LSS[161, 162] can take advantage of *IPM*, even though *IPM* requirements need to be endorsed by a tool being.

Figure 2.7 shows the different types of Data Rodeos carried out during the *Research* phase, starting with *understanding the data* to identify the steps in the process and the timestamps needed to represent them. Then it continues with the *cleaning process*, in which all data out from the standard or known process is removed or corrected in an interactive way in collaboration with HCP and IT professionals[163]. This allows starting from the beginning by identifying the principal process. Once it is done, it should be back to the discarded data to discern between *wrong data and outliers*, which in most cases are the most interesting to be analyzed. As mentioned above, the represented process is the cornerstone of the analysis. Still, further information, such as averages and media, can be extracted from the process. Finally, the *incorporation of indicators* in clinical process analysis and *providing enriched perspectives* using Process Mining enhancement techniques for a better understanding will be vital for reaching the adequate level of utility in the *IPI* developed.

Interactive models that incorporate the clinical expert in the middle of the learning process make it more adaptable, reducing the probability of rejection against the *Black Box* effect[67].

In short, table 2.1 shows a comparison between *IPIs* and KPIs. KPIs can provide an overview of where the process needs more attention, but these are not enough to reveal pitfalls, for example, efficiency problems of the care process. Instead, *IPIs* break with KPIs limitations by going a step further and building process-based indicators that provide insights into how treatments and protocols evolve in time as human-understandable and contextualized KPIs. Moreover, KPIs are static, but *IPIs* propose a dynamic way to show the evolution of the process indicator. While the KPIs make assumptions about the process *IPIs* represent the real process, depicting its actual behaviour. Furthermore, KPIs are mainly created by data engineers. Rather, *IPIs* are

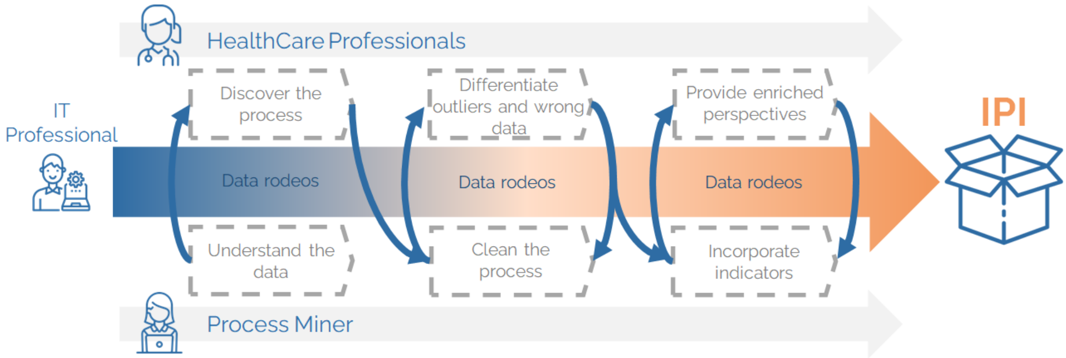


FIGURE 2.7: Interactive Process Data Rodeo sessions

co-created with HCPs, favouring their acceptance. KPIs are thought to answer closed questions, while *IPIs* are able to represent questions not previously predefined. So that, KPIs provide a single number, where *IPIs* allow the analysis of individual and personalized aspects of the processes, offering a bottom-up and top-down approach to answer open questions and navigate through comprehensible visual exploration and analysis techniques such as colouring, statistics, etc. These characteristics permit *IPIs* to incorporate feedback from HCPs for refinements and the integration of new data at any moment, being a very flexible and agile process[156].

| **KPI** | **IPI** |
|---|---|
| Is static | Evolves |
| Requires assumptions about the process behaviour | Handles the real process |
| Requires data engineers | Created for healthcare professionals |
| Answers predefined questions | Answers open questions |
| Provides quantitative answers | Provides visual and navigable model |

TABLE 2.1: Benefits of IPIs over alone KPIs

Over the last years, Process Mining has continued being used in different use cases[72, 73]. Moreover, a specific manuscript has been presented, emphasizing the characteristics and challenges faced by Process Mining in healthcare[74, 75], where *IPM* can contribute by diminishing difficulties presented by KPIs. Thus, in this work, it is proposed a dynamic alternative to the use of KPIs in EDs in order to be able to measure their characteristics and help their continuous optimization.

# Part II

# Interactive Process Indicators In Emergency Departments

# Chapter 3

# Hypothesis

In previous chapters, it has been introduced the necessity of reducing harm and adverse events to increase patient safety and improve the efficiency and effectiveness of the care process through equitable, timeless and patient-centred attention, which in turn enhances the Quality of Care (QoC). Furthermore, Value-Based Healthcare (VBHC) relies on this and rearranges health organizations differently from the traditional to provide the maximum possible value to patients with fewer costs. In this regard, Continuous Quality Improvement (CQI) theories contribute to this purpose, such as Lean methodology to diminish waste in health organizations or Six Sigma to reduce variability in care processes. To this end, Key Performance Indicators (KPIs) have been used to measure QoC and VBHC for years, Patient-Reported Outcome Measures (PROMS), Patient Reported Experience Measures (PREMS) and International Consortium for Healthcare Outcomes Measurement (ICHOM) Standard Sets to identify those indicators that most worry patients are examples of that.

With respect to this, different theoretical currents focus on enhancing processes to obtain better health outcomes. Nevertheless, KPIs present some limitations when extracting the maximum knowledge of care processes, requiring a new approach to cover this necessity. To this end, *Interactive Process Mining* (IPM) introduces *Interactive Process Indicators* (IPIs), which offer advantages rather than performance indicators that can solve the pitfalls they present to model Emergency Departments (EDs). In this chapter, the hypothesis of the present work is presented and described.

## 3.1. Hypothesis

Given the necessity already presented of enriching the overview offered by the KPIs and enhancing the vision of process indicators, a new approach will be proposed for the characterization of the processes of the ED through the use of *IPIs* techniques. The hypothesis to be validated is that:

> *IPM through the co-creation of IPIs can be used to characterize real daily practice processes qualitatively and quantitatively and support the measure of the value chain within the ED in a broad and particular manner.*

Based on this hypothesis and to propose a novel *IPI* that embraces the necessities in EDs, it is necessary to evaluate the potentiality of the Process Mining techniques to co-create *IPI* using the actual data available in health organizations. This fact was conducted to formulate the following specific Research Questions (RQs) and objectives.

## 3.2. Research questions

In order to confirm the hypothesis, the following RQs were identified:

- **RQ1.** Is it possible to use *IPIs* to characterize ED processes representing aggregated information of KPIs in a general manner?
- **RQ2.** Is it possible to use *IPIs* to measure the value chain within specific disease processes in the ED?
- **RQ3.** Is it possible to design and develop an application to support the co-creating of *IPIs* to analyze care processes iteratively and interactively in real daily practice?

## 3.3. Objectives

To achieve the RQs of the doctoral thesis, the main objective is **to show how *IPM* techniques are able to measure, characterize and support the analysis and optimization of the EDs**. In this line, a set of secondary objectives were established:

- **O1. To build an *IPI* to support the analysis of real ED processes in daily practice** QoC encompasses six dimensions (Safety, Effectiveness, Efficiency, Patient-centredness, Timeliness, and Equity) to provide optimal care while minimizing risks to patients and their families. However, achieving and measuring the best care in complex and variable clinical data, especially in high-pressure EDs, presents challenges, leading to errors and adverse events. External service delays and overcrowding further hinder ED performance. Therefore, improving care processes is crucial for enhancing patient safety. Traditional KPIs have been used to characterize ED processes but present limitations in understanding their specificities. This objective is intended to provide an *IPI* that supplies a different perspective of conventional KPIs in ED, incorporating continuous information on the process in a navigable and understandable manner within the broader context of the ED care process, and thus to facilitate a better understanding of process behaviour in EDs.
- **O2. To characterize a time-dependent care process within the ED using the general *IPI* built** In the case of a time-dependent disease like stroke, achieving an efficient care process is crucial for promoting better patient recovery. This involves rapidly detecting strokes, minimizing the time until treatment, and other factors. To optimize this care process, it is proposed to be analyzed from the perspective of VBHC. This paradigm aims to provide the highest value, in terms of the best health outcomes, to patients at the lowest possible cost. Therefore, it is necessary to characterize the behaviour of the care process for this specific disease using an *IPI* to understand its performance and identify

its particularities. Thus, this objective aims the creation an indicator to enable the measurement of the value chain in VBHC, employing techniques such as statistical significance maps to identify differences between processes.

- **O3. To design and develop a Process Mining-based application able to deal with the *IPM* paradigm and support the co-creation of *IPIs* for real daily practice** To ensure the sustainability of our healthcare systems, it is necessary to implement preventive measures and enhance the efficiency and effectiveness of care processes. In this regard, this work is focused on the creation of a Process Mining tool to facilitate the co-creation of *IPIs*. This toolkit should be specifically designed for health and Healthcare Professionals (HCPs) and address the challenges faced by healthcare systems by being adaptable to various scenarios, seamlessly integrating with legacy health organization systems, managing data quality concerns, providing customization options, and offering user-friendly, understandable, and transparent features for HCPs.

The secondary objectives have served as the framework for the work conducted in this document. This doctoral thesis aims to use *IPM* techniques to co-create *IPIs* that can be employed to evaluate and characterize the clinical practice in EDs.

This entails addressing the following key points. Firstly, if *IPIs* can effectively characterize real-world daily practice processes in both qualitative and quantitative ways. And secondly, if *IPIs* can sustain the measurement of the value chain within EDs in a comprehensive and specific manner. Finally, to develop a Process Mining-based application that enables the creation of *IPIs* for uncovering the unique aspects of care processes in EDs. This application should not only work for general *IPIs* but also contemplate the possibility of characterizing specific medical conditions as well as accomplishing the arisen features needed to manage the complexity and variability of the clinical data in real-world environments.

# Chapter 4

# An Interactive Process Indicator to Characterize Emergency Department Processes

The Quality of Care (QoC) involves six dimensions: Safety, Effectiveness, Efficiency, Patient-centredness, Timeliness, and Equity, aiming to provide optimal care while minimizing risks. However, Emergency Departments (EDs) have complex and variable clinical data and face high pressure, leading to errors and adverse events. Other aspects affecting the performance of EDs are external service delays and overcrowding. For that reason, improving care processes is essential to increase patients' safety. Classic Key Performance Indicators (KPIs) from the literature have been used to characterize the process of EDs but present limitations in understanding the specificities of EDs processes. This chapter introduces an *Interactive Process Indicator* (IPI) that offers a different perspective, incorporating continuous information about the process in a navigable and understandable manner, enhancing the understanding of process behaviour in EDs and facilitating improvements in patient safety.

## 4.1. Quality of care in emergency departments

QoC provides the best clinical practice based on evidence following current scientific knowledge with the least risk for patients and their families, where quality and efficiency are intimately linked so that there can be no QoC in its broadest sense if care is not efficient[12]. This is something difficult to achieve in EDs due to the vast complexity of care response [164], the immediacy required and the high variability of the patients. The inflow of patients is uninterrupted, with peaks in demand, with very diverse diseases of different severity. During the process, patients can change locations several times, be attended by several professionals (Emergency doctors, nurses, etc.) in different shifts, and other specialists can participate, with the communication difficulties that this entails. In addition, the difficulty of a correct clinical examination, the lack of information on clinical history data, the pressure of time to establish the diagnosis and treatment, or being aware of several tasks and patients simultaneously with frequent interruptions, can be the perfect scenario for accidents, incidents and errors that in turn can provoke adverse effects on patients health[164, 81, 165]. Likewise, the detection of adverse effects is an indicator of the quality of the service offered[166] that can be worsened, for example, by ED overcrowding[51, 167]. It is an important and widespread problem in most countries. There are factors whose compliance does not depend only on the emergency service, but also on external services that affect the care, for example, the delay in assigning a bed to hospitalize patients. In this case, coordination with other units is essential for adequately functioning hospital emergencies. Examples of these services are primary centres, hospital departments, such as cardiology, pneumology, laboratory and radiology, or special units in reference hospitals, such as the burn unit[168]. Delays in these units signify, in many cases, the postponement of relevant actions and the overcrowding of the ED. As a result, the quality of emergency care is influenced by the conditions in which the work in ED is carried out, having a wide margin for improvement in preventing errors and mitigating their impact[164].

For example, ED overcrowding is associated with increased patient Length of Stay (LoS), where the higher the *LoS*, usually the more overcrowding of patients in the service is[169, 170] that at the same time can be affected by an increase in the *revisits* (with or without readmission)[51]. Overcrowding can also increase inpatient *mortality*[166], the worst and less desirable effect together with long waiting times. During hospital admission, adverse events affect nearly one out of 10 patients seen in an ED, and this is highly preventable. It would be recommended to establish follow-up measures to prevent the occurrence of adverse events[171], being the most common related to the process of care, medication and procedures[172, 171]. These examples can be translated into indicators that, according to Donabedian[85, 137], belong to the structure of the organization, the process of care and the outcomes achieved to help in measuring the QoC. Somehow, these indicators can be modified, whereas others can not be changed, these are the determining factors that are characteristics of the patients or the context, such as the age, gender or season of the year or the time of the day, as this latter has been proved to affect the relationship between ED overcrowding and *mortality*[173].

## 4.2. Approaching key performance indicators to understand emergency departments process

The literature is plenty of examples where QoC is measured as KPIs that provide numerical information about how it is offered in a moment of time[50]. KPIs are predefined in advance and directly related to specific goals, sometimes based on subjective information gathered from surveys and questionnaires[55, 56]. Besides, in the health field, the data's complexity and variability often imply assumptions of the process that are unknown and may be relevant when interpreting KPIs values[63]. For example, *LoS* is critical to improving ED patient flow and getting more satisfactory health outcomes[25]. Those patients staying more than 4 hours have more probability of revisiting the service[51], which can affect their health outcomes negatively[52]. The indicators mentioned so far accentuate the importance of making efficient care by paying attention to outcomes and processes over time[15, 62], but it is also needed to understand the relationship between structure, process and outcomes[137] to improve them[169]. Although the number of *revisits* can be calculated from the data as a KPI, the study of the process can help in identifying system inefficiencies and understanding the characteristics of the patients, their behaviour and root causes.

Thus, experts need further information about the process over time to evaluate the value chain of the emergency process.

In this chapter, it is proposed to use *IPIs*[156] as a means to find a better understanding and overcome KPIs limitations. *IPIs* contribute with human-understandable representations of the real process and the specificities related to it through time[174]. *IPIs* provide as a central element an overview of the main process representing. In turn, this overview can offer a general understanding of the behaviour of the patients, for example, it can be easily recognized that there are patients revisiting the ED. Furthermore, *IPIs* provide complementary information as KPIs, pertaining to the structure, process and outcomes and other views of the emergency process that help experts understand where and why things are happening, allowing recognition of the effects it is having on the outcomes[117].

## 4.3. Emergency department functioning

In the ED, the patient is received at the entrance of the emergency service. If the patient's status allows, they will go to the arrival area to provide the administrative data necessary to open the urgent episode. Triage is one of the key moments in an ED. Once the administrative data has been collected, the time the patient waits until being tried is considered essential since the reason why the patient comes to the emergency room is still unknown. Ideally, this time should be less than 10 minutes. Currently, there are five structured triage systems with greater international recognition: Australian Triage Scale (ATS)[175], Canadian Triage and Acuity Scale (CTAS)[176], Emergency Severity Index (ESI)[177], Spanish Triage System (SET)[178], and Manchester Triage Standard (MTS)[148], being the latter the one of the most widespread[148]. This system defines the priority in which the patient will be assigned from level I to the most urgent patients until level V for those less acute, and therefore the assignment to a specific care circuit, where there are usually at least three circuits: 1) level I critical, 2) boxes for level II-III patients and 3) low priority (level IV-V). The response time is delimited by the triage level, where patients of level I (red) should be attended immediately, patients of level II (orange) should be attended within the next 10 minutes after the triage, level III (yellow) within 60 minutes, level IV (green) within 120 minutes and finally level V (blue) in less than 240 minutes[148]. Once the patient is assigned to a doctor, the initial treatment usually consists of taking constants and, when needed, the prescription and dosage of medication. A combination of an ECG, a blood test and an X-ray are usually done as complementary tests. The response to these tests is decisive in the management of the emergency service, where the laboratory service must respond within one hour for ordinary cases. Regarding the radiology service, the response time must be less than one hour in those time-dependent cases. Lastly, consultation with other specialists may also be necessary. Afterwards, the medical report is generated, and the patient and companions are informed. Upon discharge, the patient may be sent to the observation area for those who need to be stabilized or have it under control for some more time. In this case, it is estimated that they can be discharged within 24 hours. Then, patients may be hospitalized or in a short-stay unit for less than 72 hours or intensive care unit (ICU), in which case, the patient must reach their final destination in a maximum of 45 minutes. Another destination may be to send

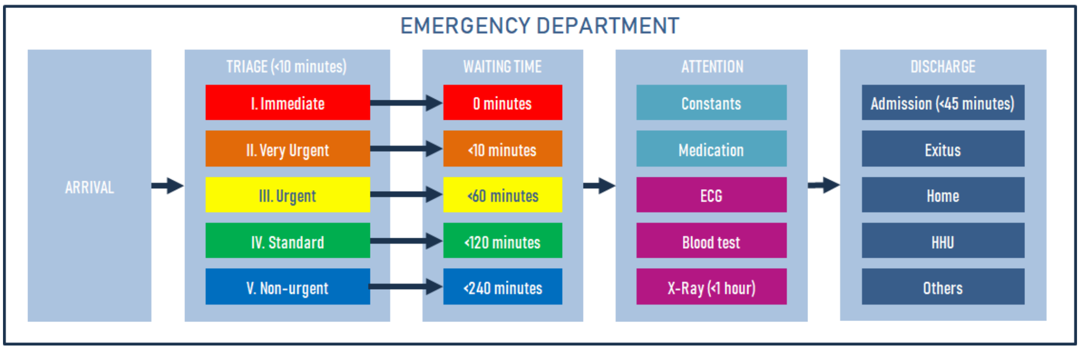


FIGURE 4.1: Emergency Department functioning

the patient home, where they must be informed with recommendations and timely information, or transfer them to other centres due to the lack of certain units (e.g. ICU or cardiology) or other facilities (e.g. endoscopy) not present in the current location. Finally, the most undesirable case is when the patient dies, known as exitus[179, 180] (figure 4.1).

## 4.4. Emergency department interactive process indicator

This chapter is intended to analyze real data from ED in order to build an *IPI* able to deal with common ED issues. This *IPI* should be able to offer an advanced analysis process-based. The study carried out to design the *IPI* was conducted at the ED (table 4.1) of the Hospital General Universitario de Valencia (HGUV) in Spain. The hospital counts with population coverage of more than 356,393 inhabitants. The ED has almost all medical specialities with physical presence guards except in the specialities of Plastic Surgery, Maxillofacial, Ophthalmology and Dermatology until 9:00 p.m.[1].

| Healthcare activity | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|
| Assistances | 138.149 | 144.525 | 142.190 | 111.607 |
| Saturation | 67,3% | 67,09% | 69,69% | 69,40% |
| Voluntary discharges | 634 | 606 | 635 | 489 |
| Transfer other centers | 658 | 708 | 747 | 617 |
| Exitus | 80 | 94 | 77 | 95 |

TABLE 4.1: Hospital emergencies

The study started in 2018 as part of the *"Process Mining as a management tool for an emergency service"* work, awarded in the Dr López Trigo 2017 call[2]. The analysis was carried out with a total of 80.164 patients that visited the ED a total of 218.965 times[174].

[1]Departmental Memory 2020 of the Hospital General Universitario de Valencia https://chguv.san.gva.es/documents/10184/81032/Memorial+Departamental+2020.pdf
[2]Resolutions Dr López Trigo 2017 Awards: https://fihgu.general-valencia.san.gva.es/promocion-de-la-investigacion

This study adopted the *Interactive Process Mining* (IPM) methodology to build the ED *IPI*, in which are involved a nurse expert in ED, a process miner expert on *IPM* and Information Technology (IT) professionals from the hospital who are aware of where the data needed for the analysis is. The team carried out interactive sessions (Data Rodeos), where the first sessions were focused on understanding the data sources to represent the standard process. At this step, the IT professional and the nurse were vital to understanding the daily practice in the ED service and how this data is reflected in the Hospital Information System.

The mapped *IPI* with the Healthcare Professionals (HCPs) during the Data Rodeo sessions is presented in figure 4.2. The ED *IPI* considers the *Arrival* node when the patient enters the ED. The time the patient's episode is open in the Health Information System (HIS) determines when the admission event is initiated. Then, the *Triage* node represents the moment when the patient's seriousness is assessed, and the nurse in charge of prioritizing patients registers this information in the information system. The *Wait* duration corresponds to the interval from the triage until the first attention. This action is split into five levels, depending on the priority of the patient, as well as the *Attention* node, when a patient is called to be attended to by a doctor according to the assigned triage level. Finally, the patient is released from the hospital, in this case, is separated into different destinations: *Admission* in the hospital, *Home*, *Exitus*, when the patient passes away and *Others* that comprises other discharges. The *IPI* also represents when the patient returns in less than 72 hours or 30 days, otherwise, the process ends after the discharge. Furthermore, nodes labelled as *@Start* and *@End* represent the starting and ending points within the process, respectively.

The model obtained followed in the ED according to the MTS that would fit in other hospitals following the same standard. Using enhancement techniques, the *IPI* presented can be upgraded with the existing data in the HGUV[174], providing information about the real daily practice of the ED. Each node is coloured with a gradient that shows the duration of the median of each patient in each stage, as well as the transitions that represent the number of patients. In this specific case, this *IPI* provides a vision of the *footprint* of the HGUV that may vary depending on its current status, the number of patients and their seriousness, as well as other factors affecting the ED, such as the number of professionals or their experience. This *IPI* can be used in other hospitals to state their *footprint* to subsequently compare and evaluate the factors affecting the behaviour of the EDs. This *footprint IPI* is presented in figure 4.3. In this example, the colours represent the basic statistics of the process. The colour of the nodes illustrates the duration average of the activities in each one, and the arrows depict the number of patients that follow this path.

The following sections analyze how the *IPI* can represent classical KPIs existing in the literature to characterize the ED process.

### 4.4.1. Age

Many studies highlight age as one of the factors influencing the behaviour of the patients in ED and the differences between older and younger people[181, 30], about how it affects the length of stay [181, 182, 183], the higher number of visits of elderly compared with young people[184, 182], the greater level of urgency of older people in ED or higher rates of suffering adverse events after discharge[182]. These studies give

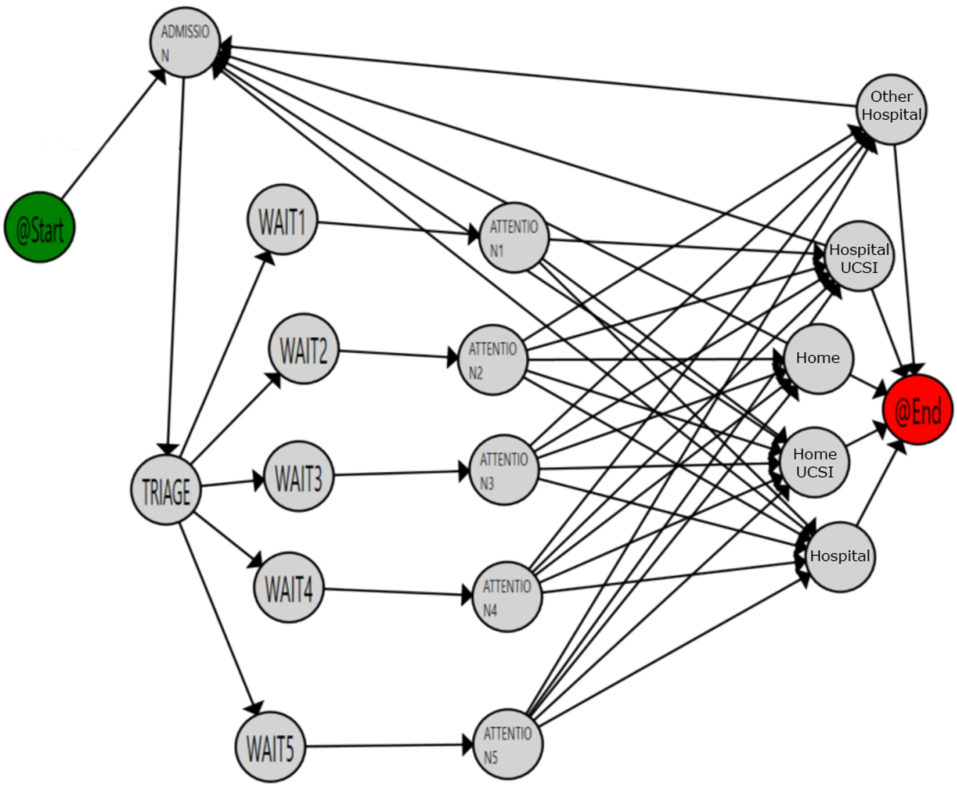


FIGURE 4.2: Interactive Process Indicator in Emergency Department

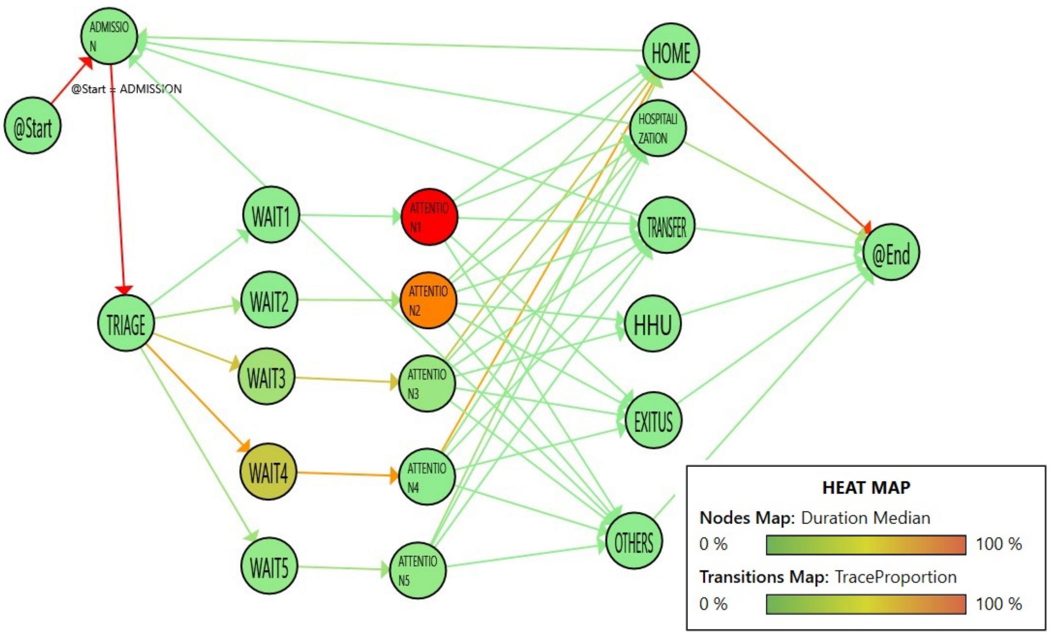


FIGURE 4.3: Interactive Process Indicator in Emergency Department with footprint information

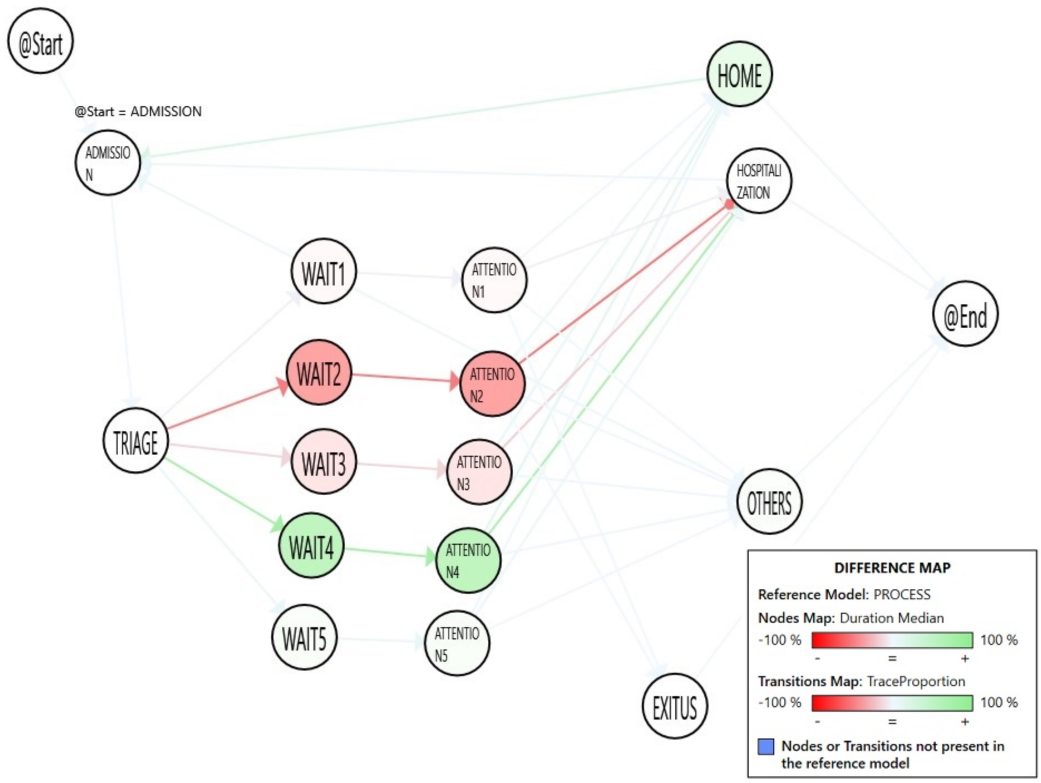


FIGURE 4.4: Hospitalization differences between elderly >65 and the rest of patients

insights into what may be occurring, however most important is to understand what is happening in each health centre, and *IPIs* can provide information to comprehend this.

In this case, a *difference map* is used to compare the process behaviour of different cohorts based on the age of the patients in the ED. A *difference map* shows the difference in colour gradients between two cohorts of patients.

Figure 4.4 shows the difference between people >65 and the rest of the patients. The red colour is where there is more presence of the elderly, and the green younger patients. The red transitions from *Triage* node to *Wait2* and *Wait3* indicate that older patients are more assigned to levels 2 and 3. Also, older people spend more time getting attention (*Attention2* and *Attention3* nodes) than the rest and especially those with higher prioritization (*Attention2*) have more chances to become inpatient (red transitions from *Attention2* to *Hospitalization* node). Whereas younger patients assigned to lower prioritization levels (*Wait4*) also have a high probability of being admitted.

### 4.4.2. Week days

As in the case of the age, the literature is plenty of works speaking about the differences between working and weekend days and the decrease in the QoC during weekends, reaching the point of increasing the *mortality*[185, 186, 187].

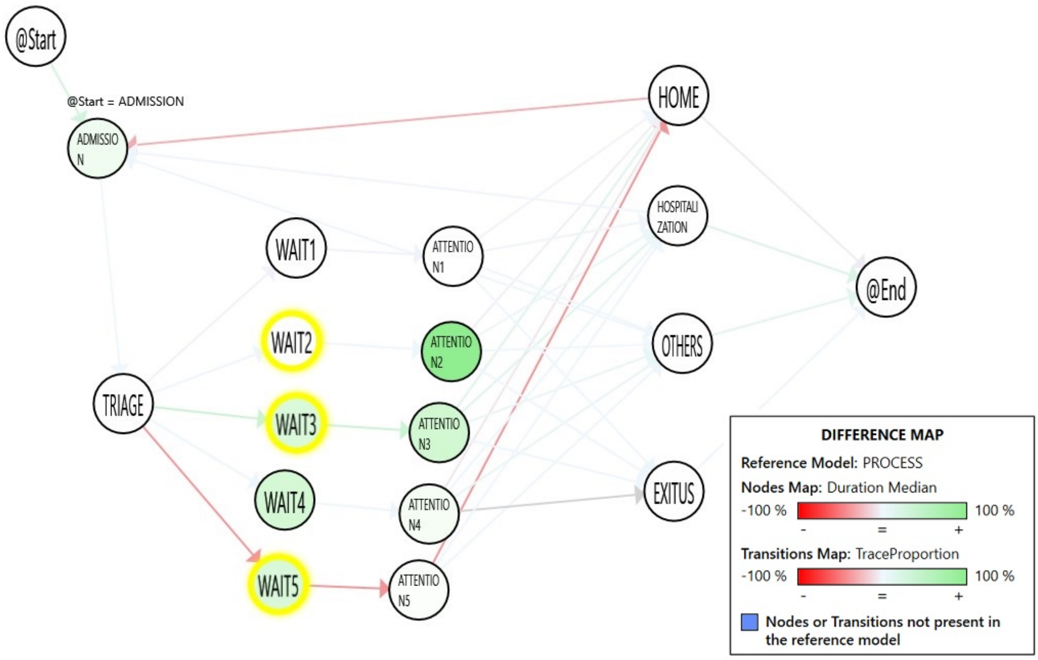


FIGURE 4.5: Differences between weekends and working days

In addition to the *difference map*, a *statistical significance map* is applied, which emphasizes in yellow the nodes that have statistical significance in the duration of the activities.

Looking at figure 4.5, the general flow of patients has changed compared with figure 4.3, where common patients were assigned to level 4. Instead, the number of non-urgent patients (*Wait5*) have increased during weekends, something that can occur because most primary care centres are closed. Consequently, as the literature highlights, the QoC can be affected during weekends, being reflected in the number of *revisits*, as it can be appreciated in the figure 4.5, where the red transitions were going from *Triage*, to *Attention5* and *Home* nodes until *Admission* node, representing an increase on the number of returns. The nodes underlined with a yellow ring have significant differences (computing P-Value with confidence of 95%).

### 4.4.3. Revisits

Revisits are the returns of patients to the ED department in a relatively short time. The ED's purpose is to stabilize the patients and eradicate the necessity of immediate care, but if, after the discharge, the patient needs to return in a relatively short time, it is an indicator that the QoC provided was not good enough. Returns of patients within 48 or 72 hours are associated with poor management of the patient in emergency[188, 189, 190, 191], where 30 days returns are more related to improper managing of chronic diseases[192, 193] or older adults with comorbidities[194]. The number of returns and readmissions can affect the QoC provided due to the increase of patients in the service since both raise the pressure in the unit that can produce delays[170, 195].

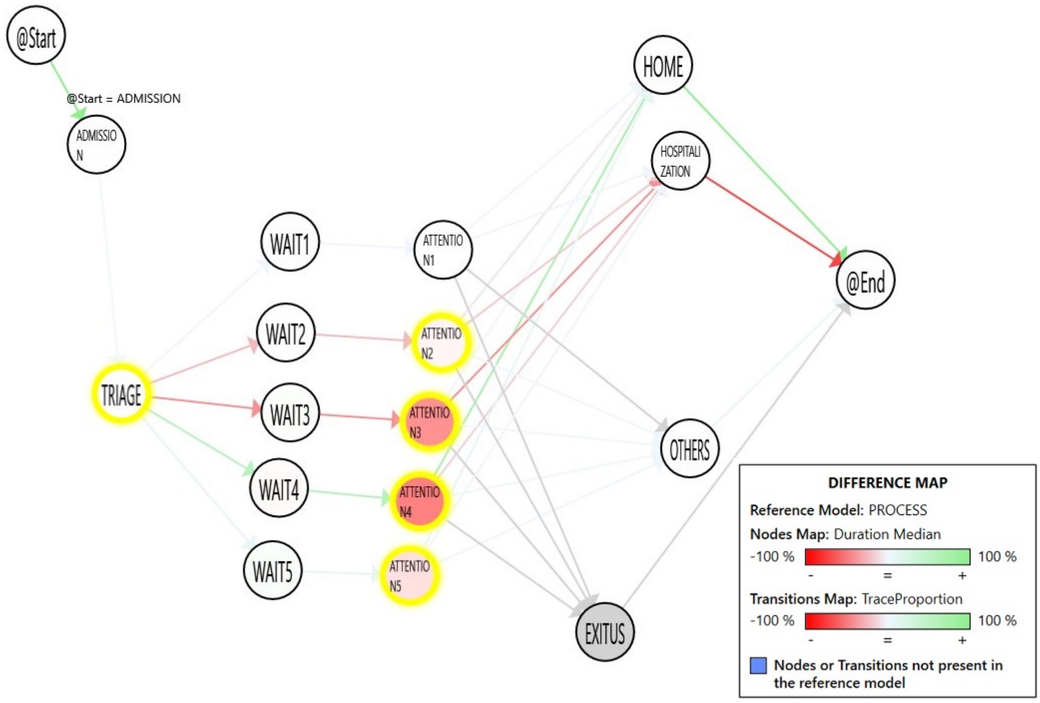


FIGURE 4.6: Differences between readmissions and non-return flow

Figure 4.6 represents the differences between the readmitted patients in less than 72 hours and those that did not return in that short term. The triage time has increased slightly (less than one minute) in the readmissions, which may be caused to longer explanations of the previous ED episodes. Where waiting times stay similar, the attention time has increased (red colour of *Attention3* and *Attention4* nodes) in those patients returning to the ED, which can be caused because have increased the number of tests done, especially in non-urgent patients.

In the comparison between *Returns* with no admissions and *Readmissions* (figure 4.7), it can be seen that this effect is more noticeable, the returned patients wait for more time until the first attention than readmitted patients (yellow ring in the red nodes are those that have significant differences, computing P-Value with confidence of 95%).

### 4.4.4. Length of stay

As mentioned above, readmissions and returns increase the number of visits to the ED, which can contribute to the overcrowding of the service. The hospital occupancy can delay admissions in the hospital, where patients should stay in the service until they are assigned to a bed, contributing to increasing the LoS[169, 170]. Also, other aspects can contribute to this increase as the triage level, the tests realized to the patients and the efficiency in the care[169], reducing QoC and increasing adverse events[157, 196]. In this regard, there is a wide-known rule named *4-hour* focused on preventing this increase and improving the quality of the ED care by instituting a maximum length of ED stay of 4 hours[197, 198]. Figure 4.8 represents the differences

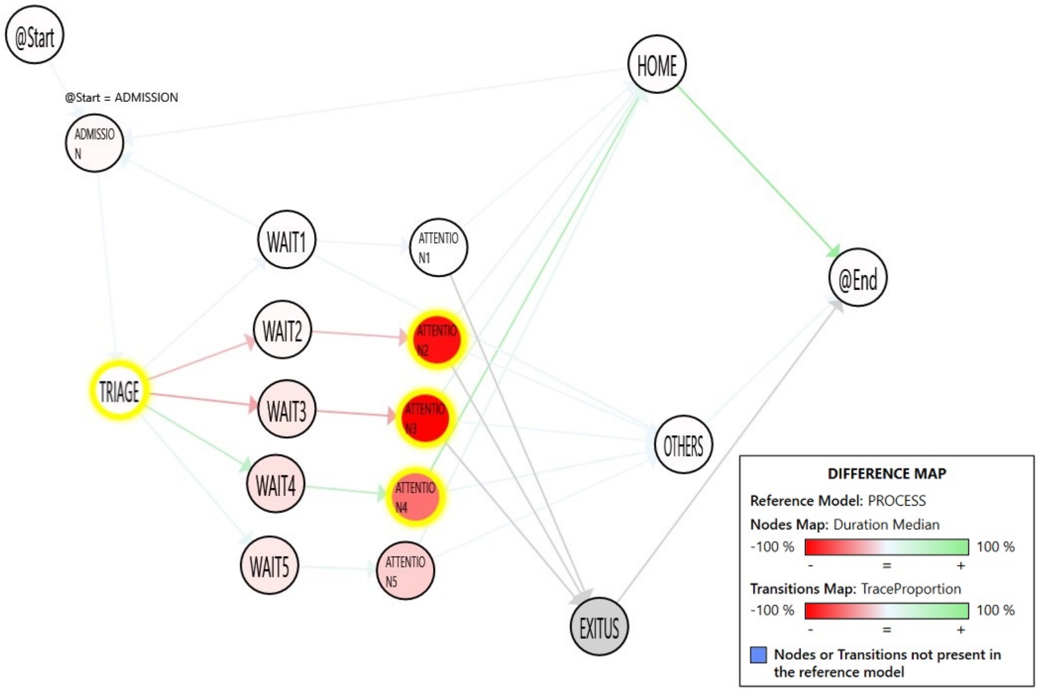


FIGURE 4.7: Differences between return and readmission flow

between the patients staying less than 4 hours (green transitions) contrasted with those that last more than 4 hours (red transitions). As expected, the LoS is directly related to the time expended in the attention stage, as more evident in the more urgent patients (*Attention1*, *Attention2*, and *Attention3* nodes) and having differences in the waiting times for non-urgent levels. Finally, patients returning and admitted to the hospital have a higher relationship with lower *LoS*.

### 4.4.5. Exitus

The ED provides medical assistance and nursing care until the stabilization of patients who are finally admitted to the hospital or those who have attended the ED are finally discharged. One of the worst possible outcomes is the death of the patient, which is, in the medical field, usually known as *Exitus*. Usually, in EDs *Exitus* only occurs with very acute patients. This is generally because these sorts of critical patients are quickly transferred to *Intensive Care Unit*, or *Surgery areas*[199, 200].

In this case, an *influence map* has been used, depicting in gradient colours the probability of patients passing away through the node. Figure 4.9 shows an *influence map* of the process in the *Exitus*, representing the higher number of patients finally deceased after the activity with redder nodes. As can be seen, the mortality is representative of critical and urgent people, as expected according to the literature.

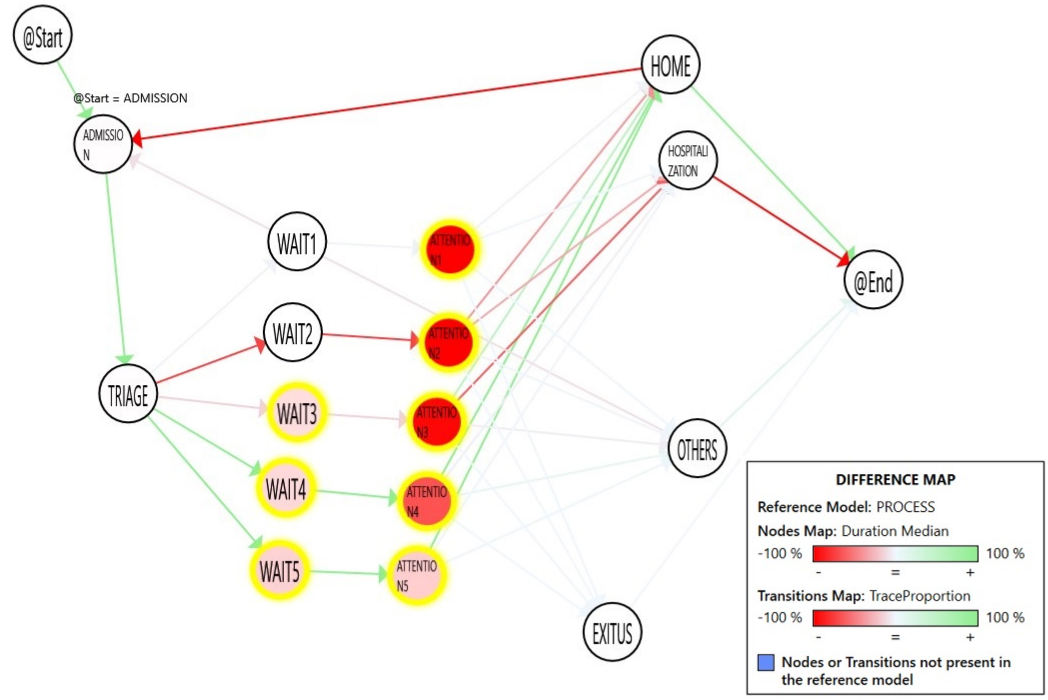


FIGURE 4.8: Comparing patients with a length of stay of >4h and of <4h

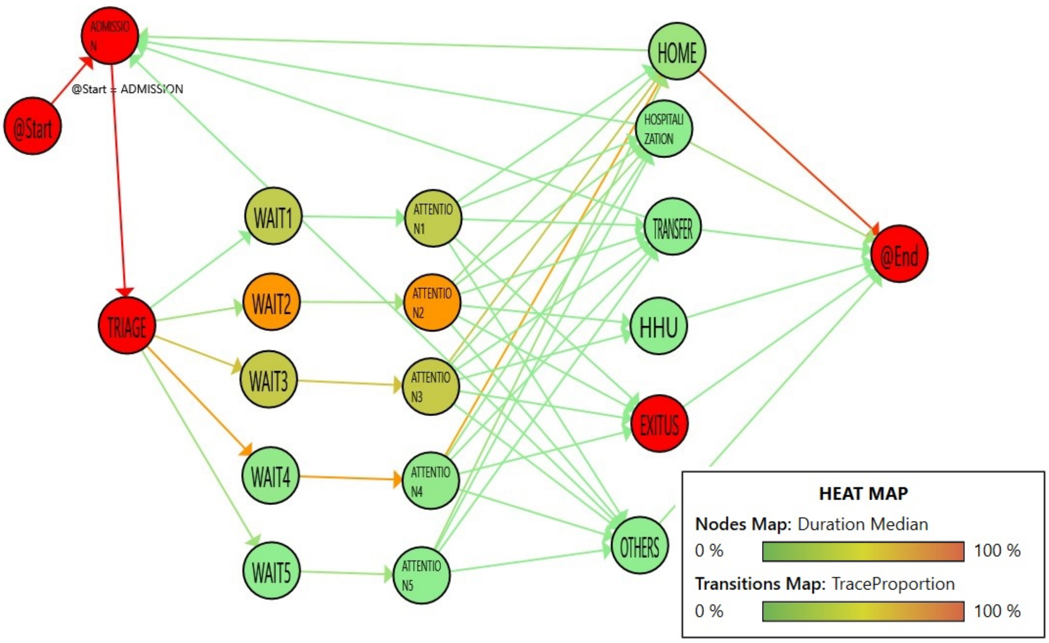


FIGURE 4.9: Gradient of the total number of patients finally passing away in each step of the process: Total Influence over exitus

## 4.5. A new approach to measuring quality of care

This chapter has presented a general *IPI* that is able to represent the characteristics needed for the analysis of the care processes in the ED. This *IPI* is in line with the literature and can be used to analyze process behaviours, as well as KPIs, but in a more comprehensive, navigable and understandable manner. This result accomplishes the **O1** and the **RQ1** of this work.

An *IPI* is a way of understanding, measuring, and optimizing a process, letting HCPs navigate through the model, discovering process characteristics, and facilitating the analysis of individual and custom aspects that range from general to individual. An *IPI* is not just numbers but also advanced views as enriched processes that bring an understandable view to the expert, helping to better perceive the processes for a deeper evaluation. Techniques such as influence and difference maps or statistical significance have been used for the analysis.

An *IPI* can be considered a set of enriched KPIs, where the KPIs make assumptions about the process in order to perform the calculations. However, the *IPIs* work with the actual process. KPIs need to be designed by a data analyst. On the other hand, *IPIs* are created by clinical staff (with the help of process miners during Data Rodeo sessions). KPIs answer predefined questions, while *IPIs* allow you to ask as many questions as necessary. KPIs give quantitative answers. Instead, *IPIs*, in addition to giving quantitative answers, are visual and navigable models that let go from general to individual information. Thus, KPIs give a partial vision of overcrowding, however, the *IPI* gives a continuous vision, which could be used to give a more complete and dynamic vision, not giving information from a specific moment.

Hence, the idea of comparing hospitals is challenging due to the fact that each one has its circumstances, for example, each hospital serves a population that, due to their social status, follows different lifestyles that affect clinical results. However, taking this fact into account, it can be stated that comparing a hospital with itself over time is a practice that can help measure the quality of the service offered.

# Chapter 5

# An Interactive Process Indicator to Measure the Value Chain Within Stroke Processes in the Emergency Department

Previously, a general *Interactive Process Indicator* (IPI) is introduced, representing needed characteristics for comprehensively analyzing care processes in the Emergency Department (ED). The *IPI* allows Healthcare Professionals (HCPs) to navigate, understand, and optimize the process, providing advanced views that will enable deeper analysis. Optimizing the care process in stroke care is crucial for better patient recovery, requiring rapid detection and treatment. To achieve this, it is proposed to use the defined ED *IPIs* for dealing with the Value-Based Healthcare (VBHC) paradigm, aiming to provide the best health outcomes to patients at the lowest cost. To understand and identify specificities in the care process for stroke in ED, the *IPI* is used, allowing measurement of the value chain to identify process differences and comprehend the stroke disease process behaviour.

## 5.1. Towards value-based healthcare in the emergency department for stroke patients

The previous chapter focused on introducing the *IPI* of the ED of the Hospital General Universitario de Valencia (HGUV). The main objective of this *IPI* was to characterize the general ED process in a visual and navigable manner. Thus, this work continues in this chapter by analyzing a concrete process in the ED: *The Stroke*. This analysis was done under a VBHC perspective, bringing two main objectives. On the one hand, it should be able to characterize the specific behaviour of the disease in the *IPI* built. On the other hand, to answer questions related to VBHC by measuring the value chain with *Interactive Process Mining* (IPM) techniques.

According to data from the Spanish Society of Neurology (Sociedad Española de Neurología)[1], in Spain, every year 120.000 people suffer a stroke, of which about 40,000 die. In addition, about 30% of patients suffer some type of disability after a

[1]https://www.sen.es/

stroke, which entails a direct healthcare cost of 2 billion euros per year and an indirect cost of 6,500 million euros per year.

In this regard, the Spanish Society of Emergency Medicine and Emergencies (Sociedad Española de Medicina de Emergencias y Urgencias)[2] remarks that treatment in the acute phase requires rapid and efficient action between the emergency services and the ED service since early treatment continues to be essential in reducing mortality and sequelae[201]. A correct diagnosis and treatment in this phase can result in a 20% reduction in the risk of disability and mortality[202]. Thus, due to the complexity of care response required in ED, delving into this process to respond to patient needs is mandatory to provide individualized, comprehensive, multidisciplinary and coordinated care, directly impacting the Quality of Care (QoC).

Relatively new trends to measure and improve QoC are paradigms such as Value-Based Health Care introduced by Porter and Teisberg [38] or the Triple Aim [40] promoted by the Institute for Healthcare Improvement (IHI) recognized the complexity of the ecosystem around the healthcare and presenting both a more holistic approach to providing care taking into account all the important factors to measure the QoC and influencing the future sustainability of healthcare, where the Tripe Aim is focused on[40]:

- *Better care*. Enhance the individual perception of the care experience by selecting the best treatments.
- *Better health*. Improve the general health status of the patient by seeking the best and specific protocols for specific patients.
- *Lower costs*. Reduce the per capita costs of the population at the time that is maximized the value delivered to the patient.

VBHC is based on the delivery of as much value as possible for the patient when delivering care, considering value as the best health outcomes at the most minor likely costs at the time under a different organization approach of the healthcare institution into patients' medical conditions, taking care of the full care journey. Moreover, health outcomes were related to what matters most to patients: to survive the medical condition, recover from the recovery process and keep the quality of life.[41].

VBHC looks to provide value to individuals by obtaining better outcomes and optimizing costs. By improving the health of individuals, it is possible to improve the health of society, as is the objective of the Triple Aim, which tries to keep a healthy community with better care at a lower cost. In a world concerned about the sustainability of health systems due to increased life expectancy, age-related decline and chronic diseases, reform of health systems is required to make them more effective[41].

According to Porter and Lee[203], VBHC introduction is expected to contribute to organizational learning about improving outcomes in relation to patients' medical conditions. But the process of adopting VBHC is not trivial. Several experiences pinpointed[204] key topics to consider during its implementation, including a culture change and a supporting Information Technology (IT) system. On the one hand, the culture change includes allocating (time, human and administrative) resources

[2] https://www.semes.org/

to support the VBHC implementation and the development-oriented leadership with the power of decision. The hospital's management team needs to transmit the power of decision to the teams explicitly. Finally, to create engagement among patients and hospital staff to settle the change and the provision of a supporting IT system. Traditional Key Performance Indicators (KPIs) have been used for years as a tool to measure the QoC and value chain benefits to patients, even though they present some limitations, such as the long time needed for their selection and design and the assumptions required for their implementation sometimes can generate refusal, tending to be based on easy to obtain data that do not necessarily reflect the complexities of everyday healthcare practice[205]. In addition, according to the VBHC approach, to be sure that the maximum value is being provided to patients, it needs to be periodically checked, which requires tools for linking outcomes to QoC processes and Continuous Quality Improvement (CQI) iterations[206]. Thus, the lack of tools to measure health outcomes and costs meant the most consuming task because the participants were uncertain whether or not this work could negatively influence the validity of the data[204], being very tough to measure the value chain.

Since the arrival of Data Science, its application to health has increased[66, 65]. Big Data technologies are capable of supporting diagnostic and therapeutic processes and offer added value for both HCPs and patients. However, health care is not a standard product. Patients have different needs derived from their medical condition, social circumstances, and genotype, among other characteristics, being this uncertainty is reflected in very complex and inefficient care processes. To this end, CQI enables health organizations to optimize their care processes to create value for patients[43].

Thus, these technologies, especially Process Mining[74, 75], can help in this continuous improvement process by offering the knowledge needed about care processes performing and their evolution after applying specific advancements, which in turn, is reflected in the increase of the value provided to patients when the QoC is improved and the fewer costs. Optimizing outcomes that matter for patients means aligning all the pieces of delivering health care, including supportive services, process optimization efforts, research and innovation. Consequently, to implement VBHC, it is necessary to measure outcomes and costs through supportive IT systems[207].

These can also contribute to better management of the cost of patients, making health systems sustainable. However, specific Data Science solutions are shown as *Black Boxes* by HCPs[67], who need to understand how their daily practice affects the value provided to patients. Although data available in hospitals is growing, there are still all kinds of acceptance barriers, implementation, and organizational challenges that prevent the adoption of the digital health transformation to support standards such as VBHC.

Hence, Chapter 4 presents how the *IPIs* can model the QoC provided in the EDs, contributing to delivering enriched information about the QoC offered to patients using process-based indicators that help understand what is occurring. In this regard, this chapter goes a step forward by proposing an *IPI* as a facilitator to empower CQI strategies towards VBHC applied in EDs by characterizing the stroke treatment. In addition, to represent the stroke process and consider that timing is crucial in this sort of disease, it is necessary to analyze the time spent in each step.

## 5.2. The stroke process in the emergency department

In Chapter 4 was introduced the general *IPI* of the ED where one of the most critical diseases treated is stroke. It remains one of the leading determinants of death and severe disability worldwide. Moreover, it is a time-sensitive medical emergency with a narrow time window for rapid evaluation and administration of outcome-modifying treatment. For that, it has its circuit known as *Stroke Code* to activate a specific protocol to treat these patients, the main goal is to maximize safety, quality and efficiency in the early diagnosis and treatment of acute stroke. Several studies have consistently demonstrated that early diagnosis and treatment of stroke patients is the major determinant of clinical outcome and quality of life after stroke[208, 209].

In this line, using *IPM* techniques can produce *IPIs* that support discovering the behaviour of the process, which enables HCPs to evaluate better the particularities and differences among the stroke process[210, 211]. This facilitates them to influence the service offered to patients, directly reflected in their health and, consequently, in the patients' perception when resources invested can be optimized. In the case of stroke, it is of paramount importance because the time of reaction between a stroke event and the administration of adequate treatment is crucial in reducing brain injury and disabilities associated can decrease the quality of life of patients and increase costs. In this regard, the objective of this chapter is to illustrate how *IPM* can show the characteristics of a specific disease inside ED, such as stroke, within the VBHC umbrella. For that, these are defined five Research Questions (RQs) that are based on the main principles of the VBHC and Triple Aim:

- *Q1. Can Process Mining detect and measure the special characteristics of stroke emergency processes?*
- *Q2. Is Process Mining able to measure organizational changes that affect the emergency process?*
- *Q3. Can Process Mining reveal differences in Emergency process protocols depending on Patients' personal characteristics?*
- *Q4. Can Process Mining evaluate the status of the Emergency protocol according to existing Gold Standards?*
- *Q5. Can Process Mining provide a Healthcare Value-Based view of the effects of the care provided?*

The questions were formulated based on the core principles of the VBHC and Triple Aim frameworks to showcase the potential of Process Mining in this domain (see figure 5.1). The research aims to contribute ideas for supporting VBHC in EDs, specifically for patients with critical conditions like stroke, utilizing the available data in the Hospital Information System. The research design of the questions is summarized as follows:

- *Q1.* Demonstrates that Process Identification serves as the foundation for analyzing the subsequent questions.

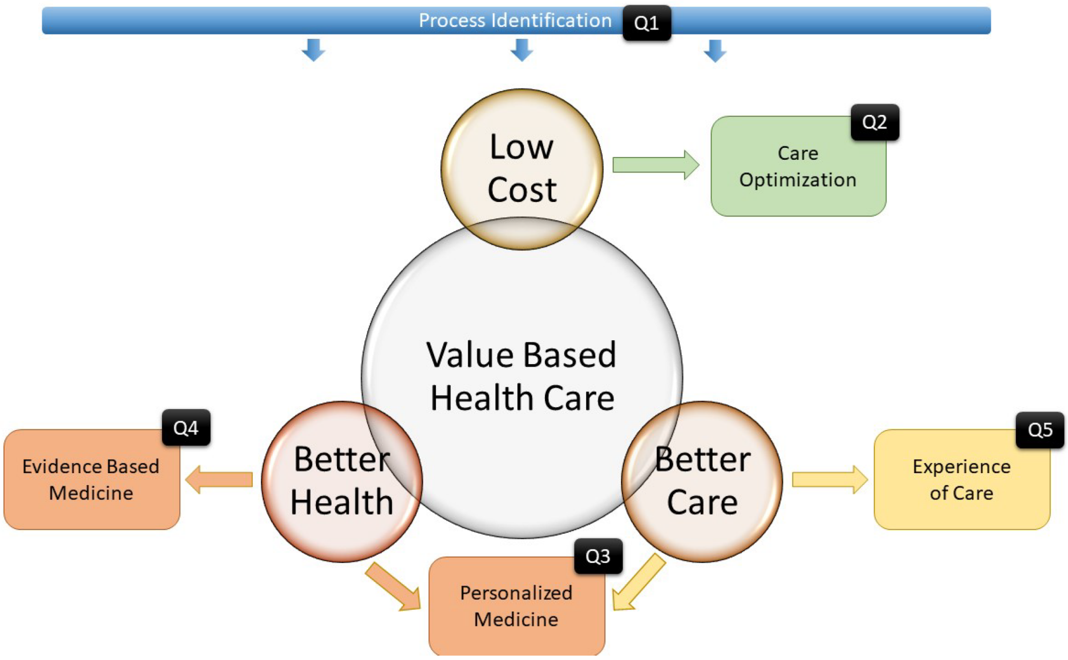


FIGURE 5.1: Value-Based Healthcare and Triple Aim paradigms related to the research questions

- *Q2.* Illustrates how IPM can enhance patient care by examining whether the organizational changes yield valuable outcomes compared to the required resources invested.
- *Q3.* Evaluates using Process Mining techniques to identify disparities among patient groups or individual patients, emphasizing personalized care and improved patient well-being.
- *Q4.* Aims to compare the implementation of clinical protocols with established evidence-driven clinical knowledge through delta analysis. This allows for both quantitative and qualitative evaluations.
- *Q5.* Proposes a method to assess not only the QoC provided to patients but also to detect abnormal readmissions and offer support for case-by-case assessments conducted by HCPs.

The primary objective of this research is to examine stroke cases and understand their distinct characteristics thoroughly. To accomplish this, it was conducted a comprehensive analysis of a genuine log consisting of 9,046 Emergency episodes involving 2,145 patients who experienced at least one stroke event during the period spanning from January 2010 to June 2017 in the Hospital General de Valencia. This extensive log served as the foundation for addressing the research inquiries utilizing advanced Process Mining technologies. By leveraging these tools, it was able to extract valuable insights and provide insightful answers to the posed questions. Additionally, statistical analysis techniques were employed to quantify the significance of the obtained results, ensuring their reliability and relevance.

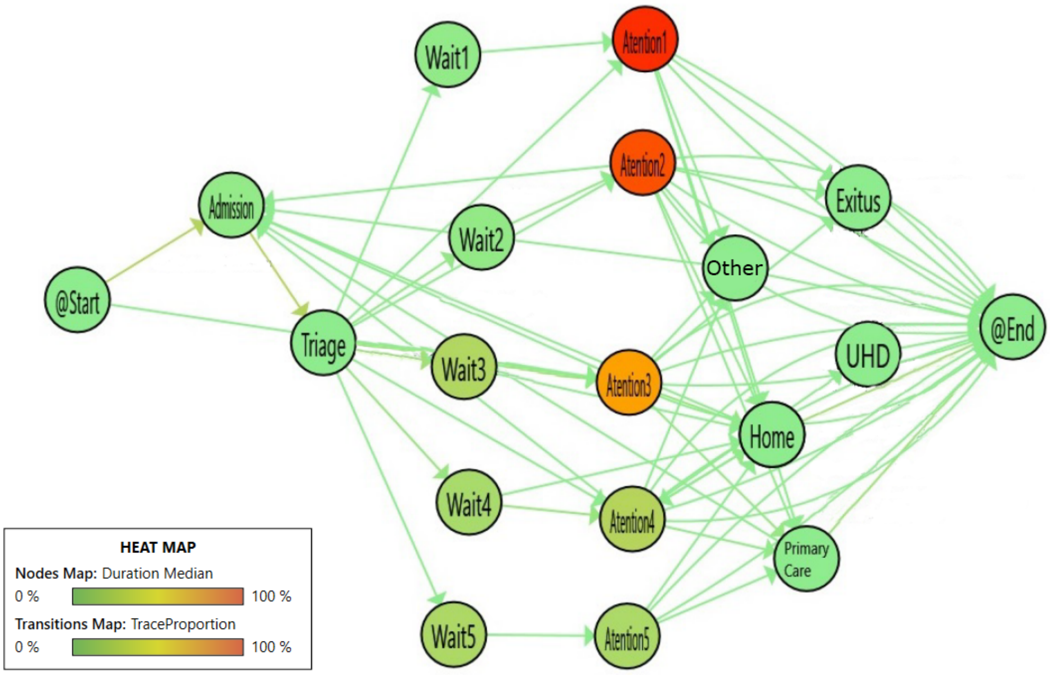


FIGURE 5.2: Flow of the ordinary discharge episodes in Emergency Department

### 5.2.1. Q1: Can process mining detect and measure the special characteristics of stroke emergency processes?

When analyzing a process, some standards provide recommendations and guidelines on how it should work, but the reality is that the processes depicted may differ from the standard ones. The process represented uses the existing data coming from the hospital that, in practice, reflects the actual use of the system by the HCPs, as is the case of the patients triaged as level 1, who require immediate attention, the waiting times can be erroneously recorded because the patient is prioritized over the administrative tasks. The nodes have been separated from 1 to 5 to see the differences between the triage levels.

In figure 5.2, the colours in the nodes represent the average time spent in each activity and can be easily recognized the general process of the ED where the nodes represent the *footprint* of the patients in the ED of the hospital, being the redder the node, the more time spent on the activity. As expected, the low-priority levels spend more time waiting than those with high-priority. On the contrary, patients who need more urgent attention spend more time in the attention stage than those who are not. Transitions between nodes also provide relevant information. For example, incoming flows to the *Admission* node represent those patients that have returned to emergencies in less than 24 hours, considered one of the KPIs for emergency management.

Data presented in Table 5.1 corresponds to a log consisting of 9,046 Emergency episodes involving 2,145 patients who experienced at least one stroke event during the period spanning from January 2010 to June 2017 in the Hospital General de Valencia. It is patients who have suffered from a stroke but may visit ED other times during that period (January 2010 - June 2017) to treat ordinary emergencies. Then, table 5.1 shows the numerical information derived from the statistical comparison between stroke and ordinary emergencies of patients suffering from at least one stroke. Bold rows are for statistically significant differences between groups.

| | Ordinary Emergency | | Stroke Emergency | | |
|---|---|---|---|---|---|
| **Activity** | $N$ | $IQRange$ | $N$ | $IQRange$ | $p$-**Value** |
| **Admission** | **5630** | **9.27 [4.62, 18.53]** | **1475** | **7.12 [4.13, 13.80]** | **0.00** |
| **Triage** | **5630** | **1.00 [0.00, 2.00]** | **1475** | **1.00 [0.00, 2.00]** | **0.05** |
| Wait1 | 41 | 7.97 [2.97, 15.47] | 126 | 4.97 [2.72, 8.97] | 0.13 |
| **Attention1** | **53** | **389.50 [208.82, 667.47]** | **180** | **110.82 [74.60, 213.07]** | **0.00** |
| Wait3 | 2960 | 53.47 [21.97, 110.97] | 555 | 36.97 [12.97, 83.97] | 0.07 |
| Attention3 | 3016 | 220.56 [128.48, 355.56] | 576 | 247.07 [152.45, 373.81] | 0.72 |
| Wait2 | 829 | 7.97 [4.97, 15.97] | 613 | 7.97 [3.97, 16.97] | 0.83 |
| Wait4 | 1571 | 51.97 [22.97, 103.97] | 43 | 61.97 [23.97, 121.97] | 0.62 |
| **Attention4** | **1590** | **27.68 [10.54, 99.55]** | **43** | **240.15 [116.78, 384.62]** | **0.00** |
| **Attention2** | **866** | **305.53 [195.90, 568.57]** | **673** | **210.62 [133.84, 304.88]** | **0.00** |
| Wait5 | 105 | 73.97 [34.97, 116.47] | 3 | 3.97 [0.97, 185.97] | 0.77 |
| Attention5 | 105 | 25.17 [9.22, 68.44] | 3 | 86.30 [54.05, 563.27] | 0.45 |

TABLE 5.1: Sample size and descriptive statistics for the time (in minutes) for ordinary and stroke unit admission nodes

In comparison with the regular *IPI*, figure 5.3 shows the flow for stroke patients. It is emphasized with a yellow border on those nodes (*Admission*, *Triage*, *Attention 1*, *Attention 2*, and *Attention 4*) where there is a *statistically significant difference* in their duration. In addition, the information represented in this map can be complemented with numerical information derived from the statistical comparison between both processes. In this regard, it is shown that the patients who are quickly diagnosed with stroke in the high-priority levels are immediately sent to the stroke unit and, consequently, spend less time receiving attention. Conversely, patients diagnosed on low-priority levels increases the time significantly receiving attention (up to 8.67 times worse than the ordinary patients in level 4).

### 5.2.2. Q2: Is process mining able to measure organizational changes that affect the emergency process?

Once the process is identified, policies can be applied to improve the efficiency and efficacy of the process to provide better care, at the same time, the value delivered to the patient can be assessed. With the *IPI*, it is possible to evaluate those changes and the impact on the organization by comparing the process before and after the application of the said policy, helping policymakers with their daily decisions.

In March 2017, a second triage station was established to improve the admission time, especially in the most complex cases, to improve the quality of the service offered. Figure 5.5 shows the flow inferred from the double triage that can be compared

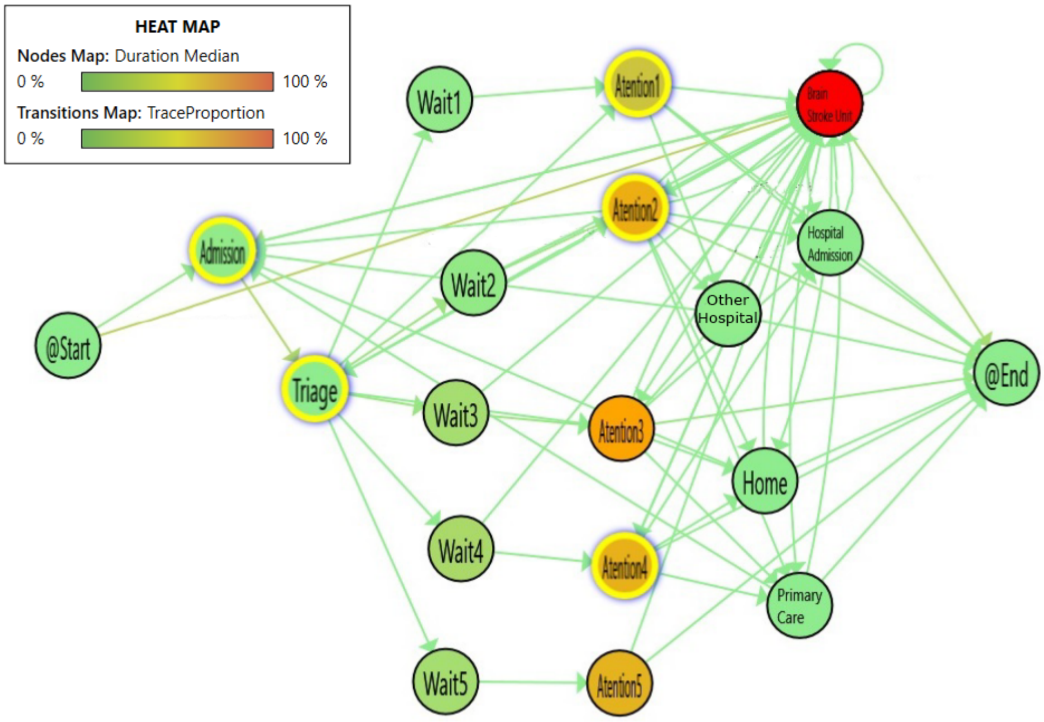


FIGURE 5.3: Flow for stroke patients represented in a statistical significance map

to figure 5.4 that represents the flow three months before with one triage. By looking at the nodes with *statistical significance* and the numbers, it can be observed that the reduction time in the *Admission* and *Wait 3* nodes contribute to reducing the time to the treatment by stroke patients, which is critical, taking into account that those treated in less than one hour reduces the severe risk lesions. As a result, the costs derived from those consequences are reduced.

Data presented in Table 5.2 corresponds to a log consisting of 9,046 Emergency episodes involving 2,145 patients who experienced at least one stroke event during the period spanning from January 2010 to June 2017 in the Hospital General de Valencia. Table 5.2 shows the stats associated with the analyzed logs. Bold rows are for statistically significant differences between groups.

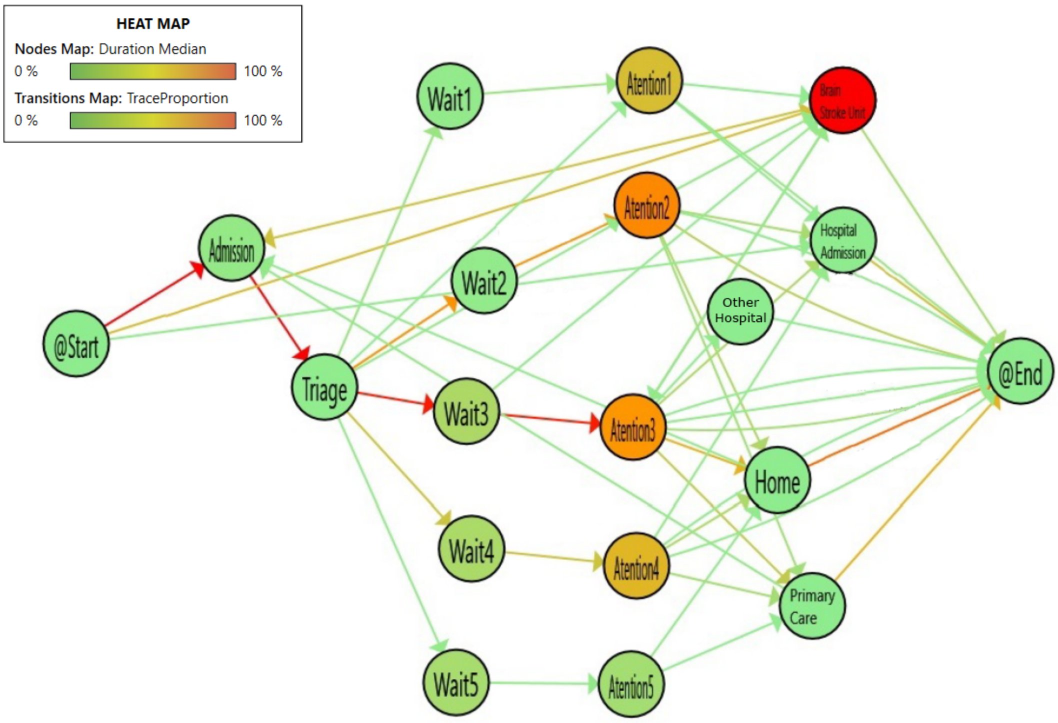


FIGURE 5.4: Flow for single triage

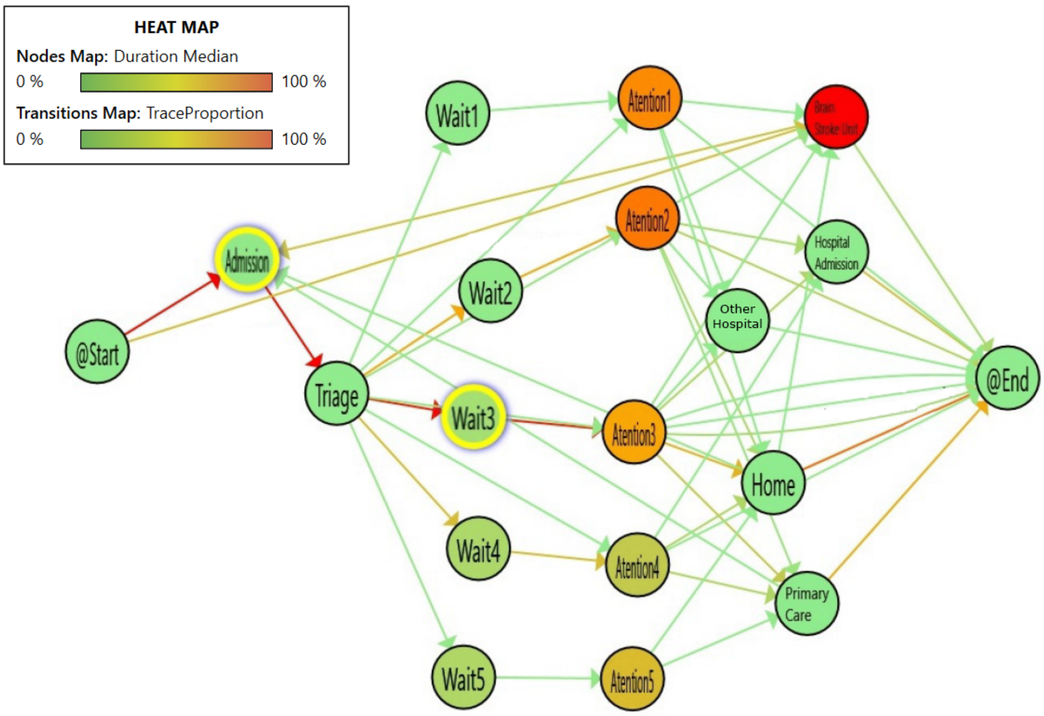


FIGURE 5.5: Flow for double triage

| | Single Triage | | Double Triage | | |
|---|---|---|---|---|---|
| **Activity** | ***N*** | ***IQRange*** | ***N*** | ***IQRange*** | ***p*-Value** |
| **Admission** | **284** | **11.01 [4.71, 24.27]** | **425** | **7.75 [3.53, 17.96]** | **0.00** |
| Triage | 284 | 2.00 [2.00, 4.00] | 425 | 2.00 [1.00, 4.00] | 0.29 |
| Wait5 | 3 | 26.97 [24.97, 151.97] | 7 | 73.97 [20.97, 157.97] | 0.66 |
| Attention5 | 3 | 25.13 [9.62, 141.52] | 7 | 56.68 [33.78, 254.33] | 0.27 |
| Wait2 | 85 | 6.97 [3.97, 12.47] | 108 | 6.97 [4.97, 13.97] | 0.44 |
| Attention2 | 88 | 242.48 [170.38, 399.66] | 119 | 275.58 [195.95, 497.25] | 0.48 |
| **Wait3** | **142** | **56.47 [21.97, 128.22]** | **210** | **40.47 [15.97, 79.47]** | **0.00** |
| Attention3 | 142 | 222.09 [123.20, 410.48] | 216 | 209.33 [124.15, 344.74] | 0.35 |
| Wait4 | 43 | 51.97 [22.97, 110.97] | 74 | 59.97 [25.72, 107.22] | 0.92 |
| Attention4 | 43 | 63.42 [22.18, 255.33] | 76 | 36.48 [13.51, 190.50] | 0.19 |
| Stroke | 63 | 8640 [5760, 14400] | 90 | 8640 [5760, 13305] | 0.56 |
| Wait1 | 7 | 7.97 [2.97, 10.97] | 4 | 6.97 [4.22, 10.47] | 0.69 |
| Attention1 | 8 | 112.41 [47.95, 314.73] | 7 | 149.57 [63.35, 563.50] | 0.33 |

TABLE 5.2: Sample size and descriptive statistics for the time (in minutes) for stroke unit admission nodes with one and two triage stations

### 5.2.3. Q3: Can process mining reveal differences in emergency process protocols depending on patients' personal characteristics?

In this case, the work is focused on identifying differences in the process that depends on the specific behaviour of patients, as is the age of the patients, which affects the management of the illnesses in ED. Table 5.3 shows the distribution of the age groups in the ED episodes analyzed.

| Age Group | N | % |
|---|---|---|
| 65+ | 6624 | 80.88% |
| 40–65 | 1446 | 17.66% |
| 20–40 | 113 | 1.38% |
| 0–20 | 7 | 0.09% |

TABLE 5.3: Age groups in Q3

In figure 5.7 can be seen a comparison of patients between 40 and 65 years old and patients 65+ years old (figure 5.6. Table 5.4 shows the statistical results of comparing the logs. Bold rows indicate statistical significance. This comparison shows apparent differences in the time spent at the attention stage for the most urgent levels 1, 2 and 3, with differences of less than one hour in the three cases.

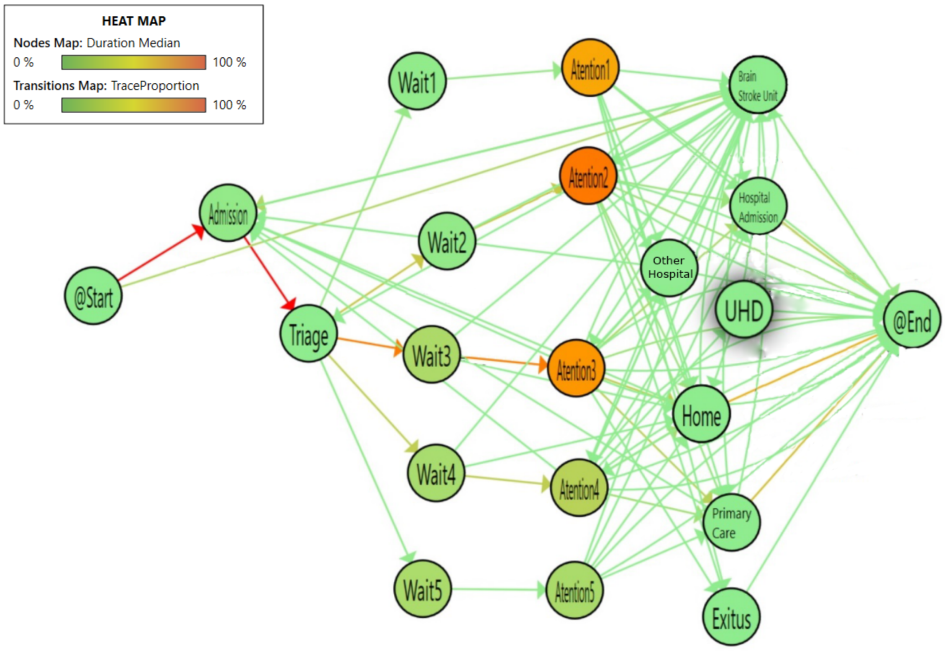


FIGURE 5.6: Emergency Department flow determined for patients aged 65+ years

| | 65+ | | 40–65 | | |
|---|---|---|---|---|---|
| Admission | 6744 | 0.14 [0.07, 0.29] | 1482 | 0.14 [0.07, 0.29] | 0.48 |
| Triage | 6744 | 0.02 [0.00, 0.03] | 1482 | 0.02 [0.00, 0.03] | 0.39 |
| Wait2 | 1513 | 0.13 [0.07, 0.27] | 353 | 0.12 [0.07, 0.23] | 0.55 |
| **Attention2** | **1513** | **4.72 [3.05, 8.16]** | **353** | **4.12 [2.72, 6.69]** | **0.00** |
| Wait1 | 202 | 0.05 [0.00, 0.13] | 72 | 0.05 [0.00, 0.13] | 0.96 |
| **Attention1** | **202** | **3.02 [1.46, 6.81]** | **72** | **2.46 [1.36, 4.09]** | **0.03** |
| Wait3 | 3661 | 0.77 [0.30, 1.73] | 662 | 0.80 [0.33, 1.67] | 0.70 |
| **Attention3** | **3660** | **4.06 [2.52, 6.68]** | **662** | **3.31 [1.68, 5.64]** | **0.00** |
| Wait4 | 1283 | 0.83 [0.38, 1.70] | 372 | 0.88 [0.33, 1.77] | 0.66 |
| Attention4 | 1283 | 0.54 [0.19, 2.06] | 372 | 0.42 [0.15, 1.74] | 0.27 |
| Wait5 | 85 | 1.08 [0.49, 1.84] | 23 | 1.38 [0.75, 2.53] | 0.11 |
| Attention5 | 85 | 0.52 [0.16, 1.22] | 23 | 0.28 [0.16, 1.41] | 0.49 |

TABLE 5.4: Analysis of statistical significance between the 65+ and 40–65 age groups (Interquartile range in hours)

Figure 5.8 shows the flow of patients from 20 to 40 years and the differences with patients age 65+. In this case, the differences between both groups are up to two hours in *Attention* time. Data presented in Table 5.5 corresponds to a log consisting of 9,046 ED episodes involving 2,145 patients who experienced at least one stroke event during the period spanning from January 2010 to June 2017 in the Hospital General de Valencia. Table 5.5 shows the numerical results of the comparison between the two groups. Bold rows indicate statistical significance. According to this data, older adults have more length of stay in *Attention* node than adult people.

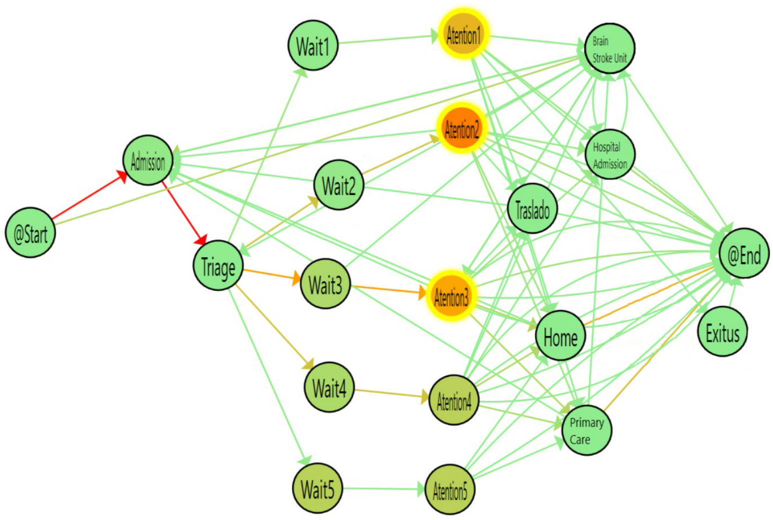


FIGURE 5.7: Emergency Department flow determined for patients from 40 to 65 years old and the statistical significance comparison with patients age 65+ years

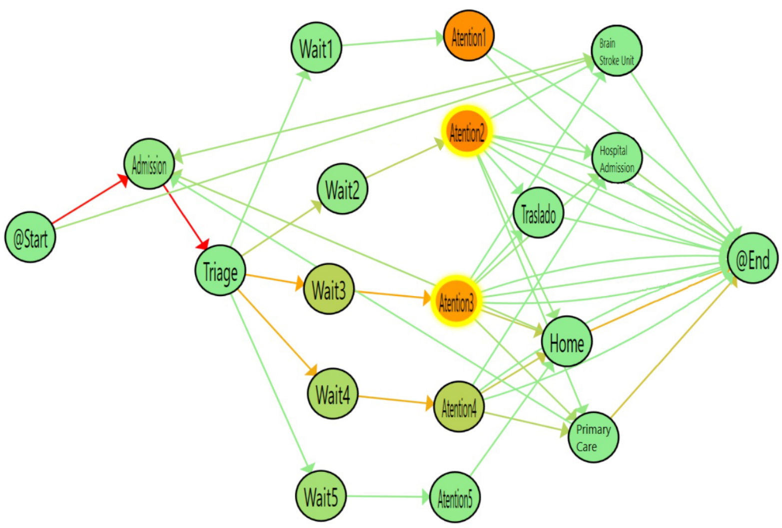


FIGURE 5.8: Emergency Department flow determined for patients from 20 to 40 years old and the statistical significance comparison with patients age 65+ years

| | 65+ | | 20–40 | | |
|---|---|---|---|---|---|
| Admission | 6744 | 0.14 [0.07, 0.29] | 127 | 0.14 [0.08, 0.23] | 0.13 |
| Triage | 6744 | 0.02 [0.00, 0.03] | 127 | 0.02 [0.00, 0.02] | 0.11 |
| Wait2 | 1513 | 0.13 [0.07, 0.27] | 21 | 0.13 [0.09, 0.22] | 0.58 |
| **Attention2** | **1513** | **4.72 [3.05, 8.16]** | **21** | **2.34 [1.49, 4.63]** | **0.04** |
| Wait4 | 1283 | 0.83 [0.38, 1.70] | 47 | 0.57 [0.23, 1.28] | 0.12 |
| Attention4 | 1283 | 0.54 [0.19, 2.06] | 47 | 0.36 [0.19, 0.66] | 0.16 |
| Wait3 | 3661 | 0.77 [0.30, 1.73] | 53 | 0.98 [0.46, 1.58] | 0.93 |
| **Attention3** | **3660** | **4.06 [2.52, 6.68]** | **53** | **2.72 [0.43, 4.11]** | **0.01** |
| Wait1 | 202 | 0.05 [0.00, 0.13] | 4 | 0.07 [0.00, 0.20] | 0.95 |
| Attention1 | 202 | 3.02 [1.46, 6.81] | 4 | 3.85 [1.34, 6.35] | 0.66 |
| Wait5 | 85 | 1.08 [0.49, 1.84] | 2 | 0.65 [0.22, 1.08] | 0.36 |
| Attention5 | 85 | 0.52 [0.16, 1.22] | 2 | 0.13 [0.12, 0.14] | 0.50 |

TABLE 5.5: Analysis of statistical significance between the 65+ and 20–40 age groups (Interquartile range in hours)

### 5.2.4. Q4: Can process mining evaluate the status of the emergency protocol according to existing gold standards?

Clinical guidelines are used across the world to support health professionals and offer concise instructions on how to proceed in their daily practice. The ED is not an exception and as it has been described above, one of the guidelines followed is the Manchester Triage Standard (MTS), where patients are allocated to one of the five urgency categories, determining the maximum time until first attention. With the *IPI* is possible to measure the fulfilment of these recommendations. With a gradient range from green to red, the greener nodes reflect the waiting times meeting the standard. The redder ones are the nodes where the waiting time is exceeded the most.

Looking at figure 5.9 can be seen that stroke patients assigned to level 1 are in red, although still within the time limit. It displays the enhancement map depicting the flow analysis of stroke patients. The map highlights the presence of red colour, indicating level 1 patients. Levels 2 and 3 exhibit darker shades but still fall within the acceptable time limits. It is worth noting that the recording of waiting times for level 1 patients, who require immediate attention, can be prone to errors due to the priority given to patient care over administrative tasks. Consequently, the imprecision in the data may result in colour gradients that inaccurately represent the actual situation. The numerical data corresponding to these findings can be found in table 5.6. The factor to compute the gradient was normalized using the median of the times spent in each activity, depending on the level. Formally, the factor $M_{level}$ is computed according to the following equation:

$$M_{level} = \frac{Median(Durations_{level})}{Factor_{level} * 2} \tag{5.1}$$

It is worth mentioning that these patients require immediate attention, which means that the administrative work is relegated until the patient's status is under control.

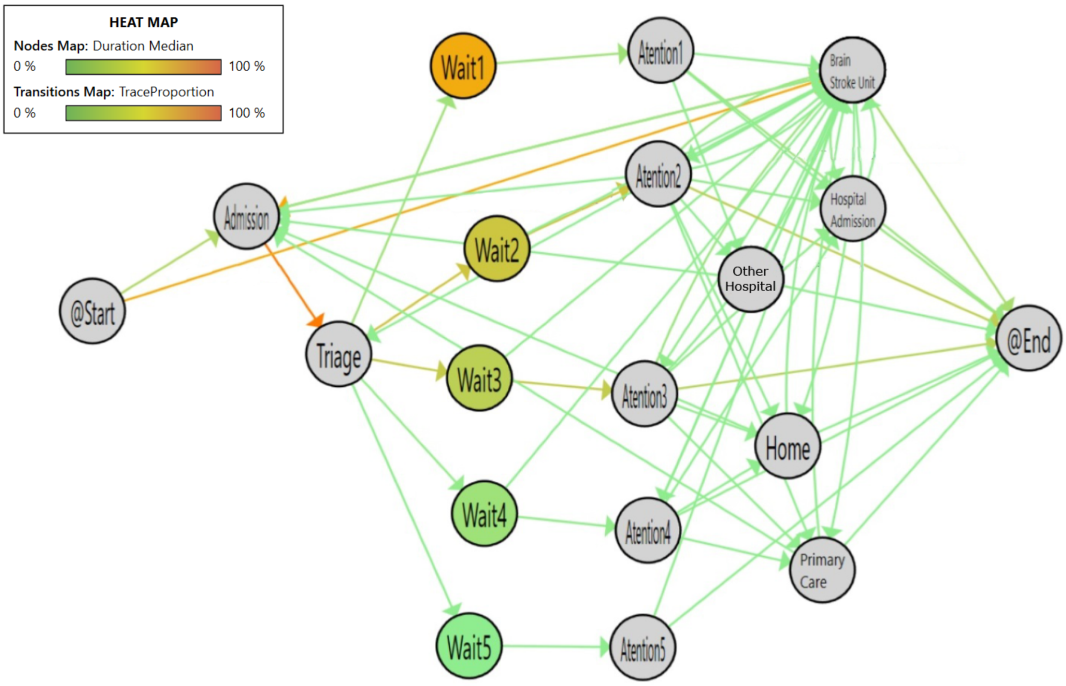


FIGURE 5.9: Time to attention of stroke patients according to the Manchester Triage Standard

| Level | Manchester Time Factor | Gradient Range |
|---|---|---|
| 1 | 0 | [0–2] |
| 2 | 10 | [0–20] |
| 3 | 60 | [0–120] |
| 4 | 120 | [0–240] |
| 5 | 240 | [0–480] |

TABLE 5.6: Urgency levels and expected waiting times according to the MTS[212] (in minutes) and the range defined for the gradient map for Process Mining enhancement

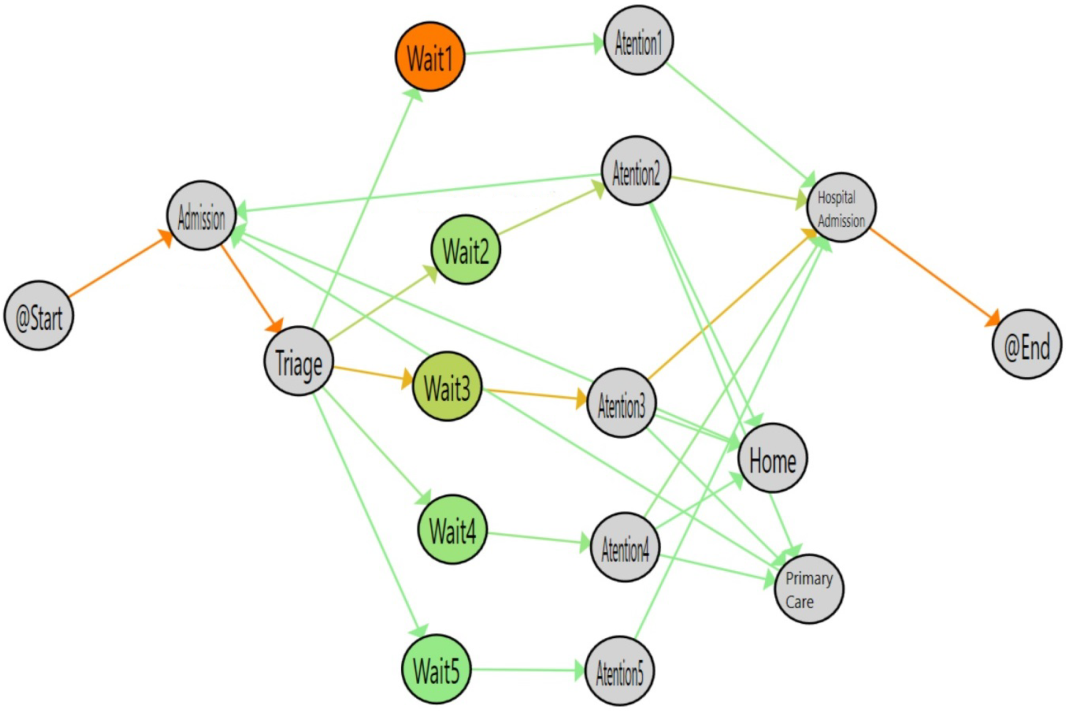


FIGURE 5.10: Time to attention of patients admitted in the hospital according to the Manchester Triage Standard

Alternatively, figure 5.10 shows the ordinary patients admitted to the hospital and figure 5.11 are ordinary patients without admission.

Figure 5.10 showcases the Manchester enhancement map of the Admission Log. A noticeable difference can be observed between the deviations in level 1 compared to the stroke log, while waiting times for level 2 are comparatively shorter.

Figure 5.11 presents the Manchester *enhancement map* of the log for ordinary patients. In these cases, there is a greater degree of deviation compared to the previous instances mentioned.

### 5.2.5. Q5: Can process mining provide a VBHC view of the effects of the care provided?

VBHC's main objective is to maximize the available resources to provide the best care to obtain the best health for patients. With this in mind, minimizing adverse effects such as returns or readmissions to ED measures the QoC provided to the patient, becoming an indicator of the value delivered. It is able to fuse those emergency episodes that occurred within 72 hours and represent the flow of the patients that are back to the ED after a home discharge (5.12). Moreover, it is possible to identify the individual path followed by each patient. According to this data, acute patients, that require more care, have less readmission rate than the rest of the patients.

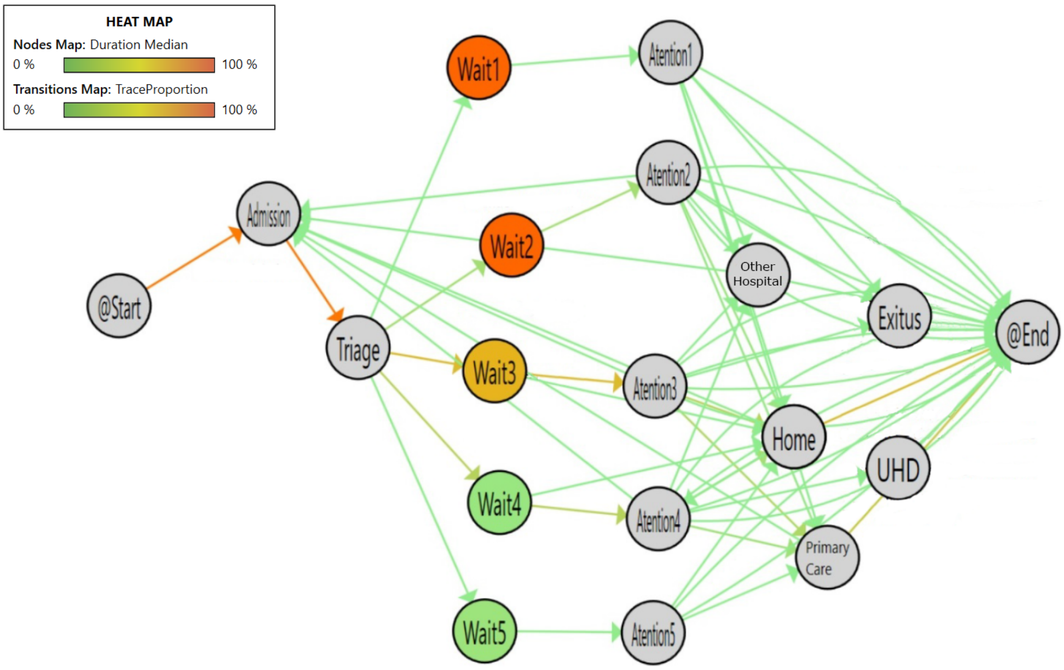


FIGURE 5.11: Time to attention of ordinary patients according to the Manchester Triage Standard

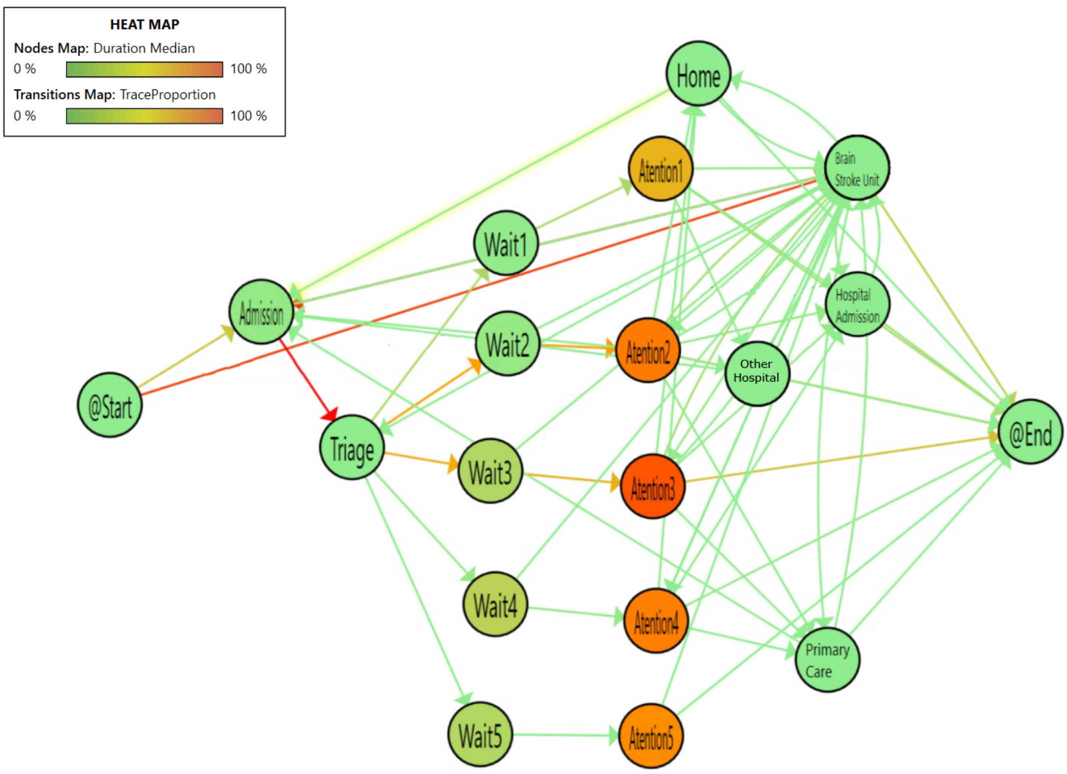


FIGURE 5.12: Patients readmitted after a home discharge

## 5.3. Toward measuring the value chain

The application of VBHC in real scenarios requires that data is presented in an understandable, explorable and objective way to HCPs. Classical data mining technologies are seen as *Black Boxes* since clinical experts are not able to know where the results come from. Using computing human-understandable techniques as PM allows health professionals to interpret the information from general to individual. This fact will lead to adopting this technology that facilitates the real implementation of VBHC in the healthcare systems.

In this chapter has been presented the *IPM* paradigm as the mean to support healthcare practitioners through the provision of information under different prisms by comparing the emergency and the stroke processes, analyzing whether the value delivered to patients is worth it according to the changes done in the organization and the spend resources. Furthermore, with *IPIs* is possible to reveal the differences between groups of patients or individual patients, emphasizing personalized care and better patient health, proposing a way to not only evaluate the quality of the care delivered to patients but also detect outliers patients or anomalous situations such as returns or readmissions. It noticed a set of under-triaged stroke patients who were incorrectly classified, which dramatically increased (by 867%) the time in the attention stage. It was discovered how using an additional nurse in the triage could save crucial minutes in the recovery of stroke patients. It was identified how the age of patients affects attention time, especially in older adults that may require two hours more than younger people. This result accomplishes the **O2** and the **RQ2** of this work.

In summary, *IPIs* allow characterizing both general processes and specific ones such as stroke; evaluate and measure how changes affect the process, discover differences in the behaviour of patients; compare the actual process with the Gold Standards; and show the chain-value of the process of the patient to the HCPs.

# Chapter 6

# PMApp for Co-creating Interactive Process Indicators in Real Daily Practice

In Chapter 4 has been presented the general *Interactive Process Indicator* (IPI) of the Emergency Department (ED). It was demonstrated that the *IPI* can characterize this process. A further step was presented in Chapter 5, where the stroke process in the ED was depicted according to its specificities, and it was demonstrated that this *IPI* can contribute to measuring the value provided to the patients according to the Value-Based Healthcare (VBHC) paradigm.

*IPIs* enhance the understanding of processes in the healthcare professionals'(HCPs) daily practice, which are built during *Interactive Process Mining Data Rodeos* sessions[160]. These are carried out in the *Interactive Process Mining* (IPM) methodology[155], which main aim is to incorporate domain expertise by involving HCPs in these multidisciplinary sessions. However, the challenge lies in providing suitable tools for this co-creation process. Thus, to ensure the successful implementation of *IPM* and the build of *IPIs*, an interoperable, customizable, expandable, and user-friendly Process Mining application is essential, as it is recognized by the Process Mining community the need for tools, methodologies, and algorithms tailored to HCPs[74, 75].

Since the inception of Process Mining, several dedicated applications have been developed for improving processes in different domains, including ProM, Disco, and Celonis. ProM offers extensive plugin support and extensibility options, but its complexity can be overwhelming for HCPs, lacking sufficient user-friendliness. On the other hand, applications like Celonis and Disco prioritize data extraction, performance analysis, and scalability, potentially sacrificing customization and flexibility[69, 75].

This chapter introduces *PMApp*, an *Interactive Process Mining Toolkit* designed to facilitate the initiation of Data Rodeos and enable the application of the *IPM* methodology in real-world scenarios[213], thereby promoting its acceptance among HCPs. *PMApp* has been employed in numerous case studies across Europe, spanning disciplines such as cardiology[214, 215], cancer[216], obesity[217], rheumatology[218] or stroke[210, 211], in hospitals located in Spain, The Netherlands, Sweden, and Portugal.

## 6.1. Through an interactive process mining solution for healthcare

As said, *IPM*[155] incorporates HCPs in the process learning method, enabling co-creation and comprehension of their daily practice. *IPM* utilizes processes discovered through various techniques to create *IPIs* that represent the reality for HCPs in a continuous, interactive, and understandable manner[156]. *IPIs* combine process models with domain knowledge in the form of Key Performance Indicators[50] (KPIs), allowing for a more comprehensive analysis. The iterative process involves *Interactive Process Data Rodeos* (Data Rodeos), interactive data analysis sessions where multidisciplinary teams curate data, co-create indicators, analyze and validate them, and train HCPs to extract maximum value from the *IPIs*.

Having this in mind, *IPM* is a particular methodology that needs the favour of a tool with denoting features such as:

- **Flexible**. Flexibility is the software's ability to provide tools for dealing with heterogeneous data sources, natively interconnecting them, non-intrusive, and supporting data transformation. The application should be flexible to deal with problems related to the data: data curation, semantic interoperability, and data filtering. For that reason, it should enable the adaptation of *IPIs* to the specific needs of each use case. Flexible tools should enable the possibility of creating data pipelines for correcting, transforming and filtering the data for adequate data management or even for allowing the reuse of the *IPI* co-created with other data sources. For example, an *IPI* can be defined as depicting the standard care path. This *IPI* can be used by another hospital. However, it will need to be modified the data entries of the new hospital information system and struggle with its quality.

- **Automatable**. An automatable tool permits configuring and interpreting the data ingestion, processing, discovering, and post-discovering workflow of the Process Mining process to be repeated as often as necessary with different data sources with the same data input format. An automatable tool is able to configure, save and load the Process Mining process applied to data from the data sources to the visualization module. Thus, it is necessary to define a configuration file that is a description of the data processing flow, which works with a set of data but at the same time can incorporate new data following the same structure. This requirement is essential in the *Research* phase, where this configuration file will be built incrementally until it is mature enough and has the *IPI* fully defined to be later reused in the *Production phase*. Also, this incremental configuration file will help make this build process traceable.

- **Customizable**. A customizable tool can incorporate new algorithms and techniques into the list of systematic actions to define the process. The tool should allow the incorporation of all the resources the process miners, HCPs or Information Technology (IT) staff need for data analysis. This includes new Process Mining techniques - discovery, enhancement, conformance - and new ways to view the information, indicators, etc.

- **User-friendly**. Software is user-friendly when well-designed and easy to use[219]. The application should offer a good user experience to the HCPs to ensure their acceptance and enable the analysis, empowering HCPs to apply these techniques in daily practice.
- **Understandable**. Understandability is the capacity of the HCPs to understand the models generated by the system. The tool should allow HCPs to analyze the data in a way that adds value to them. This requirement also contemplates translating *IPIs* into other medical domain languages understandable by HCPs as formal clinical guidelines in GLIF[220], ProForma[221], Asbru[222], or BPMN[223].
- **Transparent**. A transparent application aims to provide methods for assessing the effects of the data quality in data transformation and filtering, navigating through the process structures (transitions and nodes), and accessing the associated data. For HCPs to trust the application, they must be transparent in each step it takes when working with the data and at the time of analysis. For example, after dealing with data quality, HCPs need to know what data was kept and what data wasn't good enough and was removed. Another example is when the HCPs are looking at the process, at the indicators included in the *IPI*, need to understand and know what information is presented and how it was calculated.

According to previous systematic reviews[72, 224] and more recent publications[225, 73, 226], Process Mining has been increasingly applied to a multitude of healthcare use cases since 2005, where some examples of the applications used in them, which are potential candidates to fulfil *IPM* requirements are:

- *ProM* is a basic open-source Process Mining tool supporting many Process Mining algorithms as plug-ins[70]. However, according to the survey conducted by Claes and Poels[227], the weaknesses of ProM were related to data access in terms of data preparation, the lack of guidance and the hardness of understanding the discovered models.
- *RapidProM* is an extension of RapidMiner based on ProM, where complex Process Mining workflows can be modelled and executed quickly and reused for other data sets. RapidProM allows the inclusion of different types of analysis available through the RapidMiner marketplace. RapidProM runs techniques and algorithms on a manually built event log. RapidProM facilitates the study of the same process over different periods, being possible to replicate the same research in other medical centres.
- Comercial tools like *Celonis* or *Disco* consist of a licensed tool with a user-friendly interface, which helps to create visual maps from process data in an understandable and more straightforward quick manner. The Disco tool includes filtering features to explore the data and remove those cases that do not match the defined criteria[71]. Nevertheless, it is not possible to add new modules to upgrade the functionality of the tool[224].

- *UpFlux* is the only one more oriented towards analyzing health data, although it is not customizable.

In short, ProM is easy to customize but not intuitive enough for HCPs. Disco is a commercial tool easy to use but not personalizable. On the other hand, RapidMiner is automatable but does not meet the rest of the requirements. Finally, Upflux is the only one more oriented towards analyzing health data, although it does not meet all the above conditions. Lastly, to our knowledge, no tools offer the level of transparency described.

## 6.2. PMApp: An interactive process mining toolkit

Thus, it is presented *PMApp*, a desktop application specifically designed to implement the *IPM* paradigm in real scenarios. For that, the application is thought to explicitly follow the Data Rodeo process. *PMApp* can tackle the complexity and variability of the data as well as other limitations such as interoperability. The toolkit grants the configuration of different Process Mining techniques and the tailoring of further views of the data for conceiving *IPIs* to be valuable for the HCPs in a unique configuration file, providing an easy-to-use and configurable dashboard that HCP could use for daily data analysis, taking especial care of the trustworthy of end-users on the application.

*PMApp* is a Microsoft .NET-based software explicitly designed to support the Data Rodeo process of the (*Research* phase). The toolkit incorporates two main features - *Experiment Designer* and *Ingestor Editor* - for that purpose, making *PMApp* highly configurable to meet each hospital's specific needs and permitting the creation of custom *PMApp* dashboards according to the requirements of the health scenarios for daily practice (*Production* phase).

To the best of our knowledge, *PMApp* is the only toolkit that can be used by .NET Developers to create Process Mining research, covering the spectrum of .NET developers uncovered so far. *PMApp* can be freely downloaded for research purposes[1].

### 6.2.1. Experiment designer

The *Experiment Designer* is a *PMApp* module (see figure 6.1) that allows the creation of schemes that formally define the flow of Process Mining algorithms that must be applied to build an *IPI*. This module is in charge of assuring the tool's *Automatability*. It is done using drag-and-drop blocks already available in the toolkit or developing new ones according to the health organization's needs. These blocks represent calls to functions and algorithms implemented in the software to create the *IPI*. New blocks can be added easily by implementing plugins for the *PMApp* toolkit, enabling the *customization* of the application. The *Experiment Designer* is used for creating the *IPIs* during the *Research* phase, being aimed at process miners, who conduct conversations with HCPs to define, in different Data Rodeos sessions, the collection of operations to pass from the data available in the hospital to a final *IPI*. Thanks to the *Experiment Designer*, the process miner is capable of translating the *IPI* into an *Interactive Process*

[1]https://www.pm4health.com/download/

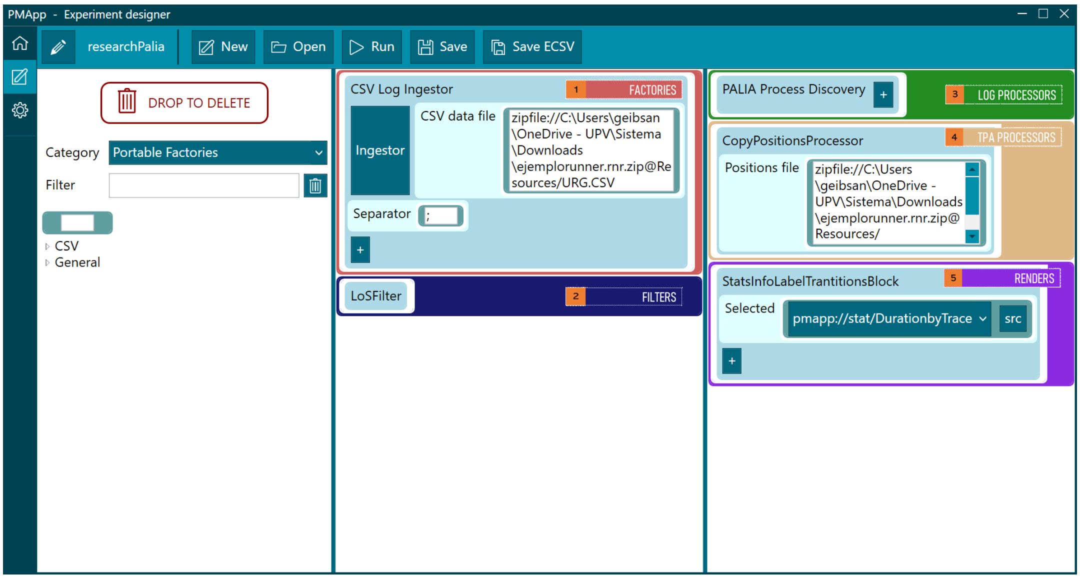


FIGURE 6.1: Experiment Designer: Feature of PMApp to configure Runners

*Mining Runner* (or simply *Runner*), which is a configuration file that defines the automation of the *IPI* creation process.

The first section of the *Experiment Designer* is a module containing the set of blocks available on the tool, which are listed in different steps, depending on their functionality. The kind of blocks available are *Factories*, which are in charge of the creation of logs, *Filters* that perform events and traces transformation and filtering, *Log Processors* that enable the process discovery, *TPA Processors*, for post-processing the models after discovery and *Renders* for enabling visual characteristics in the models.

The first step is the creation of the log. These sorts of blocks in charge of these actions are called *Factories (1)*. Figure 6.1 is an example of a *Runner* of an ED from synthetic data, where can be identified a *CSV Log Ingestor* block, which manages data sources and establishes the rules to model the process in subsequent phases, being in this example reading a CSV file. Factory blocks are a tool for connecting *PMApp* toolkit with different data sources (XES[228], CSV, SQL Data Bases,...). *Factories* allow not only the connection of data sources but also provides a data ingestion utility that permits to select the data that will be used for creating *Events*, *Traces* and *data* associated with them.

*Filtering (2)* is the next step after creating the log. Filters are mechanisms that can be applied to correct, split and group traces, as well as make all the possible modifications on the log before the discovery process. For example, according to the ED example, different blocks are used to model KPIs, for example, the length of stay (*LoSFilter*), which in this case, is already available in *PMApp* free version, but new blocks can be implemented explicitly under the criteria provided by the HCPs of a hospital.

*Log processors (3)* is the next step in the *Experiment Designer* to provide support to the Data Rodeos. *Log processors* are process discovery algorithms to create the graphical model from the log. In this example (figure 6.1, the selected algorithm block is *Parallel Activity Log Inference Algorithm* (PALIA)[229]. *PMApp* uses Timed Parallel Automatons (TPA)[230] as basic formalism. TPA is a formal mathematical model based on an automata theory with an expressiveness equivalent to Safe Petri Nets, keeping the complexity to a regular language level. The usability of this formalism has been successfully tested in medical environments[231]. Although TPA is the main formalism, *PMApp* has blocks for translating TPA to other formalisms like BPMN or ProForma.

Once obtained the TPA in the *Discovery* phase, it is processed for creating and computing specific maps and stats or other post-discovery modifications in the models (*TPA processors (4)*), for example, to compute median or average numbers or keep the positions of the nodes and transitions of the process discovered for future executions (*CopyPositionsProcessor* block of the ED example, which contains a "json.tpa" file for indicating the positions).

In the final step (*Renders (5)*), different renders are applied to highlight specific insights in the TPA (graphical model) and underline the particularities that HCPs need to understand, measure and compare in their clinical process. In this example, the block *StatsInfoLabelTrantitionsBlock* lets the information displayed in the transitions between nodes be selected. In this case, the information shown is the average duration per trace, but other measures can be chosen before executing the *Runner*. Furthermore, *Runners* can be saved as a one-file-pack containing all the related data (i.e. CSV data files, customized blocks or any resource required). This invaluable characteristic reduces potential issues related to the location of the resources used in the *Runner* when executing it on a different computer, for example, when the process miner generates a *Runner* and gives it to the HCPs to be analyzed. Besides, in those cases needed, *PMApp* enables the execution of heavy processing algorithms on supercomputers when additional resources are required for computation, moving effortlessly this all-in-one file to the supercomputer.

As figure 6.1 depicts, the *Experiment Designer* is organized into five sections, in line with the five stages of the Data Rodeo flow seen in figure 6.3 described later on, and containing drag-and-drop blocks in each to let the process miner configures the *Runner* file in a manageable way. Some remarkable characteristics are the possibility to assign a name and describe the *Runner* to maintain a history of changes according to HCPs' instructions. It can facilitate the maintenance of the new blocks included in the configuration file as well as better communication with the HCPs. As mentioned before, there is a chance of adding new kinds of blocks in the *Runners*, but also, if new views or other resources are needed can be developed. In both cases, it can be done by creating a plugin in the .NET Core Framework, being *PMApp* toolkit prepared to be upgraded with ease in the Settings menu.

### 6.2.2. Ingestor editor

The *Ingestion Editor* (figure 6.2) is a *PMApp* module that allows creating logs, from different data sources, in the form of tables such as CSV, SQL, etc. The *Ingestion Editor* offers features for managing data quality. For example, a CSV file is defined in the *CSV Log Ingestor* block added into the *Experiment Designer*. At the opening of the

*Ingestor Editor*, the fields coming from the indicated data source (based on tabular data) are shown in the form of blocks.

The *Ingestion Editor* is organized into five steps, where the first is the *Validators (A)*. This tab contains the validators blocks, which are specific algorithms able to accept or reject each of the rows in the data table ingestion. In this example, the process miner defines *Validators (A)* to reject or accept raw data based on the criteria specified by the HCPs, for example, there is a block named *Line Rejector* that refuses those lines when the triage start timestamp is null or empty.

The second tab corresponds to *Variables (B)* tab, where new variables can be computed as a combination of current data available in the data table. For example, sometimes it is needed to calculate specific information and turn it into virtual fields[2]. For example, to calculate a patient's age at the moment of arrival in the ED. It can be done with a *C# Operation* block, where C# code can be combined with the fields coming from the CSV.

The following tab corresponds to the *Events (C)*. This kind of block is the core of the ingestion. These blocks are intended to create events using the existing variables. The data is prepared to define the events represented as nodes in the final model. The information used to define the events are a name, caseID, start and, in some cases, end values. There are two different types of blocks for defining events: a) *FieldEventExtractor* where the name of the event is obtained directly from the value of the selected field, for example, a node per type of *Discharge* (*Home*, *Primary care*, *Admission*...) and b) *NamedEventExtractor*, this block acts similar to the *FieldEventExtractor*, but in this case, the name is defined manually. *EventMetadataField* is a particular block used to add metadata in the events, for example, *Triage* events have the triage level assigned.

As specific data can be appointed to *Events (C)*, it also can be established in the *Trace Data (D)* tab. Some blocks aim to provide categorical information associated with each trace that can be used to stratify or characterize them. That information usually is data that does not change over time, such as gender (*Sex* field). They enable performing statistics and extracting domain details. The last tab is for *Filters (E)*. These are similar to those applied in the *Experiment Designer* (see *Filtering (2)* of section 6.2.1).

Figure 6.3 summarizes the execution of the steps that take place in the *Experiment Designer* and the *Ingestor Editor*. The data is accessed, and an initial cleaning is done - *Factories (1)* - until a first Log is generated, where quality is dealt with, and techniques are applied to improve and solve problems in the data - *Filters (2)* -. Following, a first model of the process is obtained - *Log Processors (3)* -, and information is extracted from the process - *TPA Processors (4)* -, for example, the length of stay of each patient in the ED, until finally applied techniques of improvement - *Renders (5)* - on the process in the form of, for example, colours, to underline differences in the behaviour of patients.

### 6.2.3. PMApp dashboard

The *PMApp* dashboard is the module of *PMApp* toolkit that allows visualization and navigation through the *IPI*, and where HCPs and process miners conduct the

[2]Virtual fields are those that do not exist in the log, but they may be used in the following tabs as if they existed there.

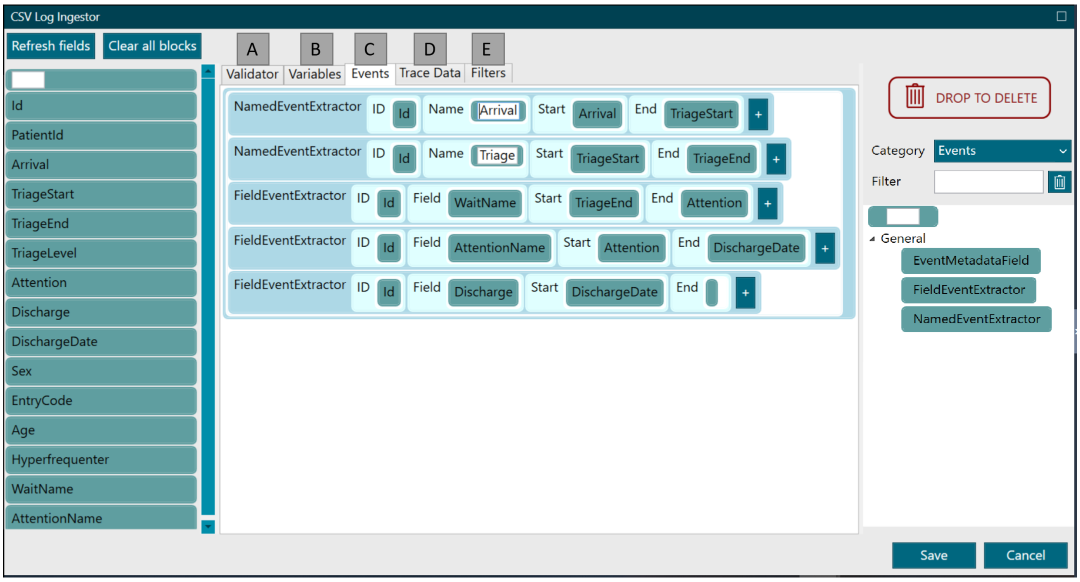


FIGURE 6.2: Ingestor Editor: Feature of PMApp to configure data ingestion

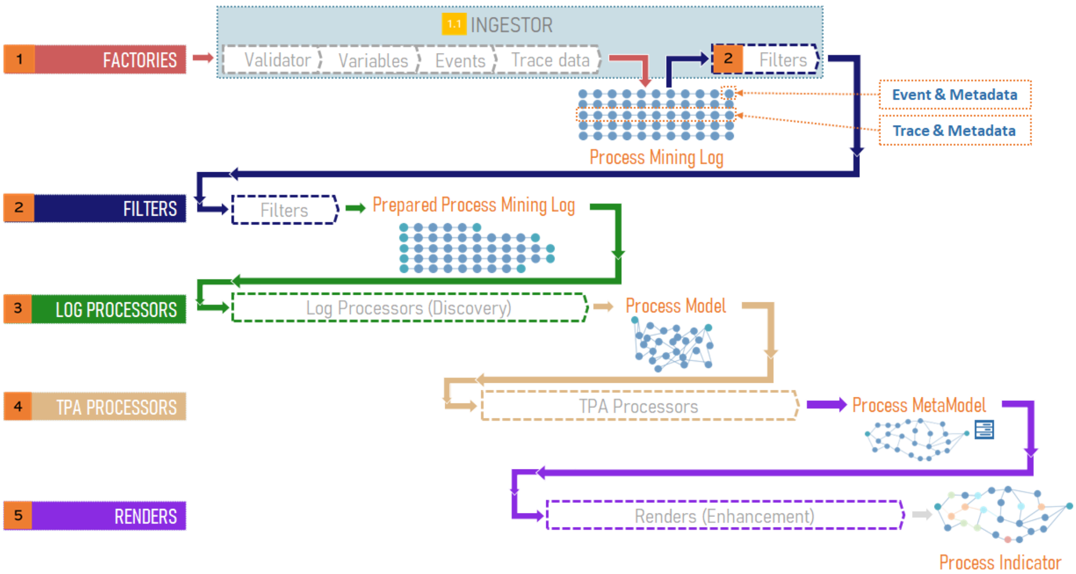


FIGURE 6.3: Process execution of the Experiment Designer and Ingestor Editor

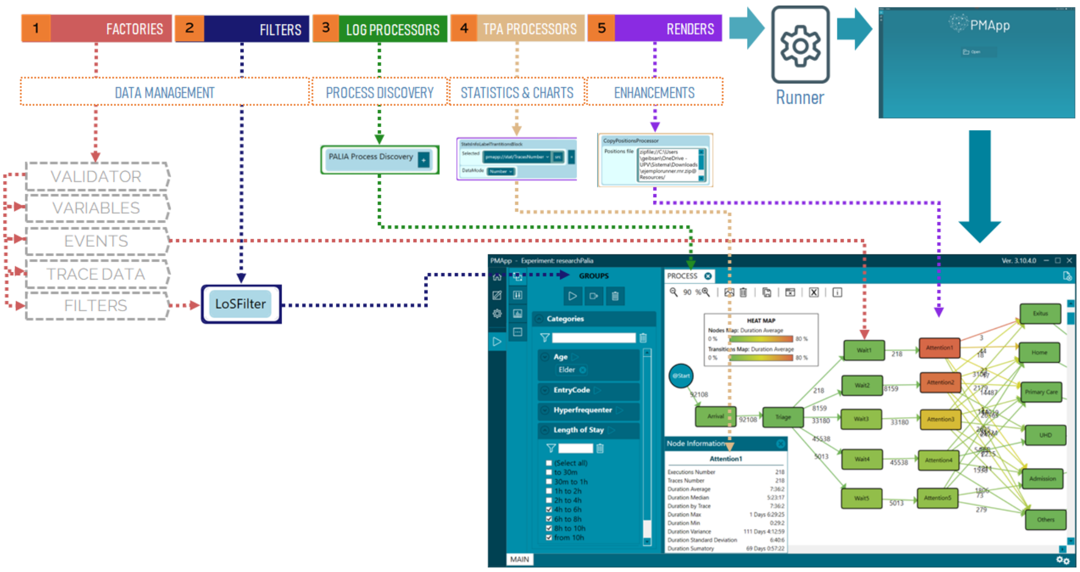


FIGURE 6.4: PMApp dashboard customization

research. *PMApp* toolkit acts as a container which constructs customized dashboards from the *Runner* configuration file and the developed plugins with the new resources (for example, a calendar) installed in the toolkit. The composed *Runner* is open, transforming every block into an element envisioned in the *PMApp* dashboard.

An illustration of this transformation can be seen in figure 6.4, where *PMApp* dashboard presents the model co-created with the HCPs. Derived from the steps *Factories (1)* and *Filters (2)*, trace metadata is turned into categories and options at the *Groups* menu. The process discovery occurs in the *Log Processors (3)* step, which in this example was used PALIA algorithm[229]. Continuing with the *TPA Processors (4)*, statistics based on trace metadata can be calculated at this step. In the model, block *StatsInfoLabelTrantitionsBlock* presents the number of patients going through the different paths. During the *Renders (5)* phase, the block *CopyPositionsProcessor* keeps the arrangement of the nodes and transitions of the model. Furthermore, the customization can be done in terms of look and feel or distribution of the graphical components[216].

Once the *PMApp* dashboard is ready, HCPs and process miners can start exploring the *IPI*. The analysis usually begins by examining the *Main Perspective*, which is the central element of the *PMApp* dashboard and that depicts the model with all the data (figure 6.5). Perspectives are the different views offered of the data and models obtained by means of Process Mining techniques. The perspectives are co-created with the process miners to improve the user-friendliness and usability of the dashboard and can be added in the form of plugins to the toolkit.

Continuing with the ED example, the HCPs want to know more about the profile and characteristics of the process corresponding to the patients that stay more than 4 hours. According to the literature, there is an association between the length of ED boarding and patient mortality rates[158], so instituting a maximum length of stay of 4 hours[197] could improve the quality of the service.

At the top (1) of the figure 6.5 can be observed in the model that clicking on


FIGURE 6.5: Visual model representing the IPI in the main perspective of PMApp

the *@Start* node shows that the total number of emergency episodes in that year is 92.108. Furthermore, the redder the nodes are, the more time the patients spend in that activity (see legend), then it makes sense to assume that patients of level 1 (the most urgent) need more *Attention*.

Additionally, the model can be combined with further information, as are domain-specific indicators. Measurable values are used to evaluate and quantify the performance of the process in terms of efficacy and efficiency, among others. The top right (1) of the figure 6.5 presents the length of stay distribution, where most patients stay between 2 and 4 hours, and still, a considerable number of patients remain more than 4 hours. This information can be used in the *Group* menu, where the categories can be combined. In the example, it can be obtained a subprocess with the elder patients (category Age of figure 6.4) that have stayed more than 4 hours in the ED (category Length of Stay of figure 6.4). The result is shown at the bottom (2) of the figure 6.5, with a total of 15395 episodes, but it can be done as many combinations as needed to obtain as many subprocesses as wanted.

In addition to the main model, *other perspectives* can be provided to deliver the information in diverse manners to contribute to apprehending the info. An example could be the calendar perspective (at the bottom (2) of the figure 6.6) illustrating the number of patients per day, which in the case of needing to conduct the analysis, could be incorporated with ease. This new perspective is added as an add-on to the *PMApp* toolkit in the form of a plugin. Therefore, the *PMApp* dashboard is designed to model any kind of data at different levels of granularity. The top (1) of the figure 6.6 shows the detail of the patients' episodes going through the *Attention1* node. In this perspective, traces, events and data are presented, providing information about the profile of the patients and the characteristics of the path followed.

## 6.3. Conclusions

This chapter presents a new Process Mining application designed for dealing with *IPM* methodology in healthcare. This application was created based on the experience of several years dealing with Process Mining problems in the healthcare domain. *PMApp* covers the main needs of *IPM*. It has specific modules for defining data transformation and curation from different data sources, ensuring their *flexibility*. The *Experiment Designer* aims the creation of *automation* files called *Runners* that allow the configuration and repetition of Process Mining experiments easily. To perform this configuration, *PMApp* provides a drag-and-drop system of blocks that enable the *customizability* of the tool that can be extended by allowing the Process Mining community to develop blocks in the same way as other tools like ProM. In addition, *PMApp* can be reconfigured to be connected to hospital information systems and to follow the look and feel[216] of hospital systems. *PMApp* structure is created based on feedback from HCPs to make it *user-friendly*[232]. In addition, it has some blocks to allow converting the main representation model (TPA) in others (BPMN, ProForma,..) for ensuring the *undertandability* in different cases. Finally, the system provides perspectives to navigate through the structures (nodes and transitions) until single patients and events, ensuring the *transparency*. This result accomplishes the **O3** and the **RQ3** of this work.

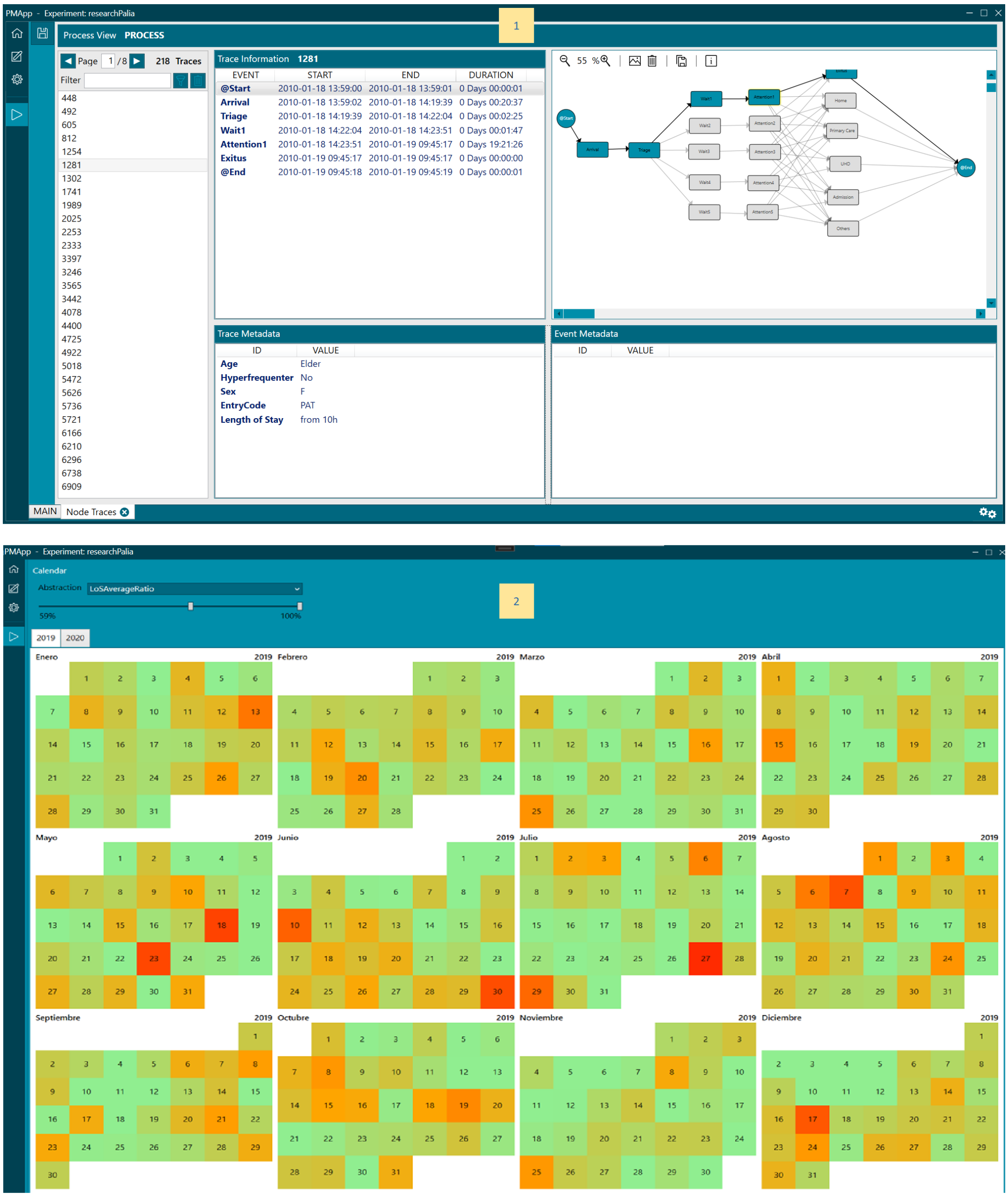


FIGURE 6.6: Other possible ways to represent the process in PMApp: traces detail of individual patients, and a calendar showing IPIs per day

*PMApp* was designed according to the challenges of the Process Mining for Healthcare Manifesto[75] and to provide an architecture based on the most common Process Mining methodologies and specifically designed to support the application of *IPM*. Provide tools (*C1*), algorithms and perspectives for offering information beyond discovery (*C2*). It was created and tested to struggle with real data (*C4*) by involving multidisciplinary teams and supporting HCPs using Process Mining technologies (*C5*). It has specific blocks for dealing with data quality and providing ingestion reports to assess data quality and security (*C6*, *C7*). It was tested in the application of different medical domain paradigms like Evidence-based Medicine (EBM) or VBHC[210, 211](*C10*).

*PMApp* has been tested in various use cases throughout Europe. In Portugal, it assessed the impact on ST-segment elevation myocardial infarction patients according to distance to primary percutaneous coronary intervention centres[214]. In Salamanca (Spain), the analysis focused on determining the root causes of bottlenecks to help reduce waiting lists in the cardiology outpatient department[215]. In various hospitals in Valencia (Spain), several pilots have been carried out to analyze oncological processes[216], dynamic risk models for chronic diseases such as obesity[217], how the Quality of Care (QoC) could be measured in EDs[174] and with specific conditions as stroke, following a VBHC approach[210, 211] as well as rheumatological care of patients with chronic polyarthritis[218]. ED processes have also been analyzed to reduce the waiting time for frailty people in Stockholm (Sweden) and Rotterdam (The Netherlands) concerning stroke disease.

# Part III

# Conclusions

# Chapter 7

# Conclusions and Future Work

Throughout this document, it has been stated that Key Performance Indicators (KPIs) are valuable tools to coordinate the organization's efforts in the same direction, assess the progress and highlight those aspects that need more attention to meliorate the Quality of Care (QoC) and Value-Based Healthcare (VBHC). Notwithstanding, the reality is that they do also present some limitations as they are understood, as they do usually encapsulate information of the process that does not contemplate the complexity and variability of the care process data. To tackle this limitation, the work included in this document has presented a novel approach by the definition of the *Interactive Process Indicators* (IPIs) to deal with part of the shortcomings of the KPIs in Emergency Departments (EDs), together with the design and implementation of a Process Mining-based application to build them in EDs. This chapter concludes the work and demonstrates how the specific Research Questions (RQs) and objectives posed in Chapter 3 have been addressed to confirm their proper achievement. For this, the main results obtained throughout this doctoral thesis are listed and analyzed below.

## 7.1. Conclusions

The content presented throughout the entire document relies upon the hypothesis, RQs, and secondary objectives initially outlined in the early stages of this work (Chapter 3). Concretely, three secondary objectives were identified to address the RQs. These secondary objectives were articulated across three fundamental dimensions: evaluating the feasibility of the innovative medical approach employing Process Mining methodology, tailoring it to the context of time-dependent stroke conditions, and devising and implementing a Process Mining-oriented application derived from the undertaken work and accumulated expertise. Accordingly, the primary objective was to:

**O1. To build an *IPI* to support the analysis of real ED processes in daily practice**

To reach this objective, Process Mining techniques were applied to a dataset of patients visiting the ED of a hospital. This enabled the analysis of patients' journey through the modelling of the care protocol by incorporating continuous information of the process in a human-understandable manner, at the time of combining process indicators to quantify the different dimensions of the QoC to deal with their limitations as included in Chapter 4. The build of the *IPI* followed the *Interactive Process Mining* (IPM) paradigm through Data rodeo sessions. The first step was to model the emergency care process. Afterwards, quality indicators already recognized by the scientific community were selected and incorporated into the *IPI*. This was done by extracting this information from the curated data representing the model. Enhancement techniques and statistical significance were used to emphasize process behaviour and compare and detect potential issues. The combination of this analysis with traditional indicators enabled a new approach, more understandable and explorable, with a broader view. This is published in [174]. Thus, these results confirmed that *IPIs* incorporate process information that enriches traditional indicators, enabling a more profound knowledge of the QoC.

Once the viability of the *IPI* was validated, the work carried out dealt with the particularization of a life-threatening disease, as was stated in the second objective defined at the beginning of the document:

> **O2. To characterize a time-dependent care process within the ED using the general *IPI* built**

To achieve this goal, Process Mining techniques were used in combination with retrospective data to discover and depict the stroke care process at the ED. The first step was to model a medical condition thanks to a bounded population as presented in Chapter 5 that allowed validating of the approach and the needed steps, so the *IPI* was particularized to a specific time-dependent disease, and investigated whether VBHC could be rated based on the patient evolution using Process Mining.

As results showed in [210, 211], Process Mining techniques have permitted to characterize the population attending the ED and suffering from a stroke, allowing to measure the chain value from different perspectives of the Triple Aim. This is published in [211].

The utilization of Process Mining techniques in specific healthcare scenarios permitted to obtain valuable and innovative *IPIs* that could be used to understand and measure the QoC and VBHC approaches underlying process abstractions, following concrete procedures and experiments. In this line, the third objective proposed at the beginning of the work was:

> **O3. To design and develop a Process Mining-based application able to deal with the *IPM* paradigm and support the co-creation of *IPIs* for real daily practice**

To pursue this objective, Chapter 6 proposed a Process Mining-based application for characterizing care processes in the form of *IPIs*. The application defined as *PMApp for co-creating IPIs in real practice* is presented in the paper [233].

This work was the result of the knowledge acquired during the definition of several *IPIs* in different hospitals in Europe. *PMApp* was designed according to the necessities identified during the co-creation sessions as well as those features relevant to the analysis and the better understanding of the data.

These secondary objectives have contributed to achieving the main objective of the thesis, that is: **to show *IPM* techniques are able to measure, characterize and support the analysis and optimization of the EDs.**

The attainment of the aforementioned objectives was directly related to the achievement of the RQs proposed in Chapter 3, concretely the first RQ identified was:

> **RQ1. Is it possible to use *IPIs* to characterize ED processes representing aggregated information of KPIs in a general manner?**

To validate the Process Mining techniques' capability of modelling the care process of the ED and to answer this RQ, which is directly related to **O1**[174] described in Chapter 4. The experiments and results have confirmed that the ED care process can be modelled using Process Mining techniques in an understandable manner for humans to quantify the QoC.

> **RQ2. Is it possible to use *IPIs* to measure the value chain within specific disease processes in the ED?**

To solve this RQ, it was started from the fact that Process Mining techniques can be used to represent more specialized care processes, allowing to include individual determinants and variability over time to the disease evolution. An *IPI* has been proposed that enables healthcare experts in the understanding to evaluate not only the care process but also the organizational changes compared to existing gold standards and concrete indicators under the VBHC approach in an iterative and interactive manner. This is related to **O2** and was explained in Chapter 5, [210, 211].

> **RQ3. Is it possible to design and develop an application to support the co-creating of *IPIs* to analyze care processes iteratively and interactively in real daily practice?**

To answer this RQ, it was designed and implemented an *IPM*-based application. The lessons learned acquired after the definition of diverse *IPIs* were employed to settle the basis for enriching the user experience and features of the application[233]. In addition, due to the nature of the analysis performed and the complexity and variability of the data, the application was designed as a container to be fed easily from different data sources, as well as accomplish the challenges proposed by the Process-Oriented Data Science for health community as presented in Chapter 6. This is related to **O3**.

The proposed application and the corresponding *IPIs* have been implemented and developed with the main goal of achieving the central hypothesis of the present work:

> *IPM through the co-creation of IPIs can be used to characterize real daily practice processes qualitatively and quantitatively and support the measure of the value chain within the ED in a broad and particular manner.*

According to this hypothesis, the experiments and procedures carried out throughout this work show that it is possible to model both a general and specific care process using historical data and Process Mining techniques. Results have offered a novel approach to assessing QoC and VBHC approaches with a process-oriented view that has permitted a better understanding of process improvements can affect the outcomes of the patients, as included in Chapters 4, 5 and 6 where new ways to show the reality was presented to show to the healthcare professionals (HCPs) participating in the work thanks to the analysis of the results.

## 7.2. Future work

This thesis has tackled the appraisal of the QoC by representing care processes using Process Mining techniques. One of the main interests of these novel *IPIs* is that the health experts in the field understand them, so they can be continuously updated, improved and adapted based on their needs, expectations, knowledge or population under study, thanks to the interactive application to support the *IPM* methodology. Furthermore, the proposed *IPIs* could be defined and personalized for concrete populations with particular needs or characteristics. Factors outside the healthcare system, such as social determinants, including education, income, or social inclusion, play an important role in healthcare outcomes and how individuals perceive care. Including those determinants in the *IPIs* is possible thanks to the application and the different procedures implemented. Another of the potentialities of the results presented in this work is that *IPIs* can contribute to establishing particularized Gold Standards in each hospital, being more realistic in assessing the QoC and consequently VBHC. Moreover, an interactive and modular application based on Process Mining has been proposed that allows understandable generalization of these models for HCPs in the health domain, where a free version is available for the research community.

The work presented in the different chapters of this document supposes the author as the point of departure for a new promising framework that enables extracting knowledge from clinical data. Furthermore, this research work has been performed within the registered trademark Process Mining for Health (PM4H®)[1]. Related to this, the following lines are identified for future work:

- **Change Management**. The introduction of any change in health organizations presents barriers and resistance to their adoption, and although *IPM* settles the basis to involve stakeholders, it does not assess the organization's readiness nor deal with individuals. In this regard, the author of this work has already started working to prepare health organizations to tackle the introduction of a disruptive solution, as is *PMApp* and the *IPIs*, with techniques to adopt and normalize the change[234]. This was motivated by the lessons learned during *Pathways*[2] and *VALUE*[3] projects.

- **Integration**. The interconnection of *PMApp* with other tools of state of the art, as *bupaR*[4] of *pMineR*[5], can contribute to enriching the toolkit and fostering research.

[1] https://www.pm4health.com/
[2] https://pathwayseit.eu/
[3] https://valueproject.eu/
[4] https://bupar.net/
[5] https://github.com/PMLiquidLab/pMineR.v046

- **Interactive Data Curation**. Data quality plays a key role in the expectations of the actors involved at the time of analysis, affecting their willingness to embrace the *IPM* methodology and everything that entails (*IPIs* and *PMApp*). The Interactive Data Curation concept arises from the necessity to deal with the quality of the data in the health domain, which is well-known for its complexity. Thus, the involvement of HCPs is necessary and needs special care. In this line, the investigation of new techniques to deal with these challenges and contribute to transparency on the fixing and data selection, which in consequence, will affect their acceptance.

- **New Quantitative Methods**. The knowledge acquired during the development of this doctoral thesis was reverted in *VALUE* project, especially in those use cases related to EDs. Additionally, to delve into health-related topics, such as climate change[235] or ergonomy[236, 237] can tender new proposals to characterize the data. The combination of statistical techniques and process representation, the multiple care processes in a single model or new ways to incorporate semantic information in the *IPIs*, can be in line with the inclusion of participatory methodologies and techniques during Data Rodeos to agile the building of *IPIs* and thus reduce the time until the analysis.

- **Purpose-Oriented**. The study of Lean Six Sigma (LSS), Health economics[238] or VBHC concepts in more detail can establish the basis for defining specialized *IPIs* in these fields. The objective would be to identify which values need to be represented and how they would be calculated, being able to be enclosed in new *IPIs*, as well as in existing ones.

- **Training**. Although health experts are getting more familiar with new technologies, the reality is that it is still far away from an ideal where experts are effortlessly adopting them. Conversely, they usually do not have enough time to invest in training themselves. For that reason, it is of paramount importance to alleviate this task by introducing new and innovative ways of training, such as educational escape rooms. Besides, it is planned to prepare certifications (colour belts similar to LSS) for health experts and process miners.

- **Consultancy**. *VALUE* project was key to defining the scope of *IPM*. From the six hospitals involved in the project, it was possible to work on identifying different business models that have been put into practice in several contracts with *MEDTRONIC*[6] and *Grünenthal*[7] multinationals of the health sector. Given the interest aroused by the solution, it is considering creating a spin-off to continue this activity and benefit health organizations. Thus, a step further is needed to go from research to service, taking into account regulations such as the **Regulatory Framework on Artificial Intelligence**[8],[9] that was recently voted by the European Parliament and is currently being reviewed by the

[6]https://www.medtronic.com/
[7]https://www.grunenthal.com/
[8]https://shorturl.at/cgpvK
[9]https://shorturl.at/jGHW9

EU lawmakers or the *Conduct Code*[10] and *Certifications*[11] of the General Data Protection Regulation (GDPR).

[10]https://gdprinfo.eu/art40gdpr/
[11]https://gdprinfo.eu/art42gdpr/

# Chapter 8

# Main Original Contributions

In this doctoral thesis, it is provided new process indicators as solutions to problems not covered by traditional techniques, such as Key Performance Indicators (KPIs) or new technologies, such as Artificial Intelligence (AI). In this way, a new method has been created and published to measure the Quality of Care (QoC) in Emergency Departments (EDs) and also in any service in a hospital, as well as the design and implementation of a Process Mining-based application to support the method. The objective of this chapter is to collect the main and original contributions performed in each of the sections of this work. The achievement of the previous objectives has allowed the dissemination of the results in several scientific forums, such as book chapters, international conferences, and indexed journals.

## 8.1. Main original contributions

This research work has been carried out within the Process Mining for Health (PM4H) Lab[1] at SABIEN research group[2] (Technological Innovation for Health and Well-Being) part of the Institute of Applied Information Technologies and Advanced Communication (ITACA) at the Universitat Politècnica de València (UPV). The author of this doctoral thesis has performed most of the research in SABIEN during her participation in several European projects during the last twenty years.

The original contributions in each of the points discussed in this work are listed in the form of scientific publications associated with the work carried out on this doctoral thesis, as well as the research projects where the concepts studied have been applied.

## 8.2. Associated publications

During the performance of this work, a new method has been created and published for measuring the QoC offered in EDs under a general but also specific perspective, as is stroke. In addition, an application based on Process Mining has been presented to support this method. The subsequent journal articles, books, conference contributions, and dedicated sessions delineate the efforts expended within an innovative approach for assessing QoC in addition to Value-Based Healthcare (VBHC).

[1] https://www.pm4health.com/

[2] http://www.sabien.upv.es/

The contributions in each of the aspects expounded upon in this document are endorsed through scientific publications linked to this work, along with the research projects where the investigated concepts have found practical application.

### 8.2.1. Publications in journals

- **P1 -** Borges-Rosa, J.; Oliveira-Santos, M.; Simões, M.; Carvalho, P.; **Ibanez-Sanchez, G.**; Fernandez-Llatas, C.; Costa, M.; Monteiro, S.; Gonçalvez, L. on behalf of Portuguese Registry of Acute Coronary Syndromes. (2023). *Assessment of distance to primary percutaneous coronary intervention centres in ST-segment elevation myocardial infarction: Overcoming inequalities with Process Mining tools*. Digital Health, 9, 20552076221144210[214].

  The time to treatment in ST-segment elevation myocardial infarction is critical for recovering patients suffering from this pathology. The time delay between symptom onset and treatment was studied with Process Mining techniques across the national territory of Portugal to identify differences between geographical reasons of the hospitals with the needed treatment for this illness. The author of this doctoral thesis was involved in defining the *Interactive Process Indicator* (IPI). **Impact Factor 3.9, Q1**

- **P2 -** García, A. M.; Bayo-Monton, J.L.; Estevez-Muñoz, J.C.; **Ibañez-Sanchez, G.**; Lopiz-Morales, Y.; Fernández-Llatas, C.; Rodriguez, L. R. (2023). *AB1617 Differences in access to rheumatological care of patients with chronic polyarthritis and connective tissue diseases: A pilot study using interactive Process Mining analysis*. Annals of the Rheumatic Diseases 82 (Suppl 1), 2043-2043[218].

  This study has carried out an analysis based on Process Mining techniques, characterizing the journey of patients of rheumatology outpatient clinic, where have been observed that the pathways followed and the referral departments of the patients diagnosed with chronic polyarthritis and connective tissue diseases are different. This publication is available in the BMJ Journal Annals of the Rheumatic Diseases 2023. The author of this doctoral thesis was involved in the definition of the *IPI*. **Impact Factor 27.4, Q1**

- **P3 -** Munoz-Gama, J.; Martin, N.; Fernandez-Llatas, C.; Johnson, O. A.; Sepúlveda, M.; Helm, E.; Galvez-Yanjari V.; Rojas, E.; Martinez-Millana, A.; Aloini, D.; Angela Amantea, I.; Andrews, R.; Arias, M.; Beerepoot, I.; Benevento, E.; Burattin, A.; Capurro, D.; Carmona, J.; Comuzzi, M.; Dalmas, B.; de la Fuente, R.; Di Francescomarino, C.; Di Ciccio, C.; Gatta, R.; Ghidini, C.; Gonzalez-Lopez, F.; **Ibanez-Sanchez, G.**; B. Klasky, H.; Prima Kurniati, A.; Lu, X.; Mannhardt, F.; Mans, R.; Marcos, M.; Medeiros de Carvalho, R.; Pegoraro, M.; K. Poon, S.; Pufahl, L.; A. Reijers, H.; Remy, S.; Rinderle-Ma, S.; Sacchi, L.; Seoane, F.; Song, M.; Stefanini, A.; Sulis, E.; H.M. ter Horfstede, A.; J. Toussaint, P.; Traver, V.; Valero-Ramon, Z.; van de Weerd, I.; M.P. van der Aalst, W.; Vanwersch, R.; Weske, M.; Thandar Wynn, M.; Zerbato, F. (2022). *Process Mining for healthcare: Characteristics and challenges*. Journal of Biomedical Informatics, 127, 103994.[75]

  This paper is the main manifesto of process mining in healthcare community. It underlines the special characteristics of healthcare processes, which require particular attention when using Process Mining, addressing challenges and promoting data-driven improvement in healthcare processes. The author of this doctoral thesis is actively collaborating with the Process-Oriented Data Science in Healthcare Alliance[3], responsible of this manifesto. **Impact Factor 4.5, Q1**

- **P4 -** Floch, J.; Vilarinho, T.; Zettl, A.; **Ibanez-Sanchez; G.**, Calvo-Lerma, J.; Stav, E.; Halland Haro, P.; Lein Aalberg, A.; Fides-Valero, A.; Bayo Montón, J.L. (2020). *Users' experiences of a mobile health self-management approach for the treatment of cystic fibrosis: Mixed methods study*. JMIR mHealth and uHealth, 8(7), e15896. [239]

  This manuscript presents lessons learnt during the design and implementation of a digital health solution and obtaining a good user experience as a critical factor for technology adoption. This work was presented in the prestigious Journal of Medical Internet Research. The work performed in Chapter 6 took advantage of the lessons learned in the design of digital health solutions for healthcare professionals (HCPs). **Impact Factor 4.773, Q1**

- **P5 -** Martin, N.; De Weerdt, J.; Fernández-Llatas, C.; Gal, A.; Gatta, R.; **Ibañez-Sanchez, G.**; Johnson, O.; Mannhardt, F.; Marco-Ruiz, L.; Mertens, S.; Munoz-Gama, J.; Seoane, F.; Vanthienen, J.; Thandar Wynn, M.; Baltar Boilève, D.; Bergs, J.; Joosten-Melis, M.; Schretlen, S.; Van Acker, B. (2020). *Recommendations for enhancing the usability and understandability of process mining in healthcare*. Artificial Intelligence in Medicine, 109, 101962. [74]

  A summary of the recommendations identified during the international brainstorming seminar, located at Hasselt (Belgium) and organized by the Process-Oriented Data Science in Healthcare Alliance, aimed to enhance the usability and understandability of Process Mining in healthcare. These recommendations target Process Mining researchers, the community, healthcare organizations, and Health Information Systems (HIS) vendors to promote the widespread use of Process Mining in healthcare. The author was invited to participate in this brainstorming seminar to contribute with her experience. The knowledge acquired during the workshop boosted the work done in Chapter 6. **Impact Factor 5.326, Q1**

- **P6 - Ibanez-Sanchez, G.**; Fernandez-Llatas, C.; Martinez-Millana, A.; Celda, A.; Mandingorra, J.; Aparici-Tortajada, L.; **Valero-Ramon, Z.**; Munoz-Gama, J.; Sepúlveda, M.; Rojas, E.; Gálvez, V.; Capurro, D.; Traver, V. *Toward Value-Based Healthcare through Interactive Process Mining in Emergency Rooms: The Stroke Case*. International Journal of Environment Research and Public Health, 16.10 (2019), p. 1783. [211].

  An analysis of how Process Mining techniques can support health professionals in the application of VBHC technologies to demonstrate the possibilities of Process Mining in the characterization of health conditions processes. The results were published in the Special Issue Process-Oriented Data Science for Healthcare 2018 of the International Journal of Environment Research and

[3]https://pods4h.com/alliance/

Public Health. In relation to this work, the results in this paper are directly related to Chapter 5. **Impact Factor 2.849, Q2**

### 8.2.2. Book chapters

- **P7 - Ibanez-Sanchez, G.**; Celda, M.A.; Mandingorra, J.; Fernandez-Llatas, C. (2021). *Interactive Process Mining in Emergencies*. Interactive Process Mining in Healthcare, 165-180[174].

  A proof of concept of how *Interactive Process Mining* (IPM) can be used for co-creating and characterizing an *IPI* in an ED. It was presented as a chapter in the Springer book *Interactive Process Mining in Healthcare*. Concretely, the work explained how *IPM* technologies can be applied to measure the care process of patients attending EDs. This book chapter is in line with the work performed in Chapter 4.

- **P8 - Ibanez-Sanchez, G.**; Wolf, M.R. (2021). *Interactive Process Mining-Induced Change Management Methodology for Healthcare*. Interactive Process Mining in Healthcare, 267-293[234].

  The introduction of technologies in health organizations is accompanied by barriers that can be diminished by applying change management techniques to generate a changing culture in healthcare organizations. Such a change culture is essential for the successful implementation of analysis and supporting methods such as *IPM*. This work was presented in the Springer book named *Interactive Process Mining in Healthcare*. The work done in this chapter sets the basis for future research lines in terms of new methodologies to foster the adoption of new technologies in health organizations.

- **P9 - Ibáñez-Sánchez, G.**; Fides-Valero, A.; Bayo-Monton, J. L.; Gulino, M.; Pace, P. (2021). *Interoperability Application in e-Health*. Interoperability of Heterogeneous IoT Platforms: A Layered Approach, 231-256.[240].

  This work provides an interoperable solution for real health environments to prevent and reduce obesity, one of the leading causes of chronic diseases, taking special care of the security and privacy aspects of sharing sensitive patient data through different digital health solutions. It was published in the Springer book *Interoperability of Heterogeneous IoT Platforms*. This work identified the main barriers to designing and implementing health solutions. The learning acquired during this work facilitated the work done in Chapter 6.

- **P10 - Ibáñez-Sánchez, G.**; Valero-Ramon, Z.; Traver, V.; Fernández-Llatas, C. (2019). *Process Choreography for Designing and Automate Individualized Prevention Protocols in Occupational Medicine*. Transforming Ergonomics with Personalized Health and Intelligent Workplaces, 101-112.[237].

  In this work, a workflow-based solution that enables occupational health professionals was presented to create individualized prevention protocols that allow easy control of specific workers integrated into the available infrastructure in the factory. This chapter was included in the IOS Press editorial's book *Transforming Ergonomics with Personalized Health and Intelligent Workplaces*. The author of this doctoral thesis was involved in the definition of the *IPI*.

### 8.2.3. Conference contributions

- **P11 - Ibanez-Sanchez, G.**; Fernández-Llatas, C.; Valero-Ramon, Z.; Bayo-Monton, J.L. (2023). *PMApp: An Interactive Process Mining Toolkit for Building Healthcare Dashboards*. 1st International Workshop on Process Mining Applications for Healthcare (PM4H 23) Workshop at the International Conference on Artificial Intelligence in Medicine (AIME23)[233].

  This paper presents the difficulties of applying Process Mining in the health domain according to the *Process Mining for healthcare: Characteristics and challenges*[75] manifest and how they are deemed in *PMApp* in favour of the definition of *IPIs*. The author won the **Best Paper Award** with this publication, directly related to Chapter 6.

- **P12 -** Denecke, K.; von Kaenel, F.; Miletic, M.; Fernández-Llatas, C.; **Ibañez-Sánchez, G.**; Valero-Ramón, Z.; Martinez-Millana, A.; Segura, M.; Rivera Romero, O. (2023). *How to Design Successful Participatory Design Workshops for Digital Health Solutions?*. In Caring is Sharing–Exploiting the Value in Data for Health and Innovation (pp. 641-645). IOS Press[213].

  This work collects the experience and lessons learnt of the design and development of digital health solutions centred on participatory design as the *IPIs* co-creation process is during Data Rodeos. It is part of the Medical Informatics Europe Conference and has been published as an IOS Press book. The author contributed with her experience in the co-creation of *IPIs* during Data Rodeos sessions.

- **P13 -** Lull, J.J.; Cid-Menéndez, A.; **Ibanez-Sanchez, G.**; Sanchez, P.L.; Bayo-Monton, J.L.; Traver, V.; Fernandez-Llatas, C. (2021, October). *Interactive Process Mining applied in a cardiology outpatient department*. In International Conference on Process Mining (pp. 340-351). Cham: Springer International Publishing[215].

  The analysis was focused on the iterative implementation of an *IPI* to allow clinicians and managers to have a deeper understanding of the cardiology clinics' process to extract and interpret different indicators, thus, providing a high-quality source of information to improve patient-centred daily medical care. This paper was presented in the Process-Oriented Data Science in Healthcare Workshop[4], the most important conference related to Process Mining applied to healthcare and organized at the International Conference on Process Mining (ICPM). The author of this doctoral thesis was involved in the definition of the *IPI*.

- **P14 -** Lull, J.J.; Dogan, O.; Celda, A.; Mandingorra, J.; Lemus, L.; Pla, M.Á.M.; Urchueguía J.F.; **Ibanez-Sanchez, G.**; Traver, V.; Fernandez-Llatas, C. (2020, October). *Exploration with Process Mining on How Temperature Change Affects Hospital Emergency Departments*. In International Conference on Process Mining (pp. 368-379). Cham: Springer International Publishing. [235].

  This study examined how patients' treatment in hospital ED varied throughout the year, with weather temperature being a crucial factor, seasonal maladies

[4]https://pods4h.com/

like flu in cold weather and sunburn in hot weather play a key role as well. Data from a hospital in Valencia (Spain) was analyzed using Process Mining techniques to explore the effects of harsh weather on the ED and understand the potential impact of global warming on healthcare systems. The study found that illnesses like heat stroke are more prevalent during heatwaves, and patient waiting times also increase. The author of this doctoral thesis was involved in the definition of the *IPI*.

- **P15 -** Pace, P.; Aloi, G.; Caliciuri, G.; Gravina, R.; Savaglio, C.; Fortino, G.; **Ibanez-Sanchez, G**.; Fides-Valero, A.; Bayo-Monton, J.; Uberti, M.; Corona, M.; Bernini, L.; Gulino, M.; Costa, A.; De Luca, I.; Mortara, M. (2019, April). *Inter-health: An interoperable iot solution for active and assisted living healthcare services*. In 2019 IEEE 5th World Forum on Internet of Things (WF-IoT) (pp. 81-86). IEEE.[241].

  The study presents the design and implementation of a new digital health solution that enables decentralized and mobile monitoring of assisted living for preventing chronic diseases, making special emphasis on the interaction between doctors, patients and the system. The experience obtained by the author during this publication was applied in the design of the *PMApp* solution described in Chapter 6.

- **P16 -** Fernandez-Llatas, C.; **Ibanez-Sanchez, G.**; Celda, A.; Mandingorra, J.; Aparici-Tortajada, L.; Martinez-Millana, A.; Munoz-Gama, J.; Sepúlveda, M.; Rojas, E.; Gálvez, V.; Capurro, D.; Traver, V. (2019). *Analyzing medical emergency processes with Process Mining: the stroke case*. In Business Process Management Workshops: BPM 2018 International Workshops, Sydney, NSW, Australia, September 9-14, 2018, Revised Papers 16 (pp. 214-225). Springer International Publishing. [210].

  This analysis focused on the stroke care protocol in EDs. An adequate and timely protocol can signify the difference between a better recovery or a loss of quality of life as a consequence of physical and mental deterioration, being the aim of this paper is to perform an analysis of how Process Mining techniques can support health professionals in the interactive analysis of emergency processes considering timing restrictions of stroke through the characterization of the process and looking for differences of the stroke patient flow in the ED. The author of this doctoral thesis was involved in the definition of the *IPI*, and the results are included in Chapter 5.

- **P17 -** Fernandez-Llatas, C.; **Ibanez-Sanchez, G.**; Traver, V.; Seoane, F. (2018). *Empowering ergonomy in workplaces by individual behavior modeling using Interactive Process Mining paradigm*. In Intelligent Environments 2018 (pp. 346-354). IOS Press. [236].

  This study presents a proof of concept demonstrating how Process Mining can be used to discover worker flow, aiding ergonomics experts in selecting more precise interventions to enhance occupational health. This work was published in the International Conference on Intelligent Environments. The author was involved in the definition of the *IPI*.

### 8.2.4. Special sessions

In addition, the results of this doctoral thesis gave rise to present *Interactive Process Mining-based analysis for the pain management in Emergency Departments* and *Value-Based Healthcare supported by Process Mining tools* works in the Real World Data Analytics supporting High-Value Care special session at the *IEEE – Biomedical Health Informatics Conference and Health Informatics 2021*[5] and in the Special Session *Enabling Digital Health Transformations with Interactive Process Mining* at the International Conference on Biomedical and Health Informatics 2021[6] respectively.

## 8.3. Associated projects

The author of this doctoral thesis has participated in several Information Technology (IT) projects applied to the healthcare sector. This experience has served to learn about the problems and needs of the healthcare sector in real life. Moreover, the work performed during this thesis has been tested in different scenarios coexisting in various research projects funded by the European Commission, listed below:

- **SUPPORT4LHS, 2021**. It is a national coordinated project funded by the Ministry of Science and Innovation, which comprises two subprojects: MINEGRAPH and MINEGUIDE. These aim to enable knowledge graph methods for Process Mining and clinical guideline models and the integration and exploitation of Process Mining models and clinical guideline models in support of the learning health system.

  The author of this doctoral thesis is actively involved in the subproject MINEGUIDE. This work has been used to redesign and implement the *PMApp* toolkit.

- **VALUE, 2020**[7] (Value-Based healthcare supported by Process Mining Tools, activity 20328, and 211017). VALUE was an international innovation project funded by EIT Health supported by the EIT. It enabled a service with the aim of creating value through clinical pathways, and care flows optimization. This service was validated with real data in six different hospitals in Europe.

  In the context of this document, the co-creation process of *IPIs* was enhanced and supported by *PMApp*, which was redesigned in order to improve the user experience, reduce resource consumption, and enhance security, among others. The author acted as the product owner of the service defined during the project, which implied the redesign and implementation of *PMApp* toolkit. She coordinated a team which comprised hospitals (customers), developers, assessment and business experts. Similarly, she acted as process miner, participating in the construction of the *IPIs* of the different hospitals involved in the project.

- **OR4.0 - 2019**[8] (Development of an intelligent and multi-hospital end-to-end surgical process management system, Programme under Grant Agreement no.

[5] https://www.bhi-bsn-2021.org/?page_id=3212
[6] https://conference21.kosombe.or.kr/
[7] https://valueproject.eu/
[8] https://www.mysphera.com/or4-0-project/

812386). OR4.0 was an international research project partially funded by the Horizon 2020 Programme of the European Commission that intends to produce a software tool reading Real-Time Location System (RLTS) data in order to run any surgical process in an adaptable workflow software platform.

Regarding this project in the context of the present work, it was offered a *PMApp* based-customized dashboard for the analysis of the surgical process. The obtained *IPI* helped to improve the RTLS system in order to enhance its accuracy. The author of this doctoral thesis was involved in the definition of the *IPI* as process miner.

- **Pathways, 2019**[9] (Data-rodeo for a better healthcare: clinical pathways and Process Mining, activity 19372). Pathways was an international project funded by the EIT Health supported by the EIT, a body of the European Commission, which main objective was to train hospital managers and directors to create the highest possible value for patients using Process Mining. Training activities were carried out in eight different locations in Europe.

  In the framework of the present work, this project enabled the identification of shortcomings in the co-creation of *IPIs*, settling the basis to redesign and enhance features offered by *PMApp*, which took place during VALUE EIT Health project. The author of this doctoral thesis was in charge of the formative actions in applying *IPM* for VBHC support.

- **MyCyFAPP - 2018**[10] (Programme under Grant Agreement no. 643806). MyCyFAPP focused on promoting and maintaining adequate nutritional behaviours by keeping active the role of the patient and is funded by the Horizon 2020 Programme of the European Commission.

  In relation to the current work, this project offered the knowledge needed to leverage user-centred methodologies in the design and implementation of *PMApp*. She was involved in the designing and assessment phases while applying the user-centred methods and in other tasks out of the scope of this doctoral thesis.

- **Inter-IoT - 2018**[11] (Programme under Grant Agreement no. 687283). Inter-IoT aimed to design, implement and test a framework to allow interoperability among different Internet of Things platforms.

  The integrated platform supported health monitoring at the health-care centre through the centre facilities, at home through a set of medical consumer devices, and in mobility based on body sensor networks. This work offered a big picture of treating sensitive data like health data. The author was involved in the software lifecycle, profiting from the experience gained during this process to apply it to *PMApp*.

[9] https://pathwayseit.eu/
[10] https://www.mycyfapp.eu/en/
[11] Inter-IoT: https://inter-iot.eu/

## 8.4. Recognitions

The work carried out in this doctoral thesis has been carried out in the Hospital General Universitario de Valencia[12]. The outcomes of the above-presented projects, they gave rise to several recognitions:

- **Best Paper Award** of the publication *PMApp: An Interactive Process Mining Toolkit for Building Healthcare Dashboards* at the 1st International Workshop on Process Mining Applications for Healthcare (PM4H 23) Workshop.
- Award for the **Entrepreneurial Potential of Research Projects of Young Researchers (2021)** promoted by RUVID, the Network of Valencian Universities for the promotion of Research, Development and Innovation (Red de Universidades Valencianas para el fomento de la Investigación, el Desarrollo y la Innovación)[13].
- Award in the **Digital Transformation Category of the ENNOVA HEALTH Awards (2021)**[14], which is promoved by Diario Médico and Correo Farmacéutico, one of the most important national health press in Spain[15].
- Winners of the **VI Health Hackathon 2021 - Grünenthal Challenge on Voice in Chronic Pain (2021)** promoted by Grünenthal Spain[16] and where was proposed a solution to improve the QoC of patients attending the ED of the Hospital General Universitario de Valencia.
- Last but not least, finalists of the **SaludDigital Awards (2022)**[17] fostered by SaluDigital, an online newspaper leading the health sector.

## 8.5. Other contributions

### 8.5.1. Agreements

The endeavour invested in this work has led to the signing of a collaboration agreement between the Universitat Politècnica de València and Hospital General Universitario de Valencia to get access to the HIS of the hospital to continue with the work performed during this doctoral thesis as well as in other study cases within the same hospital.

### 8.5.2. Technology transfer

Derived from the work performed in the VALUE EIT Health project (see further information in section 8.3), Universitat Politècnica de València signed an agreement

[12] https://chguv.san.gva.es/inicio
[13] https://ruvid.org/
[14] https://www.diariomedico.com/medicina/profesion/reconocimiento-los-lideres-en-transformacion-digital-que-dibujaran-la-sanidad-del-manana.html
[15] https://www.diariomedico.com/
[16] https://www.grunenthal.es/es-es/medios/notas-de-prensa/2021/app-permite-agilizar-atencion-dolor-urgencias-voz-ganadora-reto-grunenthal-marco-hackathon-salud
[17] https://www.consalud.es/saludigital/

with MEDTRONIC Portugal[18], one of the largest medical devices companies in the world, with offices in 150 countries that offers process optimization consultancy through the Lean Six Sigma (LSS) methodology. This agreement has the aim to optimize the patient journey of a private hospital in Portugal through the use of the *IPM* paradigm and the technology behind (*PMApp*, Chapter 6). This work is still ongoing.

Moreover, due to interest aroused by the solution proposed in the VI Health Hackathon, above introduced in section 8.4, Grünenthal[19] signed an agreement with the Universitat Politècnica de València to get this system up and running in the Hospital General Universitario de Valencia to improve the attention offered in their ED.

Another offer presented jointly with MySphera company[20] to the Hospital 12 de Octubre has been considered and will be resolved in the incoming months.

Furthermore, TRL+[21], a company focused on identifying promising disruptive Science and Technology for its transference to society in the form of companies, has expressed their interest in *IPM* and *PMApp*.

Additionally, under the registered trademark *Process Mining for Health*[22] (PM4H®), the author of this doctoral thesis is acting as the product owner of the solution based on *IPM* and *PMApp* and has participated in the design of a website to promote activities focused mainly on research, technology transfer and training.

### 8.5.3. Medical societies

The author of this doctoral thesis collaborates with medical societies such are the Spanish Society of Internal Medicine (Sociedad Española de Medicina Interna - SEMI)[23], the Multidisciplinary Spanish of Pain (Sociedad Española Multidisciplinar del Dolor)[24], or the Spanish Society of Emergency Medicine and Emergencies (Sociedad Española de Medicina de Urgencias y Emergencias)[25].

### 8.5.4. Guest speaker

Furthermore, she was invited as a guest speaker at the last national congress of the *SEMI* in Oviedo (Spain) last year. Additionally, she participated in the *Redefining Health Care Summit 2022*[26] event in Barcelona (Spain), organized by **The University of Texas at Austin Value Institute for Health and Care** in the round table called *Towards value in the Spanish healthcare system: moving forward*. The roundtable showcased relevant examples of how VBHC progresses across Spain from patient, clinical, efficiency and reimbursement perspectives. At this event, she had the opportunity

[18]https://www.medtronic.com/pt-pt/index.html
[19]https://www.grunenthal.es/es-es
[20]https://www.mysphera.com/
[21]https://www.linkedin.com/company/trl-plus/
[22]https://pm4health.com/
[23]https://www.fesemi.org/
[24]https://semdor.es/
[25]https://www.semes.org/
[26]https://valueinstitute.utexas.edu/summit

to meet Scott Wallace[27], Managing Director of the institute and Elizabeth Teisberg[28], Executive Director of the institute. Notwithstanding, she is best known for writing *Redefining Health Care: Creating Value-Based Competition on Results*[242], which she co-authored with Michael E. Porter[29], considered the parents of the VBHC.

The author of this doctoral thesis has participated several times in the course *Digital Health Transformation in Healthcare, Medical Technology in Digital Health Transformation* of the *High-Value Care Ambassador*[30] programme.

### 8.5.5. Final degree projects

Besides, the author of this doctoral thesis has conducted **three final degree projects** during the execution of this thesis with the aim of acquainting students with science and contributing in that direction.

## 8.6. Contributions to the objectives

- **C1 - Study of clinical variables and quality indicators in EDs as well as for stroke illness that can be used to model the corresponding care protocol in the service**

  It contributes to objectives **O1** and **O2**, and research questions **RQ1** and **RQ2**.

  A review of the KPIs related to the QoC in ED and stroke illness was performed. The study considered a variety of indicators related to the care protocol, such as the time-to-attention, other socioeconomic factors, as well as clinical outcomes and well-known adverse event indicators, so they can be included and calculated for modelling the general care process in the ED as well as the specific protocol for stroke patients. The review confirmed the strong evidence of some process indicators with clinical outcomes in the ED. In consequence, this work demonstrated that clinical outcomes and protocol indicators could be used as inputs by Process Mining techniques to investigate the evolution models for the general process of the ED as well as for time-dependence diseases such as stroke, and consequently obtaining meaningful knowledge and information about the relationship between them.

  This contribution was published in [211, 174].

- **C2 - Analysis of the capability of Process Mining techniques to model the ED care process as well as the stroke time-dependence disease under VBHC perspective.**

  Contributes to objectives **O1** and **O2**, and research questions **RQ1** and **RQ2**.

  Hospital Information System includes a lot of valuable information about patients collected during consultations, emergency episodes, and laboratory results that might be used to enrich care processes. In this regard, Process Mining

[27]https://dellmed.utexas.edu/directory/scott-wallace
[28]https://dellmed.utexas.edu/directory/elizabeth-teisberg
[29]https://scholar.google.es/citations?user=g9WIbh0AAAAJ&hl=es&oi=ao
[30]https://eithealth.eu/programmes/hta-high-value-care/

techniques can be used to extract knowledge and discover underlying healthcare processes. Therefore, the proposed analysis used Process Mining techniques to model the general care process of the ED as well as the stroke medical condition under a VBHC perspective.

The results of this analysis can be found in Chapters 4 and 5. They have also been published in several of the contributions listed in the previous section, including the publications [211] and [174].

- **C3 - Develop an experiment strategy to characterize care processes into graphical and understandable representations with real data.**

  Contributes to objectives **O1**, **O2**, **O3**, and research question **RQ1**, **RQ2**, and **RQ3**.

  The business sector gives an interesting approach to formalize questions through the concept of KPIs that provide a measurable value on how effectively a company is achieving key objectives and therefore are used for the analysis and evaluation of processes. This philosophy has been applied in the context of QoC to obtain human-understandable and contextualized KPIs, named *IPIs*, in the form of enhanced views that help health professionals perceive processes behind the disease. Health professionals can inquire what and how they want to know about the processes in the form of posed questions translated into models using *Interactive Process Mining* techniques to measure the QoC and VBHC.

  Based on the information available in the Hospital Information System and associated indicators to the ED process and stroke disease, there was discovered the widespread process of the ED according to the Manchester Triage Standard (MTS) as well as the stroke care process in the same service under the VBHC approach. As a result, two understandable representations of the real flow were produced, incorporating dynamic and behavioural views.

  The development of this strategy has been elaborated in Chapters 4, 5, 6. It has also been published in [174, 211, 233].

- **C4 - Design and development of a Process-mining-based toolkit to build human-understandable graphical representations.**

  Contributes to objective **O3**, and research question **RQ3**.

  *PMApp* toolkit was designed and implemented according to the characteristics and challenges identified by the PODS4H community. This toolkit not only integrates features to facilitate the understandability and analysis of the models but also to facilitate their building. The toolkit not can be used to model the specific use cases described in this document, instead, it can be used for any general case in health.

  The toolkit was published in [233] and is presented in Chapter 6.

Table 8.1 presents the relationship between the different contents presented in this document and the research questions, objectives, contributions and publications they cover.

TABLE 8.1: Relationship among the research questions, objectives, publications and contributions

| Chapter # | Contents | Research Questions | Objectives | Contributions | Publications |
|---|---|---|---|---|---|
| **1** | Introduction | | | | |
| **2** | Materials and Methods | | | | P3, P5 |
| **3** | Hypothesis | | | | |
| **4** | An IPI to Characterize Emergency Departments | RQ1 | O1 | C1, C2, C3 | P7 |
| **5** | An IPI to Measure Value Chain in Stroke | RQ2 | O2 | C1, C2, C3 | P3, P5, P6, P16 |
| **6** | PMApp for Co-Creating IPIs in Real Practice | RQ3 | O3 | C3, C4 | P1, P2, P3, P5, P6, P7, P11, P12, P13, P14, P16 |
| **7** | Conclusions | | | | P8, P10, P14, P17 |
| **8** | Main Original Contributions | | | | |

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