TESIS DOCTORAL – PhD DISSERTATION

Programa de Doctorado en Ingeniería y Producción Industrial

UNIVERSITAT POLITÈCNICA DE VALÈNCIA

TITLE:

Redesigning the Barranquilla’s public emergency care network to improve the patient waiting time

TÍTULO:

Rediseño de la Red Pública de Servicios de Urgencias en Salud de Barranquilla para mejora de la oportunidad de atención.

AUTHOR/AUTOR:

Miguel Ángel Ortíz Barrios

SUPERVISED BY/DIRIGIDA POR:

Dr. Juan José Alfaro Saíz

JULIO 2020

TABLE OF CONTENTS

ACRONYMS AND ABBREVIATIONS

AdaBoost: Adaptive Boosting

AHP: Analytic Hierarchy Process

ALOS: Average Length of Stay

ALS: Advanced Life Support

ANFIS: Adaptive Neuro-fuzzy Inference System

ANN: Artificial Neural Network

ANOVA: Analysis of Variance

ANP: Analytic Network Process

ARIMA: Autoregressive Integrated Moving Average

AS: Ambulance Service

BSC: Balance Scorecard

CC: Closeness Coefficient

CFCS: Converting Fuzzy Data into Crisp Scores

CODAS: Combinative Distance-based Assessment

COPRAS: Complex Proportional Assessment

CPR: Cardiopulmonary Resuscitation

CQI: Continuous Quality Improvement

CR: Consistency Ratio

CTS: Critical to Satisfaction

DEA: Data Envelopment Analysis

DEMATEL: Decision Making Trial and Evaluation Laboratory

DES: Discrete Event Simulation

DGP: Dynamic Grouping and Prioritization

DMAIC: Define, Measure, Analyze, Improve, Control

DNN: Deep Neural Network

DOE: Design of Experiments

DPQ: Dynamic Priority Queue

DSS: Decision Support System

ECN: Emergency Care Network

ED: Emergency Department

EDAS: Evaluation Based on Distance from Average Solution

ED-LOS: Emergency Department Length of Stay

ELECTRE: Elimination and Choice Expressing the Reality

EPD: Electronic Provider Documentation

ER: Emergency Room

ESI: Emergency Severity Index

FAHP: Fuzzy Analytic Hierarchy Process

FANP: Fuzzy Analytic Network Process

FDEMATEL: Fuzzy Decision Making Trial and Evaluation Laboratory

FMEA: Failure Mode and Effect Analysis

FNN: Feed Forward Neural Network

GA: Genetic Algorithm

GP: General Practitioner

GW: Global Weight

HIT: Health Information Technology

HR: Human Resources

I: Infrastructure

IFS: Intuitionistic Fuzzy Set

ILP: Integer Linear Program

IRM: Impact Relation Map

KPI: Key Performance Index

LA: Long-acting Antibiotic

LSS: Lean Six Sigma

LM: Lean Manufacturing

LOS: Length of Stay

LWBS: Left-without-being-seen

MAPQC: Modified American Productivity and Quality Center

MAUT: Multi-attribute Utility Theory

MCDM: Multicriteria Decision-Making

ME: Medical Equipment

MOCBA: Multi-objective Computing Budget Allocation

NEAT: National Emergency Access Target

NFS: Neutrosophic Fuzzy Set

NIS: Negative Ideal Solution

NSGA II: Non-dominated Sorting Genetic Algorithm II

NSPSO: Non-dominated Sorting Particle Swarm Optimization

OR: Operations Research

PDSA: Plan, Do, Study, Act

PIS: Positive Ideal Solution

POC: Point of Care

PP: Procedures and protocols

PRIME: Preference Ratios in Multi-attribute Evaluation

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluations

PS: Patient Safety

Q: Quality

QAPC: American Productivity and Quality Center

QI: Quality Improvement

QMS: Quality Management System

REACT: Rapid Entry and Accelerated Care at Triage

RNN: Recurrent Neural Network

RPN: Resource Preservation Net/Risk Priority Number

SAA: Sample Average Approximation

SAW: Simple Additive Weighting

SCLP: Separated Continuous Linear Programming

SIPOC: Supplier-Input-Process-Output-Customers

SMA: Supplies/Medicines and Accesories

SP: Supporting Processes

TFT: Total Flow Time

TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution

UDT: Urine Drug Test

UK: United Kingdom

US: United States

USL: Upper Specification Limit

VIKOR: VlseKriterijumska Optimizcija I Kaompromisno Resenje

VOC: Voice of Customer

VSM: Value Stream Mapping

WASPAS: Weighted Aggregated Sum Product Assessment

WHO: World Health Organization

WT: Waiting Time

ABSTRACT

Waiting time is one of the most critical measures in the satisfaction of patients admitted within emergency departments. Therefore, hospitals and governmental organizations should jointly aim to provide timely attention at reasonable costs. In the case of Barranquilla's Pubic Emergency Service Network, composed by 8 Points of care (POCs) and 2 hospitals, the trend evidences a continuous growing of the waiting time with a rate of 3,08 min/semester and a 93,13% likelihood of serving patients after waiting for more than 30 minutes. This is an unmistakable symptom of the network inability for satisfying the standards established by the Ministry of Health, which may trigger the development of more complex symptoms, increase in the death rate, requirement for more complex clinical services (hospitalization and intensive care unit) and increased service costs. This doctoral dissertation then illustrates the redesign of the aforementioned Public Emergency Service Network aiming at providing the target population with an efficient and highly timely service where both hospitals and governmental institutions effectively converge. It was then necessary to implement a 4-phase methodology consolidating a proposal oriented to the effective and sustainable development of network operations. First, the Public Emergency Service Network was characterized considering its current behavior in terms of demand and waiting time. A systematic literature review was then undertaken for identifying the methodological approaches that have been implementing for improving the waiting time and other performance indicators associated with the emergency care service. Following this, a methodology for the creation of efficient and sustainable emergency care networks was designed and later validated in the Southamerican Public network for lessening the average waiting time and ensuring the equitable distribution of profits derived from the collaboration. Ultimately, a multicriteria decision-making model was created for assessing the performance of the emergency departments and propelling the design of improvement strategies focused on bettering the response against the changing demand conditions, critical to satisfaction and operational conditions. The results evidenced that the patients accessing to the network tend to wait 201,6 min on

average with a standard deviation of 81,6 min before being served by the emergency care unit. On the other hand, based on the reported literature, it is highly suggested to combine Operations Research (OR) methods, quality-based techniques, and data-driven approaches for addressing this problem. In this sense, a methodology based on collateral payment models, Discrete-event simulation, and Lean Six Sigma was proposed and validated resulting in a redesigned network whose average waiting time may diminish between 6,71 min and 9,08 min with an average profit US$29,980/node. Lately, a model comprising of 8 criteria and 35 sub-criteria was designed for evaluating the overall performance of emergency departments. The model outcomes revealed the critical role of *Infrastructure* (Global weight = 21,5%) in ED performance and the interactive nature of *Patient Safety* (C + R = 12,771).

RESUMEN

La oportunidad en la atención es uno de los críticos de mayor relevancia en la satisfacción de los pacientes que acuden a los servicios de Urgencias. Por tal motivo, las instituciones prestadoras de servicio y las organizaciones gubernamentales deben propender conjuntamente por una atención cada vez más oportuna a costos operacionales razonables. En el caso de la Red Pública en Servicios de Urgencias de Barrannquilla, compuesta por 8 puntos de atención y 2 hospitales, la tendencia marca un continuo crecimiento de la oportunidad en la atención con una tasa de 3,08 minutos/semestre y una probabilidad del 93,13% de atender a los pacientes después de una espera mayor a 30 minutos. Lo anterior se constituye en un síntoma inequívoco de la incapacidad de la Red para satisfacer los estándares de oportunidad establecidos por el Ministerio de Salud, hecho que podría desencadenar el desarrollo de sintomatologías de mayor complejidad, el incremento de la probabilidad de mortalidad, el requerimiento de servicios clínicos más complejos (hospitalización y cuidados intensivos) y el aumento de los costos asociados al servicio. En consecuencia, la presente tesis doctoral presenta el rediseño de la Red Pública en Servicios de Urgencias anteriormente mencionada a fin de otorgar a la población diana un servicio eficiente y altamente oportuno donde tanto las instituciones prestadoras del servicio como los organismos gubernamentales converjan efectivamente. Para ello, fue necesaria la ejecución de 4 grandes fases a través de las cuales se consolidó una propuesta orientada al desarrollo efectivo y sostenible de las operaciones de la Red. Primero, se caracterizó la Red Pública de Servicios de Urgencias en Salud considerando su comportamiento actual en términos de demanda y oportunidad de la atención. Luego, a través de una revisión sistemática de la literatura, se identificaron los enfoques metodológicos que se han implementado para la mejora de la oportunidad y otros indicadores de rendimiento asociados al servicio de Urgencias. Posteriormente, se diseñó una metodología para la creación de redes de Urgencias eficientes y sostenibles la cual luego se validó en la Red Pública sudamericana a fin de disminuir la oportunidad de atención promedio en Urgencias y garantizar la

distribución equitativa de los beneficios financieros derivados de la colaboración. Finalmente, se construyó un modelo multicriterio que permitió evaluar el rendimiento de los departamentos de Urgencia e impulsó la creación de estrategias de mejora focalizadas en incrementar su respuesta ante la demanda cambiante, los críticos de satisfacción y las condiciones de operación estipuladas en la ley. Los resultados de esta aplicación evidenciaron que los pacientes que acceden a la Red tienden a esperar en promedio 201,6 min con desviación de estándar de 81,6 min antes de ser atendidos por urgencia. Por otro lado, de acuerdo con la revisión de literatura, la combinación de técnicas de investigación de operaciones, ingeniería de la calidad y analítica de datos es ampliamente recomendada para abordar este problema. En ese sentido, una metodología basada en modelos colaterales de pago, simulación de procesos y lean seis sigma fue propuesta y validada generando un rediseño de Red cuya oportunidad de atención promedio podría disminuir entre 6,71 min y 9,08 min con beneficios financieros promedio de US$29,980/nodo. En último lugar, un modelo compuesto por 8 criterios y 35 sub-criterios fue diseñado para evaluar el rendimiento general de los departamentos de Urgencias. Los resultados del modelo evidenciaron el rol crítico de la *infraestructura* (Peso global = 21,5%) en el rendimiento de los departamentos de Urgencia y la naturaleza interactiva de la *Seguridad del Paciente* (C + R = 12,771).

RESUM

L'oportunitat en l'atenció és un dels crítics de major rellevància en la satisfacció dels pacients que acudeixen als serveis d'Urgències. Per tal motiu, les institucions prestadores de servei i les organitzacions governamentals han de propendir conjuntament per una atenció cada vegada més oportuna a costos operacionals raonables. En el cas de la Xarxa Pública en Serveis d'Urgències de Barrannquilla, composta per 8 punts d'atenció i 2 hospitals, la tendència marca un continu creixement de l'oportunitat en l'atenció amb una taxa de 3,08 minuts / semestre i una probabilitat de l' 93,13% d'atendre els pacients després d'una espera major a 30 minuts. L'anterior es constitueix en un símptoma inequívoc de la incapacitat de la Xarxa per satisfer els estàndards d'oportunitat establerts pel Ministeri de Salut, fet que podria desencadenar el desenvolupament de simptomatologies de major complexitat, l'increment de la probabilitat de mortalitat, el requeriment de serveis clínics més complexos (hospitalització i cures intensives) i l'augment dels costos associats a el servei. En conseqüència, la present tesi doctoral presenta el redisseny de la Xarxa Pública en Serveis d'Urgències anteriorment esmentada a fi d'atorgar a la població diana un servei eficient i altament oportú on tant les institucions prestadores de el servei com els organismes governamentals convergeixin efectivament. Per a això, va ser necessària l'execució de 4 grans fases a través de les quals es va consolidar una proposta orientada a el desenvolupament efectiu i sostenible de les operacions de la Xarxa. Primer, es va caracteritzar la Xarxa Pública de Serveis d'Urgències en Salut considerant el seu comportament actual en termes de demanda i oportunitat de l'atenció. Després, a través d'una revisió sistemàtica de la literatura, es van identificar els enfocaments metodològics que s'han implementat per a la millora de l'oportunitat i altres indicadors de rendiment associats a el servei d'Urgències. Posteriorment, es va dissenyar una metodologia per a la creació de xarxes d'Urgències eficients i sostenibles la qual després es va validar a la Xarxa Pública sud-americana a fi de disminuir l'oportunitat d'atenció mitjana a Urgències i garantir la distribució equitativa dels beneficis financers derivats de la col·laboració. Finalment, es va construir un model multicriteri que va permetre avaluar el rendiment

dels departaments d'Urgència i va impulsar la creació d'estratègies de millora focalitzades en incrementar la seva resposta davant la demanda canviant, els crítics de satisfacció i les condicions d'operació estipulades en la llei. Els resultats d'aquesta aplicació van evidenciar que els pacients que accedeixen a la Xarxa tendeixen a esperar de mitjana 201,6 min amb desviació d'estàndard de 81,6 min abans de ser atesos per urgència. D'altra banda, d'acord amb la revisió de literatura, la combinació de tècniques d'investigació d'operacions, enginyeria de la qualitat i analítica de dades és àmpliament recomanada per abordar aquest problema. En aquest sentit, una metodologia basada en models col·laterals de pagament, simulació de processos i llegeixin 6 sigma va ser proposada i validada generant un redisseny de Xarxa la oportunitat d'atenció mitjana podria disminuir entre 6,71 min i 9,08 min amb beneficis financers mitjana d'US $ 29,980 / node. En darrer lloc, un model compost per 8 criteris i 35 sub-criteris va ser dissenyat per avaluar el rendiment general dels departaments d'Urgències. Els resultats de el model evidenciar el paper crític de la infraestructura (Pes global = 21,5%) en el rendiment dels departaments d'Urgència i la naturalesa interactiva de la Seguretat de l'Pacient (C + R = 12,771).

AGRADECIMIENTOS

El camino hacia la finalización de este doctorado ha estado plagado de desafíos que he sorteado efectivamente gracias a la ayuda, dirección y amor de Papá Dios a quien agradezco públicamente por renovar mis fuerzas cuando eran pocas, por darme empuje volitivo para continuar con este sueño a pesar de las circunstancias adversas y brindarme sabiduría para tomar las decisiones que finalmente derivaron en un proceso exitoso.

Por otro lado, agradezco a mi esposa Giselle Paola Polifroni Avendaño quien me apoyó incondicionalmente y de manera continua a lo largo de esta formación. Mi esposa estuvo a mi lado esforzándose hombro a hombro por finalizar este proyecto familiar, me brindó soporte emocional en los momentos más difíciles de este proyecto doctoral. Agradezco también a mi hijo Alessio Ortíz Polifroni quién se convirtió en una constante motivación para terminar mi proceso doctoral de manera exitosa y sobresaliente.

También extiendo mis más sinceros agradecimientos a mi tutor de tesis, PhD. Juan José Alfaro Saíz quién me brindó su constante, oportuna y acertada colaboración en cada una de las fases de mi estudio doctoral. Destaco su continuo acompañamiento impulsándome y motivándome a consolidar mi formación doctoral con alta calidad y contribución a la sociedad.

Igualmente, me permito agradecer a mis padres Aida Beatríz Barrios Osorio y Alfonso Enrique Ortíz Borrero, a mis hermanos Alfonso Enrique Ortíz Barrios e Iván de Jesús Ortíz Barrios quiénes me apoyaron incondicionalmente en todo mi proceso académico.

Finalmente, manifiesto mi agradecimiento a Giussepe Polifroni Avendaño, Natalia Jaramillo Rueda y Jeferson de Ávila Villalobos quiénes también me asistieron en la ejecución sincronizada y efectiva de esta tesis doctoral.

ACKNOWLEDGEMENTS

The path towards the completion of this doctorate has been plagued with challenges that I have effectively addressed with the support, guidance, and love of the Lord to whom I publicly thank for renewing my strength when it was too little, providing me with volitional thrust to continue with this dream despite the adverse circumstances, and giving me the wisdom for making the decisions that finally resulted in a successful process.

On the other hand, I thank my wife Giselle Paola Polifroni Avendaño who fully and continuously supported me throughout this formation. My wife was next to me working hard with the purpose of finalizing this family project; she additionally provided me emotional assistance during the most difficult moments of this doctoral research. I also thank my son Alessio Ortíz Polifroni who became a constant motivation for finishing my doctoral process in an outstanding and achiever manner.

My heartfelt thanks also go to my PhD supervisor, Juan José Alfaro Saíz who gave me his constant, timely, and precise collaboration in all the phases of my doctoral study. I highlight his support by propelling me to consolidate my doctoral formation with high quality and contribution to society.

Similarly, I thank my parents Aida Beatríz Barrios Osorio and Alfonso Enrique Ortíz Borrero, and my brothers Alfonso Enrique Ortíz Barrios and Iván de Jesús Ortíz Barrios who unconditionally help me throughout my academic process.

Ultimately, I am grateful to Giussepe Polifroni Avendaño, Natalia Jaramillo Rueda y Jeferson de Ávila Villalobos who also assisted me in the synchronized and effective execution of my doctoral thesis.

1 INTRODUCTION AND OBJECTIVES

1.1 Problem Statement

Health is one of the most relevant elements for the development of a long and high-quality life. In this sense, the health importance lies on granting that a person's body maintains the operating standards and thereby performing the different activities of daily living. In this regard, patients try to alleviate any pain or symptom by immediately accessing to an emergency department. A fast response at this level tackles the overcrowding problem and contributes to the reduction of mortality, inability, sequels, and the risks inherent to the pathological process generating the service demand (Hoot and Aronsky, 2008).

It is therefore necessary to estimate the response of healthcare providers through the waiting time indicator which is directly associated with the access to the ambulatory services, an aspect that is vital for ensuring the safety and effectiveness of healthcare offered to patients. Upon analyzing the case of Barranquilla (Colombia), it is evident that the emergency departments (EDs) experience overcrowding and longer waiting times. Indeed, a patient must wait for 29,86 min on average with a standard deviation of 9,91 min before being served by a doctor (Ministerio de Salud y Protección Social de Colombia, 2016). Additionally, the above waiting time is over the national mean which was reported to be 28,6 min in the second semester of 2015 (Ministerio de Salud y Protección Social de Colombia, 2016). Barranquilla is also ranked as the 5th worst region concerning the average waiting time in Colombia (Observatorio de la Calidad de la Atención en Salud de Colombia, 2016).

It is good to note that the average waiting time in emergency care tends to increase 3,08 min per each past semester (Figure 1). On the other hand, the Cpu was found to be 0,003 which indicates that the emergency care process is not capable of satisfying the upper specification limit established by the government in reference to the waiting time (30 min). On a different tack, the total process error was calculated to be 93,13% denoting that 931360 out of 1000000 of patients requiring emergency care will have to wait for more than 30 minutes before being served by doctors. These indicators evidence a process requiring very serious modifications and immediate intervention is then needed for satisfying the standard and reducing the subsequent patient risks. This conclusion is also supported by the short-term and long-term sigma levels which were found to be 0,01 and -1,49 correspondingly.

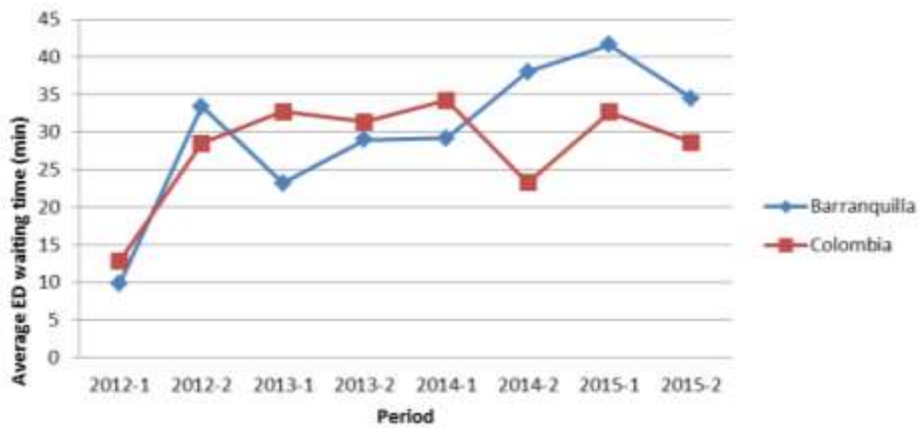


Figure 1. Comparative analysis between Barranquilla and Colombia in terms of waiting time (Source: Observatorio de la Calidad de la Atención en Salud, 2016)

In a similar vein, the patient satisfaction level was found to diminish below 90% in the last semester of 2015 which confirms the need for urgent interventions so that waiting times can be significantly lessened (Figure 2).

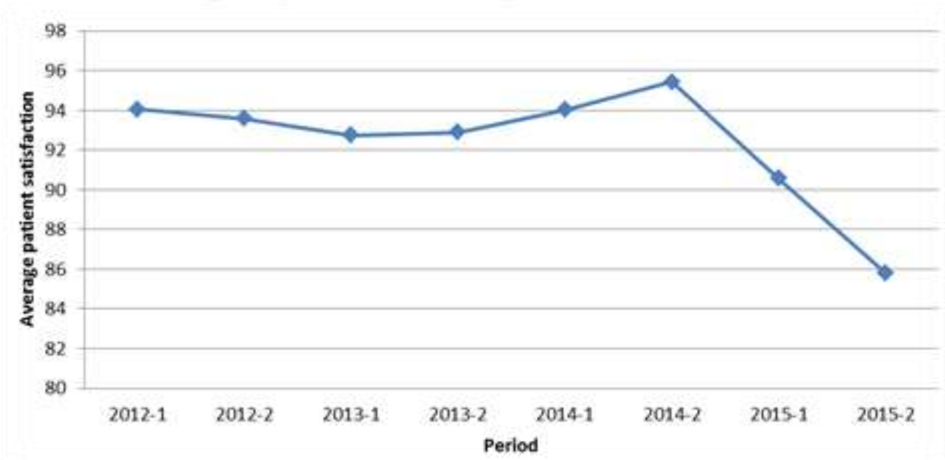


Figure 2. Evolution of patient satisfaction regarding emergency care services provided in Barranquilla (Source: Observatorio de la Calidad de la Atención en Salud, 2016)

According to Alemán and Montes (2016), the lack of service authorization by the insurance companies, the low availability of beds in hospitalization, insufficient infrastructure, and lack of caregivers are the main causes associated with the long waiting times experienced in hospitals located in this region. In their study, the findings also pointed out that most patients do not discriminate the symptoms needing ED intervention. Therefore, EDs end up serving patients whose pathology could be effectively addressed by an outpatient service unit. In Barranquilla, 22 to 70 percent of the patients accessing to emergency care services present non-urgent conditions which causes long waits, patient dissatisfaction, overcrowding, and cost overruns.

Given the above-mentioned problem, the Regulatory Center of Urgency and Emergency (RCUE) services has proposed to intervene the Public Emergency Care Network so that integral, timely, efficient, and efficacious healthcare can be fully provided to patients through the coordination, guidance, and monitoring of emergency care services. Currently, the network comprises of 2 hospitals and 8 POCs that should coordinately operate so that average ED waiting time can be adjusted based on the government standards. Nonetheless, the here described panorama dictates that this network must be redesigned for addressing the existing and future demands on emergency care services and thereby slowing the rate of growth described in Figure 1. The RCUE supports this finding upon establishing that the main cause of long waits in EDs is the non-availability of beds, an aspect evidencing the need for more high-quality emergency care units (Secretaría de Salud de Barranquilla, 2016).

The insurance companies play a vital role in the management of interactions occurring among the different providers of emergency care in this region (Ministerio de Salud y Protección Social, 2014). Nevertheless, according to the evidence shown by the Community Care Service (CCS), 87% of the complaints put forward by emergency care users are due to the inefficiency of insurance companies distributed as follows: 42% (Contributory scheme) and 45% (Subsidized scheme). This finding evidences the need for restructuring not only the healthcare providers (hospitals and

POCs) but the external agents affecting the network operation so that better synergies can be achieved and long waits can be effectively tackled.

In view of the above, the following question is raised:

¿How to redesign the Barranquilla's Public Emergency Care Network so that patient waiting times can be improved?

1.2 Objectives

General objective

- Redesign the Barranquilla's public emergency care network to improve the patient waiting time.

Specific objectives

- Characterize the public emergency care network to identify the factors contributing to the gap between the current status and the desired performance in terms of waiting time.
- Design a simulation model representing the current status of the public emergency care network.
- Establish a methodology for the design of efficient emergency care networks.
- Propose strategies improving the waiting time in the public emergency care network and validate its effectiveness through simulation.
- Develop multicriteria decision-making models to evaluate the overall performance of emergency departments integrating the public emergency care network.

1.3 Research Methodology and Resources

The current proposal is based on a deductive research aiming to create a methodology for the design of efficient emergency care networks in parallel to the development of a KPI-based multicriteria model assessing the overall performance of emergency departments integrating the network. The above-described methodology and model has been validated in the Barranquilla's public emergency care network with the support of different stakeholders. It was hence necessary the application of a 4-phase methodology consolidating a proposal oriented to the effective and sustainable development of network operations (see Figure 3).

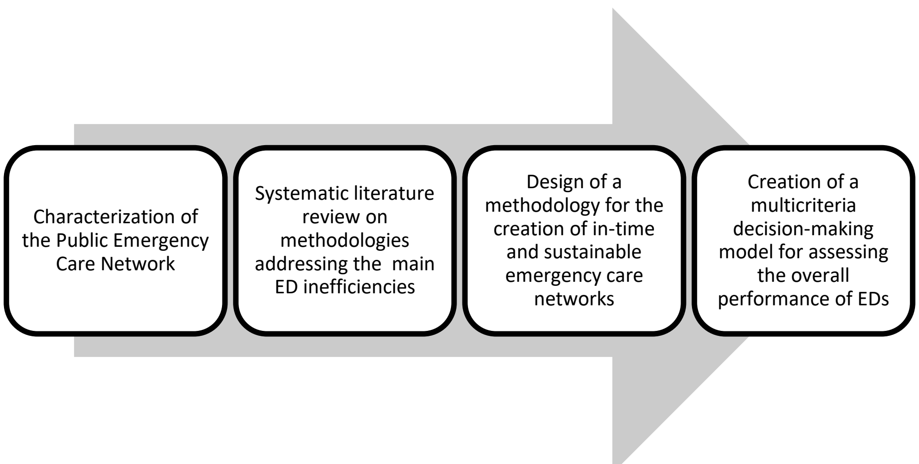


Figure 3. The proposed methodology for the redesign of Barranquilla's public emergency care network.

Table 1. Detailed description of activities performed within the redesign of Barranquilla's public emergency care network

Specific objectives	Phase	Activity	Techniques
		Legal characterization	Bar diagram. Correlation analysis Lean Six-Sigma. SIPOC. Line graph. Normality test. Capability analysis.
		Search for resolutions and decrees related to the average waiting time in emergency departments.	
		Search for legislation regulating the activities within the public emergency care networks.	

Characterize the public emergency care network to identify the factors contributing to the gap between the current status and the desired performance in terms of waiting time.	Characterization of the Public Emergency Care network	Search for resolutions and decrees related to the current healthcare model in Colombia.	Hypothesis tests for comparing means and variances. ANOVA.
		Development of a legal framework covering the operations performed within public emergency care networks.	
		Operational characterization	
		Identification of stakeholders	
		Description of each stakeholder's function and role.	
		Identification of current operational procedures.	
		Network geographical distribution.	
		Description of the current operational structure of the network.	
		Characterization of demand	
		Target population description	
		Identification of seasonal patterns related to emergency care demands.	
		Financial characterization	
		Identification of financial policies regulating the network operations.	
		KPI analysis	
		Analysis of ED waiting time indicators.	
Design a simulation model representing the current status of the public emergency care network.		Identification of endogen and exogen variables.	**Intra-variable independence test:** Run test, auto-correlation test and scatterplot. **Homogeneity test:** Tukey test, Fisher test, ANOVA and Kruskal-Wallis test. **Goodness of fit**
		Data collection of aforementioned variables.	
		Input data analysis.	
		Construction of simulation model.	

		Output analysis for verifying the equivalence with the real-world system.	**Equivalence test** Hypothesis test for comparing means, variances, and medians. **Discrete-event simulation (Hung et al. 2007; Hoot et al. 2008).**
Establish a methodology for the design of efficient emergency care networks.	Systematic literature review on methodologies addressing the main ED inefficiencies	Literature review on the adoption of methodologies for the design of emergency care networks. Comparative analysis among the identified methodologies. Identification of strengths and gaps in the application of the aforementioned methodologies. Adoption of a methodology satisfying the gaps identified in the comparative analysis.	Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). Comparative graphs.
Propose strategies improving the waiting time in the public emergency care network and validate its effectiveness through simulation.	Design of a methodology for the creation of in-time and sustainable emergency care networks	Demonstration of the proposed methodology in the Barranquilla's public emergency care network using simulation. Statistical comparison between the current and projected waiting time (if the proposed methodology is implemented). Financial analysis (if the redesigned ECN is implemented).	Discrete-event simulation (Ahmed and Alkhamis, 2009). Hypothesis test for the comparison between means and variances (De Souza, 2009; Mandahawi et al. 2010). Payment colateral models (Barrios, Caballero, and Sánchez, 2015).
Develop multicriteria decision-making models to evaluate the overall performance of emergency departments integrating the public	Creation of a multicriteria decision-making model for assessing the overall performance of EDs	Identification of evaluation criteria and sub-criteria based on pertinent literature, related regulations, and experts' opinion. Creation of the multicriteria performance model. Selection of MCDM techniques.	Surveys. **MCDM techniques** (Günal and Pidd, 2010; Çalışkan, 2013; Saaty, 2016): FAHP, FDEMATEL, and TOPSIS. Bar diagram.

emergency care network.		Definition of decision-making team.	
		Design of data-collection tools.	
		Data collection.	
		Data recording process using decision software.	
		Calculation of criteria weights (De Felice and Petrillo, 2014)., interdependence evaluation, and ranking of EDs.	
		Creation of improvement stragies and recommendations.	
		Sensitivity analysis.	

Apart from the people involved in the research from the Universidad Politécnica de Valencia and participating institutions from the healthcare sector where data was extracted, other resources were utilized during the development of this project. On one hand, software packages for advanced modeling (Arena Rockwell 15®, Superdecisions) and statistical analysis (Minitab 17®, Excel data analysis package) were employed; on the other hand, several databases (Scopus, WoS, Google Scholar, PubMed, IEEE, ACM Digital Library, and Science Direct) were consulted for undertaking the PRISMA approach. Open applications (OCAS, Google Maps) were also used to support this research.

1.4 Structure

This thesis is structured in four different parts (see Fig. 3) corresponding to the five main objectives already exposed in Section 1.2. The development of these objectives was exposed through three publications as follows:

The details of the publications are:

Title: <u>Methodological approaches to support process improvement in emergency departments: a systematic review</u>

Authors: Miguel Angel Ortíz-Barrios, Juan-José Alfaro-Saíz

Publication: International Journal of Environmental Research and Public Health

Status: Published

Link: https://doi.org/10.3390/ijerph17082664

Abstract: The most commonly used techniques for addressing each Emergency Department (ED) problem (overcrowding, prolonged waiting time, extended length of stay, excessive patient flow time, and high left-without-being-seen (LWBS) rates) were specified to provide healthcare managers and researchers with a useful framework for effectively solving these operational deficiencies. Finally, we identified the existing research tendencies and highlighted opportunities for future work. We implemented the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to undertake a review including scholarly articles published between April 1993 and October 2019. The selected papers were categorized considering the leading ED problems and publication year. Two hundred and three (203) papers distributed in 120 journals were found to meet the inclusion criteria. Furthermore, computer simulation and lean manufacturing were concluded to be the most prominent approaches for addressing the leading operational problems in EDs. In future interventions, ED administrators and researchers are widely advised to combine Operations Research (OR) methods, quality-based techniques, and data-driven approaches for upgrading the performance of EDs. On a different tack, more interventions are required for tackling overcrowding and high left-without-being-seen rates.

Title: An integrated approach for designing in-time and economically sustainable emergency care networks: A case study in the public sector

Authors: Miguel Ortíz-Barrios, Juan-José Alfaro-Saíz

Publication: Plos One

Status: Published

Link: https://doi.org/10.1371/journal.pone.0234984

Abstract: Emergency Care Networks (ECNs) were created as a response to the increased demand for emergency services and the ever-increasing waiting times experienced by patients in emergency rooms. In this sense, ECNs are called to provide a rapid diagnosis and early intervention so that poor patient outcomes, patient dissatisfaction, and cost overruns can be avoided. Nevertheless, ECNs, as nodal systems, are often inefficient due to the lack of coordination between emergency departments (EDs) and the presence of non-value added activities within each ED. This situation is even more complex in the public healthcare sector of low-income countries where emergency care is provided under constraint resources and limited innovation. Notwithstanding the tremendous efforts made by healthcare clusters and government agencies to tackle this problem, most of ECNs do not yet provide nimble and efficient care to patients. Additionally, little progress has been evidenced regarding the creation of methodological approaches that assist policymakers in solving this problem. In an attempt to address these shortcomings, this paper presents a three-phase methodology based on Discrete-event simulation, payment collateral models, and lean six sigma to support the design of in-time and economically sustainable ECNs. The proposed approach is validated in a public ECN consisting of 2 hospitals and 8 POCs (Point of Care). The results of this study evidenced that the average waiting time in an ECN can be substantially diminished by optimizing the cooperation flows between EDs.

Title: A Hybrid Fuzzy Multi-criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study

Authors: Miguel Ortíz-Barrios, Juan-José Alfaro-Saíz

Publication: International Journal of Information Technology and Decision Making

Status: Accepted.

Link: See attachment in Section 5.1

Abstract: Performance evaluation is relevant for supporting managerial decisions related to the improvement of public emergency departments (EDs). As different criteria from ED context and several alternatives need to be considered, selecting a suitable Multicriteria Decision-Making (MCDM) approach has become a crucial step for ED performance evaluation. Although some methodologies have been proposed to address this challenge, a more complete approach is still lacking. This paper bridges this gap by integrating three potent MCDM methods. First, the Fuzzy Analytic Hierarchy Process (FAHP) is used to determine the criteria and sub-criteria weights under uncertainty, followed by the interdependence evaluation via fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL). The fuzzy logic is merged with AHP and DEMATEL to illustrate vague judgments. Then, FAHP and FDEMATEL are integrated to determine the final criteria and sub-criteria weights considering interdependence and uncertainty. Finally, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used for ranking EDs. This approach is validated in a real 3-ED cluster. The results revealed the critical role of Infrastructure (21.5%) in ED performance and the interactive nature of Patient safety (C+R =12.771). Furthermore, this paper evidences the weaknesses to be tackled for upgrading the performance of each ED.

1.5 Publications Authors' Contributions

This section summarizes the main contributions of each of the two authors:

Author 1 (Thesis author)

Name: Miguel Ortíz-Barrios

Contributions: The main contribution of Miguel Ortíz-Barrios has been on the conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing-original draft preparation, writing-review and editing, visualization, and project administration parts of the above-mentioned publications.

Author 2

Name: Juan-José Alfaro-Saíz

Contributions: The main contribution of Juan-José Alfaro Saíz was on the conceptualization, methodology, supervision, review, and visualization of papers.

1.6 References

Ahmed MA, Alkhamis TM. Simulation optimization for an emergency department healthcare unit in Kuwait. Eur J Oper Res 2009; 198(3):936-942.

Barrios MAO, Caballero JE, Sánchez FS. A methodology for the creation of integrated service networks in outpatient internal medicine. Lect Notes Comput Sci 2015; 9456:247-257.

Çalişkan H. Selection of boron based tribological hard coatings using multi-criteria decision making methods. Mater Des 2013; 50:742-749.

De Felice F, Petrillo A. Proposal of a structured methodology for the measure of intangible criteria and for decision making. Int J Simul Process Model 2014; 9(3):157-166.

de Souza LB. Trends and approaches in lean healthcare. Leadersh in Health Serv 2009; 22(2):121-139.

Günal MM, Pidd M. Discrete event simulation for performance modelling in health care: A review of the literature. J Simul 2010; 4(1):42-51.

Hoot NR, LeBlanc LJ, Jones I, Levin SR, Zhou C, Gadd CS, et al. Forecasting Emergency Department Crowding: A Discrete Event Simulation. Ann Emerg Med 2008; 52(2):116-125.

Hoot NR, Aronsky D. Systematic Review of Emergency Department Crowding: Causes, Effects, and Solutions. Ann Emerg Med 2008; 52(2):126-136.e1.

Hung GR, Whitehouse SR, O'Neill C, Gray AP, Kissoon N. Computer modeling of patient flow in a pediatric emergency department using discrete event simulation. Pediatr Emerg Care 2007; 23(1):5-10.

Mandahawi N, Al-Shihabi S, Abdallah AA, Alfarah YM. Reducing waiting time at an emergency department using design for Six Sigma and discrete event simulation. Int J Six Sigma Compet Advantage 2010; 6(1-2):91-104.

Saaty TL. The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making. Int Ser Oper Res Manag Sci 2016; 233:363-419.

2 PUBLICATIONS

2.1 Methodological Approaches to Support Process Improvement in Emergency Departments: A Systematic Review

2.1.1 Introduction

Emergency departments (EDs) are perceived as 24/7 portals where a rapid and efficient diagnosis, urgent attention, primary care, and inpatient admission is provided for stabilizing seriously ill and wounded patients, including those with life-threatening conditions ranging from different head injuries to heart failures. EDs have assumed a wider role in the integrated healthcare system and are therefore cataloged as the cornerstone of the safety net. Furthermore, EDs play a key social role by offering access to the healthcare system for both insured and uninsured patients. Their importance in the healthcare system is also underpinned by the fact that more than half of the hospital activity takes place in their settings. Besides, as a “care hub”, it is a point of interaction between communities and hospitals.

Nonetheless, several serious problems have become glaring in EDs, even in developed countries, and must be therefore thoroughly addressed to ensure low early mortality rates and complications, increased patient satisfaction, timely emergency care, and long-term morbidity. Not surprisingly, these growing deficiencies greatly contribute to the acceleration of healthcare costs which increases the financial pressures on hospitals and shrinks their profits. The problem is even more critical as demands on ED services are expected to continue to steadily and dramatically rise in the near future which will end up amplifying the negative effects here described, while keeping EDs under a constant strain (Soril et al., 2015). There is then an urgent need for aggressive improvements through the efficient use of inpatient resources and the implementation of operational changes in the healthcare delivery.

From this perspective, it is essential to count on the support of suitable methodological approaches to assist decision makers along the emergency care journey. The novelty of the study then lies on the need of providing orientation as well as a scientific evidence base to healthcare administrators, clinicians, researchers, and practitioners on what process-improvement methodologies can be used to fully understand and tackle the top-five leading problems presented in EDs (Jarvis, 2016; Health Catalyst Editors, 2020): Overcrowding, prolonged waiting time, extended length of stay (LOS), excessive patient flow time, and patients who leave without being seen (LWBS). Previous reviews have been conducted relating to this topic; some of them focused on critically reviewing the implementation of specific approaches to address different ED problems. . For instance, some authors analyzed the use of lean thinking and its effects on ED processes (Migita et al., 2018; Holden, 2011; Mazzocato et al., 2016), while others studied the contribution of discrete-event simulation implementations to tackle overcrowding and model the ED performance (Günal and Pidd, 2010; Paul et al., 2010; Vanbrabant, 2019). Saghafian et al. (2015) have also discussed the contribution of operations research/management methods to the optimization of patient flow within EDs. Other works directly concentrated on assessing the effectiveness of interventions to reduce the number of frequent users of EDs (Soril et al., 2015; Althaus et al., 2011), minimize ED utilization (Flores-Mateo et al., 2012), decrease overcrowding (Boyle et al., 2012; Crawford et al., 2014), diminish the number of non-urgent visits (Uscher-Pines et al., 2013), shorten the total flow time (TFT) (Oredsson et al., 2011) and reduce the number of patients who leave the ED without being seen (Clarey and Cooke et al., 2012). Despite the considerable effort made in these studies, the review of the evidence base is still scant and narrow since: (i) the above-cited reviews are mostly focused on a particular ED problem, (ii) the aforementioned works are predominantly skewed to the use of a specific technique or approach in the ED context; therefore, there are no studies considering the wide variety of process-improvement methodologies that can be applied for the solution of the leading ED deficiencies (overcrowding, prolonged waiting time, extended length of stay, excessive patient flow time, and patients who leave without being seen - LWBS), and (iii) the use of hybrid methods has not been incorporated in the aforementioned works, thereby greatly restricting their application in the wild and the subsequent achievement of better operational outcomes. This paper hence addresses these gaps in knowledge through a systematic review focused on establishing the most popular process-improvement approaches that have been used for tackling each of the five-top leading problems in EDs. Thereby, our article lays the groundwork for analyzing the continuing evolution of this research field, devising and implementing cost-effective solutions to the leading ED problems, detecting the limitations in current practice, and identifying promising opportunities for future investigation.

Although more deficiencies have been addressed and reported throughout the literature, we particularly focused on the above-mentioned problems due to their big impact on financial sustainability and emergency care delivery. Indeed, these problems are interconnected in several ways along the ED patient journey as described in Figure 1 (where the red and blue arrows represent feedback and dependence interrelations, respectively). On one hand, crowded emergency departments hamper the delivery of timely care which ends up increasing the total flow time within the ED setting. Indeed, some patients decide to leave the ED without being seen when these units experience long overcrowding episodes. The LWBS rates are also correlated to excessive patient flow time, long waits in the ER, and extended LOS as also pointed out in (Clarey and Cooke et al., 2012). In the meantime, long stays in ED settings break the balance between demand and ED capacity which leads to overcrowding, long queuing time, and non-optimal patient journey. The aforementioned statements are evidence of strong interrelations among the foremost leading problems in EDs which is often found in healthcare environments (Clarey and Cooke et al., 2012). It can be therefore inferred that improvement initiatives on some of these elements may cause a positive effect on the entire emergency delivery system by contributing to the solution of highly correlated problems. Our study will delve into these deficiencies for better understanding on their causes and consequences while identifying the methodological approaches used for their solution.

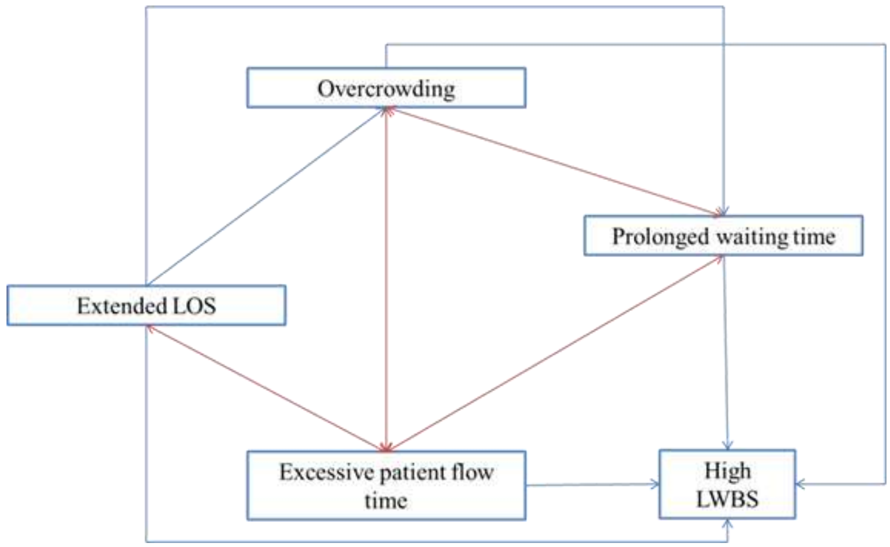


Figure 1. Impact-digraph map for interrelations among leading problems in eds.

2.1.1.1 The Top-Five Leading Problems in EDs: Causes and Consequences

2.1.1.1.1 Overcrowding

Overcrowding in EDs is the result of the imbalance between the demand for emergency care and their physical or staffing capacity. Overcrowding has become a global serious concern and continues to cause excessive waiting time, poor clinical results, patient dissatisfaction, aggressive behavior and augmented suffering for patients on pain (Oredsson et al., 2011). In some cases, this problem has reached desperate proportions and crisis levels (Marcozzi et al., 2018). After critical analysis, it was found that this phenomenon is caused by a set of mismatches along the supply chain within the healthcare systems (Bellow and Gillespie, 2014). Some mismatches are inpatient bed availability, demand growth, and the increased proportion of non-urgent visits. It is then urgent to devise a variety of initiatives for alleviating this problem and minimizing the aforementioned negative effects on patients.

2.1.1.1.2 Prolonged Waiting Time

Waiting time (WT) is defined as the interval between patient arrival and the first contact with a doctor. This is a common measure in EDs which are interested in delivering timely medical care. In addition, multiple studies have concluded that timeliness is an essential contributor to patient satisfaction with EDs (Ashour and Okudan Kremer, 2016; Tiwari et al., 2014). In fact, prolonged waiting times result in patient dissatisfaction, delayed admission of new patients, more severe complications and increased morbidity. In this regard, WTs are considered as barriers to access to healthcare which is one of the primary concerns of governments and control agencies. As noted above, long waits for care are dangerous for patients; it is thus necessary to examine the determinants responsible for this problem and attempts to tackle it by implementing effective initiatives that better comply with government healthcare standards.

2.1.1.1.3 Extended Length of Stay (LOS)

Emergency department length of stay (ED-LOS) is described as the time elapsed from a patient is admitted to the ED until the patient is physically discharged from this unit (Driesen et al., 2018). An extended ED-LOS may cause bypass, critical-care divert status, increased inpatient costs, higher risk of adverse events and low patient satisfaction. ED-LOS is also an important indicator of crowding and provides a decision-making basis for performance and efficiency improvement. Delays in delivery of lab and/or radiology test results, lack of hospital beds, hospital transfers taking a long time, insufficient medical staff during peak hours and other factors have been found to explain ED-LOS variation (Driesen et al., 2018). To face this problem, health authorities have incorporated policies to decrease ED-LOS as outlined with the 4-hour target in the UK (Mason et al., 2012). Some of them have led to fewer extended LOS within the ED. However, it is still necessary to deploy interventions along the entire ED patient journey with a special focus on each component of the acute care chain.

2.1.1.1.4 Excessive Patient Flow time

Patient flow is critical for delivering high quality care to patients admitted within EDs. Being aware of its importance; ED managers should continuously tackle the factors hampering the emergency care provided along the patient journey. Major causes contributing to prolonged flow time include departmental layout, insufficient medical staff, and inefficiencies of parallel assisting processes. Also, mismatches between the demand on emergency services ED capacity have been associated to this problem (Jarvis, 2016). If improved, elevated patient satisfaction rates and reductions in mortality and morbidity can be expected in conjunction with a significant lessening of the consequent financial burden assumed by healthcare systems. However, as patient journey is affected by intrinsic factors and multiple interactions with other services, more robust and advanced methodological approaches are required for assisting decision-makers in designing cost-effective interventions considering both the complexity of emergency care systems and the expected increased demand.

2.1.1.1.5 High Number of Patients Who Leave the ED without Being Seen

Patients who leave without being seen (LWBS) are more prone to experience worsening health compared to those who were attended. Additionally, LWBS are more likely to be readmitted within the next few hours with more severe complications which results in the use of more complex services and increased healthcare costs. The rate of LWBS is then considered as a quality metric of concern in healthcare systems (Clarey and Cooke et al., 2012). Meanwhile, restricted ED capacity, long WT for triage classification, and diversion status are among the most common causes of this problem. It is therefore important to ensure a correct provision of ED services by developing effective initiatives that consider the above-mentioned factors and their interactions.

2.1.2 Methods

2.1.2.1 Framework for Literature Review

This review aims at identifying research papers published in high-quality journals and focused on interventions addressing the above-mentioned leading problems in EDs. A paper is considered in this review if it evidences and discusses the implementation of methodological approaches for process improvement in EDs. The articles also had to be written in English and present data supporting the results obtained from the application. Research articles presenting conceptual models without validation in the wild were discarded from this study. Moreover, conference papers, doctoral dissertations, textbooks, master's thesis, and review papers were excluded from this study. Based on this perspective, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA). PRISMA guidelines help to report systematic reviews, especially appraisal of interventions as aimed in this study. By using different search algorithms (Figure 2) in a set of high-quality databases, we covered an extensive range of methodological approaches that have been implemented for the solution of the leading ED problems. Initially, we conducted an extensive review of the international literature published from April 1993 (the date in which the first paper was published) until October 2019, in multiple databases including ISI Web of Science, Scopus, PubMed, IEEE, Google Scholar, ACM Digital Library and Science Direct. The search algorithms used in this review are presented in Figure 2. Such algorithms include the most popular improvement techniques and the top-five leading problems in EDs. In particular, techniques like "simulation", "lean", "six sigma", "queuing", "critical pathways", "continuous quality improvement", "regression", "decision-making", "integer programming", "linear programming", "optimization", "game theory", and "markov" were considered in these algorithms.–Although our coverage is limited to approaches from the industrial engineering domain, other strategies including clinical-related interventions, personnel training, the ABCDE of Emergency care, and Triage can be also implemented for minimizing the impact of the leading ED problems.

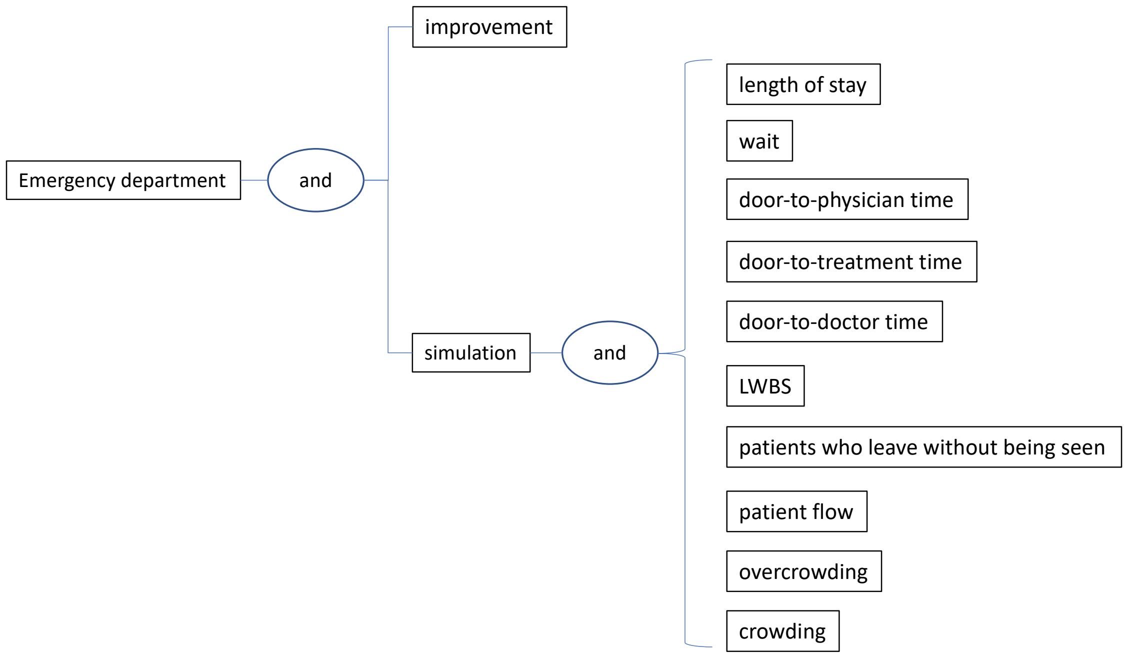


Figure 2. Search algorithms used in the literature review.

Figure 3 shows the PRISMA flow diagram describing the review process. Two independent reviewers studied the paper abstracts returned by the search engines for first screening. After initial selection, both reviewers thoroughly revised the papers to determine whether they met the aforementioned inclusion criteria. The articles satisfying these conditions were thoroughly examined in full size for a deeper understanding of the methodological approach. The papers were then independently extracted and classified according to the targeted ED problem (overcrowding, prolonged waiting time, extended length of stay, excessive patient flow time, and patients who leave without being seen - LWBS). In this classification scheme, we also pointed out the techniques that have been used for tackling each of these deficiencies so that healthcare managers, researchers, and practitioners can effectively implement them in the wild. The articles were further categorized and analysed considering the publication time. After applying this review scheme, we narrowed the initial list of papers (n = 1178) to 203 distributed in 120 journals. The classification results are presented in the next section.

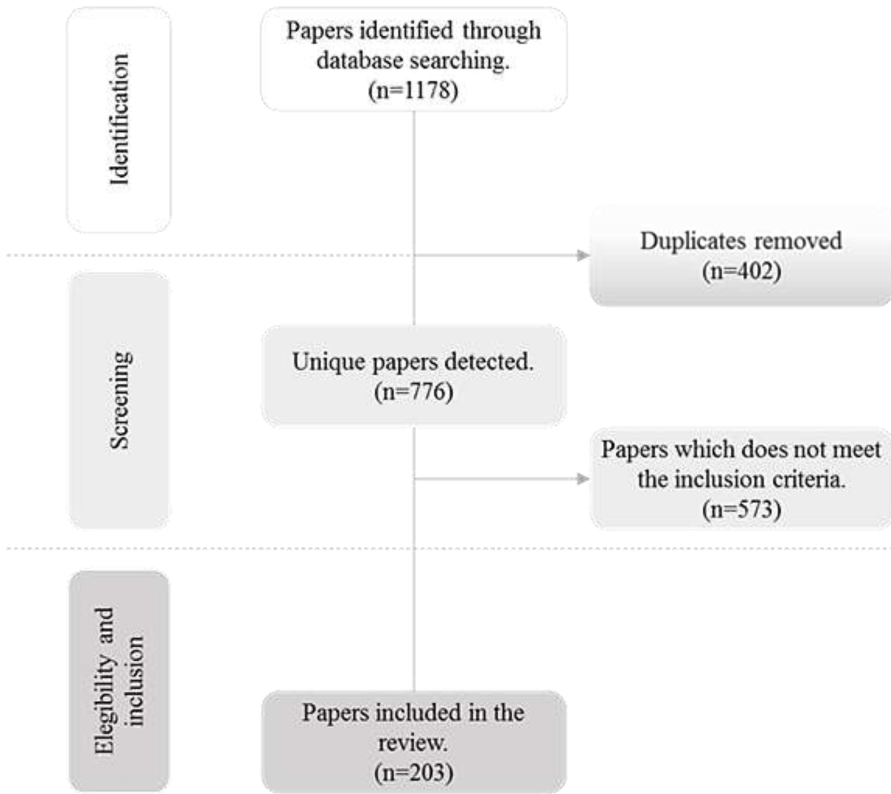


Figure 3. PRISMA flow diagram.

2.1.2.2 The Process-Improvement Methodologies Used for Tackling the 5-Top Leading Problems in EDs

The increasing concern of policy makers, ED managers, practitioners, and researchers for constantly improving the emergency care delivered to patients while reducing cost overruns is the main motivation for classifying the selected papers according to the targeted ED problem. In this scheme, 203 papers were categorized as follows: (1) Extended length of stay (LOS) (2) Prolonged waiting time (3) Excessive patient flow time in ED (4) Overcrowding, and (5) High number of patients who leave without being seen (LWBS). Table 1 summarizes the number and percentage of selected papers contributing to the solution of each problem. Table 1 also presents useful information in reference to the annual frequency of publication. Then, Tables 2–6 list the articles per each of the 5-top leading problems in conjunction with the related process-improvement techniques. These tables also specify whether the studies have used either a single or hybrid approach for solving the related ED problem. Further comments are made on these studies for identifying useful insights that can be considered for implementations in the real ED context. Additionally, the most popular techniques solving each ED problem are identified and discussed on the use of single/hybrid approaches. Thereby, we provide decision-makers with a robust methodological framework underpinning the design of cost-effective solutions.

Table 1. Classification of papers according to the targeted ED problem and publication year.

Period	*N* (Papers/Period)	Extended LOS	Prolonged Waiting Time	Excessive Patient Flow Time in ED	Overcrowding	High LWBS
1993–2004	11 (5.41%)	4	2	8	0	1
2005–2006	5 (2.46%)	2	2	0	1	2
2007–2008	7 (3.44%)	3	3	3	0	1
2009–2010	9 (4.43%)	8	2	2	1	2
2011–2012	26 (12.80%)	14	19	8	7	3
2013–2014	20 (9.85%)	10	6	10	9	1
2015–2016	34 (16.74%)	17	21	12	10	5
2017–2018	64 (31.52%)	34	22	19	18	5
2019	27 (13.30%)	16	18	9	9	5
N (papers/problem-period)		108	95	71	55	25
Participation (%)		53.20	46.79	34.97	27.09	12.31

According to Table 1, the ED problems with the highest number of papers evidencing the use of process improvement methodologies were (Table 1): "Extended length of stay" (53.20%; *n* = 108 papers) and "Prolonged waiting time" (46.79%; *n* = 95 papers). On a different tack, only 25 papers (12.31%) were related to targeting a reduced LWBS which proves that this research field as at the earlier stages. Further details on these papers are commented below for deeper understanding and analysis.

2.1.3 Results

Identifying the process-improvement approaches that have been implemented for addressing the top-five leading problems is critical for guiding healthcare managers, decision-makers, researchers, and other stakeholders towards the design of effective interventions improving the emergency care provided to patients while shortening the operational costs. For this purpose, the following sub-sections will focus on pointing out the most prominent techniques, either single of hybrid, in each

ED problem whereas highlighting the main advantages justifying their use in the practical clinical scenario.

2.1.3.1 Papers Focusing on Reducing the Extended LOS

Table 2 lists all the contributions targeting a reduced LOS within EDs. According to the reported literature, this is the ED problem with major interest among researchers and practitioners. This is since extended LOS has become an international threat to public health considering its significant association with decreased disaster response, cost overruns, patient dissatisfaction, and poor clinical outcomes including increased mortality rates (Herring et al., 2009). In an effort to address this problem, several studies have presented different process improvement approaches with implementation in the real ED context. Based on the review, 66.66% (n = 72 papers) of the papers evidenced the use of a single approach whilst 33.34% (n = 36 papers) tackled the extended LOS using a combination of two or more techniques. In particular, 63.88% (n = 23 papers) out of the hybrid-approached papers employed two methods, 30.55% (n = 11 papers) integrated three techniques, and 5.55% (n = 2 papers) mixed four methods as evidenced in Easter et al. (2019) and Fuentes et al. (2017).

Table 2. Papers evidencing the use of process improvement techniques for shortening LOS within EDs.

Authors	Technique Type
Single	
Ajdari et al. (2018); Best et al. (2014); Bokhorst and van der Vaart (2018); Coughlan et al., (2011); Gul and Guneri (2012); Hung and Kissoon (2009); Ibrahim et al. (2018); Keyloun, Lofgren, and Hebert (2019); Khare et al. (2009); Konrad et al. (2012); La and Jewkes (2013); Baia Medeiros et al. (2019); Oh et al. (2016); Paul and Lin (2012); Rasheed et al. (2012); Rosmulder et al. (2011); Saoud et al., (2016); Steward et al., (2017); Thomas Schneider et al. 2018); Wang et al. (2009); Zeng et al. (2012)	Simulation or Discrete-event simulation (DES)
Allaudeen et al. (2017); Arbune et al. (2017); Carter et al. (2012); Dickson et al. (2008, 2009a, 2009b); Elamir (2018); Hitti *et* al. (2017); Kane et al. (2015); Migita et al. (2011); Murrell et al. (2011); Ng et al. (2010); Peng et al. (2019); Polesello et al. (2019); Rotteau et al. (2015); Sánchez et al. (2018); Sayed et al. (2015); Van der linden et al. (2019); Vermeulen et al. (2014); White et al. (2014)	Lean manufacturing

Cheng et al. (2018); Forero et al. (2019); Kaushik et al. (2018); Maniaci et al. (2019); Singh et al. (2019); Street et al. (2018); Van der Veen et al. (2018); Yau et al. (2018);	Regression
Brent et al. (2009); Fernandes and Christenson (1995); Fernandes, Christenson, and Price (1996); Higgins III and Becker (2000); Lovett et al. (2014); Preyde et al.(2012); Rehmani and Amatullah (2008)	Continuous quality improvement
Ajmi et al. (2019)	Agent-based dynamic optimization
Haydar et al. (2016); Prybutok (2018)	PDSA (Plan, Do, Study, Act) cycle
Oueida et al. (2018); Derni et al. (2019)	Petri nets
Bellew et al. (2018); Than et al. (2018)	Critical pathways
Brouns et al. (2015)	Cohort study
Chan et al. (2005)	Rapid Entry and Accelerated Care at Triage (REACT)
Christensen et al. (2016)	Pivot nursing
Christianson et al. (2005)	Six sigma
DeFlitch et al. (2015)	Process redesign
Liu et al. (2017)	Agent-based model
Oueida et al. (2018)	Resource Preservation Net (RPN)
Sloan et al. (2009)	Evidence-base care pathways
Stone-Griffith et al. (2012)	ED dashboard and reporting application
Hybrid	
Ashour and Okudan Kremer (2016)	Dynamic grouping and prioritization (DGP), Discrete-event simulation
Bish et al. (2016)	Simulation, Queuing analyses
Blick (2013)	Lean Six Sigma
Chadha et al. (2012)	Lean manufacturing, Queuing theory
Chen and Wang (2016)	Non-dominated sorting particle swarm optimization (NSPSO), Multi-objective computing budget allocation (MOCBA), Discrete-event simulation
Easter et al. (2019)	Discrete-event simulation, Analysis of Variance (ANOVA), Linear regression, Non-linear regression
Elalouf and Wachtel (2015)	Approximation algorithm, Simulation
Feng et al. (2017)	Non-dominated sorting genetic algorithm II (NSGA II), Multiple computing budget allocation (MOCBA), Discrete-event simulation
Ferrand et al. (2018)	Simulation, Dynamic priority queue (DPQ)
Fuentes et al. (2017)	Logistic regression, Linear regression, Paired t test, Wilcoxon signed rank
Furterer (2018)	Lean Six Sigma
Ghanes et al. (2015)	Optimization, Discrete-event simulation
Goienetxea Uriarte et al. (2017)	Discrete-event simulation, Simulation-based multi-objective optimization, Data mining
He, Sim, and Zhang (2019)	Mixed integer programming, Queuing network, Stochastic Programming
Huang et al. (2018)	Descriptive statistics, Two-sample t-test, Multivariate linear regression

Kaner et al. (2014)	Discrete-event simulation, Design of experiments
Lee et al. (2015)	Machine learning, Simulation, Optimization
Lo et al. (2015)	Lean principles, Simulation, Continuous process improvement
Oueida et al. (2019)	Discrete-event simulation, Optimization
Rachuba et al. (2018)	Process mapping, Discrete-event simulation
Romano et al. (2015)	System dynamics simulation, Lean techniques, Causal loop diagram
Ross et al. (1997)	Critical pathways, Continuous quality improvement
Ross et al. (2019)	Multivariate logistic regression, Ordinary least squares regression
Shin et al. (2018)	Discrete-event simulation, Linear integer programming
Sinreich and Jabali (2007)	Linear optimization model (S-model), Heuristic iterative simulation based algorithm
Sinreich et al. (2012)	Discrete-event simulation, Optimization
Sir et al. (2017)	Classification and regression trees, Mixed integer programming
Techar et al. (2019)	Multivariate logistic regression, Negative binomial models
Visintin et al. (2019)	Simulation, Experimental design
Yousefi and Ferreira (2017)	Agent-based simulation, Group Decision Making
Yousefi et al. (2018a)	Agent-based simulation, Chaotic genetic algorithm, Adaptive boosting (AdaBoost)
Yousefi et al. (2018b)	Agent based modeling, Ordinary least squares regression
Zeltyn et al. (2011)	Simulation, Queuing theory

Different process improvement methods have been combined for better assisting ED managers in addressing the prolonged stays in EDs. The first hybrid-approached contribution was produced by Ross et al. (1997) who mixed continuous quality improvement with critical pathways to diminish the LOS at the emergency department of Macomb Hospital Center (Warren, MI, USA). Thanks to this approach, LOS decreased from 7.52 days to 6.33 days for stroke patients. Other studies have combined simulation with other operations research (OR) methods. For instance, Ashour and Okudan Kremer (2013) integrated simulation with Multi-attribute Utility Theory (MAUT) and Fuzzy Analytic Hierarchy Process (FAHP) for developing a triage algorithm that classifies emergency patients. The simulation evidenced that MAUT-FAHP outperforms the Emergency Severity Index for ESI levels 2–5 with a significant reduction of ED-LOS. Another related work is presented by Bish et al. (2016) who merged simulation with queuing analysis for shortening the median LOS in an adult ED located in New Jersey. In this case, the results evidenced that this measure was shortened from 192 to 112 min. Other studies combining simulation and queuing theory can be found in Ferrand et al. (2018) and Zeltyn et al. (2011). Another related study was presented by Chen and Wang (2016) who proposed an integrated approach integrating non-dominated sorting particle swarm optimization (NSPSO), multi-objective computing budget allocation (MOCBA) and discrete-event Simulation (DES) aiming at meeting the government LOS targets in Sunnybrook Hospital emergency department.

The combination between simulation and design of experiments (DOE) has been also employed for the scientific community and decision-makers when targeting shortened LOS. An interesting related intervention is exposed by Kaner et al. (2014) who used this approach for formulating improvement scenarios with data derived from a real-life ED environment. Such framework is called to replace the well-known trial-and-error experiments often used when pretesting interventions on ED-LOS. Other works implementing the simulation-DOE approach are described in Aroua and Abdulnour (2018) and Visintin et al. (2019). Integrating simulation and lean techniques is another alternative adopted by researchers and practitioners when dealing with excessive stays in EDs. For example, Romano et al. (2015) used this approach in conjunction with causal loop diagrams for minimizing the LOS and waiting times in Italian hospitals. Specifically, a new ED configuration was pretested considering the partial reassignment of unused beds and medical staff to patients with white code only. Another research using this integration is presented by Lo et al. (2015) who implemented an electronic provider documentation (EPD) in a pediatric ED. In this case, simulation allowed testing potential affectations on ED-LOS when transitioning from paper charting to EPD. Other integrated methodologies including simulation are reported by Abo-Hamad and Arisha (2013), Ashour and Okudan Kremer (2016), Easter et al. (2019), Yousefi et al. (2018b), and Yousefi and Ferreira (2017); however, their application has not been replicated throughout the literature.

Also, hybrid approaches excluding simulation techniques were considered to address the prolonged ED-LOS. Some of them are a mix of OR approaches as noted in He et al. (2019) and Sir et al. (2017). Other papers combine different statistical techniques as evidenced in Fuentes et al. (2017), Huang et al. (2018), Techar et al. (2019), and Ross et al. (2019). Another category includes the mix of lean manufacturing and other techniques as exposed in Blick (2013), Chadha et al. (2012), and Furterer (2018). LM encompasses a wide variety of process-improvement techniques focusing on eliminating wastes detected in the value chain of ED processes. Besides, it provides a comprehensive way of shortening buffering costs, increasing process efficiency, and fostering CQI culture. Likewise, it has become a good alternative for delivering the upmost value to ED patients by delivering effective care.

As presented above, single methods have been widely used by decision-makers and researchers when targeting shortened stays in EDs. Some studies have addressed this problem through a quality improvement technique (i.e., lean manufacturing, continuous quality improvement). One of the most popular approaches in this domain is lean manufacturing (LM, 20 papers = 27.77%). In this regard, Allaudeen et al. (2017) performed a multidisciplinary lean intervention where root causes of delays were properly identified and tackled. In fact, the ED LOS for medicine admissions decreased by 26.4% from 8.7 to 6.4 h (p-value < 0.01). Another application is presented by Carter et al. (2012) who applied LM techniques for improving the clinical operations of an ED located in Ghana. Their article provides important lessons to be considered during the implementation of LM in the ED context.

The second most used method from quality domain was continuous quality improvement (CQI) (n = 7 papers = 9.72%). The most recent work employing QI is cited in Lovett et al. (2014) who reported an intervention at a multi-campus academic health system where immediate improvements were enhanced in relation to LOS. Other works employing QI can be seen in Brent et al. (2009), Fernandes and Christenson (1995), Fernandes et al. (1996), Higgins III and Becker (2000), Preyde et al. (2012), and Rehmani and Amatullah (2008). The application of six sigma (Christianson et al., 2005), PDSA cycle (Haydar et al., 2016; Prybutok, 2018), and ED dashboard/reporting application (Stone-Griffith et al., 2012) were also detected in the literature as part of the multiple quality-based methods that have been applied for solving the excessive LOS problem in EDs.

Simulation was also employed in a single way to address the prolonged stays in emergency departments. Indeed, its use was reported in 29.16% (*n* = 21 papers) of the studies using single methods. One of the simulation-related interventions is observed in Gul and Guneri (2012) who applied this method in an attempt to the patient average LOS in an ED of a regional university hospital in Turkey. In consequence, LOS was shortened with an improvement rate of 30%. A more recent work is exposed by Keyloun et al. (2019) who modeled the implementation of a new treatment pathway taking advantage of long-acting antibiotics (LAs) aiming at estimating its effects on patient throughput rate, LOS, and cost. The outcomes evidenced a 68% reduction in patient LOS; in other words, 7.2 h less compared to the initial performance.

There is also an interest from research community in applying statistical techniques for reducing prolonged stays in emergency care settings. The reported literature revealed that 12.5% (*n* = 9 papers) of the papers using single approaches, incorporate the application of these methods when addressing the extended LOS problem. In this respect, Kaushik et al. (2018) used multivariate regression analysis for identifying how a 1-minute decrease in laboratory turnaround time is associated with the emergency room LOS. In addition, Maniaci et al. (2019) used linear regression based on the log of LOS for pinpointing factors associated with excessive stays in EDs. In this case, median ED LOS was found to be associated with blood alcohol concentration, urine drug test (UDT), and UDT positive for barbiturates.

OR methods were also applied in a single form for dealing with the extended LOS within EDs. For example, Ajmi et al. (2019) developed an agent-based dynamic optimization model for improving several performance indicators (LOS, remaining patient care load, and cumulative waiting time) in EDs. OR-based studies addressing long LOS are evidenced in Chan et al. (2005), Derni et al. (2019), Liu et al. (2017), and Oueida et al. (2018a, 2018b). Apart from the aforementioned single techniques, less popular methods like critical pathways (Bellew et al., 2018; Sloan et al., 2009; Than et al., 2018), pivot nursing (Christensen et al., 2016), and process redesign (DeFlitch et al., 2015) were also used by some practitioners and researchers to diminish the total burden produced by long ED-LOS.

2.1.3.2 Papers Focusing on Reducing the Waiting Time

Table 3 presents all the papers aiming at shortening the door-to-physician time in EDs. Based on the scanned literature, this is the second most popular ED deficiency addressed by decision-makers and researchers. Prolonged waiting time has been considered as major problem within EDs given its significant association with patient dissatisfaction, increased number of complaints, and poor outcomes for patients (increased morbidity and mortality). Nonetheless, shortening waiting times at the ED is pretty challenging since it encompasses diagnosis, prioritization of patients, monitoring and management of waiting times, and provision of suitable resources. In an attempt to solve this problem, various authors have exposed different process improvement methodologies with validation in the real-world. In this respect, 55.78% (*n* = 53 articles) of the contributing works used a single method while 44.22% (*n* = 42 articles) dealt with the waiting time problem by applying an integration of two or more techniques. Explicitly, 64.28% (*n* = 27 articles) out of the hybrid-approached articles implemented 2 methods, 26.19% (*n* = 11 articles) mixed three techniques, and 9.52% (*n* = 4 articles) merged four methods as exposed in Acuna et al. (2019), Ala and Chen (2019), Easter et al. (2019) and Yousefi and Yousefi (2019).

Table 3. Articles evidencing the use of process improvement techniques for minimizing the ED waiting time.

Authors	Technique Type
Single	
Coughlan et al., (2011); Duguay and Chetouane (2007); Hung and Kissoon (2009); Ibrahim et al. (2018a, 2018b); Joshi ate al. (2016); Kaushal et al. (2015); Konrad et al. (2013); Lamprecht et al. (2019); Baia Medeiros et al. (2019); Paul and Lin (2012); Rasheed et al. (2012); Saoud et al., (2016); Taboada et al. (2012); Wang et al. (2012); Yang et al. (2016); Zeng et al. (2012)	Simulation or Discrete-event simulation

Carter et al. (2012); Elamir (2018); Hogan et al. (2012); Ieraci et al. (2008); Improta et al. (2018); Kane et al. (2015); Murrell et al. (2011); Ng et al. (2010); Piggott et al. (2011); Rees (2014); Rutman et al.(2015); Sánchez et al. (2018); Sayed et al. (2015); Vashi et al. (2019); Vermeulen et al. (2014); White et al. (2017);	Lean manufacturing
Ajmi et al. (2019); Bordoloi and Beach(2007); Meng et al. (2017);	Optimization
Leo et al. (2016); Nezamoddini and Khasawneh (2016)	Integer programming
Queuing theory	
Preyde et al. (2012); Rothwell et al. (2018)	Continuous quality improvement
DeFlitch et al. (2015); Spaite et al. (2002)	Process redesign
Derni et al. (2019); Oueida et al. (2018a)	Petri nets
Doupe et al. (2018); Eiset et al. (2019)	Regression
Chan et al. (2005)	Rapid Entry and Accelerated Care at Triage (REACT)
Christensen et al. (2016)	Pivot nursing
Cookson et al. (2011)	Value Stream Mapping (VSM)
Fulbrook et al. (2017)	Nurse navigator
Oueida et al. (2018b)	Resource Preservation Net (RPN)
Popovich et al. (2012)	Iowa Model of Evidence-Based Practice
Stone-Griffith et al. (2012)	ED dashboard and reporting application
Hybrid	
Abo-Hamad and Arisha (2013)	Simulation, Balance Scorecard (BSC), Preference ratios in multi-attribute evaluation (PRIME)
Acuna et al. (2019)	Mixed integer programming, game theory, single and bi-objective optimization models
Ala and Chen (2019)	Integer programming, Tabu search, L-shaped algorithm, Discrete-event simulation
Aminuddin et al. (2018)	Simulation, Data Envelopment Analysis (DEA)
Andersen et al. (2019)	Integer linear programming, Markov models, Discrete-event simulation
Aroua and Abdulnour (2018); Zhao et al. (2015)	Simulation, Design of experiments (DOE)
Ashour and Okudan Kremer (2016)	Dynamic grouping and prioritization (DGP), Discrete-event simulation
Azadeh et al. (2014)	Mixed integer linear programming, Genetic algorithm (GA)
Bal et al. (2017)	Value Stream Mapping (VSM), Discrete-event simulation

Benson and Harp (1994)	Discrete-event simulation, System thinking
Bish et al. (2016)	Simulation, Queuing analyses
Daldoul et al. (2018)	Stochastic mixed integer programming, Sample average approximation
Diefenbach and Kozan (2011)	Simulation, Optimization
Easter et al. (2019)	Discrete-event simulation, ANOVA, Linear regression, Non-linear regression
EL-Rifai et al. (2015)	Stochastic mixed-integer programming, Sample average approximation, Discrete-event simulation
Ferrand et al. (2018)	Simulation, Dynamic priority queue (DPQ)
Gartner and Padman (2019)	Discrete-event simulation, Machine learning
Ghanes et al. (2015)	Optimization, Discrete-event simulation
Goienetxea Uriarte et al. (2017)	Discrete-event simulation, Simulation-based multi-objective optimization, Data mining
González et al. (2019)	Markov decision process, Approximate dynamic programming
He (2019)	Mixed integer programming, Queuing network, Stochastic Programming
Izady and Worthington (2012)	Discrete-event simulation, Queuing models, Heuristic Staffing Algorithm
Kuo (2014)	Simulation-optimization
Lau et al. (2018)	Genetic algorithm, Cost-optimization model
Martínez et al. (2015)	Discrete-event simulation, Lean manufacturing
Mazzocato et al. (2012)	Lean manufacturing, ANOVA
Othman et al. (2016)	Multi-agent system, Multiskill task scheduling
Ben Othman and Hammadi (2017)	Fuzzy logic, Evolutionary algorithm
Oueida et al. (2019); Sinreich (2012)	Discrete-event simulation, Optimization
Perry (2019)	Lean manufacturing, Code critical
Romano et al. (2015)	System dynamics simulation, Lean techniques, Causal loop diagram

Sir et al. (2017)	Classification and regression trees, Mixed integer programming
Stephens and Broome (2019)	Univariate analysis, Multivariate general linear regression, Binary logistic regression
Umble and Umble (2006)	Theory of constraints, Buffer management, Synchronous management
Visintin et al. (2019)	Simulation, Experimental design
Xu and Chan (2016)	Simulation, Queuing, Predictive models
Yousefi and Ferreira (2017)	Agent-based simulation, Group Decision Making
Yousefi and Yousefi (2019)	Agent-based simulation, Adaptive neuro-fuzzy inference system (ANFIS), Feed forward neural network (FNN), Recurrent neural network (RNN)
Zeinali et al. (2015)	Discrete-event simulation, Metamodels, Cross validation
Zeltyn et al. (2011)	Simulation, Queuing theory

As evidenced in the aforementioned statistics, the use of hybrid approaches has received increasing attention from decision-makers and the scientific community when targeting reduced door-to-treatment times in emergency departments. The first contribution employing this methodological framework was provided by Benson and Harp (1994) who merged DES and system thinking for reducing ED waiting times. After several simulations of different improvement scenarios, the ED managers decided to reorganize the patient flow and automat hospital-wide bed control. Thanks to these interventions, door-to-doctor times were slackened by 19% in parallel to increases in patient satisfaction rates. The evidence base also reveals that 66.66% (*n* = 28 articles) out of the integrated-approached studies have adopted this technique as part of their methodological framework. Merging simulation with other OR methods has been a popular alternative for addressing the waiting time problem. For example, Zeinali et al. (2015) combined metamodel techniques and simulation for minimizing the total average waiting time of an Iranian ED considering capacity and budget constraints. After intervention, the total waiting time of ED patients was reduced by approximately 48%. A similar research was presented by Kuo (2014) used a simulation-optimization algorithm to support the waiting time improvement in an ED located in Hong Kong. The results revealed that the implementation of staggered shifts is helpful to decrease this metric.

The OR technique that has been mostly mixed with simulation is Queuing theory. In this regard, Izady and Worthington (2012) applied discrete-event simulation, queuing models, and a heuristic staffing algorithm in a real emergency care setting for meeting the target established by the UK government (98% of the patients to be discharged, transferred, or admitted to emergency care within 4 h of arrival) and consequently applying for incentive schemes. In this case, it was concluded that meaningful improvement on the target can be gained, even without augmenting total medical staff hours. A second study utilizing this combination was performed by Xu and Chan (2016). These authors demonstrated that, based on this predictive approach, decision-makers can identify when congestion is going to increase, thus facilitating a rapid intervention on patient flow for ensuring reduced waiting times. Such an approach was proved to outperform the current policies due to its ability of reducing lengthy waiting times by up to 15%. Interesting interventions employing this integration can be also evidenced in Bish et al. (2016), Ferrand et al. (2018), and Zeltyn et al. (2011). Other papers integrating OR methods and simulation can be found in Ala and Chen (2019), Diefenbach and Kozan (2011), El-Rifai et al.(2015), Ghanes et al. (2015), Goienetxea Uriarte et al. (2017), Oueida et al. (2019), Sinreich et al. (2012), and Yousefi and Yousefi (2019).

Over the recent years, the use of computer simulation and DOE also set out to receive attention from practitioners related to emergency care field. For instance, Aroua and Abdulnour (2018) mixed these methods for improving patient LOS of a university emergency hospital. Specifically, DOE underpinned the evaluation of improvement scenarios based on LOS variations. Other contributions employing this hybrid approach are available in Visintin et al. (2019) and Zhao et al. (2015). Meanwhile, the use of DES-lean methodology is beginning to become prominent when addressing patient waiting time within EDs. Bal et al. (2017) provide a walkthrough of how computer simulation and lean manufacturing can be utilized for tackling the waiting time problem. In this paper, the very-well known “Value Stream Mapping” was found to be useful for detecting non-value added times within Sadi Konuk hospital ED. Similar implementations can be also found in studies such as Martínez et al. (2015) and Romano et al. (2015). As a step towards reducing lengthy waiting times, other methods have been integrated with simulation: BSC PRIME (Abo-Hamad and Arisha, 2013), DEA (Aminuddin et al., 2018) DGP (Ashour and Okudan Kremer, 2016), statistical methods (Easter et al., 2019), machine learning (Gartner and Padman, 2019) and group decision-making (Yousefi and Ferreira, 2017). This demonstrates the flexibility and adaptability of this tool in hybridized methodologies.

Mixing OR methods, excluding simulation, has also become a popular approach among researchers and practitioners with major interest in diminishing ED waiting times. In one case, mixed integer linear programming and genetic algorithm (GA) were coupled for minimizing the total waiting time of patients in the emergency department laboratories. The proposed combination was proved to significantly reduce the total waiting time of prioritized patients (Azadeh et al., 2014). More recently, Acuna et al. (2019) opted to use a robust approach integrated by mixed integer programming, game theory, and single/bi-objective optimization models for improving ambulance allocation and consequently reducing patients’ waiting time in 11 EDs located in Florida. Other examples in the application of integrated OR methods when dealing with lengthy ED waits are provided in Daldoul et al. (2018), He et al. (2019), Lau et al. (2018), Ben Othman et al. (2016), Sir et al. (2017), and Umble and Umble (2006). Other combinations aiming at facing the extended waiting times are simplified in Mazzocato et al. (2012), Ben Othman and Hammadi (2017), Perry (2019), and Stephens and Broome (2019).

Overall, single methods are also common for supporting improvement strategies targeting decreased door-to-doctor times. Undoubtedly, simulation has provided good support for reducing door-to-physician times in EDs even when used in a single way (n = 17 papers; 32.07% of single-approached contributions). Coughlan et al.

(2011) developed a simulation model to cope with the lengthy door-to-treatment times in a district general hospital in London. Such an approach allowed decision-makers assessing its capability to meet the government target in regard to this metric. A simulation model is also used in Joshi et al. (2016) for helping managers of a real emergency department to balance workload, reduce burnout and decrease patient waiting time. In this case, the patient flow was improved and the average wait dropped by 73.2%.

Equal number of contributions addressing the waiting time problem is based on single lean manufacturing (LM) applications (n = 17 papers; 32.07% of single-approached papers). For instance, Cookson et al. (2011) pinpointed over 300 instances of waste along the ED patient journey by employing VSM. Such intervention helped healthcare leaders to improve the time to initial assessment. Generally speaking we also observe some papers that have validated the effectiveness of LM when facing the lengthy waiting times in EDs. Kane et al. (2015) demonstrated that ED patient experience can be significantly improved by incorporating lean approaches. More recently, Sánchez et al. (2018) applied lean thinking in triage acuity level-3 patients to improve waiting time of a tertiary hospital ED. As a result, significant reductions were achieved in waiting time (71 vs. 48 min, $p < 0.001$) and other critical measures.

The literature also reports a growing trend (n = 8 papers; 15.09%) in the use of OR methods (different from simulation) in a single form upon addressing lengthy door-to-treatment times in EDs. Oueida et al. (2018a) used petri nets for improving LOS, resource utilization, and patient waiting time in a real emergency care institution. Similar objectives were pursued by Bordoloi and Beach (2007) who, unlike the previous work, used optimization models encompassing the entire patient journey within the ED. Single OR-based approaches are also extensively used in Ajmi et al. (2019), Derni et al. (2019), Leo et al. (2016), Meng et al. (2017), Nezamoddini and Khasawneh (2016), and Oueida et al. (2018b). Other non-hybrid methods that have been employed for tackling this ED deficiency are as follows: REACT (Chan et al., 2005), pivot nursing (Christensen et al. 2016), process redesign (DeFlitch et al., 2015; Spaite et al., 2002), regression (Doupe et al., 2018; Eiset et al., 2019), nurse navigator (Fulbrook et al., 2017) Iowa model of evidence-based practice (Popovich et al., 2012), CQI (Preyde et al., 2012; Rothwell et al., 2018), and ED dashboard/reporting (Stone-Griffith et al., 2012).

2.1.3.3 Papers Focusing on Tackling the Overcrowding

Table 4 presents all the interventions focused on reducing overcrowding in EDs. As discussed in previous studies (Günal and Pidd, 2010; Paul et al., 2010; Vanbrabant, 2019) and evidenced in this review, there is an increased interest on solving the overcrowding problem in EDs. Such interest is motivated by the negative effects that have been pinpointed in several congested EDs. These effects include delayed diagnosis and treatment, extended pain and suffering, and risk for poor outcomes. As the population ages and life expectancy augments, aggressive solutions are expected from practitioners and research community. In this regard, several studies have suggested a variety of process improvement approaches that can be also adopted by the emergency department directors for addressing this serious problem. In these studies, either a single approach (n = 32 papers; 58.18%) or a hybrid method (n = 23 papers; 41.81%) was proposed for counteracting this international issue.

Table 4. Articles evidencing the use of process improvement techniques for tackling the ED overcrowding.

Authors	Technique Type
Single	
Ahalt et al. (2018); Ajmi et al. (2019); Best et al. (2014); Fitzgerald et al. (2011); Hung and Kissoon (2009); Ibrahim et al. (2018a, 2018b); Paul and Lin (2012); Peck et al. (2014); Rasheed et al. (2012); Restrepo-Zea et al. (2018); Thomas Schneider et al. (2018); Yang et al. (2016)	Simulation or Discrete-event simulation
Aaronson et al. (2017); Al Owad et al. (2018); Elamir (2018); Hitti et al. (2017); Migita et al. (2011); Murrell et al. (2011); Van der linden et al. (2019); Vose et al. (2014); White et al. (2014, 2017)	Lean manufacturing
Nezamoddini and Khasawneh (2016)	Integer programming
Eiset et al. (2019); Hu et al. (2018); Singh et al. (2019); Van der Veen et al. (2018)	Regression
Popovich et al. (2012)	Iowa Model of Evidence-Based Practice
Wang (2013)	Separated continuous linear programming (SCLP)

Fulbrook et al. (2017)	Nurse navigator
DeFlitch et al. (2015)	Process redesign
Hybrid	
Abo-Hamad and Arisha (2013)	Simulation, Balance Scorecard (BSC), Preference ratios in multi-attribute evaluation (PRIME)
Acuna (2019)	Mixed integer programming, game theory, single and bi-objective optimization models
Aldarrab (2006)	Lean Six Sigma
Ashour and Okudan Kremer (2013)	Fuzzy Analytic Hierarchy Process (FAHP), Multi-attribute Utility Theory (MAUT), Discrete-event simulation
Ashour and Okudan Kremer (2016)	Dynamic grouping and prioritization (DGP), Discrete-event simulation
Bal et al. (2017)	Value Stream Mapping (VSM), Discrete-event simulation
Beck et al. (2016)	Lean Six Sigma
Chen and Wang (2016)	Non-dominated sorting particle swarm optimization (NSPSO), Multi-objective computing budget allocation (MOCBA), Discrete-event simulation
Elalouf and Wachtel (2015)	Approximation algorithm, Simulation
El-Rifai et al. (2016)	Integer linear program (ILP), Sample Average Approximation (SAA)
Fuentes et al. (2017)	Logistic regression, Linear regression, Paired t test, Wilcoxon signed rank
Garrett et al. (2018)	Regression analysis, Vertical split flow
González et al. (2019)	Markov decision process, Approximate dynamic programming
He et al. (2019)	Mixed integer programming, Queuing network, Stochastic Programming
Hussein et al. (2017)	Six Sigma, Discrete-event simulation
Kaner et al. (2014)	Discrete-event simulation, Design of experiments
Kuo (2014)	Simulation-optimization
Landa et al. (2018)	Multi-objective optimization, Discrete-event simulation
Ben Othman et al. (2016)	Multi-agent system, Multiskill task scheduling
Peltan et al. (2019)	Multivariate regression, Markov multistate models
Romano et al. (2015)	System dynamics simulation, Lean techniques, Causal loop diagram
Sinreich et al. (2012)	Discrete-event simulation, Optimization
Visintin (2019)	Simulation, Experimental design

Given the multifactorial origin and complexity of ED congestion, robust approaches are beginning to be often considered in the literature. Unsurprisingly, most of these approaches include simulation techniques (*n* = 13 papers; 54.16%). For example, some authors have proposed the integration of optimization models and simulation to determine the best bed allocations considering both tactical and operational decisions as exemplified in Landa et al. (2018). In this work, the simulation model represented the patient flows of a medium-size hospital ED located in Genova, Italy. The intervention was motivated by the increased congestion experience in this department and the growing concern on decreasing the number of inpatient ward beds. Similar applications using DES and optimization models can be found at Kuo (2014) and Sinreich et al. (2012). Other studies expose the integration of simulation with BSC and PRIME (Abo-Hamad and Arisha, 2013), FAHP and MAUT (Ashour and Okudan Kremer, 2013), DGP (Ashour and Okudan Kremer, 2016), lean manufacturing (Romano et al., 2015; Bal et al., 2017), six sigma (Hussein et al., 2017), DOE (Kaner et al., 2014; Visintin et al., 2019), approximation algorithm (Elalouf and Wachtel, 2015), and other OR methods (Chen and Wang, 2016) for reducing overcrowding within emergency departments. However, none of these integrations has been widely adopted in the ED context.

Different OR methods were also merged for addressing the overcrowding problem in EDs. Initially, Ben Othman et al. (2016) used multi-agent system along with multiskill task scheduling for helping physicians of a French pediatric ED to anticipate the feature of overcrowding. Another intervention using a mix of OR methods can be seen in El-Rifai et al. (2016) where a two-stage stochastic integer linear program and sample average approximation were conjointly used for managing staff allocation and consequently coping with congestion in an ED located in Lille, France. Decreasing overcrowding by combining OR methods were also found in González et al. (2019), Acuna, et al. (2019), and He et al. (2019). Apart from these works, some authors proposed the use of lean six-sigma (Aldarrab, 2006; Beck et al., 2016) and regression analysis (Fuentes et al., 2017; Garrett, et al., 2018; Peltan et al., 2019).

Various methods were also employed separately by authors as an aid to reduce crowding in emergency departments. For example, the ability of simulation to model the multi-causality nature of ED overcrowding in a great level of detail makes this technique a potential tool for administrators and policy makers, even when employed in a single form. In fact, our review reports 12 papers (37.5%) evidencing the use of this technique in congested EDs. We noted that as Ahalt et al. (2018) discuss, simulation can serve as a way of measuring crowdedness, a metric that avoids efforts being expanded on unnecessary interventions and guides administrators towards the design of cost-effective solutions. On the other hand, Fitzgerald (2011) described how simulation has propelled cultural changes in congested Australian EDs through providing fast and accurate predictions on change outcomes. Since then, innovative studies endorsing the use of simulation in overcrowded EDs has been ample.

The use of lean manufacturing also continues to rise among researchers and practitioners who are concerned on systematically evaluating interventions as well as implementing evidence-base policies. In this review, 10 papers (31.25%) were found to offer solutions to the overcrowding problem after employing LM. A fruitful LM program is exposed in Van der Linden et al. (2019) where after a 9-month intervention, the modified National ED Overcrowding Score (mNEDOCS) dropped from 18.6% to 3.5%. An earlier LM project is presented in Al Owad et al. (2018) where voice of costumer, voice of process, and voice of staff were integrated for diminishing overcrowding in a hospital ED located in Saudi Arabia.

Regression applications are relatively new in the literature in relation to supporting improvements in busy emergency departments. Eiset et al. (2019) adopted a transition regression model based on past departures and pre-specified risk factors to predict the expected number of departures and waiting time in the ED unit at Aarhus University Hospital (Denmark). The authors concluded that the number of arrivals has the biggest effect on departures with an odds ratio of 0.942. Multipronged efforts in tackling this problem were also demonstrated in Singh et al. (2019) where a multivariate logistic regression model was developed considering four ED crowding scores, patient-related, system-related, and provider-related risk factors. Other contributing studies utilizing regression are available at Hu et al. (2018) and Van der Veen et al. (2018). Less explored single approaches include: agent-based dynamic optimization (Ajmiet al., 2019), process redesign (DeFlitch et al., 2015), Fulbrook et al. (2017), integer programming (Nezamoddini and Khasawneh, 2016) SCLP (Wang, 2013), and Iowa model of evidence-base practice (Popovich et al., 2012).

2.1.3.4 Papers Focusing on Diminishing the Patient Flow Time in ED

The papers targeting decreased patient flow times within EDs are enlisted in Table 5. According to our review, lengthy patient flow time has received increasing attention due to its complexity and importance on clinical outcomes. Across many emergency care settings, patient flow problems have reached epidemic proportions. In fact, longer patient journey times are associated with patient dissatisfaction, more severe clinical complications, and increased mortality rates. The problem is even more sharpener considering the ineffective response of EDs to the growing demand of emergency care services. To substantially counteract this problem, several single (n = 45 articles; 63.38%) and integrated (n = 26 articles; 36.62%) approaches from different research fields have been proposed by authors.

Table 5. Articles evidencing the use of process improvement techniques for minimizing patient flow time within EDs.

Authors	Technique Type
Single	
Coughlan et al., (2011); Joshi et al. (2016); Khanna et al. (2016); Konrad et al. (2013); Lamprecht (2019); Rasheed et al. (2012); Thomas Schneider et al. (2018); Vile et al.(2017); Yang et al. (2016); Zeng et al. (2012)	Simulation or Discrete-event simulation
Al Owad et al. (2018); Dickson et al. (2008); Elamir (2018); Ieraci et al. (2008); Improta et al. (2018); Matt et al. (2018); Ng et al. (2010); Rees (2014); Rotteau et al. (2015); Sánchez et al. (2018); Vermeulen et al. (2014); Vose et al. (2014); White et al. (2014);	Lean Manufacturing
Fernandes and Christenson (1995); Fernandes et al. (1996); Goldmann et al. (1993); Henderson et al.(2003); Jackson and Andrew (1996); Lovett et al. (2014); Markel and Marion (1996); Preyde et al. (2012);	Continuous quality improvement
Ajmi et al. (2019); Bordoloi and Beach (2007)	Optimization
Yau et al. (2018)	Regression models
Courtad et al. (2017)	Mixed integer programming,
DeFlitch et al. (2015); Spaite et al. (2002)	Process redesign
Derni et al. (2019)	Colored petri net
Fulbrook (2017)	Nurse navigator
Haydar (2016)	PDSA (Plan-do-study-act) cycle
Iyer et al. (2011)	Acute care model
Mohan et al. (2018)	Critical pathways

Ollivere et al. (2012)	Fast track protocols
Oueida et al. (2018b)	Resource Preservation Net (RPN)
Popovich et al. (2012)	Iowa Model of Evidence-Based Practice
Hybrid	
Ala and Chen (2019)	Integer programming, Tabu search, L-shaped algorithm, Discrete-event simulation
Andersen et al. (2019)	Linear programming, Discrete-event simulation
Azadeh et al. (2013)	Fuzzy logic, Simulation
Benson and Harp (1994)	Discrete-event simulation, System thinking
Bish (2016)	Simulation, Queuing analyses
Brenner et al. (2010)	Simulation, What-if analysis
Diefenbach and Kozan (2011)	Simulation, Optimization
Easter et al. (2019)	Discrete-event simulation, ANOVA, Linear regression, Non-linear regression
Elalouf and Wachtel (2015)	Approximation algorithm, Simulation
Ferrand et al. (2018)	Simulation, Dynamic priority queue (DPQ)
Garrett et al. (2018)	Regression analysis, Vertical split flow
Gartner and Padman (2019)	Discrete-event simulation, Machine learning
González et al. (2019)	Markov decision process, Approximate dynamic programming
Guo et al. (2017)	Random boundary generation with feasibility detection (RBG-FD), Discrete-event simulation
Hajjarsaraei et al. (2018)	Discrete-event simulation, System dynamics
Huang and Klassen (2016)	Six Sigma, Lean manufacturing, Simulation
Keeling et al. (2013)	Capability analysis, simulation
Lau et al. (2018)	Genetic algorithm, Cost-optimization model
Romano et al. (2015)	System dynamics simulation, Lean techniques, Causal loop diagram
Ross et al. (2019)	Multivariate logistic regression, Ordinary least squares regression
Ryan et al. (2013)	Lean manufacturing, Theory of constraints, Logistic regression
Shirazi (2016)	Simulation-based optimization
Stanton et al. (2014)	Lean Six Sigma
Weimann (2018)	Standardized project management, Change management, Continuous quality improvement, Lean manufacturing
Yousefi and Ferreira (2017)	Agent-based simulation, Group Decision Making
Zeinali et al. (2015)	Discrete-event simulation, Metamodels, Cross validation

As we will next briefly describe, the combined approaches have provided sustained support for restructuring patient flows within EDs. Most studies have emerged proposing the use of simulation as the cornerstone of several combined methodologies (n = 19 papers; 82.6%). In particular, the literature reports several studies mixing OR methods and simulation to cope with the patient flow problem. Zeinali et al. (2015) used a simulation-based metamodeling approach to deal with patient's congestion in an Iranian ED. The experimental outcomes confirmed that patient flow can be substantially improved with this approach even under budget and capacity constraints. The continuous strain caused by the increased number of emergency admissions also motivated Elalouf and Wachtel (2015) to develop an approximation algorithm whose results were later embedded in a simulation procedure. Such procedure underpinned the design of cost-effective triage solutions facilitating the patient flow within an ED located in Israel. The problem here considered was extended by incorporating uncertainty inherent to the real-life scenario.

A few studies presented a comprehensive combination between simulation and lean to additionally eliminate non-value added activities along the ED patient journey. A tremendous effort, for instance, was documented in Huang and Klassen (2016) who also incorporated six-sigma for improving the phlebotomy process in the ED of the St. Catharines Site of the Niagara Health System. Such integration led decision-makers to identify potential improvement opportunities and propose solutions with an estimated 7-minute flow time reduction. The amount of time spent in EDs was also evaluated in Romano et al. (2015) through the combination of lean healthcare, simulation, and causal loop diagrams. This framework was implemented in an Italian ED where positive results in patients' flow were further evidenced with subsequent reductions of profit loss. Scientific evidence also point out the presence of simulation-based hybrid approaches incorporating other less prominent techniques such as: fuzzy logic (Azadeh et al., 2013), what-if analysis (Brenner et al., 2010), capability analysis (Keeling et al. 2013), statistical methods (Easter et al., 2019), and decision-making (Yousefi and Ferreira et al., 2017). In addition, a highlighted study is presented by Gartner and Padman (2019) who integrated machine learning and DES to improve the patient flow of a real ED. The results revealed that changing staffing patterns can lead to shorter patient journey times.

Some investigators have tackled the patient flow problem through mixing other process-improvement methods. It is worth noting, for example, the use of lean manufacturing combined with quality management techniques. A related case is exposed by Stanton et al. (2014) who implemented lean six-sigma for improving the patient flow from the ED to the wards of an Australian hospital. The LSS project also had significant positive impact on involved staff and resource leveraging. Similar lean-based hybrid applications can be also found at Ryan et al. (2013) and Weimann (2018). To substantially redesign ED patient journey other authors preferred using integrated approaches including statistical methods (Ross et al., 2019; Garrett et al., 2018) or only OR methods as cited in González et al. (2019) and Lau et al. (2018).

As evidenced above, a considerable percentage of the studies targeting reduced patient flow (63.6%) employed a single approach as a methodological basis. The most popular method used in a single way upon facing the patient flow challenge is lean manufacturing (13 papers; 28.88%). Dickson et al. (2008) reported a 2-year experience of an academic emergency treatment center employing LM for continuously improving the patient flow. After implementation, the direct expense per patient has dropped by 9% (from US$112 to US$102.5) and patient satisfaction has increased by almost 10%. A similar work is seen in Matt et al. (2018) where a LM program demonstrated to be beneficial for four different ED hospitals in Northern Italy. The results revealed that the patient lead-time from registration to discharge was significantly lessened by 17%.

Definitively, simulation is one of the most used techniques for underpinning improvements in emergency department even when employed separately. Door-to-discharge times are not the exception to this rule. A comprehensive simulation model implemented in Khanna et al. (2016) confirms the previous statement. The DES model here designed was employed for evaluating operationally realistic scenarios on flow performance. As a result, the National Emergency Access Target (NEAT) performance increased by 16% whilst average bed occupancy diminished by 1.5%. Patient pathways from hospital presentation to discharge were also studied in Vile et al. (2017) where a DES model was implemented for helping a major UK hospital

ED to enhance the key ED performance target to admit or discharge 95% of patients within 4 h of arrival. This implementation has propelled the continuous use of simulation as a robust platform supporting the design of flexible EDs. Thereby, managers can establish whether the resources are well managed while providing high-quality emergency care to patients.

Another quality-related methodology found to offer solutions to the patient flow problem is CQI. Although most of this literature was published between 1996 and 2003, meaningful insights can be extracted by policy makers for addressing this burden properly. Goldmann et al. (1993) presented a CQI program whose implementation led to a 71-minute reduction in the time from triage to discharge experienced by patients attending to a pediatric teaching hospital ED. Over the recent years, Preyde et al. (2012) exposed a CQI program whose implementation led to a reduction of 1.16 h in the total time spent for patients admitted at a Canadian hospital ED. Other single techniques were used for tackling lengthy patient journey times within EDs; however, their application has been poorly explored as further evidenced throughout the literature. These include optimization models (Ajmi et al., 2019; Bordoloi and Beach, 2007), petri nets (Derni et al., 2019; Oueida et al., 2018b), process redesign (DeFlitch et al., 2015; Spaite et al., 2002), mixed integer programming (Courtad et al., 2017), nurse navigator (Fulbrook et al., 2017), acute care model (Iyer et al., 2011), critical pathways (Mohan et al., 2018), fast track protocols (Ollivere et al., 2012), Iowa model of evidence-based practice (Popovich et al., 2012), and regression analysis (Yau et al., 2018).

2.1.3.5 Papers Focusing on Diminishing the Number of Patients Who Leave the ED Without Being Seen

Table 6 depicts the articles focusing on diminishing the number of patients who leave the ED without being seen. Given the low number of papers contributing to this research field (*n* = 25 papers), we can conclude that improvement processes in this area are at the earlier stages and more interventions from research community are therefore expected for building a solid evidence base. Moreover, there is a great need for addressing the increased LWBS rates reported internationally (Clarey and

Cooke et al., 2012) which, in the meantime, are associated with elevated readmission rates and patient dissatisfaction. Such deficiencies may result in reputational damage, profit loss, and other financial implications related to repeated episodes of presentation. Additionally, there is a potential risk of ambulance misuse considering that approximately a third of LWBS patients arrive by ambulance. In response, several initiatives based on single (n = 19 articles; 76.0%) and multi-methods (n = 6 articles; 24.0%) approaches. Unsurprisingly, simulation tools continue to be the most preferred technique in multi-methods approaches addressing the leading problems in emergency departments. For instance, simulation has been applied along with statistical methods to deal with the LWBS problem. This is the case exposed in Yousefi et al. (2018b) who integrated agent-based simulation and ordinary least squares regression for representing the behavior of patients leaving a public hospital emergency department. In this study, four preventive policies were pretested for minimizing the LWBS rate. After intervention, the average LWBS and ED-LOS diminished by 42.14% and 6.05% respectively. A similar research study is reported in Easter et al. (2019) who used DES, ANOVA, linear regression, and non-linear regression for evaluating different improvement scenarios in terms of LWBS and other critical emergency care measures. The results evidenced that LWBS can decrease between 0.66% - 2% if an additional internal-waiting room is adopted within the emergency department. Much effort was also evidenced in papers integrating simulation with other approaches. For example, Lee et al. (2015) coupled machine learning, simulation, and optimization to reduce the number of patients who leave without being seen in the ED at Grady Memorial Hospital (Atlanta, Georgia). As a result, the LWBS was reduced by more than 30% along with cost savings and annual revenue of approximately $190 million. The rest of studies based on integrated methods used a combination of statistical methods (Hitti et al., 2019) and a mix of OR techniques (Yousefi and Ferreira, 2017; Jiang et al., 2018) for tackling elevated LWBS and their consequences mainly affecting the financial sustainability of EDs.

In general, single methods were found to be most popular compared to hybrid approaches when targeting minimized LWBS. International evidence reveals that most of research studies focused on this problem used a quality-improvement approach (n = 16 papers; 84.21%). These approaches have provided an excellent step forward in counteracting the LWBS causes by removing special causes of variation, non-value added activities, and unpleasant environment conditions in waiting rooms. Evidently, the most prominent technique was Lean Manufacturing (n = 11 papers; 57.89%) which entails a variety of tools perfectly addressing the above-mentioned causes. The first related contribution was presented by Dickson et al. (2009a) who described the lean effects on the percentage of patients who left without being seen associated with two hospital EDs. After 1 year post-lean the LWBS in the hospital A dropped from 8% to 5% while hospital B experienced a 22% decrease after 3 years of implementation. More recently, Peng et al. (2019) used lean healthcare for reducing the LWBS rates of rural EDs. After intervention, this metric was reduced from 4.1% to 2.0% ($p < 0.001$) while LOS was also significantly diminished with a $p < 0.001$.

Another quality-improvement approach found to address the left-without-being-seen rates was CQI. In particular, Rothwell et al. (2018) struggled to manage this problem in an Arabic ED by implementing a 3-month quality improvement project including a new fast-track unit. A longer project is observed in Preyde et al. (2012) where a 6-month process improvement program was applied for reducing LWBS patients of a Canadian hospital ED. After implementation, fewer patients (n = 425) left without being seen was reported along with additional improvements in other important emergency care metrics. Other studies using CQI-based implementations for addressing this problem can be found at Rehmani and Amatullah (2008) and Welch and Allen (2006). Aside from the above-cited single methods, investigators have employed REACT, pivot nursing, process redesign, and statistical process control as correspondingly evidenced in Chan et al. (2005), Christensen et al. (2016), DeFlitch et al. (2015), and Schwab et al. (1999). Surprisingly, simulation tools have not used in a single way for coping with this problem and its side effects.

Table 6. Articles evidencing the use of process improvement techniques for reducing LWBS.

Authors	Technique Type
Single	
Carter et al. (2012); Dickson et al. (2009a); Kane et al. (2015); Murrell et al. (2011); Ng et al. (2010); Peng et al. (2019); Sánchez et al. (2018); Sayed et al. (2015); Van der linden et al. (2019); Vashi et al. (2019); Vermeulen et al. (2014)	Lean manufacturing (S)
Preyde et al. (2012); Rehmani and Amatullah (2008); Rothwell et al., (2018); Welch and Allen (2006)	Continuous quality improvement (S)
Chan et al. (2005)	Rapid Entry and Accelerated Care at Triage (REACT)
Christensen et al. (2016)	Pivot nursing
Schwab et al. (1999)	Statistical Process Control
DeFlitch et al. (2015)	Process redesign
Hybrid	
Easter et al. (2019)	Discrete-event simulation, ANOVA, Linear regression, Non-linear regression
Hitti et al. (2019)	Logistic regression, Case-control study
Jiang et al., (2018)	Deep neural network (DNN), Genetic algorithm (GA)
Lee et al. (2015)	Machine learning, Simulation, Optimization
Yousefi and Ferreira (2017)	Agent-based simulation, Group Decision Making
Yousefi et al. (2018b)	Agent-based simulation, Ordinary least squares regression

2.1.4 Discussion

Our review reveals a considerable growth in the number of papers exposing process improvement methodologies addressing the main problems reported in EDs. In particular, the increasing publication trend initiated around 2011 concentrates 84.23% of the total related scientific contribution (*n* = 171 papers). This, of course, evidences the growing interest of policy makers, ED administrators, decision makers, researchers, and practitioners in this research field and the latent need for providing a high-quality and sustainable emergency care to patients. This is also consistent with the recent bunch of interventions that have been propelled by governments from different countries (as the 4-hour target – NEAT – established by the UK) searching for reducing mortality and morbidity rates, cost overruns, and adverse events. On the other hand, most of the evidence base is provided by journals from medical sciences, operations research, and quality fields, which demonstrates the multidimensional nature of ED context and the wide variety of process improvement approaches that can be used by ED administrators when facing the ED problems cited in this review.

One of the major findings from the review is the prominent use of simulation and LM techniques in the solution of ED deficiencies (Figure 4). The only exception was evidenced in *High LWBS* where LM was found as the most preferred approach. Authors have mostly employed this approach since: i) it provides a reliable representation of the patient journey within EDs so that factors and interactions affecting emergency care can be easily identified, ii) it records individual entity experience which is desirable for analyzing inefficiency patterns, iii) it facilitates engagement with decision-makers through animation, and iv) it allows ED managers to pretest potential improvement scenarios (Nuñez-Perez et al., 2017; Troncoso-Palacio et al., 2018; Ortiz-Barrios et al., 2019; Ortiz et al., 2016). It is also noteworthy that researchers have decided to utilize lean manufacturing preferentially since it i) allows ED managers identifying and removing the causes of emergency care variability, thus minimizing prolonged stays within these departments, ii) enables managers to detect and reduce wastes of resources (including time and cost overruns), iii) increases patient satisfaction rates, and iv) promotes collaborative work and increases the competences of medical staff. Another major benefit of LM is the ability to reduce the service lead time by adopting standard operating procedures that diminish expenses, increase efficiency, and improve operations. Lean thinking, as a bunch of concepts and tools directed towards the operational excellence, empowers medical and administrative staff to continuously identify significant opportunities in the ED which ends up increasing their technical competences whilst leading to a sustainable reduction of patient flow time, behavioral changes, and increased throughput. On a different note, the simplicity and efficiency of Queuing theory endorses its application on improving the emergency care experienced by ED patients. Also, the use of optimization techniques is a desired alternative when decision-makers need to maximize the impact of investments (for example, minimizing ED-LOS) under constrained resources as often observed in public EDs.

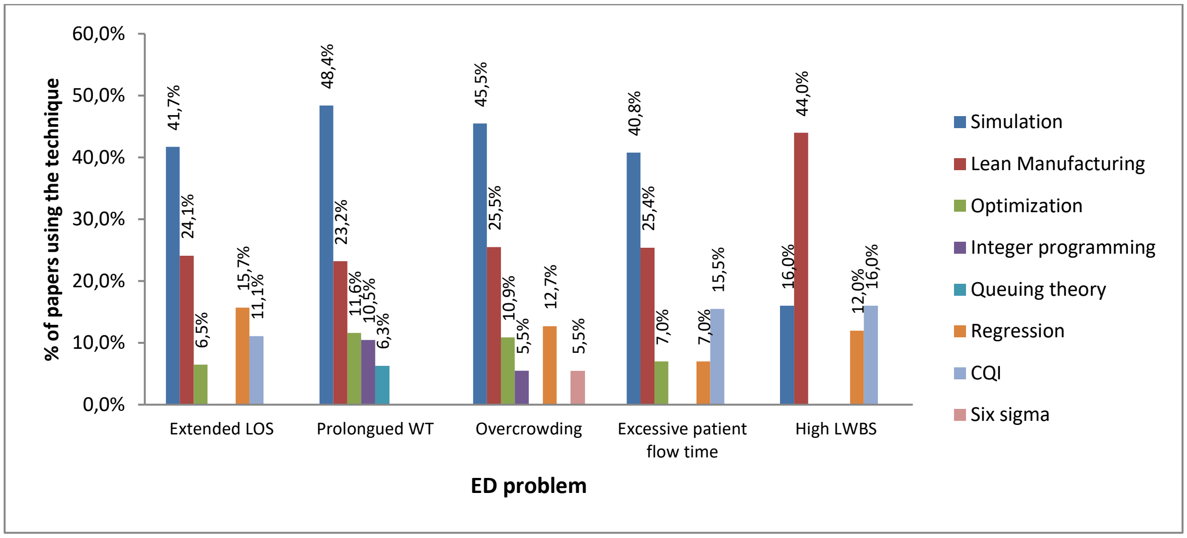


Figure 4. The most prominent techniques used for addressing the top-five leading problems in EDs.

We also noted that 36 different methods have been employed by authors for dealing with the excessive stays in emergency department. To date, most of work has focused on the use of OR methods. This is validated by the presence of simulation (*n* = 45 papers = 41.7%), optimization (*n* = 7 papers = 6.5%), and queuing theory (*n* = 5 papers = 4.6%) in the top-five of most popular techniques. On a different tack, quality improvement techniques can be also highlighted as a good option for addressing this problem. For instance, some authors are skewed to continuous quality improvement interventions (*n* = 10 papers = 9.3%) given their easy adoption by administrative and clinical staff, patient centered nature, and ability of constantly upgrading ED performance (as expected with LOS and other critical ED measures). Surprisingly, regression (*n* = 17 papers = 15.7%) was ranked third in the list of popular improvement tools. This technique has been often applied due to its ability of evidencing improvement or decline in key operational variables (such as LOS). It is clear from these findings that there is much room for the application of combined approaches considering the most popular OR (simulation, queuing theory, and optimization), regression, and quality improvement (lean manufacturing, CQI) techniques which is highly suggested for ED managers, decision-makers, practitioners, and researchers when dealing with long stays in emergency care settings. Such integration lays the groundwork for implementing a high-performance system-wide approach that would greatly lower ED stays even in the presence of growing and peak demands. In addition to this research opportunity, the reported literature revealed various gaps that should be properly addressed within the upcoming interventions targeting shortened LOS: (i) There are only a few initiatives considering data-driven approaches and behavioral aspects of emergency care, (ii) There is no reported literature concerning how LOS can be reduced in emergency care networks, (iii) There are no case studies considering patient heterogeneity and multiple care options, (iv) Only few works contemplate the participation of EDs, government, and academic sector in the design of improvement strategies shortening ED LOS.

On a different tack, 48 different techniques have been utilized by authors for coping with the lengthy door-to-doctor times in emergency departments. Most of the research has been skewed to the application of OR methods as observed in interventions reducing LOS. In fact, four OR methods were listed among the six most popular approaches: simulation (*n* = 46 articles = 48.4%), optimization (*n* = 11 articles = 11.6%), integer programming (*n* = 10 articles = 10.5%), and queuing theory (*n* = 6 articles = 6.3%). An interesting finding is related to the use of integer programming for decreasing the door-to-treatment times. The increasing use of this method is founded on its ability to achieve near optimal solutions in a realistic time frame. On the other hand, it is seen that some practitioners have preferred using lean manufacturing (*n* = 22 articles = 23.2%) and regression (*n* = 5 articles = 5.3%) for reducing waiting times within EDs as similarly found in the previous ED problem. Moreover, 43 interventions targeting shortened ED stays were simultaneously directed towards the improvement of door-to-treatment times. The above-mentioned findings endorse the integration of these methods as a powerful and robust framework addressing extended waiting times and lengthy stays in emergency departments. This approach is then highly attractive and useful for decision-makers considering their need for allocating scarce resources in high-impact solutions. There are, however, very few studies evidencing the use of hybrid methods for this particular aim. The reported related literature also revealed that data-driven approaches were not considered when tackling the waiting time problem. Besides, there is no research dealing with this phenomenon in emergency care networks. Therefore, future efforts in this research field should be directed towards the aforementioned lines.

It is also noteworthy that 30 different methods have been used by researchers and practitioners to deal with ED “admission hold”. A great portion of the interventions has mostly adopted OR methods as also observed in the above-cited ED problems. In this case, three OR methods were ranked among the most prominent approaches: simulation (n = 25 articles = 45.5%), optimization (n = 6 articles = 10.9%), and integer programming (n = 3 articles = 5.5%). We also see a high percentage of research considering lean thinking (n = 14 articles = 25.5%) and regression models (n = 7 articles = 12.7%) for tackling ED overcrowding as also detected in the previous ED problems. The multifaceted nature of these approaches is then attractive for ED directors, administrators, and policy makers who search for methodological frameworks able to address different problems at once. This is motivated by the need for continuously providing urgent care and allocating scarce resources properly. It is also important to stress the inclusion of six-sigma as an alternative for minimizing process variability in supporting services like radiology and laboratory which often contribute to ED congestion. In light of these facts, combining all these techniques can be a fruitful path for research and interventions underpinning the day-to-day management of ED congestion. On a broader scale, decisions such as hiring or firing new doctors or nurses, buying new beds and building new observation rooms can be properly assessed through the use of these methodologies. Other gaps detected in the related literature are as follows: (i) A small number of interventions are related to overcrowding in developing countries, (ii) The methodological approaches here cited do not consider patient heterogeneity and multiple care options, and (iii) Most overcrowding-related case studies do not evidence close collaborations amongst academic sector, government, and EDs.

Not coincidentally, the presence of OR (simulation and optimization), quality-improvement (lean manufacturing and CQI) and regression techniques was also evidenced in studies targeting reduced door-to-discharge times in EDs. Using the aforedescribed methods in a combined approach may be then useful for administering patient flows robustly. These methods can suitably deal with an operational context compounded by multiple transient stages, interactions, treatment alternatives, and outcomes. Thereby, decision makers may better predict the potential impact of demand changes and ED configurations on downstream operations, critical emergency care measures, and financial metrics of interest. Other research challenges related to this problem are the following: (i) The implementation of data-driven approaches (i.e., data mining, process mining) combined the large amount of data derived from emergency care, (ii) The replication of the aforementioned interventions in developing countries where the financial budget is highly restricted, and (iii) The application of multi-phase models that better represent the multifactorial context of emergency care while outlining the interrelations with other healthcare services (i.e., hospitalization, surgery, intensive care unit, radiology).

The review also led to identify the variety of process-improvement methods (n = 15) that have been trialed for reducing the left-without-being-seen rates in different countries. In this case, lean manufacturing (n = 11 papers; 44.0% out of the total contributions) was found to be the most prominent technique when addressing this problem. The second place in the rank is shared by CQI (n = 4 papers = 16% of the total contributions) and computer simulation (n = 4 papers = 16% of the total contributions) while regression (n = 3 paper = 12.0%) was also listed among the most popular approaches addressing elevated LWBS rates. This evidence supports the integration of simulation approaches and process improvement techniques originated from the automotive industry (such as LM and CQI) in an effort to improving several critical emergency care measures (i.e., average LWBS) (Saghafian et al., 2015). A concern, however, is the availability of high-quality and suitable data, an aspect also pointed out in Clarey and Cooke (2012). Modelers require detailed and intricate data for providing a good representation of patient pathways directly affecting ER waiting times, one of the major factors associated with high LWBS rates. Decision makers should then establish strategies for ensuring proper data collection underpinning the deployment of the aforementioned combined approach. As discussed above, this research field is at the earlier stages and more advanced contributions are hence expected for expanding the evidence base of improvements addressing this problem. Apart from the previous considerations, future investigations should consider the inclusion of behavioral aspects explaining the LWBS rates. Moreover, more interventions are needed in developing countries where this problem has reached desperate proportions (Nuñez-Perez et al., 2017).

Our vision is also consistent with the WHO document entitled as “Delivering quality health services: A global imperative for universal health coverage” (World Health Organization (WHO) et al., 2020) which reinforces the need for the continuous collaboration between EDs, government, and academic partners for ensuring scale-up and sustainable improvement interventions in emergency care. The techniques here described will serve as a platform for interventions focused on upgrading the emergency care performance in terms of lead-time, equity, coordination, and efficiency as pursued by WHO. It is, however, critical to tackle some general methodological limitations that became evident from the literature. For instance, the use of hybrid approaches emerging from the combination of several prominent approaches is at the earlier stages and more contributions are then expected to increase the evidence base related to these applications. In particular, the use of combined interventions using simulation and lean manufacturing remains limited in the reported literature (Lo et al., 2015; Rachuba et al., 2018; Romano et al., 2015; Bal et al., 2017; Martínez et al., 2015; Huang and Klassenet al., 2016). Likewise, researchers are advised to take into account the methodological trends regarding process improvement in emergency departments. For example, over the recent years, there has been a growing tendency to undertake multi- objective interventions as cited in Easter et al. (2019) and Ajmi et al. (2019). Furthermore, there has been a downward trend in recent years concerning the use of CQI-based approaches which may be explained by the adoption of more robust approaches like LM. By considering the findings discussed in this section, decision-makers and other stakeholders can better define short-term and long-term improvement plans pursuing high-quality emergency care and reduced operational cost whereas providing new evidence base for the development of more effective interventions and research.

2.1.5 Concluding Remarks and Future Directions

A wide variety of process improvement methodologies have been employed by researchers and practitioners for addressing leading emergency department inefficiencies including Overcrowding, Prolonged waiting time, extended length of stay (LOS), excessive patient flow time, and High number of patients who leave the ED without being seen (LWBS). In order to lay groundwork for devising and implementing cost-effective solutions as well as detecting limitations in current practice, this paper provided a comprehensive literature review comprising of 203 papers spread over the period ranged between April 1993 and October 2019. The papers, distributed in 120 journals, were then examined and classified according to the: (i) targeted ED problem and (ii) publication year. We also identified the most prominent process-improvement approaches that have been used for tackling each of the aforementioned ED deficiencies. In particular, we particularly noted that process-improvement studies in EDs are ample when coping with prolonged waiting time, extended LOS, and excessive patient flow time; nonetheless, there is still a lack of interventions tackling overcrowding and high left-without-being-seen rates. This is mainly caused by the poor involvement of ED administrators, policy makers, and other stakeholders in the design of multifaceted suitable strategies addressing the complexity and implementation conditions inherent to the real ED context.

It is noteworthy that simulation has been the most popular approach for addressing the leading operational problems due to their capability to deeply analyse the current performance of emergency services, pre-test improvement scenarios, and facilitate user engagement through the animation of patient flows and resources. Lean manufacturing, regression analysis, optimization, and CQI were also found to be highly used by practitioners and researchers when addressing the ED deficiencies. In particular, authors employed OR methods (simulation and optimization), quality-improvement techniques (lean manufacturing and CQI), and regression for tackling extended patient flow times and lengthy ED stays. On a different tack, researchers utilised lean manufacturing, simulation, optimization, regression, and integer programming for addressing overcrowded emergency departments. Meanwhile, CQI, lean manufacturing, simulation, and regression were mostly used for decreasing the left-without-being-seen rates. However, we look for hybrid approaches using these methods for fully exploiting the advantages of each technique so that more robust results can be achieved in the real-life scenario.

Unsurprisingly, the application of single approaches is more widespread compared to integrated techniques when addressing the above-mentioned ED problems. There is, however, a growing trend in the use of hybrid methods justified by the complexity of emergency care operations, the interactions with other services, and the continued increased demand. There are no, however, studies combining simulation, lean manufacturing, optimization, CQI, and regression for tackling any of the leading ED problems. Both combinations are projected to effectively underpin ED operations for delivering optimized emergency care under reasonable costs. Therefore, such approaches are expected to be fruitful paths for future research.

There are also a limited number of studies addressing different emergency department deficiencies at once. Hence, more similar contributions are expected to expand the current research body and widespread the use of these approaches in real-life EDs. Furthermore, there is a definite need for implementing these methods in emergency care networks (ECNs) to identify key lessons underpinning the deployment of effective and timely ECNs in the future. We also expect to see more advancement regarding the use of data-driven approaches considering behavioral aspects inherent to emergency care. Thereby, more realistic and representative models can be designed for supporting multifaceted interventions encompassing upstream services.

In conclusion, future research should be directed towards: (i) more contributions integrating simulation and lean manufacturing, (ii) studies combining optimization, CQI, lean manufacturing, simulation, and regression, (iii) interventions based on data-driven approaches and behavioral aspects of emergency services, (iv) implementations of process improvement methodologies underpinning emergency care networks, (v) more projects addressing different emergency department problems at once, vi) interventions tackling overcrowding and high left-without-being-seen rates, (vii) the design and implementation of new modelling frameworks considering patient heterogeneity and the multiple care options with the goal of underpinning the deployment of strategic plans within emergency care and its associated services, viii) the promotion of international collaboration to develop comparative studies among countries and new guidelines for process improvement, (ix) propel the widespread application of the identified approaches in developing countries where financial budget is largely limited, (x) foster closest collaborations among EDs, government, and academic partners for designing scale-up and sustainable improvement interventions in emergency care, (xi) review research progress related to interventions addressing non-urgent ED admissions considering the high waste of resources reported by hospitals and clinics, especially on weekends, and (xii) review the literature regarding improvement strategies including clinical-related interventions, personnel training, the ABCDE of Emergency care, and Triage which have not been covered in this paper. If properly addressed, these research lines will provide decision makers with a potent decision-making platform for effectively facing the expected growing demand at a minimum operational cost.

2.1.6 References

Aaronson E, Mort E, Soghoian S. Mapping the process of emergency care at a teaching hospital in Ghana. Healthcare 2017;5(4):214-220.

Abo-Hamad W, Arisha A. Simulation-based framework to improve patient experience in an emergency department. Eur J Oper Res 2013;224(1):154-166.

Acuna JA, Zayas-Castro JL, Charkhgard H. Ambulance allocation optimization model for the overcrowding problem in US emergency departments: A case study in Florida. Socio-Econ Plann Sci 2019.

Ahalt V, Argon NT, Ziya S, Strickler J, Mehrotra A. Comparison of emergency department crowding scores: a discrete-event simulation approach. Health Care Manage Sci 2018;21(1):144-155.

Ajdari A, Boyle LN, Kannan N, Wang J, Rivara FP, Vavilala MS. Simulation of the Emergency Department Care Process for Pediatric Traumatic Brain Injury. J Healthc Qual 2018;40(2):110-118.

Ajmi F, Zgaya H, Othman SB, Hammadi S. Agent-based dynamic optimization for managing the workflow of the patient's pathway. Simul Model Pract Theory 2019;96.

Al Owad A, Samaranayake P, Karim A, Ahsan KB. An integrated lean methodology for improving patient flow in an emergency department–case study of a Saudi Arabian hospital. Prod Plann Control 2018;29(13):1058-1081.

Ala A, Chen F. Alternative mathematical formulation and hybrid meta-heuristics for patient scheduling problem in health care clinics. Neural Comput Appl 2020;32(13):8993-9008.

Aldarrab A. Application of Lean Six Sigma for patients presenting with ST-elevation myocardial infarction: the Hamilton Health Sciences experience. Healthc Q 2006;9(1):56-61,2.

Allaudeen N, Vashi A, Breckenridge JS, Haji-Sheikhi F, Wagner S, Posley KA, et al. Using Lean Management to Reduce Emergency Department Length of Stay for Medicine Admissions. Qual Manage Health Care 2017;26(2):91-96.

Althaus F, Paroz S, Hugli O, Ghali WA, Daeppen J-, Peytremann-Bridevaux I, et al. Effectiveness of interventions targeting frequent users of emergency departments: A systematic review. Ann Emerg Med 2011;58(1):41-52.

Aminuddin WMWM, Ismail WR, Harunarashid H. Resources improvement in emergency department using simulation and data envelopment analysis. Sains Malays 2018;47(9):2231-2240.

Andersen AR, Nielsen BF, Reinhardt LB, Stidsen TR. Staff optimization for time-dependent acute patient flow. Eur J Oper Res 2019;272(1):94-105.

Arbune A, Wackerbarth S, Allison P, Conigliaro J. Improvement through Small Cycles of Change: Lessons from an Academic Medical Center Emergency Department. J Healthc Qual 2017;39(5):259-269.

Aroua A, Abdulnour G. Optimization of the emergency department in hospitals using simulation and experimental design: Case study. Procedia Manufacturing; 2018;17:878–885

Ashour OM, Okudan Kremer GE. A simulation analysis of the impact of FAHP-MAUT triage algorithm on the Emergency Department performance measures. Expert Sys Appl 2013;40(1):177-187.

Ashour OM, Okudan Kremer GE. Dynamic patient grouping and prioritization: a new approach to emergency department flow improvement. Health Care Manage Sci 2016;19(2):192-205.

Azadeh A, Hosseinabadi Farahani M, Torabzadeh S, Baghersad M. Scheduling prioritized patients in emergency department laboratories. Comput Methods Programs Biomed 2014;117(2):61-70.

Azadeh A, Rouhollah F, Davoudpour F, Mohammadfam I. Fuzzy modelling and simulation of an emergency department for improvement of nursing schedules with noisy and uncertain inputs. Int J Serv Oper Manage 2013;15(1):58-77.

Baia Medeiros DT, Hahn-Goldberg S, Aleman DM, O'Connor E. Planning Capacity for Mental Health and Addiction Services in the Emergency Department: A Discrete-Event Simulation Approach. J Healthc Eng 2019;2019.

Bal A, Ceylan C, Taçoğlu C. Using value stream mapping and discrete event simulation to improve efficiency of emergency departments. Int J Healthc Manage 2017;10(3):196-206.

Beck MJ, Okerblom D, Kumar A, Bandyopadhyay S, Scalzi LV. Lean intervention improves patient discharge times, improves emergency department throughput and reduces congestion. Hosp Pract (1995) 2016;44(5):252-259.

Bellew SD, Collins SP, Barrett TW, Russ SE, Jones ID, Slovis CM, et al. Implementation of an Opioid Detoxification Management Pathway Reduces Emergency Department Length of Stay. Acad Emerg Med 2018;25(10):1157-1163.

Bellow AA, Gillespie GL. The evolution of ED crowding. J Emerg Nurs 2014;40(2):153-160.

Ben Othman S, Hammadi S. A multi-criteria optimization approach to health care tasks scheduling under resources constraints. Int J Comput Intell Syst 2017;10(1):419-439.

Ben Othman S, Zgaya H, Hammadi S, Quilliot A, Martinot A, Renard J-. Agents endowed with uncertainty management behaviors to solve a multiskill healthcare task scheduling. J Biomed Informatics 2016;64:25-43.

Benson R, Harp N. Using systems thinking to extend continuous quality improvement. Qual Lett Healthc Lead 1994;6(6):17-24.

Best AM, Dixon CA, Kelton WD, Lindsell CJ, Ward MJ. Using discrete event computer simulation to improve patient flow in a Ghanaian acute care hospital. Am J Emerg Med 2014;32(8):917-922.

Bish PA, McCormick MA, Otegbeye M. Ready-JET-Go: Split Flow Accelerates ED Throughput. J Emerg Nurs 2016;42(2):114-119.

Blick KE. Providing critical laboratory results on time, every time to help reduce emergency department length of stay: How our laboratory achieved a six sigma level of performance. Am J Clin Pathol 2013;140(2):193-202.

Bokhorst JAC, van der Vaart T. Acute medical unit design – The impact of rearranged patient flows. Socio-Econ Plann Sci 2018;62:75-83.

Bordoloi SK, Beach K. Improving operational efficiency in an Inner-city Emergency Department. Health Serv Manage Res 2007;20(2):105-112.

Boyle A, Beniuk K, Higginson I, Atkinson P. Emergency Department Crowding: Time for Interventions and Policy Evaluations. Emerg Med Int 2012;2012:1–8.

Brenner S, Zeng Z, Liu Y, Wang J, Li J, Howard PK. Modeling and analysis of the emergency department at university of Kentucky Chandler Hospital using simulations. J Emerg Nurs 2010;36(4):303-310.

Brent AS, Rahman WM, Knarr LL, Harrison JA, Kearns KL, Lindstrom DS. Reducing cycle times in pediatric emergency medicine. Pediatr Emerg Care 2009;25(5):307-311.

Brouns SHA, Stassen PM, Lambooij SLE, Dieleman J, Vanderfeesten ITP, Haak HR. Organisational factors induce prolonged emergency department length of stay in elderly patients - A retrospective cohort study. PLoS ONE 2015;10(8).

Carter PM, Desmond JS, Akanbobnaab C, Oteng RA, Rominski SD, Barsan WG, et al. Optimizing clinical operations as part of a global emergency medicine initiative in Kumasi, Ghana: Application of lean manufacturing principals to low-resource health systems. Acad Emerg Med 2012;19(3):338-347.

Chadha R, Singh A, Kalra J. Lean and queuing integration for the transformation of health care processes A lean health care model. Clin Gov 2012;17(3):191-199.

Chan TC, Killeen JP, Kelly D, Guss DA. Impact of rapid entry and accelerated care at triage on reducing emergency department patient wait times, lengths of stay, and rate of left without being seen. Ann Emerg Med 2005;46(6):491-497.

Chen T-, Wang C-. Multi-objective simulation optimization for medical capacity allocation in emergency department. J Simul 2016;10(1):50-68.

Cheng I, Zwarenstein M, Kiss A, Castren M, Brommels M, Schull M. Factors associated with failure of emergency wait-time targets for high acuity discharges and intensive care unit admissions. Can J Emerg Med 2018;20(1):112-124.

Christensen M, Rosenberg M, Mahon E, Pineda S, Rojas E, Soque V, et al. Pivot Nursing: An Alternative to Traditional ED Triage. J Emerg Nurs 2016;42(5):395-399.

Christianson JB, Warrick LH, Howard R, Vollum J. Deploying Six Sigma in a health care system as a work in progress. Jt Comm J Qual Patient Saf 2005;31(11):603-613.

Clarey AJ, Cooke MW. Patients who leave emergency departments without being seen: Literature review and English data analysis. Emerg Med J 2012;29(8):617-621.

Cookson D, Read C, Mukherjee P, Cooke M. Improving the quality of Emergency Department care by removing waste using Lean Value Stream mapping. Int J Clin Leadersh 2011;17(1):25-30.

Coughlan J, Eatock J, Patel N. Simulating the use of re-prioritisation as a wait-reduction strategy in an emergency department. Emerg Med J 2011;28(12):1013-1018.

Courtad B, Baker K, Magazine M, Polak G. Minimizing flowtime for paired tasks. Eur J Oper Res 2017;259(3):818-828.

Crawford K, Morphet J, Jones T, Innes K, Griffiths D, Williams A. Initiatives to reduce overcrowding and access block in Australian emergency departments: A literature review. Collegian 2014;21(4):359-366.

Daldoul D, Nouaouri I, Bouchriha H, Allaoui H. A stochastic model to minimize patient waiting time in an emergency department. Oper Res Health Care 2018;18:16-25.

DeFlitch C, Geeting G, Paz HL. Reinventing emergency department flow via healthcare delivery science. Health Environ Res Des J 2015;8(3):105-115.

Derni O, Boufera F, Khelfi MF. Coloured Petri net for modelling and improving emergency department based on the simulation model. International Journal of Simulation and Process Modelling 2019;14(1):72-86.

Dickson E, Anguelov Z, Bott P, Nugent A, Walz D, Singh S. The sustainable improvement of patient flow in an emergency treatment centre using Lean. Int J Six Sigma Compet Advantage 2008;4(3):289-304.

Dickson EW, Anguelov Z, Vetterick D, Eller A, Singh S. Use of Lean in the Emergency Department: A Case Series of 4 Hospitals. Ann Emerg Med 2009;54(4):504-510.

Dickson EW, Singh S, Cheung DS, Wyatt CC, Nugent AS. Application of Lean Manufacturing Techniques in the Emergency Department. J Emerg Med 2009;37(2):177-182.

Diefenbach M, Kozan E. Effects of bed configurations at a hospital emergency department. J Simul 2011;5(1):44-57.

Doupe MB, Chateau D, Chochinov A, Weber E, Enns JE, Derksen S, et al. Comparing the Effect of Throughput and Output Factors on Emergency Department Crowding: A Retrospective Observational Cohort Study. Ann Emerg Med 2018;72(4):410-419.

Driesen BEJM, Van Riet BHG, Verkerk L, Bonjer HJ, Merten H, Nanayakkara PWB. Long length of stay at the emergency department is mostly caused by organisational factors outside the influence of the emergency department: A root cause analysis. PLoS ONE 2018;13(9).

Duguay C, Chetouane F. Modeling and Improving Emergency Department Systems using Discrete Event Simulation. Simulation 2007;83(4):311-320.

Easter B, Houshiarian N, Pati D, Wiler JL. Designing efficient emergency departments: Discrete event simulation of internal-waiting areas and split flow sorting. Am J Emerg Med 2019;37(12):2186-2193.

Eiset AH, Kirkegaard H, Erlandsen M. Crowding in the emergency department in the absence of boarding - A transition regression model to predict departures and waiting time. BMC Med Res Methodol 2019;19(1).

Elalouf A, Wachtel G. An alternative scheduling approach for improving patient-flow in emergency departments. Oper Res Health Care 2015;7:94-102.

Elamir H. Improving patient flow through applying lean concepts to emergency department. Leadersh in Health Serv 2018;31(3):293-309.

EL-Rifai O, Garaix T, Augusto V, Xie X. A stochastic optimization model for shift scheduling in emergency departments. Health Care Manage Sci 2015;18(3):289-302.

El-Rifai O, Garaix T, Xie X. Proactive on-call scheduling during a seasonal epidemic. Oper Res Health Care 2016;8:53-61.

Feng Y-, Wu I-, Chen T-. Stochastic resource allocation in emergency departments with a multi-objective simulation optimization algorithm. Health Care Manage Sci 2017;20(1):55-75.

Fernandes CMB, Christenson JM. Use of continuous quality improvement to facilitate patient flow through the triage and Fast-Track areas of an emergency department. J Emerg Med 1995;13(6):847-855.

Fernandes CMB, Christenson JM, Price A. Continuous quality improvement reduces length of stay for fast-track patients in an emergency department. Acad Emerg Med 1996;3(3):258-263.

Ferrand YB, Magazine MJ, Rao US, Glass TF. Managing responsiveness in the emergency department: Comparing dynamic priority queue with fast track. J Oper Manage 2018;58-59:15-26.

Fitzgerald JA, Eljiz K, Dadich A, Sloan T, Hayes KJ. Health services innovation: Evaluating process changes to improve patient flow. Int J Healthc Technol Manage 2011;12(3-4):280-292.

Flores-Mateo G, Violan-Fors C, Carrillo-Santisteve P, Peiró S, Argimon J-. Effectiveness of organizational interventions to reduce emergency department utilization: A systematic review. PLoS ONE 2012;7(5).

Forero R, Man N, McCarthy S, Richardson D, Mohsin M, Toloo GS, et al. Impact of the national emergency access target policy on emergency departments' performance: A time-trend analysis for New South Wales, Australian capital territory and queensland. EMA Emerg Med Australas 2019;31(2):253-261.

Fuentes E, Shields J-, Chirumamilla N, Martinez M, Kaafarani H, Yeh DD, et al. "One-way-street" streamlined admission of critically ill trauma patients reduces emergency department length of stay. Intern Emerg Med 2017;12(7):1019-1024.

Fulbrook P, Jessup M, Kinnear F. Implementation and evaluation of a 'Navigator' role to improve emergency department throughput. Australas Emerg Nurs J 2017;20(3):114-121.

Furterer SL. Applying Lean Six Sigma methods to reduce length of stay in a hospital's emergency department. Qual Eng 2018;30(3):389-404.

Garrett JS, Berry C, Wong H, Qin H, Kline JA. The effect of vertical split-flow patient management on emergency department throughput and efficiency. Am J Emerg Med 2018;36(9):1581-1584.

Gartner D, Padman R. Machine learning for healthcare behavioural OR: Addressing waiting time perceptions in emergency care. J Oper Res Soc 2019.

Ghanes K, Jouini O, Diakogiannis A, Wargon M, Jemai Z, Hellmann R, et al. Simulation-based optimization of staffing levels in an emergency department. Simulation 2015;91(10):942-953.

Goienetxea Uriarte A, Ruiz Zúñiga E, Urenda Moris M, Ng AHC. How can decision makers be supported in the improvement of an emergency department? A simulation, optimization and data mining approach. Oper Res Health Care 2017;15:102-122.

Goldmann DA, Saul CA, Parsons S, Mansoor C, Abbott A, Damian F, et al. Hospital-based continuous quality improvement: a realistic appraisal. Clin Perform Qual Health Care 1993;1(2):69-80.

González J, Ferrer J-, Cataldo A, Rojas L. A proactive transfer policy for critical patient flow management. Health Care Manage Sci 2019;22(2):287-303.

Gul M, Guneri AF. A computer simulation model to reduce patient length of stay and to improve resource utilization rate in an emergency department service system. Int J Ind Eng Theory Appl Pract 2012;19(5):221-231.

Günal MM, Pidd M. Discrete event simulation for performance modelling in health care: A review of the literature. J Simul 2010;4(1):42-51.

Guo H, Gao S, Tsui K-, Niu T. Simulation Optimization for Medical Staff Configuration at Emergency Department in Hong Kong. IEEE Trans Autom Sci Eng 2017;14(4):1655-1665.

Hajjarsaraei H, Shirazi B, Rezaeian J. Scenario-based analysis of fast track strategy optimization on emergency department using integrated safety simulation. Saf Sci 2018;107:9-21.

Haydar SA, Strout TD, Baumann MR. Sustainable Mechanism to Reduce Emergency Department (ED) Length of Stay: The Use of ED Holding (ED Transition) Orders to Reduce ED Length of Stay. Acad Emerg Med 2016;23(7):776-785.

He S, Sim M, Zhang M. Data-driven patient scheduling in emergency departments: A hybrid robust-stochastic approach. Manage Sci 2019;65(9):4123-4140.

Health Catalyst Editors. Emergency Department Quality Improvement: Transforming the Delivery of Care. [Internet]. [Extracted 16 de jul 2020]. Retrieved from: https://www.healthcatalyst.com/insights/emergency-department-quality-improvement-transforming-delivery-care

Henderson D, Dempsey C, Larson K, Appleby D. The impact of IMPACT on St. John's Regional Health Center. Mo Med 2003;100(6):590-592.

Herring A, Wilper A, Himmelstein DU, Woolhandler S, Espinola JA, Brown DFM, et al. Increasing length of stay among adult visits to U.S. emergency departments, 2001-2005. Acad Emerg Med 2009;16(7):609-616.

Higgins III GL, Becker MH. A continuous quality improvement approach to IL-372 documentation compliance in an academic emergency department, and its impact on dictation costs, billing practices, and average patient length of stay. Acad Emerg Med 2000;7(3):269-275.

Hitti E, Hadid D, Tamim H, Al Hariri M, El Sayed M. Left without being seen in a hybrid point of service collection model emergency department. Am J Emerg Med 2020;38(3):497-502.

Hitti EA, El-Eid GR, Tamim H, Saleh R, Saliba M, Naffaa L. Improving Emergency Department radiology transportation time: A successful implementation of lean methodology. BMC Health Serv Res 2017;17(1).

Hogan B, Rasche C, Von Reinersdorff AB. The First View Concept: Introduction of industrial flow techniques into emergency medicine organization. Eur J Emerg Med 2012;19(3):136-139.

Holden RJ. Lean thinking in emergency departments: A critical review. Ann Emerg Med 2011;57(3):265-278.

Hu B, Wang Z, Wang S, He L, Wu J, Wang F, et al. Key factors affecting the correlation between improving work efficiency and emergency department overcrowding in the tertiary level A hospitals. Chin J Emerg Med 2018;27(8):943-948.

Huang D, Bastani A, Anderson W, Crabtree J, Kleiman S, Jones S. Communication and bed reservation: Decreasing the length of stay for emergency department trauma patients. Am J Emerg Med 2018;36(10):1874-1879.

Huang Y, Klassen KJ. Using six sigma, lean, and simulation to improve the phlebotomy process. Qual Manage J 2016;23(2):6-21.

Hung GR, Kissoon N. Impact of an observation unit and an emergency department-admitted patient transfer mandate in decreasing overcrowding in a pediatric emergency department: A discrete event simulation exercise. Pediatr Emerg Care 2009;25(3):160-163.

Hussein NA, Abdelmaguid TF, Tawfik BS, Ahmed NGS. Mitigating overcrowding in emergency departments using Six Sigma and simulation: A case study in Egypt. Oper Res Health Care 2017;15:1-12.

Ibrahim IM, Liong C-, Bakar SA, Ahmad N, Najmuddin AF. Estimating optimal resource capacities in emergency department. Indian J Public Health Res Dev 2018;9(11):1558-1565.

Ibrahim IM, Liong C-, Bakar SA, Najmuddin AF. Performance improvement of the yellow zone in emergency department using discrete event simulation approach. Int J Eng Technol 2018;7(4):102-105.

Ieraci S, Digiusto E, Sonntag P, Dann L, Fox D. Streaming by case complexity: Evaluation of a model for emergency department Fast Track. EMA Emerg Med Australas 2008;20(3):241-249.

Improta G, Romano M, Di Cicco MV, Ferraro A, Borrelli A, Verdoliva C, et al. Lean thinking to improve emergency department throughput at AORN Cardarelli hospital. BMC Health Serv Res 2018;18(1).

Iyer S, Reeves S, Varadarajan K, Alessandrini E. The acute care model: A new framework for quality care in emergency medicine. Clin Pediatr Emerg Med 2011;12(2):91-101.

Izady N, Worthington D. Setting staffing requirements for time dependent queueing networks: The case of accident and emergency departments. Eur J Oper Res 2012;219(3):531-540.

Jarvis PRE. Improving emergency department patient flow. Clin Exp Emerg Med 2016;3(2):63.

Jiang S, Chin K-, Tsui KL. A universal deep learning approach for modeling the flow of patients under different severities. Comput Methods Programs Biomed 2018;154:191-203.

Joshi V, Lim C, Teng SG. Simulation Study: Improvement for Non-Urgent Patient Processes in the Emergency Department. EMJ Eng Manage J 2016;28(3):145-157.

Kane M, Chui K, Rimicci J, Callagy P, Hereford J, Shen S, et al. Lean manufacturing improves emergency department throughput and patient satisfaction. J Nurs Adm 2015;45(9):429-434.

Kaner M, Gadrich T, Dror S, Marmor YN. Generating and evaluating simulation scenarios to improve emergency department operations. IIE Trans Healthc Syst Eng 2014;4(3):156-166.

Kaushal A, Zhao Y, Peng Q, Strome T, Weldon E, Zhang M, et al. Evaluation of fast track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department. Socio-Econ Plann Sci 2015;50:18-31.

Kaushik N, Khangulov VS, O’hara M, Arnaout R. Reduction in laboratory turnaround time decreases emergency room length of stay. Open Access Emerg Med 2018;10:37-45.

Keeling KB, Brown E, Kros JF. Using process capability analysis and simulation to improve patient flow. Appl Manage Sci 2013;16:219-229.

Keyloun KR, Lofgren E, Hebert S. Modeling operational quality metrics and costs of long-acting antibiotics for acute bacterial skin and skin structure infection treatment in the emergency department. J Med Econ 2019;22(7):652-661.

Khanna S, Sier D, Boyle J, Zeitz K. Discharge timeliness and its impact on hospital crowding and emergency department flow performance. EMA Emerg Med Australas 2016;28(2):164-170.

Khare RK, Powell ES, Reinhardt G, Lucenti M. Adding More Beds to the Emergency Department or Reducing Admitted Patient Boarding Times: Which Has a More Significant Influence on Emergency Department Congestion? Ann Emerg Med 2009;53(5):575-585.e2.

Konrad R, DeSotto K, Grocela A, McAuley P, Wang J, Lyons J, et al. Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study. Oper Res Health Care 2013;2(4):66-74.

Kuo YH. Integrating simulation with simulated annealing for scheduling physicians in an understaffed emergency department. Hong Kong Inst Eng Trans 2014;21(4):253-261.

La J, Jewkes EM. Defining an optimal ED fast track strategy using simulation. J Enterp Inf Manage 2013;26(1):109-118.

Lamprecht J, Kolisch R, Pförringer D. The impact of medical documentation assistants on process performance measures in a surgical emergency department. Eur J Med Res 2019;24(1).

Landa P, Sonnessa M, Tànfani E, Testi A. Multiobjective bed management considering emergency and elective patient flows. Int Trans Oper Res 2018;25(1):91-110.

Lau H, Dadich A, Nakandala D, Evans H, Zhao L. Development of a cost-optimization model to reduce bottlenecks: A health service case study. Expert Syst 2018;35(6).

Lee EK, Atallah HY, Wright MD, Post ET, Thomas C, Wu DT, et al. Transforming hospital emergency department workflow and patient care. Interfaces 2015;45(1):58-82.

Leo G, Lodi A, Tubertini P, Di Martino M. Emergency Department Management in Lazio, Italy. Omega 2016;58:128-138.

Liu Z, Rexachs D, Epelde F, Luque E. An agent-based model for quantitatively analyzing and predicting the complex behavior of emergency departments. J Comput Sci 2017;21:11-23.

Lo MD, Rutman LE, Migita RT, Woodward GA. Rapid electronic provider documentation design and implementation in an academic pediatric emergency department. Pediatr Emerg Care 2015;31(11):798-804.

Lovett PB, Illg ML, Sweeney BE. A Successful Model for a Comprehensive Patient Flow Management Center at an Academic Health System. Am J Med Qual 2014;31(3):246-255.

Maniaci MJ, Lachner C, Vadeboncoeur TF, Hodge DO, Dawson NL, Rummans TA, et al. Involuntary patient length-of-stay at a suburban emergency department. Am J Emerg Med 2020;38(3):534-538.

Marcozzi D, Carr B, Liferidge A, Baehr N, Browne B. Trends in the Contribution of Emergency Departments to the Provision of Hospital-Associated Health Care in the USA. Int J Health Serv 2018;48(2):267-288.

Markel KN, Marion SA. CQI: Improving the time to thrombolytic therapy for patients with acute myocardial infarction in the emergency department. J Emerg Med 1996;14(6):685-689.

Martínez P, Martínez J, Nuño P, Cavazos J. Improvement of patient care time in an emergency department through the application of lean manufacturing. Inf Tecnol 2015;26(6):187-198.

Mason S, Weber EJ, Coster J, Freeman J, Locker T. Time patients spend in the emergency department: England's 4-hour rule - A case of hitting the target but missing the point? Ann Emerg Med 2012;59(5):341-349.

Matt DT, Arcidiacono G, Rauch E. Applying lean to healthcare delivery processes - A case-based. Int J Adv Sci Eng Inf Technol 2018;8(1):123-133.

Meng F, Teow KL, Ooi CK, Heng BH, Tay SY. Minimization of the coefficient of variation for patient waiting system governed by a generic maximum waiting policy. J Ind Manage Optim 2017;13(4):1759-1770.

Migita R, Del Beccaro M, Cotter D, Woodward GA. Emergency department overcrowding: Developing emergency department capacity through process improvement. Clin Pediatr Emerg Med 2011;12(2):141-150.

Migita R, Yoshida H, Rutman L, Woodward GA. Quality Improvement Methodologies: Principles and Applications in the Pediatric Emergency Department. Pediatr Clin North Am 2018;65(6):1283-1296.

Mohan S, Nandi D, Stephens P, M'Farrej M, Vogel RL, Bonafide CP. Implementation of a clinical pathway for chest pain in a pediatric emergency department. Pediatr Emerg Care 2018;34(11):778-782.

Murrell KL, Offerman SR, Kauffman MB. Applying Lean: Implementation of a rapid triage and treatment system. West J Emerg Med 2011;12(2):184-191.

Nezamoddini N, Khasawneh MT. Modeling and optimization of resources in multi-emergency department settings with patient transfer. Oper Res Health Care 2016;10:23-34.

Ng D, Vail G, Thomas S, Schmidt N. Applying the Lean principles of the Toyota Production System to reduce wait times in the emergency department. Can J Emerg Med 2010;12(1):50-57.

Nuñez-Perez N, Ortíz-Barrios M, McClean S, Salas-Navarro K, Jimenez-Delgado G, Castillo-Zea A. Discrete-event simulation to reduce waiting time in accident and emergency departments: A case study in a district general clinic. Lect Notes Comput Sci 2017;10586 LNCS:352-363.

Oh C, Novotny AM, Carter PL, Ready RK, Campbell DD, Leckie MC. Use of a simulation-based decision support tool to improve emergency department throughput. Oper Res Health Care 2016;9:29-39.

Ollivere B, Rollins K, Brankin R, Wood M, Brammar TJ, Wimhurst J. Optimising fast track care for proximal femoral fracture patients using modified early warning score. Ann R Coll Surg Engl 2012;94(4):e267-e271.

Oredsson S, Jonsson H, Rognes J, Lind L, Göransson KE, Ehrenberg A, et al. A systematic review of triage-related interventions to improve patient flow in emergency departments. Scand J Trauma Resusc Emerg Med 2011;19.

Ortiz MA, McClean S, Nugent CD, Castillo A. Reducing appointment lead-time in an outpatient department of gynecology and obstetrics through discrete-event simulation: A case study. Lect Notes Comput Sci 2016;10069 LNCS:274-285.

Ortiz-Barrios M, Pancardo P, Jiménez-Delgado G, De Ávila-Villalobos J. Applying Multi-phase DES Approach for Modelling the Patient Journey Through Accident and Emergency Departments. Lect Notes Comput Sci 2019;11582 LNCS:87-100.

Oueida S, Kotb Y, Aloqaily M, Jararweh Y, Baker T. An edge computing based smart healthcare framework for resource management. Sensors 2018;18(12).

Oueida S, Kotb Y, Ionescu S, Militaru G. AMS: A new platform for system design and simulation. Int J Simul Model 2019;18(1):33-46.

Oueida S, Kotb Y, Kadry S, Ionescu S. Healthcare Operation Improvement Based on Simulation of Cooperative Resource Preservation Nets for None-Consumable Resources. Complexity 2018;2018.

Paul JA, Lin L. Models for improving patient throughput and waiting at hospital emergency departments. J Emerg Med 2012;43(6):1119-1126.

Paul SA, Reddy MC, Deflitch CJ. A systematic review of simulation studies investigating emergency department overcrowding. Simulation 2010;86(8-9):559-571.

Peck JS, Benneyan JC, Nightingale DJ, Gaehde SA. Characterizing the value of predictive analytics in facilitating hospital patient flow. IIE Trans Healthc Syst Eng 2014;4(3):135-143.

Peltan ID, Bledsoe JR, Oniki TA, Sorensen J, Jephson AR, Allen TL, et al. Emergency Department Crowding Is Associated With Delayed Antibiotics for Sepsis. Ann Emerg Med 2019;73(4):345-355.

Peng LS, Rasid MF, Salim WI. Using modified triage system to improve emergency department efficacy: A successful Lean implementation. Int J Healthc Manage 2019;1-5.

Perry A. Code Critical: Improving Care Delivery for Critically Ill Patients in the Emergency Department. J Emerg Nurs 2020;46(2):199-204.

Piggott Z, Weldon E, Strome T, Chochinov A. Application of lean principles to improve early cardiac care in the emergency department. Can J Emerg Med 2011;13(5):325-332.

Polesello V, Dittadi R, Afshar H, Bassan G, Rosada M, Ninno LD, et al. Improving pre-analytical laboratory turnaround time for the emergency department: Outcomes of a pneumatic tube system introduction. Biochim Clin 2019;43(2):150-155.

Popovich MA, Boyd C, Dachenhaus T, Kusler D. Improving Stable Patient Flow through the Emergency Department by Utilizing Evidence-Based Practice: One Hospital's Journey. J Emerg Nurs 2012;38(5):474-478.

Preyde M, Crawford K, Mullins L. Patients' satisfaction and wait times at Guelph General Hospital Emergency Department before and after implementation of a process improvement project. Can J Emerg Med 2012;14(3):157-168.

Prybutok GL. Ninety to Nothing: a PDSA quality improvement project. Int J Health Care Qual Assur 2018;31(4):361-372.

Rachuba S, Knapp K, Ashton L, Pitt M. Streamlining pathways for minor injuries in emergency departments through radiographer-led discharge. Oper Res Health Care 2018;19:44-56.

Rasheed F, Lee YH, Kim SH, Park IC. Development of emergency department load relief area-gauging benefits in empirical terms. Simul Healthc 2012;7(6):343-352.

Rees GH. Organisational readiness and Lean Thinking implementation: Findings from three emergency department case studies in New Zealand. Health Serv Manage Res 2014;27(1):1-9.

Rehmani R, Amatullah AF. Quality improvement program in an Emergency Department. Saudi Med J 2008;29(3):418-422.

Restrepo-Zea JH, Jaén-Posada JS, Piedrahita JJE, Flórez PAZ. Emergency department overcrowding: A four-hospital analysis in Medellín and a strategy simulation. Rev Gerencia Polit Salud 2018;17(34).

Romano E, Guizzi G, Chiocca D. A decision support tool, implemented in a system dynamics model, to improve the effectiveness in the hospital emergency department. International Journal of Procurement Management 2015;8(1-2):141-168.

Rosmulder RW, Krabbendam JJ, Kerkhoff AHM, Houser CM, Luitse JSK. Erratum to: Computer Simulation Within Action Research: A Promising Combination for Improving Healthcare Delivery? (Syst Pract Action Res, 10.1007/s11213-011-9191-y). Syst Pract Action Res 2011;24(3):273.

Ross AJ, Murrells T, Kirby T, Jaye P, Anderson JE. An integrated statistical model of Emergency Department length of stay informed by Resilient Health Care principles. Saf Sci 2019;120:129-136.

Ross G, Johnson D, Kobernick M. Evaluation of a critical pathway for stroke. J Am Osteopath Assoc 1997;97(5):269-276.

Rothwell S, McIltrot K, Khouri-Stevens Z. Addressing Emergency Department Issues Using Advanced Practice in Saudi Arabia. J Nurse Pract 2018;14(2):e41-e44.

Rotteau L, Webster F, Salkeld E, Hellings C, Guttmann A, Vermeulen MJ, et al. Ontario's emergency department process improvement program: The experience of implementation. Acad Emerg Med 2015;22(6):720-729.

Rutman LE, Migita R, Woodward GA, Klein EJ. Creating a leaner pediatric emergency department: How rapid design and testing of a front-end model led to decreased wait time. Pediatr Emerg Care 2015;31(6):395-398.

Ryan A, Hunter K, Cunningham K, Williams J, O'Shea H, Rooney P, et al. STEPS: Lean thinking, theory of constraints and identifying bottlenecks in an emergency department. Ir Med J 2013;106(4).

Saghafian S, Austin G, Traub SJ. Operations research/management contributions to emergency department patient flow optimization: Review and research prospects. IIE Trans Healthc Syst Eng 2015;5(2):101-123.

Sánchez M, Suárez M, Asenjo M, Bragulat E. Improvement of emergency department patient flow using lean thinking. Int J Qual Health Care 2018;30(4):250-256.

Saoud MS, Boubetra A, Attia S. A simulation knowledge extraction-based decision support system for the healthcare emergency department. Int J Healthc Inf Syst Inform 2016;11(2):19–37.

Sayed MJE, El-Eid GR, Saliba M, Jabbour R, Hitti EA. Improving emergency department door to doctor time and process reliability: A successful implementation of lean methodology. Medicine 2015;94(42):e1679.

Schwab RA, DelSorbo SM, Cunningham MR, Craven K, Watson WA. Using statistical process control to demonstrate the effect of operational interventions on quality indicators in the emergency department. J Healthc Qual 1999;21(4):38-41.

Shin SY, Brun Y, Balasubramanian H, Henneman PL, Osterweil LJ. Discrete-Event Simulation and Integer Linear Programming for Constraint-Aware Resource Scheduling. IEEE Trans Syst Man Cybern Syst 2018;48(9):1578-1593.

Shirazi B. Fast track system optimization of emergency departments: Insights from a computer simulation study. Intl J Model Simul Sci Comput 2016;7(3).

Singh N, Robinson RD, Duane TM, Kirby JJ, Lyell C, Buca S, et al. Role of ED crowding relative to trauma quality care in a Level 1 Trauma Center. Am J Emerg Med 2019;37(4):579-584.

Sinreich D, Jabali O. Staggered work shifts: A way to downsize and restructure an emergency department workforce yet maintain current operational performance. Health Care Manage Sci 2007;10(3):293-308.

Sinreich D, Jabali O, Dellaert NP. Reducing emergency department waiting times by adjusting work shifts considering patient visits to multiple care providers. IIE Trans 2012;44(3):163-180.

Sir MY, Nestler D, Hellmich T, Das D, Laughlin MJ, Dohlman MC, et al. Optimization of multidisciplinary staffing improves patient experiences at the mayo clinic. Interfaces 2017;47(5):425-441.

Sloan J, Chatterjee K, Sloan T, Holland G, Waters M, Ewins D, et al. Effect of a pathway bundle on length of stay. Emerg Med J 2009;26(7):479-483.

Soril LJJ, Leggett LE, Lorenzetti DL, Noseworthy TW, Clement FM. Reducing frequent visits to the emergency department:A systematic review of interventions. PLoS ONE 2015;10(4).

Spaite DW, Bartholomeaux F, Guisto J, Lindberg E, Hull B, Eyherabide A, et al. Rapid process redesign in a university-based emergency department: Decreasing waiting time intervals and improving patient satisfaction. Ann Emerg Med 2002;39(2):168-177.

Stanton P, Gough R, Ballardie R, Bartram T, Bamber GJ, Sohal A. Implementing lean management/Six Sigma in hospitals: beyond empowerment or work intensification? Int J Hum Resour Manage 2014;25(21):2926-2940.

Stephens AS, Broome RA. Impact of emergency department occupancy on waiting times, rates of admission and representation, and length of stay when hospitalised: A data linkage study. EMA Emerg Med Australas 2019;31(4):555-561.

Steward D, Glass TF, Ferrand YB. Simulation-Based Design of ED Operations with Care Streams to Optimize Care Delivery and Reduce Length of Stay in the Emergency Department. J Med Syst 2017;41(10).

Stone-Griffith S, Englebright JD, Cheung D, Korwek KM, Perlin JB. Data-driven process and operational improvement in the emergency department: The ED Dashboard and Reporting Application. J Healthc Manage 2012;57(3):167-181.

Street M, Mohebbi M, Berry D, Cross A, Considine J. Influences on emergency department length of stay for older people. Eur J Emerg Med 2018;25(4):242-249.

Taboada M, Cabrera E, Epelde F, Iglesias ML, Luque E. Agent-based emergency decision-making aid for hospital emergency departments. Emerg 2012;24(3):189-195.

Techar K, Nguyen A, Lorenzo RM, Yang S, Thielen B, Cain-Nielsen A, et al. Early Imaging Associated With Improved Survival in Older Patients With Mild Traumatic Brain Injuries. J Surg Res 2019;242:4-10.

Than MP, Pickering JW, Dryden JM, Lord SJ, Aitken SA, Aldous SJ, et al. ICare-ACS (Improving Care Processes for Patients with Suspected Acute Coronary Syndrome): A Study of Cross-System Implementation of a National Clinical Pathway. Circulation 2018;137(4):354-363.

Thomas Schneider AJ, Luuk Besselink P, Zonderland ME, Boucherie RJ, Van Den Hout WB, Kievit J, et al. Allocating emergency beds improves the emergency admission flow. Interfaces 2018;48(4):384-394.

Tiwari Y, Goel S, Singh A. Arrival time pattern and waiting time distribution of patients in the emergency outpatient department of a tertiary level health care institution of North India. J Emerg Trauma Shock 2014;7(3):160-165.

Troncoso-Palacio A, Neira-Rodado D, Ortíz-Barrios M, Jiménez-Delgado G, Hernández-Palma H. Using discrete-event-simulation for improving operational efficiency in laboratories: a case study in pharmaceutical industry. Lect Notes Comput Sci 2018;10942 LNCS:440-451.

Umble M, Umble EJ. Utilizing buffer management to improve performance in a healthcare environment. Eur J Oper Res 2006;174(2):1060-1075.

Uscher-Pines L, Pines J, Kellermann A, Gillen E. Mehrotra A. Deciding to Visit the Emergency Departement for Non-Urgent Conditions: A Systematic Review of the Literature. Am J Manag Care 2013;19(1):47.

Van Der Linden MC, Van Ufford HME, De Beaufort RAY, Grauss RW, Hofstee HMA, Hoogendoorn JM, et al. The impact of a multimodal intervention on emergency department crowding and patient flow. Int J Emer Med 2019;12(1).

Van der Veen D, Remeijer C, Fogteloo AJ, Heringhaus C, de Groot B. Independent determinants of prolonged emergency department length of stay in a tertiary care centre: A prospective cohort study. Scand J Trauma Resusc Emerg Med 2018;26(1).

Vanbrabant L, Braekers K, Ramaekers K, Van Nieuwenhuyse I. Simulation of emergency department operations: A comprehensive review of KPIs and operational improvements. Comput Ind Eng 2019;131:356-381.

Vashi AA, Sheikhi FH, Nashton LA, Ellman J, Rajagopal P, Asch SM. Applying Lean Principles to Reduce Wait Times in a VA Emergency Department. Mil Med 2019;184(1-2):E169-E178.

Vermeulen MJ, Stukel TA, Guttmann A, Rowe BH, Zwarenstein M, Golden B, et al. Evaluation of an emergency department lean process improvement program to reduce length of stay. Ann Emerg Med 2014;64(5):427-438.

Vile JL, Allkins E, Frankish J, Garland S, Mizen P, Williams JE. Modelling patient flow in an emergency department to better understand demand management strategies. J Simul 2017;11(2):115-127.

Visintin F, Caprara C, Puggelli F. Experimental design and simulation applied to a paediatric emergency department: A case study. Comput Ind Eng 2019;128:755-781.

Vose C, Reichard C, Pool S, Snyder M, Burmeister D. Using LEAN to improve a segment of emergency department flow. J Nurs Adm 2014;44(11):558-563.

Wang J, Li J, Tussey K, Ross K. Reducing length of stay in emergency department: A simulation study at a community hospital. IEEE Trans Syst Man Cybern Pt A Syst Humans 2012;42(6):1314-1322.

Wang T, Guinet A, Belaidi A, Besombes B. Modelling and simulation of emergency services with ARIS and Arena. case study: The emergency department of Saint Joseph and Saint Luc hospital. Prod Plann Control 2009;20(6):484-495.

Wang X. Emergency department staffing: A separated continuous linear programming approach. Math Probl Eng 2013;2013.

Weimann E. Lean management and continuous improvement process in hospitals. Pneumologe 2018;15(3):202-208.

Welch SJ, Allen TL. Data-driven quality improvement in the Emergency Department at a level one trauma and tertiary care hospital. J Emerg Med 2006;30(3):269-276.

White BA, Baron JM, Dighe AS, Camargo CA, Brown DFM. Applying Lean methodologies reduces ED laboratory turnaround times. Am J Emerg Med 2015;33(11):1572-1576.

White BA, Yun BJ, Lev MH, Raja AS. Applying systems engineering reduces radiology transport cycle times in the emergency department. West J Emerg Med 2017;18(3):410-418.

World Health Organization (WHO); Organisation for Economic Co-operation and Development (OECD); World Bank Group. Delivering Quality Health Services: A Global Imperative for Universal Health Coverage. [Internet]. [Extracted 16 de jul 2020]. Retrieved from: https://www.worldbank.org/en/topic/universalhealthcoverage/publication/delivering-quality-health-services-a-global-imperative-for-universal-health-coverage

Xu K, Chan CW. Using future information to reduce waiting times in the emergency department via diversion. Manuf Serv Oper Manage 2016;18(3):314-331.

Yang KK, Lam SSW, Low JMW, Ong MEH. Managing emergency department crowding through improved triaging and resource allocation. Oper Res Health Care 2016;10:13-22.

Yau FF-, Tsai T-, Lin Y-, Wu K-, Syue Y-, Li C-. Can different physicians providing urgent and non-urgent treatment improve patient flow in emergency department? Am J Emerg Med 2018;36(6):993-997.

Yousefi M, Ferreira RPM. An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department. Braz J Med Biol Res 2017;50(5).

Yousefi M, Yousefi M. Human resource allocation in an emergency department: A metamodel-based simulation optimization. Kybernetes 2019;49(3):779-796.

Yousefi M, Yousefi M, Ferreira RPM, Kim JH, Fogliatto FS. Chaotic genetic algorithm and Adaboost ensemble metamodeling approach for optimum resource planning in emergency departments. Artif Intell Med 2018;84:23-33.

Yousefi M, Yousefi M, Fogliatto FS, Ferreira RPM, Kim JH. Simulating the behavior of patients who leave a public hospital emergency department without being seen by a physician: A cellular automaton and agent-based framework. Braz J Med Biol Res 2018;51(3).

Zeinali F, Mahootchi M, Sepehri MM. Resource planning in the emergency departments: A simulation-based metamodeling approach. Simul Model Pract Theory 2015;53:123-138.

Zeltyn S, Marmor YN, Mandelbaum A, Carmeli B, Greenshpan O, Mesika Y, et al. Simulation-based models of emergency departments: Operational, tactical, and strategic staffing. ACM Trans Model Comput Simul 2011;21(4).

Zeng Z, Ma X, Hu Y, Li J, Bryant D. A Simulation Study to Improve Quality of Care in the Emergency Department of a Community Hospital. J Emerg Nurs 2012;38(4):322-328.

Zhao Y, Peng Q, Strome T, Weldon E, Zhang M, Chochinov A. Bottleneck detection for improvement of emergency department efficiency. Bus Process Manage J 2015;21(3):564-585.

2.2 An Integrated Approach for Designing In-Time and Economically Sustainable Emergency Care Networks: A Case Study in the Public Sector.

2.2.1 Introduction

Emergency Care Networks (ECNs) are considered complex healthcare systems oriented towards delivering effective emergency services to patients in the most suitable and convenient setting through the alignment of a range of EDs with a patient-centered approach. In fact, the creation of ED networks was suggested by different healthcare institutions in response to the increasing waiting time in emergency units and has been therefore included in various government agendas (Sheard and Space, 2018). Although the integration of EDs has the potential to improve the timely provision of emergency care, several drawbacks have become glaring in both the ED transferring patients and the ED receiving patients which results in non-optimal patient outcomes, long waiting times, and high operational costs. This problem is even more critical considering that the demands of emergency services continue to rise in the future (Soril et al., 2015). In the last 20 years, the number of ED admissions increased by 50% in the US (Hsia et al., 2018) whilst, in Australia, the annual admission rate rose by 3.4% (2,017-2,018) (Morley et al., 2018a). Additionally, in the UK, the number of emergency visits has grown by 42% (1,997-2,017) (Steventon et al., 2018) while this indicator was up to 10% in New Zealand and 5% in Belgium (Baier et al., 2019). This problem is more sharpener in developing countries. For instance, in Mexico, hospitals experienced an increased demand of 62% in the last three years (Bedoya Marrugo et al., 2017) while, in Colombia, the Ministry of Health and Social Protection reported that, the number of admissions augmented by 125% from 2,011 to 2,018 (Gaviria et al., 2015). These facts evidence the urgent need for ECNs providing timely diagnosis and care to patients with critical conditions. Although several efforts have been made to address this particular concern, there is still a lack of unified coordination and process inefficiencies across the ECNs.

A critical aspect to be considered in this discussion is the performance of each ED. EDs with serious deficiencies such as overcrowding (Kim et al., 2018; Morley et al., 2018b), prolonged waiting time, extended length of stay, and high number of patients who leave without seen, may reduce the effectiveness of ECNs in terms of timeliness. Nevertheless, it is not only essential to look into the functioning of emergency departments (EDs) individually but the existing interconnections that regulate the transfer and referral of patients. In this respect, legal, technological, and administrative factors have been found as some of the barriers to the effective functioning of these networks (Turner et al., 2015). Operationally, it has been identified that patient needs do not usually correctly match with the ECN capability. It is thus necessary to create robust methodological frameworks that underpin ECN design, planning, and development. Thereby, we can best integrate the EDs into a comprehensive collaboration scheme that ensures the delivery of high-quality emergency care.

Another aspect of concern is the economic gain of each ED within the network. EDs usually refuse to collaborate since they perceive that certain market share may be lost when partnering (Porter et al., 2019). In addition, ECNs must be financially viable and sustainable to guarantee the continuous and prompt provision of emergency care over time. In spite of the importance of this aspect, little attention has been paid and is then required to create schemes that ensure equitable and efficient allocation of payments. In some applications, such schemes have been related to operational performance models (Wilson, 2013; Barrios et al., 2015). These models do not only provide support for the utility distribution but generate sufficient information to detect service inefficiencies. With these insights, ECN managers may create cost-effective strategies for improving the delivery of emergency care and the ensuing patient outcomes across the ECN (Glickman et al., 2010)

To address the above-mentioned shortcomings, this paper aims to develop an integrated framework based on Discrete-event simulation, lean manufacturing and six sigma techniques for designing in-time ECNs. Such a framework also includes the creation of a scheme that guarantees the efficient distribution of payments among the ECN participants (EDs). For validation, a public ECN consisting of 2 hospitals and 8 POCs (Point of Care) is considered.

The remainder of this paper is organized as follows. In the second section, approaches used for the design of ECNs are reviewed whereas the proposed methodology for improving the timeliness of these networks is explained in the third section. In the next chapter, a case study of a public ECN is presented to validate the approach here described. Then, the results and analysis are shown in the fifth section. Finally, conclusions and future work are depicted.

2.2.2 Emergency care networks: related studies

The effective design and implementation of in-time ECNs have been projected as pillars for addressing the growing demand for emergency services in the future. For a comprehensive analysis of this topic, a review of the most recent reported literature was undertaken by consulting Scopus and Web of Science databases. Specifically, we used two search codes: "Emergency care network", "Emergency department network" After careful examination and filtering, only 19 documents (12 articles, 3 reviews, 2 conference papers, and 2 reports) were found from 2,003 (the date on which the first document appeared) to May – 2,019 (search date). Some studies recognized the need for designing ECNs for improving the timeliness of emergency care. For example, Calvello et al. (2013) suggested creating regionalized, coordinated, and accountable ECNs to address the overcrowding phenomenon. This is consistent with the recommendations provided by Konder and O'Dwyer (2016) who determined that collaboration practices may tackle the great patient dissatisfaction with emergency care. In addition, Qayyum and Wardrope (2009) concluded that ECNs are necessary to face the increasing demand for emergency and critical care, a problem that has been forecasted in different healthcare systems around the world.

The creation of ECNs, however, must overcome different barriers as identified by Glickman et al. (2010) who detected large gaps in the evidence base on how ECNs can be organized, coordinated, and measured. In particular, the authors determined that poor linkage of data systems across the EDs and lack of performance measurement models are the main barriers for effective ECN design and implementation. On the other hand, Stoner et al. (2018) established non-clinical research priorities categorized under the areas of network governance, knowledge translation, and information technology based on the weaknesses detected in pediatric ECNs. Uchimura et al., (2018) found political and governance aspects affecting the effectiveness of ECNs in Brazil. Similar work was undertaken by Konder and O'Dwyer who established that managerial fragmentation was one of the main factors for low integration among EDs in Rio de Janeiro, Brazil (Konder and O'Dwyer, 2016). The detection of governance problems within ECNs is also coherent with Qayyum and Wardrope (2009) and Almeida et al. (2015) who expressed that it was necessary to deploy strong leadership and organization considering the need for better coordination and management that ECNs require.

In spite of the research agenda created by the aforementioned studies in relation to ECN functioning, very few studies have aimed to create methodological approaches that guide policymakers towards the effective design and implementation of in-time ECNs in the wild. For instance, Navein and Mcneill (2003) described the Surrey Emergency Care System program, an attempt for the development of future integrated and unscheduled ECNs in the UK. However, their approach does not contemplate the individual diagnosis and intervention of the participant EDs before the collaborative scenario. In addition, the initiative does not consider the balance between the demand and ECN capacity, a cornerstone for the correct functioning of these networks in the real world. Harrop proposed an objective data model that can operate at different levels within the network (Harrop, 2005). This framework, however, does not consider interventions in each participant ED before the collaboration, governance arrangements, identification of risks, and creation of payment schemes. Another study was presented by Martínez who provided a conceptual framework for assigning and regionalizing emergency services within an ECN (Martinez, 2010). Nonetheless, it does not establish how this framework can be operationalized in real scenarios. On a different tack, facility-certification models have been proposed for supporting the creation of ECNs. Such traditional models, however, are incapable to balance their capacity with the demand changes

(Glickman et al., 2010). More recently, Gul and Guneri (2015), Gul and Guneri (2016), and Gul et al., (2019) have combined discrete-event simulation (DES) with different approaches such as Design of Experiments and Artificial Neural Network (ANN) to model and evaluate the response of an ECN (consisting of five EDs) located in Istanbul when facing increased demand caused by an earthquake. Despite the tremendous effort exposed in these works, several limitations still remain. For instance, the studies focused on designing collaborative scenarios for a particular disaster event. Additionally, they present the same restrictions identified in (Harrop, 2005). It is then evident that there is not an integrated methodology that leads policymakers towards the design and implementation of in-time ECNs considering the entire context of emergency care and collaboration schemes (Turner et al., 2015; Salisbury and Bell, 2010).

A starting point for the design and implementation of ECNs may include an individual intervention of the participant EDs to remove the non-value added activities that cause extended waiting times in the emergency rooms. Lean Six Sigma (LSS) is a method that can properly contribute to this particular aim. In fact, the use of LSS has recently gained prominence within EDs. Indeed, Mousavi Isfahani et al., (2019), Habidin et al., (2015), and Ahmed et al., (2013) reviewed the literature related to LSS applications in EDs and concluded that this method has significantly helped ED managers to reduce costs and prevent wastes of time. Specifically, Furterer reported significant reductions in waiting times as well as increased patient satisfaction in an ED after a 3-month project (Furterer, 2018). Another example is provided by Owad, Karim, and Ma who detailed an LSS application in the ED of Asseer Central Hospital in Saudi Arabia where waiting time during patient treatment and other key indicators were also upgraded (Al Owad et al., 2013) In spite of the significant results derived from LSS applications in EDs, there are no studies evidencing its use in ECNs. In fact, LSS may help to slacken the complexity of network interactions so that the number of patient transfers among participant EDs can be optimized.

Another key aspect that should be addressed is the correct functioning of ECNs in the wild. This begins with a design that must be simulated several times to evaluate patient flow, interactions among EDs, and other factors that may worsen waiting times in real scenarios. Given that trials and errors are non-viable, costly, and difficult to implement in the emergency care context, even in large-size ECNs; Discrete-event Simulation (DES) appears to be a suitable method for pretesting the performance of a recently designed ECN. In fact, the use of DES has become popular in the ED context (Romero-Conrado et al., 2017). For instance, Al-Assadi and Hasson (2018) utilized DES to maximize patients' throughput, minimize waiting times and optimize resources in Hilla ED- A similar study was undertaken by Ibrahim et al. who developed a computer simulation model in Arena software to test the response of an ED when facing increased levels of demand (Ibrahim et al., 2018). Another work is presented by Nuñez-Perez et al. (2017) who applied DES to model an Accident & Emergency department. In this study, the authors pretested three improvement scenarios to determine the most cost-effective strategy for decreasing patient waiting times. The use of DES for the evaluation of alternative scenarios was also evidenced in Bedoya-Valencia and Kirac (2016). More recently, DES has been combined with different approaches such as Design of Experiments (Baril et al., 2019), Machine learning (Gartner and Padman, 2019), ARIMA (Lin and Chia, 2018), Six sigma (Hussein et al., 2017; Mandahawi et al., 2017), and Data Envelopment Analysis (Aminuddin and Ismail, 2016) to provide more robust results and cover aspects that have not been considered in previous studies (e.g. identification of significant factors, demand forecasting, optimization of resources, etc.). Despite the high number of papers evidencing the application of DES in emergency care processes, studies directly concentrating on ECN design with the use of simulation approaches are largely limited and only focused on disaster events.

An additional issue of importance upon designing in-time ECNs is the definition of an equitable and efficient payment scheme. Such schemes may differ from one country to another whereas they are influenced by the payment and compensation clauses established by each government. In these clauses, some criteria such as, the maximum number of patients that can be seen in each ED and patient type are considered for regulating the collaboration practices. The attempts regarding the creation of payment models for healthcare networks can be found in Barrios et al.,

(2015) and Ortíz-Barrios et al., (2017). These studies implemented a modified version of the collateral payment model for regulating the utility distribution within an integrated network in outpatient internal medicine. In particular, the model considered the correlation between the lead time during the collaboration and the number of patients that a particular hospital received. As a result, the hospital with increased lead time (caused by the collaboration) was economically compensated in accordance with the payment table initially agreed under the collaboration scheme. As observed, the number of studies dealing with payment schemes within healthcare networks is recent and largely limited. Besides, none of the ECN-related studies focused on developing profit distribution agreements that regulate the allocation of payments among participant EDs. The lack of such agreements currently represents a serious limitation for more widespread implementation of ECNs and then becomes a research challenge that should be properly addressed by the practitioners and financial managers involved in this field.

In light of the reported literature, the evidence base on methodologies for creating in-time ECNs is scant and poorly developed with only uncontrolled descriptive studies. Under this consideration, the research question is: How to effectively design in-time and economically sustainable ECNs? To address this gaping hole, this paper presents a three-phase methodology based on DES, LSS, and collateral payment models which overcomes the limitations identified through the literature review. Consequently, the main contribution of this study will be three-fold: i) an integrated approach that helps healthcare managers to design ECNs that timely respond to the growing demand on emergency services, ii) a payment model that grants the efficient and equitable allocation of profits within the ECNs, and iii) the use of LSS and DES for propelling the timely functioning of ECNs.

2.2.3 The proposed methodology

A three-phase methodology (Fig 1) was proposed to design in-time and economically sustainable ECNs. The description of the steps contained in each phase is shown below.

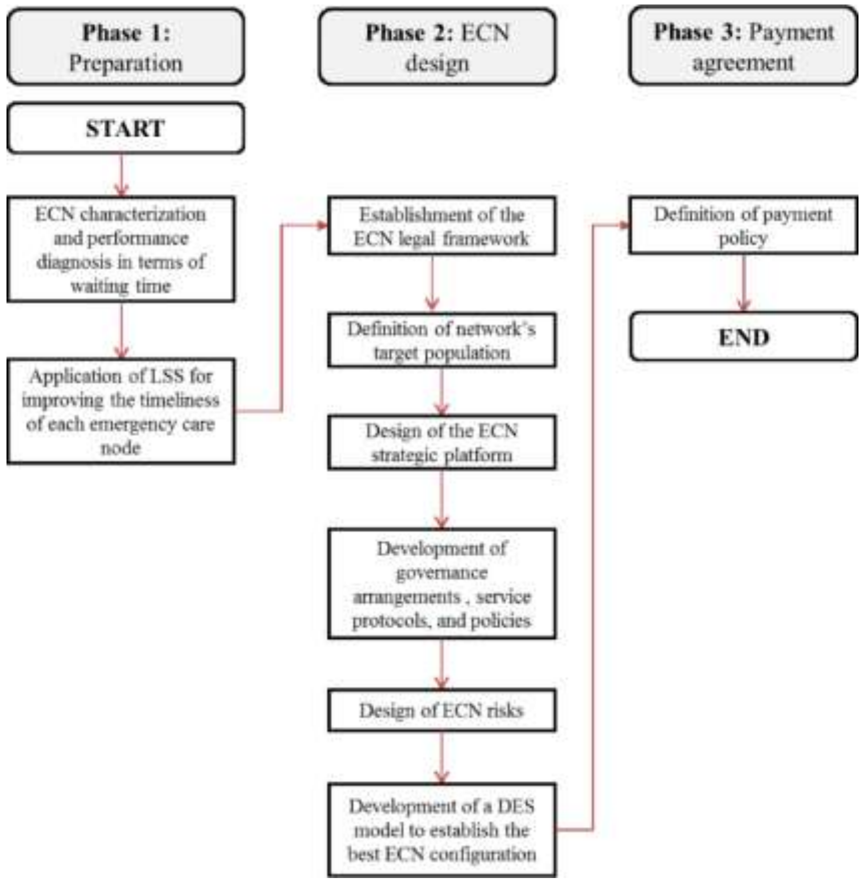


Figure 1. The proposed three-phase methodology for the design of in-time and economically sustainable ECNs

2.2.3.1 Phase 1: Preparation

Step 1. ECN characterization and performance diagnosis in terms of waiting time: ECNs can be considered as a nodal scheme where hospitals and POCs are nodes with multiple cooperation flows. Each node should be firstly described and diagnosed to: i) establish the current waiting time that patients may experience when arriving to the emergency room, ii) calculate the installed capacity, iii) identify the type of emergency that can be served in each node, iv) determine the geographical distance between nodes, v) pinpoint the health insurance companies whose patients are enabled to be diagnosed and treated in each node, and vi) estimate the standard deviation and average number of patients that EDs usually receive. Thereby, action plans can be effectively deployed to prepare hospitals and POCs for providing in-time attention within the ECN context.

Step 2. Application of LSS for improving the timeliness of each emergency care node: Removing non-value added activities in each emergency care node is critical for diminishing the expected waiting time that patients may experience within a particular ECN. Thereby, an individual preparation of EDs then contributes to the overall timeliness of ECNs and reduces operational drawbacks that may occur when implemented in the wild. LSS, as stated in the literature, can deal with this challenge (Barrios et al., 2014). The LSS procedure is supported by the DMAIC (Define, Measure, Analyze, Improve, and Control) cycle which is described below (Ortiz Barrios et al., 2016):

- *Define:* In this point, the waiting time problem is defined based on the estimations provided by Step 1. Also, the project scope, aims, and schedule are detailed through a project charter. Lately, the emergency care processes and stakeholders are fully characterized using SIPOC (Supplier-Input-Process-Output-Customers) diagrams.

- *Measure:* The measurement system is assessed to verify whether it provides reliable waiting time data. If this system is proved to be satisfactory, a capability analyze can be then undertaken to determine if the emergency care process meets with the standard waiting time.

- *Analyze:* It is necessary to analyze the value chain of emergency care process to identify the variation factors that contribute to the gap between the current waiting time and the desired standard. Some techniques like cause-and-effect analysis, design of experiments, 5 Whys, and Pareto diagram can be applied for this purpose.

- *Improve:* Solutions addressing the variation factors, as those supported by lean manufacturing techniques, need to be proposed, prioritized, and implemented by decision makers. The results are then evaluated through a before-and-after study which allows managers to determine whether the timeliness of the emergency care process is closer to the standard.

- *Control:* Lately, a control plan including individual X-R charts, is designed to monitor the waiting time behavior and maintaining the improvements achieved through the LSS intervention.

2.2.3.2 Phase 2: ECN design

Step 1. Establishment of the ECN legal framework: The design of ECNs must be coherent with the regulations established by each government concerning the provision of emergency care services. Therefore, in this step, the decision makers must collect the related laws, agreements, and regulations as well as identify the operational conditions that must be fulfilled before the ECN start. Besides, the current healthcare system should be graphically characterized for ensuring a correct ECN implementation in the wild.

Step 2. Definition of network's target population: Identifying the network's target population is critical for calculating the demand that can be expected to be covered by the ECN. This is defined through the arrangements concluded between the nodes and the health insurance companies which provide the number of affiliated patients to be potentially admitted within the ECN. Patients who are not covered by the social security should be also considered since, according to international agreements, "patient dumping" is not anymore allowed.

Step 3. Design of the ECN strategic platform: In this step, the mission, vision, and strategic goals of ECN are initially defined considering the network's target population, ECN legal framework, and current performance of participant EDs. After this, ECN corporative values are established taking into account its competitive characteristics, the most important stakeholders' expectations, critical-to-satisfaction (CTS) factors, and the external conditions. In particular, the stakeholders' needs regarding the ECN functioning are identified by performing a Voice of Customer (VOC) analysis (Ortíz Barrios et al., 2016). The needs with the highest relative frequency are then categorized as CTS factors and should be therefore prioritized by decision-makers when establishing the ECN configuration.

Step 4. Development of governance arrangements, service protocols, and policies: As ECNs are integrated by several collaborating EDs, agreed governance structures are necessary for regulating operational functioning and payment flows. Such structure should be led by an ECN Steering Committee (composed by the stakeholders: participant EDs, government, patients, ambulance service companies, and health insurers) whose primary aim is to drive the correct design, implementation, and monitoring of ECNs. In this group, cross-functional communication procedures as well as roles, authority, and responsibilities of each member should be clearly set for ensuring the correct deployment of the predefined strategic platform.

Aside from the governance aspects, service protocols and policies related to the provision of emergency care must be properly defined and disseminated among the emergency units to avoid errors that may endanger patients' safety. ECN managers should therefore: i) Collect, examine, and select the pertinent guidelines issued by the government and the related regulatory bodies; ii) Classify the selected guidelines into "indoors" and "outdoors" categories. "Indoors" represents the protocols and policies that must be applied within each ED; on the other hand, "Outdoors" refers to those implemented during patient transfers; iii) Identify the domains (Infrastructure - I, medical equipment - ME, procedures and protocols - PP, supporting processes - SP, human resources - HR, supplies/medicines and accessories - SMA, quality - Q, ambulance service - AS, and patient safety - PS) that are related to each guideline; and iv) Disseminate the selected guidelines to ~~all~~ the participant EDs before ECN start.

Step 5. Definition of ECN risks: Every risk must be adequately managed for avoiding potential failures during ECN functioning (Ortiz-Barrios et al., 2018). In this sense, risks (i.e. undertriage, patient transfer delay, etc.) must be first identified, evaluated, and prioritized. To do these, it is necessary to establish the process variables of the emergency care service (i.e. waiting time for triage consultation and average length of stay) that are critical for fulfilling the most popular stakeholder expectations. The criticality of these variables is defined by building a matrix specifying how each variable influences each expectation (influence scale – 0: No influence; 1: Extremely weak influence; 2: Weak influence; 3: Moderate influence; 4: Strong influence; 5: Extremely strong influence). Following this, potential failure modes of these variables (in this case, the ECN risks) need to be identified considering the expertise of several emergency care administrators, the pertinent scientific literature, the associated legal framework, and the ECN governance structure. Finally, FMEA (Failure Mode and Effect Analysis) is applied for their assessment and prioritization. Finally, strategies are created to diminish or eliminate the high-risk events if occurred.

Step 6. Development of a DES model to establish the ECN configuration: The use of Discrete-event Simulation (DES) in this context is supported by the following arguments: i) recording individual patient waiting time within the ECN is useful, ii) we are searching for cost-effective ECNs considering restricted resources (i.e. number of doctors, number of nurses, etc.), iii) we are interested in analyzing and optimizing the collaboration flows between EDs, iv) DES facilitates engagement with ECN managers through the animation of interactions and resources v) time-to-event behavior is better represented stochastically rather than with time intervals. The application of DES is widely recommended in all these cases according to Karnon *et al.* (2012) and Gillespie *et al.* (2016). The DES procedure for effectively establishing the best ECN configuration is as follows:

i) *Input data analysis*: The data collected in Phase 1 is initially prepared through an input analysis. First, an intra-variable independence test is performed to determine whether a specific process variable can be modeled through a statistical distribution function. Assuming that the randomness hypothesis is accepted, a heterogeneity analysis is undertaken using Kruskal-Wallis to classify the data. If the data are homogeneous, one probability distribution is enough to represent data; otherwise, a statistical expression must be defined per each group of data. The goodness-of-fit is validated through a Chi-squared test which also helps to determine the parameters that must be later incorporated into the DES model.

ii) *Creation and validation of a DES model*: The results derived from *Phase 1, Step 1* and input data analysis are entered into the simulation software to create a virtual version of the network. The model is then assessed for ensuring its reliability before implementation in the real scenario. In this regard, a pre-sample of 10 runs is first performed to calculate the sample size required for validation. Average waiting times must be collected in each run for verifying whether the simulated model is statistically equivalent to the real-world system. A comparison test between means/medians can be employed for this particular aim. If the resulting p-value is lower than the alpha level (α = 0.05), the simulated model is considered inappropriate for representing the real emergency care system; otherwise, it can be used for performance analysis and ECN design.

iii) *ECN configuration:* The next step is to create an ECN that satisfies the waiting time standards and conditions defined in the previous phases. The performance of the proposed ECN is statistically compared with the current emergency care system. If the p-value is higher than the alpha level (α = 0.05), the ECN is concluded to be satisfactory for reducing the waiting time; otherwise, it should be revised, improved, and reassessed before operation in the real scenario.

2.2.3.3 Phase 3: Payment agreement

Step 1. Definition of payment policy: The modified collateral payment model $\forall S\big(Nv(s)\big) = \left[\frac{M[1+r]}{1+\gamma\theta}\right]$ proposed by Barrios et al., (2015) is adopted in this approach. Here, the payment assignment is subject to the characteristic function $N = \{EN_1, EN_2, \dots, EN_m\}$ where EN_i represents the i-esim emergency node integrating a set of m nodes. The nodes are classified into: hospitals and POCs

The payment function covers a collaborative game $(2, v): P \to R$ where M denotes the amount of payment per admission that is provided to the coalition S depending on the health insurance company that the patient is affiliated to. On the other hand, γ and θ are constants that symbolize the contribution of each admission type to the total emergency visits. "γ" represents the percentage of 4-level-triage patients while "θ" denotes the percentage of 5-level-triage patients. The present approach only focuses on these categories due to the following reasons: i) The majority of ED patients are graded as low risk (triage levels 4-5) (Becker et al., 2015) and ii) These patients can be immediately transferred to another node since their risk of developing more severe complications (including death) is null or very low. Ultimately, “r” indicates the correlation between the waiting time of the node receiving the transferred ED patients (WT_i) and the number of admitted ED patients (nap_i). This measure is adopted to compensate those nodes whose waiting time is affected during the collaboration.

2.2.4 A case study of a public ECN

This chapter presents an application of the proposed methodology in a South American emergency care system integrated by 2 hospitals and 8 POCs. A detailed description of the case study is provided in each step to fully encompass the different key aspects that should be taken into account by practitioners and healthcare managers when designing in-time and economically sustainable ECNs.

2.2.4.1 ECN characterization and performance diagnosis in terms of waiting time

The first step is to properly characterize the EDs that can integrate the ECN and analyze the waiting time that patients may experience when admitted in the above-mentioned emergency care system. In particular, two types of nodes were identified: Hospitals and POCs. On one hand, POCs are nodes that lie at a distance of 1,500 meters from the urban zones and operate 24 hours per day. On the other hand, hospitals are the nodes with the highest installed capacity. They are, however, located further away from the community if compared to POCs. A matrix containing the transfer times (The times between nodes considering normal traffic conditions with no unforeseen eventualities) inherent to each particular slot. An example is provided in Table 1.

Table 1. Transfer times between nodes for afternoon slot (in minutes)

	H1	**H2**	**POC1**	**POC2**	**POC3**	**POC4**	**POC5**	**POC6**	**POC7**	**POC8**
H1	NA	11	6	22	10	4	8	14	13	14
H2	12	NA	18	29	19	12	13	13	9	25
POC1	6	19	NA	19	7	10	11	16	19	12
POC2	16	27	11	NA	10	20	20	20	25	22
POC3	9	19	8	14	NA	13	16	23	22	18
POC4	4	11	9	25	11	NA	10	13	12	18

POC5	8	13	11	28	15	9	NA	12	13	17
POC6	14	14	18	35	24	15	11	NA	8	17
POC7	14	9	19	32	20	12	15	6	NA	22
POC8	14	24	12	13	18	18	13	16	21	NA

Table 2 characterizes hospitals and POCs in terms of complexity level, installed capacity (beds), associated health insurance companies, demand, and waiting time. In particular, it can be observed that POC4 does not provide emergency care although it will be enabled in the future for improving the ECN timeliness. It can be also concluded that H2 is the node with the highest average and variable demand per semester (μ = 65,908.5 patients; σ^2 = 41,137). Additionally, H2 has the lowest waiting time compared to the rest of the nodes (μ = 3.71 minutes; σ^2 = 0.31) which evidences that its emergency care configuration effectively responds to the current demand. On a different tack, patients who ask for emergency care in H1 and POCs are expected to wait for more than the standard (30 minutes). Hence, cluster managers should focus on improving the timeliness of such nodes to minimize the operational drawbacks that may occur during the ECN operation.

Table 2. Characterization of nodes potentially integrating the ECN

Node	**Complexity Level**	**Installed capacity (beds)**	**Insurance companies**	**Demand (patients/semester)**		**Waiting time (min/patient)**	
				μ	**σ^2**	**μ**	**σ^2**
H1	1	12	S, BU, MS, COM, COO, SV	10,255.72	36.71	182.96	10,610.38
H2	2-3	35	S, BU, MS, COM, COO, SV	65,908.5	41,137	3.71	0.31
POC1	2	11	S, BU, MS, COM, COO, SV	11,521.08	55.26	188.36	9,854.44
POC2	2	13	S, BU, MS, COM, COO, SV	8,775.5	23.83	177.32	10,530.05
POC3	2	11	S, BU, MS, COM, COO, SV	8,370.25	20.94	184.50	11,427.58
POC4	2-3	NA	NA	NA	NA	NA	NA
POC5	2	14	S, BU, MS, COM, COO, SV	14,060.76	49.08	173.68	11,170.08
POC6	2	11	S, BU, MS, COM, COO, SV	8,339.89	42.73	190.02	10,269.51
POC7	2	12	S, BU, MS, COM, COO, SV	10,260.61	47.71	182.07	9,795.49
POC8	2	11	S, BU, MS, COM, COO, SV	8,355.67	41.67	187.15	10,519.84

2.2.4.2 Application of LSS for improving the timeliness of each emergency care node

The LSS is applied before the collaboration to reduce the waiting time of ED nodes and thereby, minimizing potential failures and operational drawbacks that may occur during emergency care and patient transfer flows. The LSS project implemented in POC3 has been taken as an example to describe how the timeliness can be improved through the DMAIC cycle:

➢ Define: Initially, a six-sigma team composed of six members (Quality manager, 2 Quality assistants, financial manager, financial assistant, and General Manager) was established to support the LSS implementation. The group was guided by two industrial engineers with a black belt level and wide experience in the execution of LSS projects.

A line chart was used to verify the current performance of POC3 in terms of waiting time. Minitab 17 ® software was employed for this particular aim. In this case, the average waiting time was found to be 201.6 min with a standard deviation of 81.6 min. In addition, Fig 2 indicates that the standard Upper Specification Limit (USL) has not been satisfied in the last operational year. POC3 then needs serious interventions to diminish the waiting time and consequently minimize patient dissatisfaction, overcrowding, operational costs, and the development of more severe complications related to patients' health.

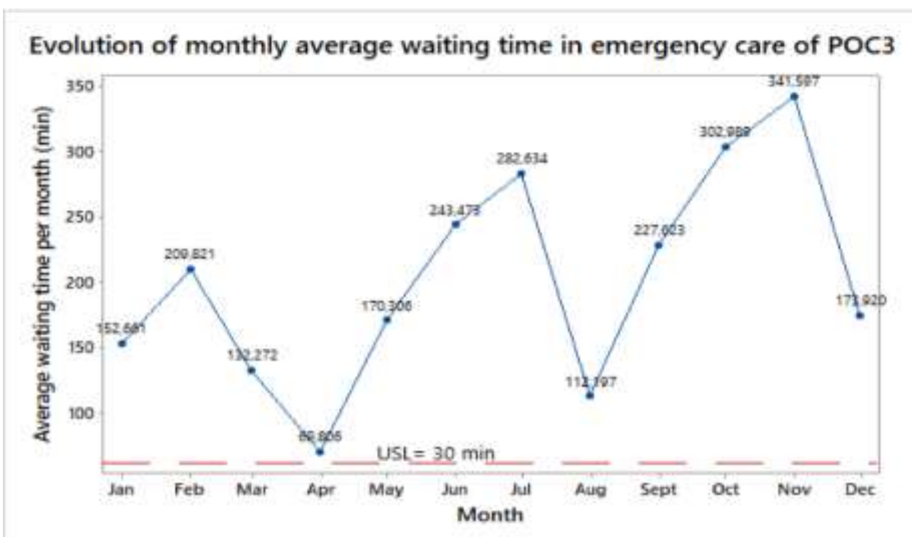


Figure 2. Average waiting time in emergency care – POC3

Considering the information above, a project charter was established. In this application, various benefits for the stakeholders (emergency patients, government, the board of directors, and clinical staff) and two key performance indexes (average waiting time in ER; operational cost per admission) were defined. In addition, the objectives were discussed to obtain formal approval from the sponsor and ethics committee before implementation. Afterward, a SIPOC diagram was created to identify the main activities of emergency care and the interactions with other departments within the node (Fig 3). By using this graph, different pathways and two instances of patients waiting for their physician (Potential intervention point) are observed; in addition, multiple and complex interactions take place in this node which is consistent with Kaushal *et al.* (2015) and Kuo *et al.* (2016).

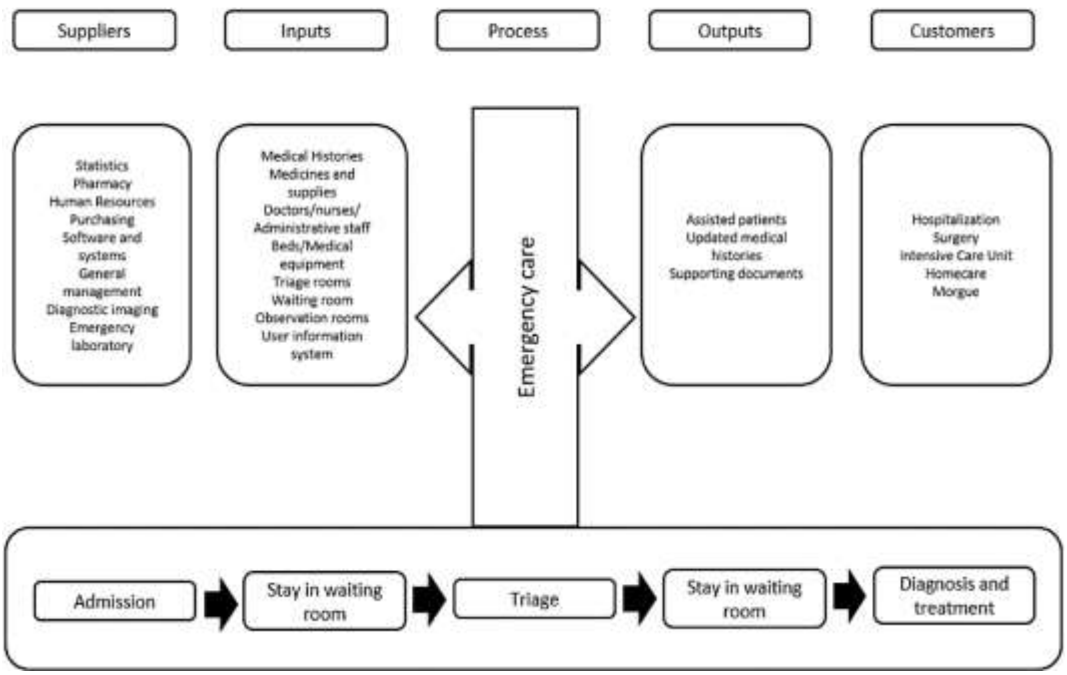


Figure 3. SIPOC diagram for emergency care in POC3

- Measure: The times of registration and initial contact with ER physician corresponding to the last operational year of POC3 (n = 16,741 admissions) were gathered using the Data Warehouse administered by the Ministry of Health and Social Protection. After this, waiting times were estimated with the support of Minitab 17® software. Then, a Ryan-Joiner test was performed to verify the normality of these data. With a p-value > 0.10, there is then sufficient evidence to conclude that waiting times follow a normal distribution.

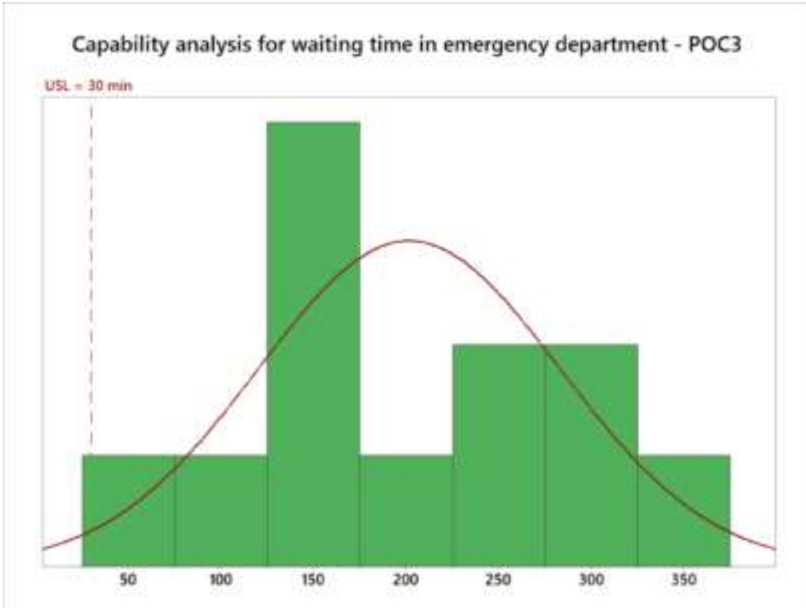


Figure 4. Capability analysis for waiting time in the emergency department – POC3

Afterwards, a capability study was undertaken to establish how capable POC3 is to meet the standards (Fig 4). Table 3 depicts the six sigma indicators that helped decision-makers to understand the current status of POC3 in terms of waiting time. First, *Cps* was found to be -0.73 which indicates that POC3 is not capable to comply with the standard. As the process is categorized in the lowest performance range, serious and profound changes are therefore necessary for improvement. This is consistent with the short-term sigma level (-2.10) which also reveals that the process is catastrophic and requires immediate intervention. In other words, it is estimated that 985,306.3 in every 1,000,000 patients will experience waiting times over 30 min.

Table 3. Six sigma indicators for waiting time in the emergency care – POC3

Waiting time in the emergency department – POC3			
USL (min)	30	Efficiency	1.47%
Mean	201.6	Cps	-0.73
Standard deviation	81.6	PPM > USL	985,306.3
Zu	-2.10	Short-term sigma level	-2.10
P(error)	98.53%	Long-term sigma level	-3.60

➢ Analyze: Considering the above-mentioned results, the emergency department in POC3 requires the development of improvement plans aiming at reducing the current waiting time experienced by patients before the first contact with the physician. In this regard, a fishbone diagram was created to find the root causes of the problem (Fig 5).

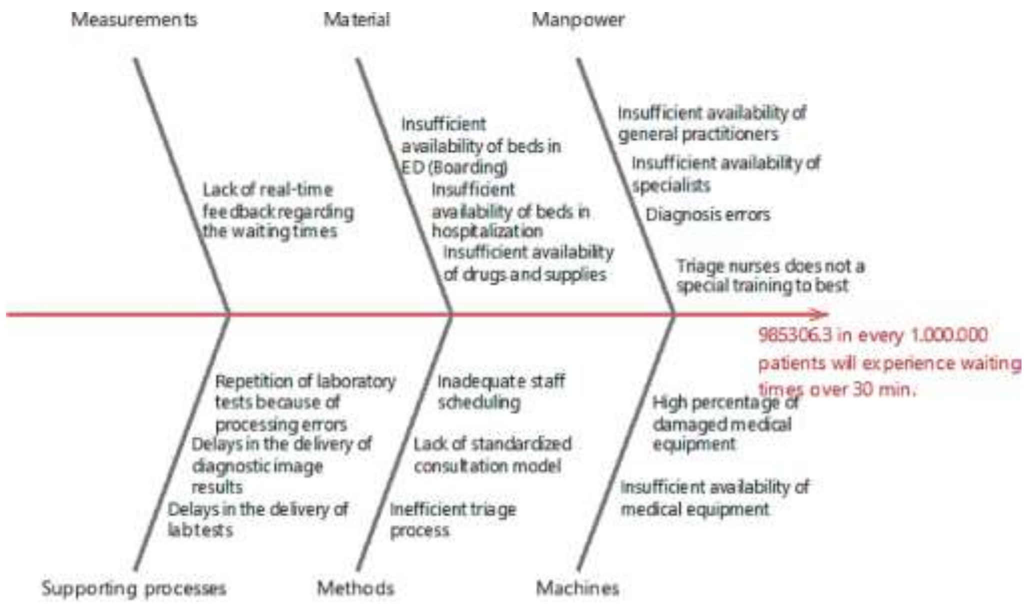


Figure 5. Fishbone diagram for establishing the potential causes of extended waiting times in the emergency department of POC3

The diagram evidences all the causes that may generate extended waiting times in the emergency department of POC3. The potential causes were identified with the aid of the Six-sigma team so that focused and further investigation can be made on the process. Statistical significance tests (α = 0.05) revealed that the *average waiting time for the delivery of diagnostic imaging to ED* was found to meaningfully contribute to the *increased waiting time experienced within the ED – POC3* (*p-value* = 0.000; β = 1.167; CL = 0.95). The potential influence of the average laboratory turnaround time was also explored. Similar to diagnostic imaging, a significant association was detected (*p-value* = 0.004; β = 0.734; CL = 0.95) (Hawkins, 2007). On the other hand, it was concluded that the *percentage of damaged equipment* also leads to the problem (*p-value* = 0.000; β = 937.8; CL = 0.95). These findings suggest that the untimely provision of diagnostic aids increases the length of stay and bed occupancy within the emergency department which, in the meantime, increases the waiting time experienced by the recently admitted patients (Brouns et al., 2015; Driesen et al., 2018). It is also evidenced that the effective provision of emergency care highly depends on the suitable management of interactions between the ED and other departments. In this regard, POC3 managers should focus on improving the response time of supporting departments so that diagnosis and treatment processes can be expedited within the ED.

On a different tack, *insufficient availability of beds in hospitalization, beds in ED, drugs and supplies, general practitioners, specialists, and medical equipment* were also found as significant regarding the extended waiting time (*p-value* < 0.005).

- Improve: Considering the analysis outputs, the six-sigma team proceeded with the creation of improvement strategies aiming at lowering the current waiting time experienced by patients. In this respect, four actions were proposed and instituted: i) Reconfiguration of work shifts according to the workload needs and the available number of laboratorians; ii) Transferring of specimens to the lab in batches so that the first batch can be processed whilst the second batch is collected; iii) A scheduling program that assigns radiologists to read studies according to a priority level that considers both patient triage category and delay; and iv) Removal of non-value activities during the reading of imaging studies through the use of Value Stream Mapping and other lean manufacturing techniques.

  After a 3-month intervention, the collected waiting times were processed with the aid of Minitab 17® software to evaluate whether the implemented changes were satisfactory. The results are summarized in Fig 6. In detail, the Cps (-0.45) has increased compared to the initial status; nonetheless, the process is not yet capable of meeting the government standards. This means that the implemented changes are not enough for propelling the ED to the desired performance. This is confirmed through the short-term sigma level (-1.41) and

PPM (921,329) which evidenced a slight improve but also a catastrophic emergency care in terms of waiting time. Consequently, the efficiency passed from 1.47% to 7.87% whilst the long-term sigma level increased to -2.91.

Table 4. Summary of results achieved through LSS projects in potential ECN nodes (except H2)

Node		H1	POC1	POC2	POC3	POC4	POC5	POC6	POC7	POC8
Short-term σ level		-0.69	-1.66	-1.23	-1.41	-1.42	0.31	2.51	3.49	3.43
PPM		755,915	951,187	890,103	921,329	922,368	376,994	5,979	237	302
Waiting time	M	69.9	126.03	89.87	103.1	126.98	26.11	17.14	13.89	13.20
	σ^2	3,305.3	3,361	2,381.3	2,671.1	4,656.9	153.74	26.18	21.25	23.99

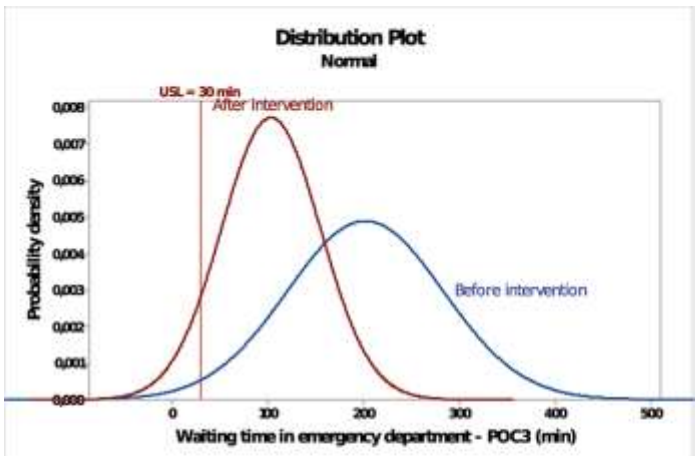


Figure 6. Before-after intervention in POC3

Similar to POC3, LSS was applied in each of the nodes (except H2 which has a short-term sigma level higher than 6) potentially integrating the ECN. The results in terms of average and standard deviation of waiting time, short-term sigma level, and PPM have been enlisted in Table 4. To sum up, all the hospitals and POCs improved their waiting time for emergency care. However, some nodes (POC1, POC2, POC3, POC4, and H1) still evidence a catastrophic process (PPM > 800,000; short-term sigma level < 0). Therefore, some changes are still necessary to diminish the patients' stay in waiting rooms. In this respect, improvement strategies regarding installed capacity and availability of resources may be explored through collaborative scenarios as detailed in the following steps of this implementation.

- Control: After implementing the improvement strategies and verifying their effectiveness in the wild, the Quality department proceeded with incorporating these changes into the Quality Management System. Besides, X-R control charts for individual observations were designed to monitor the average and variation of waiting times experienced by the emergency patients. All these activities were undertaken to keep the performance achieved during the LSS project and consequently avoid a potential decline in the timeliness of emergency care when collaborating with hospitals and POCs.

2.2.4.3 Establishment of the ECN legal framework

It was evident that further lowering of waiting times is still necessary. In this sense, a collaboration scheme may be a good option considering the restricted budget that prevents nodes from expanding their installed capacity. In this respect, an important step is the identification of the regulations governing the provision of emergency care in the region where the ECN will take place. Such regulations become a critical to satisfaction that must be taken into account by decision makers when designing the ECN. The related laws, regulations, and resolutions have been enlisted and shortly described in Table 5. The next step will be then to determine how the ECN can incorporate these insights in its daily operations so that legal requirements can be fully fulfilled.

Table 5. Laws, resolutions, and regulations related to the ECN design.

Law/Resolution/Agreement	Description	Main insights to consider in ECN design
Political Constitution	It establishes that healthcare is a public service in charge of the government. In this regard, the government must ensure the access to the promotion, protection, and habilitation of healthcare services. Also, it defines that these services must be provided under the principles of efficiency, solidarity, and universality. Finally, it specifies that healthcare attention must be organized by levels while ensuring the community involvement.	Principles of emergency care: i) Efficiency ii) Solidarity iii) Universality
System of Social and Integral Insurance	It indicates that the government is required to establish programs and policies ensuring the access to healthcare services under the principles of efficiency, solidarity, universality, integrality, community involvement, and unit.	Principles of emergency care: i) Efficiency ii) Solidarity iii) Universality iv) Integrality v) Unit
Mandatory System of Quality Assurance	It points out that healthcare providers must comply with the following conditions: i) Technical-administrative capacity, ii) financial and patrimonial proficiency, and iii) technological-scientific capacity. Besides, it specifies that healthcare services must be	a) The need for optimal balance among benefits, risks, and costs. b) Conditions for providing emergency care: i) Technical-administrative capacity

	provided in an accessible and equitable manner while considering an optimal balance among benefits, risks, and costs. This is to achieve a high satisfaction and loyalty of users. Finally, it involves specific procedures for the Quality information monitoring and management, habilitation, and accreditation.	ii) Financial and patrimonial proficiency iii) Technological-scientific capacity
Triage classification	It defines technical criteria for the selection and classification of patients in emergency departments "Triage". Specifically, 5 triage categories are described: Critical/Resuscitation, Emergency, Urgency, Minor Urgency, and Non-urgency. Besides, it outlines how triage systems can deployed in the wild.	Triage categories: i) Critical/Resuscitation ii) Emergency iii) Urgency iv) Minor Urgency v) Non-urgency

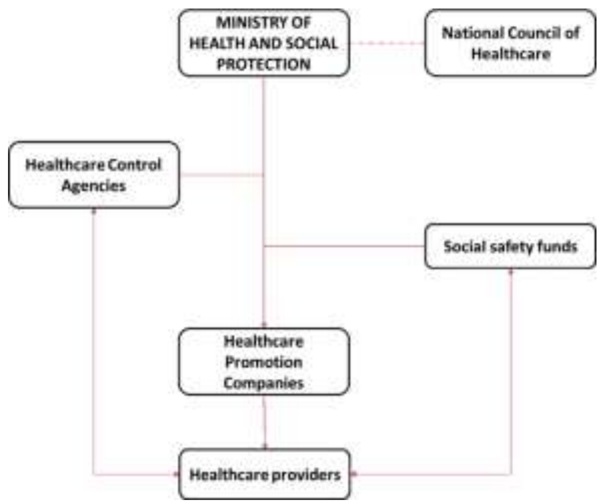


Fig 7. Configuration of healthcare system

Another important aspect to be considered within the legal framework is the current configuration of the healthcare system (Fig 7). This highly affects the flows of collaboration and information within the ECN and must be thus considered during the design process. Considering above, the ECN will be then involved in a very complex administrative and legal structure whose demands and regulations must be properly addressed to ensure a correct and efficient flow of operations, information, and earnings.

2.2.4.4 Definition of network's target population

Table 6 presents the number of affiliated patients to be potentially admitted within the ECN (1,229,996). In detail, MS is the insurance company with the highest portion of patients (n = 371,274 – 30.35%) while SV has the smallest participation (n =

92,887 – 7.59%). On the other hand, it is also necessary to consider the patients who are under a special regime (n = 37,314) or those who are not covered by social security (n = 47,973). This lies in the fact that, in accordance with the international regulations, “patient dumping” is not anymore permitted. In total, it is estimated that 1,315,283 patients will have access to the emergency services provided by the ECN.

Table 6. Number of affiliated patients to healthcare promotion companies

Health Insurance companies	S	BU	MS	COM	COO	SV	**TOTAL**
Number of affiliated patients	240,68	159,033	371,274	106,386	252,736	92,887	**1,229,996**

2.2.4.5 Design of the ECN strategic platform

Taking into account a target population of 1,315,283 patients, the ECN legal framework and the current performance of hospitals and POCs, we proceeded with the definition of the ECN strategic platform. Initially, the stakeholders and their critical-to-satisfaction (CTS) factors were identified (Table 7) through the VOC analysis. In summary, 17 stakeholders were found to be associated with the ECN functioning. Besides, the most popular expectations (CTS factors) were: *correct and complete provision of patients’ information* (n = 15; 88.23%), *nimble attention* (n = 7; 41.17%), and *respect and support from physicians and nurses* (n = 6; 35.29%). Such needs must be then highly prioritized by the managers so that stakeholders can be fully satisfied during ECN operation. This is complementary to the aforementioned legal framework and payment model that must be also incorporated into the ECN design. Considering these findings, the mission was defined as: *Our mission is to deliver nimble and high-quality emergency care for our patients through an efficient, integrated, and financially sustainable network of hospitals and points of care*. Besides, the vision was established as: *In 2,020, we will be recognized as the first regionalized, coordinated, and accountable emergency care network throughout the country.* After this, the board of directors defined four strategic goals supporting the accomplishment of mission and vision: *Aim 1:* To monitor the timeliness of care and ensure that patients do not experience excessive waiting times in ECN nodes; *Aim 2:* To ensure equitable distribution of payments within the ECN; *Aim 3:* To implement research projects targeting optimal resource allocation, patient flow, and information transfer; and *Aim 4:* To ensure the effective link among ECN nodes through a central information platform that facilitate decision-making and planning.

Table 7. ECN stakeholders and their expectations.

ECN stakeholders	Expectations
Ministry of health and social protection, National council of healthcare, Healthcare control agencies	• Nimble attention in ECN • Low readmission risk • Respect and support from physicians and nurses • Accessibility • Efficient use of resources • Correct and complete provision of patients' information
Social safety funds	• Nimble attention in ECN • Respect and support from physicians and nurses • Accessibility • Correct and complete provision of patients' information
Healthcare promotion companies	• Nimble attention in ECN • Low readmission risk • Respect and support from physicians and nurses • Correct and complete provision of patients' information
ECN Patients	• Nimble attention in ECN • EDs without overcrowding • Low transport times in ambulances • Availability of patient educational materials regarding triage classification • Appropriate diagnosis • Reasonable medical attention • Ward quality and privacy • Respect and support from physicians and nurses • Availability of drugs and supplies • Availability of appropriate and modern medical equipment • Safe care • Accessibility
Universities and other academic institutions	• Approval for executing research projects. • Employment of med students and trainees.
ED managers	• Nimble attention in ECN • Equitable distribution of payments • Low admission risk • Correct and complete provision of patients' information
ECN Physicians, ECN nurses	• Eds without overcrowding • Appropriate ECN layout • Availability of drugs and supplies • Satisfactory working conditions • Availability of appropriate and modern medical equipment • Correct and complete provision of patient's information
Hospitalization departments, intensive care units, surgery	• Correct and complete provision of patients' information • Patient transferred considering protocols.
Laboratories	• Correct and complete provision of patients' information • Optimal number of lab tests per patient • Correct and complete processing of lab test requests
Department of diagnostic imaging	• Correct and complete provision of patients' information • Optimal number of diagnostic images per patient • Correct and complete processing of diagnostic imaging requests
Supplies and drug management	• Correct and complete provision of patients' information • Optimal use of supplies and drugs.

	• Correct and complete processing of recipes and supply requests
Ambulance services	• Correct and complete provision of patients' information • Timely provision of patient transfer information (including receiving node and protocols)

Lately, the ECN corporative values were defined considering the stakeholders' expectations, external conditions, mission, and vision: *Collaboration*, *professionalism*, *evidence-based decision making*, *innovation*, *service excellence*, and *integrity*. Such values must be considered during the development of governance arrangements, service protocols, and policies, aspects that will be further analyzed in the next chapter.

2.2.4.6 Development of governance arrangements, service protocols, and policies

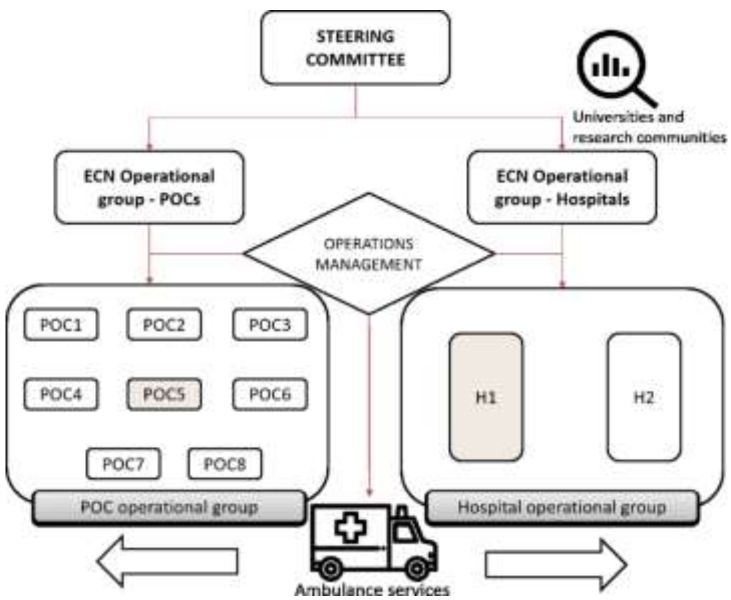


Figure 8. ECN governance structure

Fig 8 illustrates the governance structure to be adopted for regulating the ECN operations. The activities regulating this structure include: *clinical audit guideline implementation, measurement of KPIs,* and *risk management*. These tasks should be overseen by the *Steering Committee* which is also called to: i) drive improvements related to the quality, and cost-effectiveness of patient care, ii) steward resources within ECN and each node, iii) establish responsibility, authority, and accountability across the ECN, iv) propel the coherent integration among ECN nodes, v) review external conditions and national guidelines that may affect the ECN functioning, vi) supervise workforce planning across the ECN, vii) build relationships with other healthcare bodies, and viii) ensure preparedness across the ECN.

On a different tack, the *ECN operational groups* (POCs and hospitals) are led by 1 network coordinator each. Such groups are comprised of: ED managers, full-time consultants, and representatives from patients' association, ambulance services, operations management department, associated healthcare services (laboratories, hospitalization, intensive care unit, supplies and drug management, and diagnostic imaging department), ECN physicians, and ECN nurses. The functions of these groups are the following: i) supervise the implementation of improvement strategies designed by the *Steering Committee*, ii) undertake audits and examine data reports, iii) progress emergency care development and staffing matters at ECN level, iv) oversee risk management, clinical education, clinical audit, and other governance activities, v) propel effective communication among ECN nodes, vi) advise the *Steering Committee* regarding findings and aspects of relevance, and vii) govern interface flows.

On the other hand, each ECN node must continuously: i) verify advance in achieving KPI targets, ii) address staffing matters, iii) guarantee the stakeholders' participation in decision-making process, iv) monitor adverse events and ECN risks, v) revise feedback from the respective *ECN operational group*, vi) implement national guidelines related to emergency care, vii) implement educational programs regarding the ECN functioning and the correct use of emergency services. After defining the ECN governance structure, roles, authority, and responsibilities; the protocols and policies related to the provision of emergency care were established for implementation within the network (Table 8). To sum up, 6 types of protocols were identified, categorized (indoors/outdoors), and related to the pertinent domains of emergency care. Most of them (5), were classified as "indoors" while only 2 were considered as "outdoors". When relating these protocols to the ED domains, *procedures and protocols*, *human resources,* and *quality* were found to be influencing in the development of all the service regulations.

Table 8. Service protocols within ECN

Protocol	Category		Related domains
	Indoors	Outdoors	
Guide for emergency management	X	X	PP, ME, I, SMA, HR, SP, and Q.
Guide for good practices in patient safety	X		PS, I, HR, PP, SMA, ME, SP, and Q.
Basic guide for pre-hospital care		X	PS, HR, PP, SMA, ME, I, and Q.
Biosecurity, pegirase, cleaning and disinfection, and sex abuse	X		PS, HR, PP, SMA, ME, I, PS, and Q.
Guide for healthcare monitoring	X		PP, HR, SP, PS, and Q.
Guide for patients' referral and back-referral	X	X	PP, ME, SMA, HR, PS, and Q.

2.2.4.7 Definition of ECN risks

Table 9 enlists the failures that may occur during ECN operation (specifically related to waiting time) along with their severity (S), frequency (F), detection (D), and risk priority number (RPN) (Ortíz Barrios and Felizzola Jiménez, 2014). The risks with an RPN > 125 and significant severity (8-10) have been denoted with double asterisk (**) while risks with high RPN (> 125) and no meaningful impact (S < 7) were marked with one asterisk. Both types of risk must be prioritized for immediate intervention through corrective and preventive plans as detailed in Table 10. Based on the information provided by FMEA, the most critical failures (wrong triage classification and delay to triage; RPN = 450**) are related to *higher mortality rate*, no controls and frequent potential causes (misjudgment of the physical symptoms and delay during triage classification). This evidences that the triage processes are the major highest-risk sources within the ECN. Being aware of this situation, it is necessary to train doctors to categorize patients correctly, implement p control charts to monitor the percentage of correctly classified patients, and apply the Value Stream Mapping (VSM) to detect and eliminate non-value activities during the triage process.

Table 9. Failure mode and effect analysis for ECN operation.

Potential failure mode	Potential failure effects	S	Potential causes	F	Current controls	D	RPN
Wrong triage classification	Higher mortality rate	9	Misjudgment of the physical symptoms	5	None	10	450**
	Longer ER length of stay	5	Misjudgment of the physical symptoms	5	None	10	250*
	Development of more severe complications	8	Delayed authorization from HPCs	5	Delay analysis through indicators	1	40
			Heavy traffic	5	Google Maps	1	40
			Ambulance breakdown	2	Decision support system – Ambulance services	1	16

Patient transfer delay	Higher mortality rate	9	Delayed authorization from HPCs	5	Delay analysis through indicators	1	45
			Heavy traffic	5	Google Maps	1	45
			Ambulance breakdown	2	Decision support system – Ambulance services	1	18
	Longer ER length of stay	5	Delayed authorization from HPCs	5	Delay analysis through indicators	1	25
			Heavy traffic	5	Google Maps	1	25
			Ambulance breakdown	2	Decision support system – Ambulance services	1	10
	Low patient satisfaction	3	Delayed authorization from HPCs	5	Delay analysis through indicators	1	15
			Heavy traffic	5	Google Maps	1	15
			Ambulance breakdown	2	Decision support system – Ambulance services	1	6
Delay to triage	Development of more severe complications	8	Shortage of nursing staff	5	Annual capability analysis	6	240**
			Shortage of medical staff	5	Annual capability analysis	6	240**
			Lack of triage rooms	5	Annual capability analysis	6	240**
			Delay during triage classification	5	None	10	400**
	Higher mortality rate	9	Shortage of nursing staff	5	Annual capability analysis	6	270**
			Shortage of medical staff	5	Annual capability analysis	6	270**
			Lack of triage rooms	5	Annual capability analysis	6	270**
			Delay during triage classification	5	None	10	450**
	Longer ER length of stay	5	Shortage of nursing staff	5	Annual capability analysis	6	150*
			Shortage of medical staff	5	Annual capability analysis	6	150*
			Lack of triage rooms	5	Annual capability analysis	6	150*
			Delay during triage classification	5	None	10	250*
	Low patient satisfaction	3	Shortage of nursing staff	5	Annual capability analysis	6	90
			Shortage of medical staff	5	Annual capability analysis	6	90
			Lack of triage rooms	5	Annual capability analysis	6	90
			Delay during triage classification	5	None	10	150*
No access to entrance	Development of more severe complications	8	Overcrowding	9	Decision support systems/Delay analysis through indicators	1	72
	Higher mortality rate	9	Overcrowding	9	Decision support systems/Delay analysis through indicators	1	81
	Longer ER length of stay	5	Overcrowding	9	Decision support systems/Delay	1	45

					analysis through indicators		
	Low patient satisfaction	3	Overcrowding	9	Decision support systems/Delay analysis through indicators	1	27
Delay to quick register	Development of more severe complications	8	Shortage of receptionists	2	Annual capability analysis	6	96
			Unavailable user information system	3	Maintenance Inspection and reports of failures	1	24
			Extended patient admission process	2	None	10	160**
	Higher mortality rate	9	Shortage of receptionists	2	Annual capability analysis	6	108
			Lack of an user information system	3	Maintenance Inspection and reports of failures	1	27
			Extended patient admission process	2	None	10	180**
	Longer ER length of stay	5	Shortage of receptionists	2	Annual capability analysis	6	60
			Lack of an user information system	3	Maintenance Inspection and reports of failures	1	15
			Extended patient admission process	2	None	10	100
	Low patient satisfaction	3	Shortage of receptionists	2	Annual capability analysis	6	36
			Lack of an user information system	3	Maintenance Inspection and reports of failures	1	9
			Extended patient admission process	2	None	10	60
No ambulance available	Development of more severe complications	8	Shortage of ambulances	5	Decision support system – Ambulance services	1	40
			Ambulance breakdown	2	Decision support system – Ambulance services	1	16
	Higher mortality rate	9	Shortage of ambulances	5	Decision support system – Ambulance services	1	45
			Ambulance breakdown	2	Decision support system – Ambulance services	1	18
	Longer ER length of stay	5	Shortage of ambulances	5	Decision support system – Ambulance services	1	25
			Ambulance breakdown	2	Decision support system – Ambulance services	1	10

Table 10. Recommended actions for high-RPN failure modes.

Potential failure mode	Potential failure effect	Potential cause	Recommended actions
Wrong triage classification	Higher mortality rate	Misjudgment of the physical symptoms	-Train triage doctors to classify patients correctly. - Establish a p control chart for the proportion of wrong-triaged patients.
Wrong triage classification	Longer ER length of stay	Misjudgment of the physical symptoms	
Delay to triage	Development of more severe complications	Shortage of nursing staff	-Perform short-term load analysis (every month) to determine the required nursing and medical staff in triage. -According to the previous point, hire the required doctors and nurses (if necessary)
Delay to triage	Development of more severe complications	Shortage of medical staff	
Delay to triage	Development of more severe complications	Lack of triage rooms	-Implementation of fast-track triage.
Delay to triage	Development of more severe complications	Delay during triage classification	- Perform a VSM analysis to detect and eliminate non-value activities during triage classification.
Delay to triage	Higher mortality rate	Shortage of nursing staff	-Perform short-term load analysis (every month) to determine the required nursing and medical staff in triage. -According to the previous point, hire the required doctors and nurses (if necessary)
Delay to triage	Higher mortality rate	Shortage of medical staff	
Delay to triage	Higher mortality rate	Lack of triage rooms	-Implementation of fast-track triage.
Delay to triage	Higher mortality rate	Delay during triage classification	- Perform a VSM analysis to detect and eliminate non-value activities during triage classification.
Delay to triage	Longer ER length of stay	Shortage of nursing staff	-Perform short-term load analysis (every month) to determine the required nursing and medical staff in triage. -According to the previous point, hire the required doctors and nurses (if necessary)
Delay to triage	Longer ER length of stay	Shortage of medical staff	
Delay to triage	Longer ER length of stay	Lack of triage rooms	-Implementation of fast-track triage.
Delay to triage	Longer ER length of stay	Delay during triage classification	- Perform a VSM analysis to detect and eliminate non-value activities during triage classification.
Delay to triage	Low patient satisfaction	Delay during triage classification	
Delay to quick register	Development of more severe complications	Extended patient admission process	- Perform a VSM analysis to detect and eliminate non-value activities during admission process.
Delay to quick register	Higher mortality rate	Extended patient admission process	

2.2.4.8 Development of a DES model to establish the ECN configuration

The next step is to design a virtual model representing how the ECN will operate within the aforedescribed context. Such a model will serve as a platform for i) deciding whether a patient should be transferred to another node, ii) identifying which node can provide the most timely emergency care considering transfer times, iii) assessing the balance between the current installed capacity and demand, iv) evaluating new scheduling policies, and v) determining ambulance service requirements based on transferring needs. The model robustness, however, lays on the correct deployment of the step-by-step procedure explained in Phase 2~~)~~. The results of applying such a procedure in our case study network are further detailed in the following paragraphs.

2.2.4.8.1 Input data analysis

Data corresponding to 8 variables were collected for representing the real performance of each node (Table 11). Run tests (α = 0.05) were initially performed to determine if these variables were random in each node. The results obtained from H1 are provided as an example (Table 11). In this case, the p-values and *k* metrics provided enough support for accepting the independence hypothesis. This pattern was also found to be valid in the rest of ECN nodes.

Table 11. Results of randomness tests in H1

Process variable	**K**	**P-value**
Time between arrivals (min)	33.349	0.387
Triage time per patient (min)	3.495	0.235
Admission time (min)	7.482	0.553
Bed preparation time (min)	7.509	0.691
Nursing assistance time (min)	6.499	0.223
Physician assessment time (min)	16.025	0.162
Treatment time (min)	251.886	0.681

After verifying the randomness nature of these variables, Kruskal-Wallis tests (α = 0.05) were undertaken to identify potential sub-groups of data. In H1 (Table 12), mostly variables were found to be homogeneous except “time between arrivals” (p-value = 0). This outcome is explained by the presence of different demand patterns throughout time. Specifically, the weekday and period of arrival were found to explain the variation observed in the number of emergency admissions (p-value < 0.001). This means that a statistical expression must be defined for representing the time between arrivals corresponding to each combination “weekday-time slot”; in the meantime, one probability distribution is sufficient for describing the homogeneous variables considered in this network. The above-mentioned conclusions were also derived from the other hospitals and POCs.

Table 12. Results of homogeneity tests in H1

Process variable	P-value	Conclusion
Time between arrivals (min)	0.000	Heterogeneous
Triage time per patient (min)	>0.15	Homogeneous
Admission time (min)	>0.10	Homogeneous
Bed preparation time (min)	>0.15	Homogeneous
Nursing assistance time (min)	>0.15	Homogeneous
Physician assessment time (min)	>0.15	Homogeneous
Treatment time (min)	0.363	Homogeneous

Chi-squared tests (α = 0.05) were then implemented to find the statistical distribution that better fits each variable. H1 was again selected to evidence the application of these tests (Table 13). Following this, an ANOVA F-test (α = 0.05) was performed to determine whether the "time between arrivals" needed to be divided in time slots. As a result, 21 pipelines conditioned by the combination of seven weekdays (M: Monday, Tu: Tuesday; W: Wednesday; Th: Thursday; F: Friday; Sa: Saturday; Su: Sunday) and three time slots: P1 (12:00 am – 8:00 am), P2 (8:00 am – 4:00 pm), and P3 (4:00 pm – 12:00 am) were identified (p-value < 0.005); thereby confirming the heterogeneous nature of "time between arrivals" throughout the weekdays and day shifts. This process was repeated until defining the probability distributions of all variables affecting the ECN operation.

Table 13. Results of Goodness-of-fit tests in H1.

Process variable		Expression	P-value
Time between arrivals (min)	M-P1	514 * BETA(0.917, 5.4)	0.0883
	M-P2	EXPO(24.5)	0.184
	M-P3	EXPO(21.3)	>0.75
	Tu-P1	-0.001 + WEIB(63.9, 1.06)	0.282
	Tu-P2	WEIB(22.5, 1.07)	0.466
	Tu-P3	EXPO(18.5)	0.554
	W-P1	EXPO(57.2)	0.034
	W-P2	EXPO(23.8)	0.26
	W-P3	EXPO(19.5)	0.707
	Th-P1	GAMM(59.7, 1)	0.75
	Th-P2	GAMM(23.9, 0.942)	>0.75
	Th-P3	EXPO(20)	0.508
	F-P1	GAMM(57.1, 1.01)	0.75
	F-P2	GAMM(22, 0.991)	>0.75
	F-P3	EXPO(19.4)	0.168
	Sa-P1	GAMM(51.9, 1.05)	>0.75

	Sa-P2	GAMM(20, 0.989)	>0.75
	Sa-P3	GAMM(14.5, 1.07)	0.653
	Su-P1	EXPO(52.4)	0.341
	Su-P2	GAMM(20.1, 1.01)	0.75
	Su-P3	EXPO(17.4)	0.598
Triage time per patient (min)		UNIF (2, 5)	>0.15
Admission time (min)		UNIF (5, 10)	>0.15
Bed preparation time (min)		UNIF (5, 10)	>0.15
Nursing assistance time (min)		UNIF (6, 7)	>0.15
Physician assessment time (min)		UNIF (5, 27)	0.072
Treatment time (min)		19 + WEIB (247, 1.21)	0.718

2.2.4.8.2 Creation and validation of a DES model

A DES model was created through Arena® 15 to provide a virtual representation of the current emergency care system and internal configuration of hospitals and POCs (Fig 9). The model incorporated the results of previous steps including the input analysis and system characterization. Given the continuous operation of emergency departments, a replication length time (365 days – 24 hours per day) assumed during the simulation. Also, the warm-up period was defined to be 100 days since, at this point, the variation of the blocking probability was found to be near 0 (95% CI [1.85%; 1.89%]); thereby denoting that the steady state of the system has been achieved. Ten replications were later carried out for estimating the number of iterations that should be finally run for validating the simulated system. In this case, 4,532 replications were found to be necessary for representing the waits experienced by patients within this network. After gathering the waiting times derived from each replication, we proceeded to evaluate the equivalence hypothesis ($H_0: \mu = 58.9 \frac{min}{admission} || H_0: \mu \neq 58.9 \frac{min}{admission}$). In this case, the 1-sample t test (Confidence level = 0.95) evidenced that the simulated model is statistically comparable with the real system (*p*-value = 0.586; T = 0.54; 95%CI [62.37 – 65.87] min). This outcome was corroborated through a one-sample variance test whose *p*-value (0.099) confirms that the model is suitable to support performance analysis and ECN design.

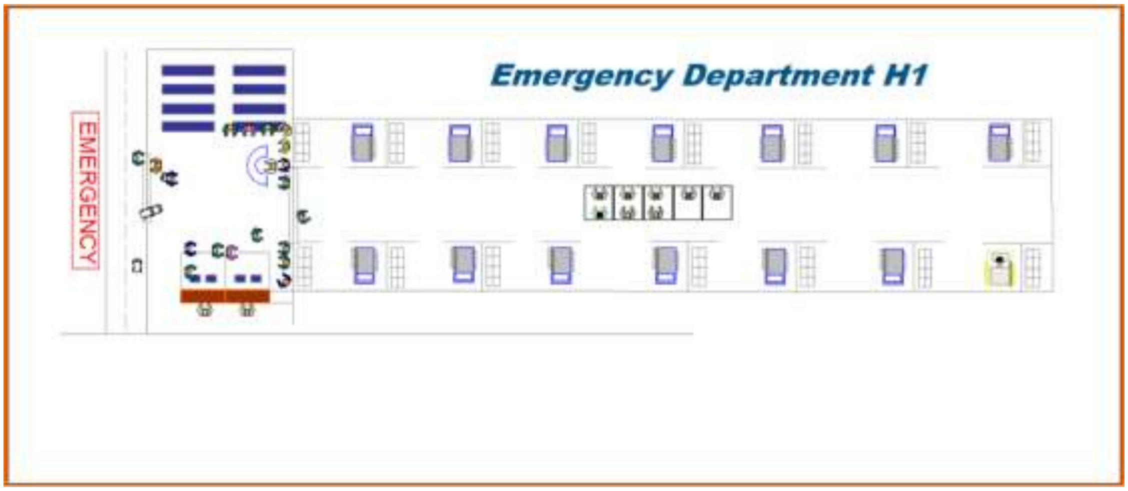


Figure 9. Simulation model of emergency department H1

2.2.4.8.3 ECN configuration

It is noteworthy that hospitals and POCs involved in the current emergency care system do not consider transferring patients admitted in their emergency rooms. In other words, each node takes care of their patients no matter how much time they have to wait before diagnosis and treatment. Our proposal is then to design an ECN where hospitals and POCs can collaborate so that patient waiting times can be plummeted while ensuring financial sustainability. To do these, several policies should be adopted into the network: i) Only 4-level-triage and 5-level-triage patients can be transferred from one node to the other; ii) A patient is transferred if the waiting time offered by the origin node is higher than the sum between the transfer time and the waiting time expected in destination node; otherwise, the patient should be treated in the origin node. If there are several transferring alternatives, managers should select the alternative with the lowest sum; iii) Conditions regarding emergency care provision and triage classification system must be fulfilled by nodes to interact within the network; iv) Both origin and destination nodes must hold an agreement with the healthcare promotion company to which the patient belongs. If this condition is not met, the patient cannot be transferred; v) “Patient dumping” is not permitted in this network; vi) Correct and complete provision of patients’ information, nimble attention, and respect/support from physicians and nurses must be granted during ECN operation; vii) Every participating node must adopt a DSS to verify if another node can provide faster emergency care considering transfer times.

The DSS is also called to support the transferring process if this is finally approved by the Operations Management department; viii) Participating nodes are required to assume the ECN governance structure during operation; and ix) Hospitals and POCs must adhere to the recommendations derived from FMEA application to effectively deal with the predefined risks.

The ECN incorporating all these policies was later modeled, simulated, and assessed to define whether it was effective for minimizing waiting times. Table 14 presents the door-to-physician times that may be experienced by patients if hospitals and POCs operate collaboratively as a network. From this table, it can be inferred that the waiting time mean and variance were minimized in H1, POC1, POC2, POC3, and POC4 nodes; while these metrics increased in H2, POC5, POC6, POC7, and POC8. The next step was to perform a before-and-after analysis for verifying the effectiveness of the network if implemented in the wild.

Table 14. Projected waiting times (if the ECN is implemented)

Node		H1	H2	POC1	POC2	POC3	POC4	POC5	POC6	POC7	POC8
Waiting time	M	48.23	4.19	80.65	70.99	76.29	96.50	29.5	19.53	15.69	15.04
	σ^2	2,082.33	0.35	2,083.82	1,857.41	1,762.92	2,840.7	173.72	29.84	24.01	27.34

The null and alternative hypothesis associated to this analysis are as follows: $Ho: n_{ECN-}n_c = 0||Ha: n_{ECN-}n_c < 0$. Here, n_{ECN} denotes the median waiting time experienced by emergency patients if the ECN is implemented while n_C represents the median ED waiting time experienced by patients under the current configuration. Given the non-normality of n_{ECN} and n_C, a non-parametric comparison test (in this case, Mann Whitney) was decided to be applied (using Minitab 19® software) for validating the hypothesis. In this case, the Mann-Whitney test provided sufficient support to conclude that the ECN is satisfactory for lowering the ED waiting time (*p*-value = 0; W = 17,791,765.5; 95%D[-9.08; -6.71]). In particular, if the ECN is implemented, the patients may experience a faster emergency care with an expected reduction of waiting times ranging from 6.71 min and 9.08 min. On the other hand, a paired t-test (using Minitab 19® software) was undertaken to verify whether the median ED bed occupancy would increase after implementing the proposed framework ($Ho: n_{BO(ECN)-}n_{BO(c)} = 0||Ha: n_{BO(ECN)-}n_{BO(c)} < 0$).

Here, $n_{BO(ECN)}$symbolizes the median bed occupancy in POCs and hospitals if the ECN is implemented while $n_{BO(C)}$ denotes the median bed occupancy in POCs and hospitals under the current configuration. The results revealed that hospitals and POCs would have resource utilization rates (*p*-value = 0; T = 5.85; 95%D [8.06%; 18.21%]) ranging from 8.06% and 18.21% increase (Confidence level = 95%) if the proposed network design is adopted. In light of these results, the proposed methodology is hence considered as effective for ensuring not only the timeliness of the ECN here designed but the resource usage within each node.

2.2.4.9 Definition of payment policy

After verifying the advantages of collaboration in terms of waiting times, it is necessary to ensure the efficient and equitable distribution of payments among participant hospitals and POCs either origin or destination nodes. The collateral payment model is proposed within this study to deal with this challenge. One of the variables influencing the model is *M* which denotes the amount of payment that is provided to the coalition *S* when a patient is transferred to a destination node. The unit utility value depends on the healthcare promotion company that the patient is affiliated to (Table 15). Other variables of interest in this scheme are γ (percentage of 4-level-triage patients) and θ (percentage of 5-level-triage patients). In this network, γ and θ were found to be 0.19 and 0.46 respectively. After defining these parameters, we proceeded to establish the payment distribution between the origin and destination nodes (Table 16).

Table 15. Unit utility values agreed with healthcare promotion companies

Healthcare promotion company	S	BU	MS	COM	COO	SV
M (Unit utility value) in US$	10.34	4.91	4.91	4.91	5.11	9.97

Table 16. Payment distribution arrangements between origin and destination nodes

		Destination Node									
		H1	**H2**	**POC1**	**POC2**	**POC3**	**POC4**	**POC5**	**POC6**	**POC7**	**POC8**
Origin Node	**H1**	M	A	B	B	B	B	B	B	B	B
	H2	C	M	B	B	B	B	B	B	B	B
	POC1	C	A	M	B	B	B	B	B	B	B
	POC2	C	A	B	M	B	B	B	B	B	B
	POC3	C	A	B	B	M	B	B	B	B	B
	POC4	C	A	B	B	B	M	B	B	B	B

	POC5	C	A	B	B	B	B	M	B	B	B
	POC6	C	A	B	B	B	B	B	M	B	B
	POC7	C	A	B	B	B	B	B	B	M	B
	POC8	C	A	B	B	B	B	B	B	B	M

If the origin and destination nodes are the same, the hospital or POC receives *M*; otherwise, payment arrangements *A*, *B,* or *C* must be applied according to Table 16. The arrangements are described as follows:

- *"A"*- Origin node: $M - Máx\{US\$3.92; \frac{M(1+r)}{1+\gamma\theta}\}$ || Destination node: $Máx\{US\$3.92; \frac{M(1+r)}{1+\gamma\theta}\}$
- *"B"*- Origin node: $M - Máx\{US\$3.50; \frac{M(1+r)}{1+\gamma\theta}\}$ || Destination node: $Máx\{US\$3.50; \frac{M(1+r)}{1+\gamma\theta}\}$
- *"C"* - Origin node: $M - Máx\{US\$4.50; \frac{M(1+r)}{1+\gamma\theta}\}$ || Destination node: $Máx\{US\$4.50; \frac{M(1+r)}{1+\gamma\theta}\}$

Table 17 specifies how payments have been settled for coalition H1-H2 considering the above-cited collateral model. In this case, transfer flow "p" from H1 to H2 (6,052 patients) was found to be significantly higher compared to the number of remissions taking place from H2 to H1 (450 patients). On the other hand, non-significant differences were detected when comparing the correlation values of H1-H2 and H2-H1 (p-value = 0.123; T = -1.85; 95%D[-0.1145; 0.0185]). Moreover, the low correlation values observed in this coalition (r ≤ 0.152) indicate that transferred ED patients caused slight affectations on waiting times experienced in destination nodes. It is also good to highlight that two different payment arrangements were applied: "A" (H1-H2) and "C" (H2-H1). In the scheme "A", the destination node (H2) received US$3.92 for patients affiliated to BU, MS, COM, and COO while this rate increased to US$6.36 and US$6.13 when receiving patients from S and SV respectively. A similar pattern was observed upon applying the arrangement "C". In this case, H1 earned US$7.08 and US$6.25 per S-covered and SV-covered patient correspondingly. Likewise, the lowest payment rate (US$4.5) was adopted when admitting patients from BU, MS, COM, and COO. Such results are mainly due to the combination of low correlation scores and utility values. On a different tack, both H1 and H2 obtained financial gains (H1: US$12,662; H2: US$29,980) from the coalition. This is highly attractive considering the need for ensuring the financial sustainability of nodes while providing timely emergency care to patients.

Table 17. Payment distribution for coalition between H1 and H2 (1 year of simulation)

H1-H2							H2-H1						
	S	**BU**	**MS**	**COM**	**COO**	**SV**		**S**	**BU**	**MS**	**COM**	**COO**	**SV**
nap_i	1,190	788	1,833	529	1,249	463	**nap_i**	89	59	136	39	93	34
R	0.015	0.054	0.043	0.046	0.016	0.021	**R**	0.13	0.152	0.024	0.018	0.124	0.035
P(H1)	4,735	780	1,814	523	2,485	1,759	**P(H1)***	290	24	55	15	56	126
P(H2)*	7,569	3,089	7,185	2,073	4,896	2,856	**P(H2)**	630	265	612	175	418	212
TP(H1) = P(H1) + P(H1)*				US$ 12,662									
TP(H2) = P(H2) + P(H2)*				US$ 29,980									

The payment settlement process was then repeated until obtaining the total profits of each node (Table 18). In this case, H2 and POC8 were found to be the nodes with the highest total gain within the network (US$212,142 and US$77,064 respectively). It is good to highlight that the significant difference (in terms of total profit) observed between H2 and the rest of nodes is explained by the high number of patients transferred to this hospital (31,810) and the increased waiting time resulting from the collaboration (WT_2 = 4.19; σ^2 = 0.35). Lately, it is noteworthy that all nodes obtained financial benefits (μ = US$58,152/node) while ensuring the earliest possible emergency care to patients.

Table 18. Total profits of nodes after 1-year collaboration

Node	H1	H2	POC1	POC2	POC3	POC4	POC5	POC6	POC7	POC8
Total profit (in US$)	36,067	212,142	24,756	19,132	18,721	8,138	47,73	61,847	75,923	77,064

2.2.5 Concluding remarks

ECNs are an important alternative to deal with the excessive waiting time perceived by patients requiring emergency care. These structures, however, are complex to design due to the presence of multiple nodes, resources, and collaboration flows. Moreover, they are called to ensure an equitable and efficient distribution of profits within the network considering different utility functions, healthcare promotion companies, and payment arrangements. In this paper, we proposed a three-phase methodology for the effective creation of ECNs. This approach initiated by characterizing and preparing the nodes through lean six-sigma; thereby the network complexity could be meaningfully diminished before collaboration. We then proceeded to design the ECN considering the legal framework, network's target population, strategic platform, governance arrangements, service protocols, policies, and risks. After this, the ECN configuration was defined using DES. Finally, payments derived from the collaboration were established by applying the collateral model.

From the managerial perspective, our proposed methodology is suitable for providing decision support to policymakers, government authorities, ED administrators, and stakeholders when addressing the following scenarios: i) deciding whether a patient should be transferred to another node, ii) defining the node providing the most timely emergency care considering transfer times, iii) evaluating the balance between the network capacity and demand, iv) assessing staffing policies, v) estimating ambulance service requirements based on transferring needs, and vi) efficiently distributing profits among participant ECN nodes. From the scientific angle, our paper bridged the gap detected in the literature by laying the methodological groundwork required for the creation of new ECNs in a plethora of healthcare contexts (Ortíz-Barrios and Alfaro-Saíz, 2020).

Concerning the scenario under study, an emergency care system integrated by 2 hospitals and 8 POCs, the results revealed that H2 is the node with the highest average and variable demand per semester (μ = 65,908.5 patients; σ^2 = 41,137) while H2 has the lowest door-to-doctor time compared to the rest of nodes (μ = 3.71 minutes; σ^2 = 0.31). Overall, patients requiring emergency care in H1 and POCs were found to wait for more than the government target which was corroborated through negative six sigma levels in most cases. Although the efficiency scores were augmented in all nodes using LSS, collaboration practices were concluded to be necessary. Along the path towards the ECN consolidation, it was determined that: i) 1,229,996 patients are projected to be admitted within the ECN, ii) "*correct and complete provision of patients' information"* (n = 15; 88.23%), "*nimble attention"* (n = 7; 41.17%), and "*respect and support from physicians and nurses"* (n = 6; 35.29%)

were found to be the critical to satisfaction, iii) the most critical failures were: wrong triage classification and delay to triage with RPN = 450, and iv) the ECN configuration was found to be satisfactory for lowering the ED waiting time (p-value = 0; W = 17,791,765.5; 95%D[-9.08; -6.71]). On a different tack, three payment arrangements were designed as a basis of the collateral payment model. Such a model was concluded to be satisfactory for nodes upon offering good compensation schemes while propelling lower waiting times for patients.

Given the considerable potential of this approach, we plan in the future to incorporate transferring costs and ambulance routing optimization models for increasing the ECN competitiveness. Thereby, more informative and detailed simulations can be provided for assessing more complex scenarios and interactions. It is also intended to contrast our modified collateral payment scheme with other utility distribution models to improve the profit allocation efficiency within the network.

2.2.6 References

Ahmed S, Manaf NHA, Islam R. Effects of Lean Six Sigma application in healthcare services: A literature review. Rev Environ Health 2013;28(4):189-194.

Al Owad A, Karim MA, Ma L. Integrated Lean Six Sigma approach for patient flow improvement in hospital emergency department. Adv Mater Res 2013;834-836:1893-1902.

Al-Asadi RY, Hasson. Modeling the Healthcare Services in Hilla Emergency Department. ICOASE 2018 - International Conference on Advanced Science and Engineering; 2018.

Almeida AC, Gusmão Filho FAR, Caldas AF, Vidal SA, Campello RIC. From normative imaginary reality of the Network of Emergency Care. Medicina 2015;48(6):557-572.

Aminuddin WMWM, Ismail WR. Integrated simulation and data envelopment analysis models in emergency department. AIP Conference Proceedings; 2016.

Baier N, Geissler A, Bech M, Bernstein D, Cowling TE, Jackson T, et al. Emergency and urgent care systems in Australia, Denmark, England, France, Germany and the Netherlands – Analyzing organization, payment and reforms. Health Policy 2019;123(1):1-10.

Baril C, Gascon V, Vadeboncoeur D. Discrete-event simulation and design of experiments to study ambulatory patient waiting time in an emergency department. J Oper Res Soc 2019;70(12):2019-2038.

Barrios MAO, Caballero JE, Sánchez FS. A methodology for the creation of integrated service networks in outpatient internal medicine. Lect Notes Comput Sci 2015;9456:247-257.

Barrios MO, Jiménez HF, Isaza SN. Comparative analysis between anp and anp-dematel for six sigma project selection process in a healthcare provider. Lect Notes Comput Sci 2014;8868:413-416.

Becker JB, Lopes MCBT, Pinto MF, Campanharo CRV, Barbosa DA, Batista REA. Triage at the Emergency Department: Association between triage levels and patient outcome. Rev Escola Enferm 2015;49(5):783-789.

Bedoya Marrugo EA. Emergency care service in the city Cartagena Colombia. Nova 2017; 15(27):91-101.

Bedoya-Valencia L, Kirac E. Evaluating alternative resource allocation in an emergency department using discrete event simulation. Simulation 2016;92(12):1041-1051.

Brouns SHA, Stassen PM, Lambooij SLE, Dieleman J, Vanderfeesten ITP, Haak HR. Organisational factors induce prolonged emergency department length of stay in elderly patients - A retrospective cohort study. PLoS ONE 2015;10(8).

Calvello EJB, Broccoli M, Risko N, Theodosis C, Totten VY, Radeos MS, et al. Emergency care and health systems: Consensus-based recommendations and future research priorities. Acad Emerg Med 2013;20(12):1278-1288.

Driesen BEJM, Van Riet BHG, Verkerk L, Bonjer HJ, Merten H, Nanayakkara PWB. Long length of stay at the emergency department is mostly caused by organisational factors outside the influence of the emergency department: A root cause analysis. PLoS ONE 2018;13(9).

Furterer SL. Applying Lean Six Sigma methods to reduce length of stay in a hospital's emergency department. Qual Eng 2018;30(3):389-404.

Gartner D, Padman R. Machine learning for healthcare behavioural OR: Addressing waiting time perceptions in emergency care. J Oper Res Soc 2019. DOI: 10.1080/01605682.2019.1571005.

Gaviria A, Ruíz F, Dávila C, Burgos G, Escobar G. Informe Nacional de Calidad de Atención en Salud 2015. Bogotá, Colombia: Ministerio de Salud y Protección Social, 2015. Available from: http://calidadensalud.minsalud.gov.co/Paginas/INCAS.aspx

Gillespie J, McClean S, Garg L, Barton M, Scotney B, Fullerton K. A multi-phase DES modelling framework for patient-centred care. J Oper Res Soc 2016;67(10):1239-1249.

Glickman SW, Kit Delgado M, Hirshon JM, Hollander JE, Iwashyna TJ, Jacobs AK, et al. Defining and measuring successful emergency care networks: A research agenda. Acad Emerg Med 2010;17(12):1297-1305.

Gul M, Fuat Guneri A, Gunal MM. Emergency department network under disaster conditions: The case of possible major Istanbul earthquake. J Oper Res Soc 2019.

Gul M, Guneri, AF. A discrete event simulation model of an emergency department network for earthquake conditions. 6th International Conference on Modeling, Simulation, and Applied Optimization, ICMSAO 2015 - Dedicated to the Memory of Late Ibrahim El-Sadek; 2015.

Gul M, Guneri, AF. Preparedness of an emergency department network for a major earthquake: A discrete event simulation-based design of experiments study. Uncertainty Modelling in Knowledge Engineering and Decision Making - Proceedings of the 12th International FLINS Conference, FLINS 2016; 2016.

Habidin NF, Yahya NZ, Ramli MFS. Using LSS DMAIC in improving emergency department waiting time. Int J Pharm Sci Rev Res 2015;35(2):151-155.

Harrop SN. Links between systems in Accident & Emergency and primary care. Informatics Prim Care 2005;13(3):223-226.

Hawkins RC. Laboratory turnaround time. Clin Biochem Rev 2007; 28(4):179-194.

Hsia RY, Sabbagh SH, Guo J, Nuckton TJ, Niedzwiecki MJ. Trends in the utilisation of emergency departments in California, 2005-2015: A retrospective analysis. BMJ Open 2018;8(7).

Hussein NA, Abdelmaguid TF, Tawfik BS, Ahmed NGS. Mitigating overcrowding in emergency departments using Six Sigma and simulation: A case study in Egypt. Oper Res Health Care 2017;15:1-12.

Ibrahim IM, Liong C-, Bakar SA, Ahmad N, Najmuddin AF. Estimating optimal resource capacities in emergency department. Indian J Public Health Res Dev 2018;9(11):1558-1565.

Karnon J, Stahl J, Brennan A, Caro JJ, Mar J, Möller J. Modeling using discrete event simulation: A report of the ISPOR-SMDM modeling good research practices task force-4. Value Health 2012;15(6):821-827.

Kaushal A, Zhao Y, Peng Q, Strome T, Weldon E, Zhang M, et al. Evaluation of fast track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department. Socio-Econ Plann Sci 2015;50:18-31.

Kim J, Yun BJ, Aaronson EL, Kaafarani HMA, Linov P, Rao SK, et al. The next step to reducing emergency department (ED) crowding: Engaging specialist physicians. PLoS ONE 2018;13(8)

Konder MT, O'Dwyer G. The integration of the emergency care units (UPA) with healthcare services in the city of Rio de Janeiro, Brazil. Interface Commun Health Educ 2016;20(59):879-892.

Kuo Y-, Rado O, Lupia B, Leung JMY, Graham CA. Improving the efficiency of a hospital emergency department: a simulation study with indirectly imputed service-time distributions. Flexible Serv Manuf J 2016;28(1-2):120-147.

Lin WD, Chia L.Combined forecasting of patient arrivals and doctor rostering simulation modelling for hospital emergency department. IEEE International Conference on Industrial Engineering and Engineering Management; 2018.

Mandahawi N, Shurrab M, Al-Shihabi S, Abdallah AA, Alfarah YM. Utilizing six sigma to improve the processing time: a simulation study at an emergency department. J Ind Prod Eng 2017;34(7):495-503.

Martinez R. Keynote address-redefining regionalization: Merging systems to create networks. Acad Emerg Med 2010;17(12):1346-1348.

Morley C, Stankovich J, Peterson G, Kinsman L. Planning for the future: Emergency department presentation patterns in Tasmania, Australia. Int Emerg Nurs 2018;38:34-40.

Morley C, Unwin M, Peterson GM, Stankovich J, Kinsman L. Emergency department crowding: A systematic review of causes, consequences and solutions. PLoS ONE 2018;13(8)

Mousavi Isfahani H, Tourani S, Seyedin H. Lean management approach in hospitals: a systematic review. Int J Lean Six Sigma 2019;10(1):161-188.

Navein J, McNeil I. The Surrey emergency care system: A countywide initiative for change. Emerg Med J 2003;20(2):192-195.

Nuñez-Perez N, Ortíz-Barrios M, McClean S, Salas-Navarro K, Jimenez-Delgado G, Castillo-Zea A. Discrete-event simulation to reduce waiting time in accident and emergency departments: A case study in a district general clinic. Lect Notes Comput Sci 2017;10586 LNCS:352-363.

Ortiz Barrios MA, Felizzola Jiménez H. Use of Six Sigma Methodology to Reduce Appointment Lead-Time in Obstetrics Outpatient Department. J Med Syst 2016;40(10).

Ortíz Barrios MA, Felizzola Jiménez HA. Miceps methodology for statistical process control: a case study applied in production process of tempered glass. Prospectiva 2014, 12(2): 73-81.

Ortíz-Barrios MA, Alfaro-Saíz J-. Methodological Approaches to Support Process Improvement in Emergency Departments: A Systematic Review. Int J Environ Res Public Health 2020;17(8): 2664

Ortíz-Barrios MA, Escorcia-Caballero JP, Sánchez-Sánchez F, De Felice F, Petrillo A. Efficiency Analysis of Integrated Public Hospital Networks in Outpatient Internal Medicine. J Med Syst 2017;41(10).

Ortiz-Barrios MA, Herrera-Fontalvo Z, Rúa-Muñoz J, Ojeda-Gutiérrez S, De Felice F, Petrillo A. An integrated approach to evaluate the risk of adverse events in hospital sector: From theory to practice. Manage Decis 2018;56(10):2187-2224.

Porter ME, Kramer MR. Creating Shared Value. In: Lenssen G, Smith N, editors. Managing Sustainable Business. Springer; 2019. pp. 323-346.

Qayyum H, Wardrope J. The future organisation of the emergency services. Care Crit Ill 2009;25(1):1-4.

Romero-Conrado AR, Castro-Bolaño LJ, Montoya-Torres JR, Jiménez-Barros MÁ. Operations research as a decision-making tool in the health sector: A state of the art. DYNA 2017;84(201):129-137.

Salisbury C, Bell D. Access to urgent health care. Emerg Med J 2010;27(3):186-188.

Sheard S. Space, place and (waiting) time: Reflections on health policy and politics. Health Econ Policy Law 2018;13(3-4):226-250.

Soril LJJ, Leggett LE, Lorenzetti DL, Noseworthy TW, Clement FM. Reducing frequent visits to the emergency department:A systematic review of interventions. PLoS ONE 2015;10(4).

Steventon A, Deeny S, Friebel R, Gardner T, Thorlby R. Briefing: Emergency hospital admissions in England: which may be avoidable and how? London, UK: The Health Foundation, 2018. Available from: http://reader.health.org.uk/emergency-admissions.

Stoner MJ, Mahajan P, Bressan S, Lam SHF, Chumpitazi CE, Kornblith AE, et al. Pediatric Emergency Care Research Networks: A Research Agenda. Acad Emerg Med 2018;25(12):1336-1344.

Turner J, Coster J, Chambers D, Cantrell A, Phung V-H, Knowles E, et al. What evidence is there on the effectiveness of different models of delivering urgent care? A rapid review. Southampton, UK: University of Lincoln, 2015. Available from: http://eprints.lincoln.ac.uk/17833/

Uchimura LYT, da Silva ATC, Viana ALD. Integration between primary health care and emergency services in brazil: Barriers and facilitators. Int J Integr Care 2018;18(4).

Wilson KJ. Pay-for-performance in health care: What can we learn from international experience. Qual Manage Health Care 2013;22(1):2-15

2.3 A Hybrid Fuzzy Multi-Criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study

2.3.1 Introduction

Emergency departments (EDs) play an important role in the delivery of acute diagnostic and treatment 24 hours a day and 365 days per year for patients of all age groups who need immediate care for major injuries and life-threatening medical conditions. Much attention should be paid to EDs since their use has been significantly growing and has, therefore, become one of the major contributors to the aggregate healthcare spending (Lord et al., 2018). Moreover, EDs are at the interface between the healthcare system and the community and should be then prepared for providing high-standard medical care avoiding readmissions, increasing the patient satisfaction, reducing mortality and decreasing healthcare costs (Wong, 2010).

Considering the aforementioned framework, it is necessary to properly and continuously evaluate the effectiveness of EDs in the context of the entire delivery system by using high-reliable methods. In this regard, performance evaluation, as a constructive process, can offer managers an opportunity for ensuring constant improvement and accountability (Ortiz et al., 2015). In ED context, it aims to provide a foundation for understanding the response of this healthcare service while improving the quality of decisions made by all the participants within this department. Therefore, it is important to define a clear, consistent and pertinent approach so that implementation can be facilitated with a high level of effectiveness. In this regard, although considerable effort has been made in measuring different types of healthcare (e.g. acute hospital care, primary care), little progress has been evidenced regarding the design of methodologies evaluating the overall performance of EDs (Sørup et al., 2013).

The reasoning for continuously evaluating the overall performance of EDs is first and foremost to address the increased demand for emergency services while ensuring efficiency, high quality and safety. It is then necessary to select a set of metrics representing the domains of interest in emergency care management. Such metrics enable healthcare managers to have a broad and comprehensive view of the core operations and the effectiveness of improvement actions (Farokhi and Roghanian, 2018; Ortiz and Jiménez, 2016). Although there are widely acknowledged performance evaluation approaches (e.g. Business Excellence (Sunder et al., 2018) and Balance Scorecard (Bergeron, 2017) that have been used to face this challenge, some studies have reported serious difficulties during their implementation due to unsuitable design, low pertinence and high complexity (Sørup et al., 2013; Santos et al., 2018). Additionally, much attention has been only paid to single time-related measures which, although they contribute to the timeliness, efficiency and effectiveness domains, do not evidence high levels of performance. It is hence relevant to consider hybrid frameworks additionally taking into account other domains that may affect the response of EDs. If this is not considered, areas of interest in emergency care can be unmonitored and not targeted for continuous improvement.

The development of performance evaluation frameworks requires concerted expert and political participation in order to better define the healthcare domains (criteria) (Hsiao and Chen, 2019) and sub-criteria that are directly attributable to the EDs. Yet, as in different fields, since there are several decision elements (criteria and sub-criteria) to be deemed in the healthcare sector, selecting a suitable decision-making approach has become a critical step for assessing the performance of EDs. Several frameworks have been developed for this purpose. Such frameworks involved combining quantitative and qualitative criteria considering government regulations and ED goals. In this respect, multicriteria decision-making methods (MCDM) seem to be the appropriate tool for prioritizing these quantitative and qualitative factors based on experts' opinion (Ho and Ma, 2018; Dargi et al., 2014; Saaty and Ergu, 2015). However, it is also relevant to consider the vagueness and vagueness of human judgments (Jing et al., 2018). To do this, it is necessary to incorporate the fuzzy concept into the MCDM structure (Samanlioglu et al., 2018). The advantage of using the fuzzy approach is its capability of representing the uncertain nature of real decision-making problems through triangular numbers (Chen et al., 2005). On the other hand, according to the review reported by Sørup et al. (2013) it is imperative to define the interconnectivity between the criteria for a better understanding of the ED performance which can be properly addressed by an MCDM hybrid approach. The hybrid methods address the limitations of single methods and provide more robust solutions in accordance with the decision-making context. Nevertheless, the studies directly concentrating on evaluating the ED performance with the use of MCDM hybrid methods are largely limited which evidences that this research area is at a much earlier stage. Additionally, a more complete decision-making model for ED performance assessment is lacking since several domains (e.g. medical equipment, procedures and protocols, infrastructure and medical supplies) have not been considered in previous studies. This paper then bridges this gap through the integration of potent MCDM methods: Fuzzy Analytic Hierarchy Process (FAHP), Fuzzy Decision Making Trial and Evaluation Laboratory (FDEMATEL) and Technique for Order Preference and Similarity to Ideal Solution (TOPSIS).

In summary, the motivation of this research lies in several facts: i) the lack of an ED performance assessment model covering the multifactorial context of emergency care, ii) the need for analyzing the interrelations between the criteria/sub-criteria affecting the performance of EDs, iii) the demand for realistic performance assessment approaches considering the human thought nature and the practical implications of real-world applications in EDs, iv) the absence of a unified MCDM approach for appropriately ranking EDs based on their performance and v) the urgency of assisting cluster managers and decision-makers in identifying the weaknesses of each ED and designing focused improvement strategies. The model usefulness will be tested through a real case study consisting of 3 EDs from the public healthcare sector of a Colombian region. Practical insights will be provided throughout the paper to easily guide ED decision-makers and cluster managers towards the effective implementation of the proposed approach in the wild.

The remainder of this paper is organized as follows. In Section 2.3.2, a literature review on related studies is provided whereas Section 2.3.3 describes the proposed approach. In Section 2.3.4, the results from a real case study are detailed and discussed. Section 2.3.5 presents a sensitivity analysis while Section 2.3.6 exposes the practical and managerial implications. Finally, the conclusions are shown in Section 2.3.7.

2.3.2 Literature review

For a complete literature review on methods assessing the overall performance of emergency departments, an investigation of different library databases was conducted. Scholarly journals are a relevant source of high-quality research information and were therefore selected for this review. Meanwhile, textbooks, doctoral dissertations and master's theses were therefore excluded from this review. The primary aim of this initial search was to define the level of attention paid to this research area when considering the annual number of publications. The analysis on the above-mentioned databases indicated that from 2005 (the time in which the first paper appears) to June 2018 (research date), only 30 documents have been published: 23 articles and 7 conference papers. Considering our field of interest, we refined our search by using the next string: "emergency department and performance evaluation" The extensive search was performed in the (a) ARTICLE TITLE, (b) ABSTRACT and (c) KEYWORDS of journal papers. Out of 30 documents, 7 papers from 2012 to 2018 (research date). Most of them were published in the last three years.

Among the selected papers, Mohammadi et al. (2016) used single measures (e.g. percent of failed CPR, waiting time duration, percent of released emergency departments with personal responsibility, percent of released emergency patients in specific times) and paired independent t-tests to evaluate the emergency department's performance. In this study, percent of failed CPR, waiting time duration in level 4 triage, the emergency patients who were settled in 6 hours and patients who moved out of the department in 12 hours; were found as significant (p-value < 0.05). Another application of single indicators was exposed by Yamani et al. (2012)

where a 360-degree evaluation was performed to assess the emergency medicine departments in the areas of education, service provision and interaction with other departments. The above-mentioned metrics were compiled in a review study carried out by Sørup et al. (2013) who identified a total of 55 ED performance measures. The study recommended using indicators related to patient-centeredness and safety performance. Also, it established that employee-related performance measures are rarely considered in the reported literature. Interesting frameworks were proposed by Zhao and Paul (2012) and Pan et al. (2016). Specifically, Zhao and Paul (2012) proposed a modification of the American Productivity and Quality Center (QAPC) method for assessing the performance of hospital emergency departments. This approach is based on efficiency and price recovery ratio to better connect quality and financial domains. Pan et al. (2016) applied the kinetics analysis for ED performance considering the relationship between the ED retained patients and the ED departure velocity. Other authors proposed MCDM methods to address the performance evaluation problem. For instance, Ketabi et al. (2018) applied Data Envelopment Analysis (DEA) to evaluate the efficiency of ED's. In their work, 24 ED's of hospitals in Iran were assessed by considering input (4 criteria) and output (4 criteria) factors. A similar DEA application was undertaken by Yeh and Cheng (2016) who assessed the performance of 28 hospitals in Taiwan. In both cases, the approach was also found to be useful for designing focused improvement strategies in the performance of each hospital. Likewise, Gul et al. (2016) combined Interval Type-2 Fuzzy Analytic Hierarchy Process (IT2-FAHP) and ELECTRE (Elimination and Choice Expressing the Reality) for performance evaluation of an ED system in a university hospital. Particularly, this method enables decision-makers to select the best scenarios based on the number of shifts, nurses and physicians.

Table 1. Summary of studies exposing ED performance evaluation approaches

Authors	Aim	Method	Criteria	Results	Limitations
Mohammadi et al. (2016)	The study aims to measure and compare emergency departments' performance before and after the health reform.	Descriptive statistics and paired independent t-test	% of patients settled in < 6 h, % of temporary hospitalized patients in the ED in < 12 h, Failed CPR, % of release with personal responsibility, and triage time in each triage level.	Failed CPR, waiting time in triage level 4, % of patients settled in < 6h, and % of temporary hospitalized patients in the ED < 12h were found to be significantly lower compared to the initial status ($p < 0.05$).	- The criteria here considered do not entirely represent the multifactorial context of ED performance. - The criteria were not weighted. -No potential interrelations between criteria were taken into account.
					-Vagueness and imprecision of data were not incorporated. - No ranking of EDs was provided. -No improvement strategies were proposed based on detected weaknesses.
Yamani et al. (2012)	The primary aim is to evaluate the performance of EDs in Alzahra Hospital	360-degree evaluation	Therapeutic, interactional, and educational.	The results revealed that the hospital has a good overall performance in educational, therapeutic, and interactional domains.	- The criteria here considered do not entirely represent the multifactorial context of ED performance. - The criteria were not weighted -No potential interrelations between criteria were taken into account. -Vagueness and imprecision of data were not incorporated. - Only one hospital was assessed. -No improvement strategies were proposed based on detected weaknesses.

Zhao and Paul (2012)	The objective is to evaluate the profitability and productivity performance of hospital emergency departments.	Modified American Productivity and Quality Center (MAPQC)	Financial and operational	The results evidenced that the inclusion of the price change ratio removes the confounding effect of changes in sales which distort the performance measures.	- The criteria here considered do not entirely represent the multifactorial context of ED performance. -Vagueness and imprecision of data were not incorporated. -No improvement strategies were proposed based on detected weaknesses.
Pan et al. (2016)	The aim is to develop an improved and robust global standard model for ED performance.	Kinetic analysis	ED departure, ED length of stay, ED medical personal unit, ED working bed, and retained patients.	The outcomes of this research proved that there is a significant relationship between ED retained patients and ED departure velocity. However, it concludes that the proposed measure (EDMPU TON) cannot completely solve every issue of ED performance.	- The criteria here considered do not entirely represent the multifactorial context of ED performance. -Vagueness and imprecision of data were not incorporated. -Not all the interrelations are evaluated. -No improvement strategies were proposed based on detected weaknesses.
Yeh and Cheng (2016)	This study aimed to conduct operation performance evaluations of Taiwan's national hospitals during the period 2005–2008 and propose appropriate suggestions for performance improvements	DEA and Malmquist productivity index	Number of doctors, medical personnel, nurses, administration personnel, patient beds, operation and management costs, number of outpatients and emergency patients, hospital man-time and medical care revenues.	The study concluded that nearly 60% of national hospitals ran inefficiently. In addition, a significant gap was observed between urban and non-urban hospitals.	- The criteria here considered do not entirely represent the multifactorial context of ED performance. -Vagueness and imprecision of data were not incorporated.
Gul et al. (2016)	The research aims to evaluate the performance of an ED in a university hospital and select the best scenario considering different number of doctors and nurses.	Computer simulation, IT2-FAHP and ELECTRE	Number of patients discharged, length of stay in the ED, utilization of human resources (doctors, nurses, etc.), and multiple capacity locations (monitors bed area, emergency-1 area, etc.)	The study concluded that the hospital can upgrade his performance by adding one nurse and decreasing number of doctors by one at the least busy shift. The integrated approach was found to be useful for assessing the ED performance and	- The criteria here considered do not entirely represent the multifactorial context of ED performance. - No potential interrelations between criteria were taken into account. - Only one hospital was assessed.

				selecting the best improvement scenario considering capacity changes.	
Ortíz-Barrios and Alfaro-Saíz (The current research)	This paper aims to evaluate the overall performance of Colombian EDs. The study also reveals the weaknesses to be tackled for upgrading the performance of each ED. In the meantime, it considers the multifactorial context of ED performance, the presence of interrelations among criteria, the vagueness/imprecision of data, and ED ranking.	FAHP, FDEMATEL, and TOPSIS	8 criteria (Infrastructure, Medical equipment, Procedures and protocols, Supporting processes, Human resources, Supplies, medicines, and accessories, Quality, and Patient safety) and 35 sub-criteria.	See Section 2.3.4-2.3.6	- It does not consider interval valued indicators.

Table 1 summarizes the research on ED performance evaluation. Despite the efforts made through these studies, a more complete decision-making model for ED performance assessment is lacking since several domains (e.g. medical equipment, procedures and protocols, infrastructure and medical supplies) have been not taken into account. It can be also observed that none of the approaches simultaneously consider: i) the interdependence among criteria, ii) the high uncertainty inherent in ED operations, iii) a performance-based ranking of EDs, and iv) suggestions for performance improvements. Additionally, considering the literature, it became apparent that the studies concentrating on the use of MCDM techniques to evaluate the overall performance of emergency departments are largely limited; such methods can provide a wide understanding of the ED performance context given the multidimensional nature of emergency services and the presence of causal effects. In this regard, several MCDM methods (e.g. Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), TOPSIS, Data Envelopment Analysis (DEA), VIKOR, Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), Simple Additive Weighting (SAW) (Chen, 2014) and their fuzzy versions can be applied by researchers (Saaty and Ergu, 2015). In this respect, researchers employ either a single MCDM method, (Jovčić et al., 2019; Saaty and Vargas, 2012; Vargas, 2016) or a combination of two or more techniques called hybrid as shown in Lee et al. (2018), Labib and Read (2015) and Hosseini and Al Khaled (2019). However, the use of hybrid methods has been found to provide more robust results (Zavadskas et al., 2016). The combination of different methods also allows overcoming the limitations of several techniques (Saksrisathaporn et al., 2016; Chang et al., 2014). Particularly, PROMETHEE (Preference Ranking Organization Method) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) do not provide an explicit procedure to allocate the relative importance of criteria and sub-criteria (Lolli et al., 2019; Almeida et al., 2018; Sun et al., 2018; Frazão et al., 2018; Barrios et al., 2016). Therefore, there may be some imprecision, arbitrariness and lack of consensus regarding the weights used in the decision-making model. Concerning AHP method, several authors have highly concerned on the rank reversal phenomenon relating to the preference order changes after an alternative is added or deleted (Ortiz-Barrios et al., 2018; Al Salem and Awasthi, 2018; Farias and Ferreira, 2019; Ho and Ma, 2018). The same drawback was observed in Data Envelopment Analysis – DEA, (Emrouznejad and Yang, 2018; Arya and Yadav, 2018; Hsiao and Chen, 2019) and the Simple Additive Weighting – SAW techniques (Mufazzal and Muzakkir, 2018; Kaliszewski and Podkopaev, 2016; Mousavi-Nasab and Sotoudeh-Anvari, 2018). Another limitation of the DEA method is that all outputs and inputs are assumed to be known (Frazão et al., 2018)). Regarding ANP, it has been concluded as a highly complex and time-consuming methodology when performing sensitivity analysis (Chen et al., 2019; Jumaah et al., 2018). Hence, by taking into account the aforementioned facts and aiming at delivering more robust, realistic and reliable results, a hybrid approach is decided to be implemented in this study.

In addition, to overcome the vagueness derived from human judgments, which are the cornerstone of several MCDM methods (e.g. AHP, ANP and DEMATEL), fuzzy sets are introduced in the present research. The reasoning of employing a fuzzy framework is based on the fact that the preference relationships provided by decision-makers are vague, uncompleted and imprecise (Singh and Prasher, 2019;

Otay et al., 2017; Gou et al., 2019). Furthermore, high uncertainty in ED operations has been reported in Gul et al. (2016). In this sense, several fuzzy approaches can be proposed for dealing with the human thought nature. For example, the fuzzy set theory is able to represent vague data by introducing interval judgments (triangular numbers) while enabling us to generate scales between different criteria and subsequently allocate a specific weight to each one (Singh and Prasher, 2019). On a different tack, the Intuitionistic fuzzy set theory (IFS) is applied when the decision-makers do not possess a precise or sufficient knowledge of the decision-making scenario. Such condition may be exhibited during the judgment process through the characteristics of “affirmation” (agreement/truthiness degree) and “negation” (disagreement/falsity degree) (Kahraman et al., 2015). In addition to these characteristics, Neutrosophic set theory (NFS) incorporates the “hesitation” (abstention) or indeterminacy that could also occur due to the lack of information and knowledge relating, in this case, to the performance evaluation context (Abdel-Basset et al., 2018). However, if there are experts with extensive experience in the decision-making context, it is not then necessary to incorporate falsity degrees and indeterminacy. Thereby, unnecessary complexity and long processing time associated with IFS and NFS could be avoided. Grey numbers can be also used for this particular aim; however, fuzzy sets are easier to implement and better adapt to the MCDM techniques proposed in this study (ANP and DEMATEL).

In light of the above-mentioned aspects and findings from the reported literature, the research question is: How to evaluate the performance of EDs considering the different components of emergency care? To answer this question, this study proposes a novel hybrid method based on FAHP, FDEMATEL and TOPSIS methods which addresses the limitations of previous studies and is useful to provide a decision support system for assisting emergency department managers and practitioners. The hybrid approach is a combination of the three methods that allows benefiting from the advantages of fuzzy AHP in establishing the weights of criteria and sub-criteria under vagueness, the application of fuzzy DEMATEL to evaluate complex interrelations (under uncertainty) among criteria; followed by the use of TOPSIS for ranking the EDs and detecting primary areas of intervention. The novelty of this study is then six-fold: i) an ED performance evaluation model representing the multifactorial context of emergency care (8 criteria and 35 sub-criteria), ii) the assessment of interdependence among performance criteria/sub-criteria, iii) the inclusion of fuzzy logic for representing the uncertainty of ED operations, iv) the performance-based ranking of EDs, v) the provision of potential improvement strategies considering the weaknesses of each ED, and vi) the integration of FAHP, FDEMATEL, and TOPSIS methods whose application has not been reported in the context of ED performance evaluation.

2.3.3 Proposed Methodology: FAHP, FDEMATEL and TOPSIS

An approach comprised of four phases has been proposed to evaluate the overall performance of EDs considering the different components of emergency service. This methodology, described step by step in Fig. 1, has been developed with the foresight to be replicated in a wide range of healthcare clusters and can be applied without any restriction. In Phase 1, a group of experts is formed to perform the paired judgments required in both FAHP and FDEMATEL techniques. A performance evaluation model is then set up by considering the expertise of decision-makers and the performance metrics regulated by the Columbian Ministry of Health and Social Protection. Afterwards, in Phase 2, FAHP is applied to calculate the weights of decision elements under uncertainty and define improvement interventions in the short run. In particular, Fuzzy AHP considers linear dependency and vagueness associated with the uncertainty of decision-makers' judgments. However, FAHP does not take into account the feedback and interdependence between the decision elements as often found in the ED context (Abdullah and Zulkifli, 2015; Ashtiani and Azgomi, 2016; Ortiz-Barrios et al., 2018). To tackle this disadvantage and offer more solid outcomes, in Phase 3, FDEMATEL is used separately to support the interdependence evaluation among criteria, identify the receivers and dispatchers, and develop long-term improvement strategies (Govindan et al., 2015). Short term and long term interventions are consistent with the time horizons specified in the development plans of goverments, healthcare clusters, and EDs. In Phase 4, the final criteria and sub-criteria weights are used by TOPSIS as an input to rank the emergency departments in accordance with their overall performance. In addition, improvement opportunities for each ED are proposed by considering their closeness to both ideal and anti-ideal scenarios. The methods here used respond to the emergency care context: i) the presence of complex interrelations among criteria (FDEMATEL), ii) the need for developing short-term (FAHP) and long-term (FDEMATEL) interventions in line with the time horizons of improvement plans, iii) proper assessment of criteria and sub-criteria weights under uncertainty (FAHP), iv) the need for ranking hospitals and detecting improvement areas in each institution (TOPSIS). The MDCM techniques considered in this approach are further explained in the next sub-sections.

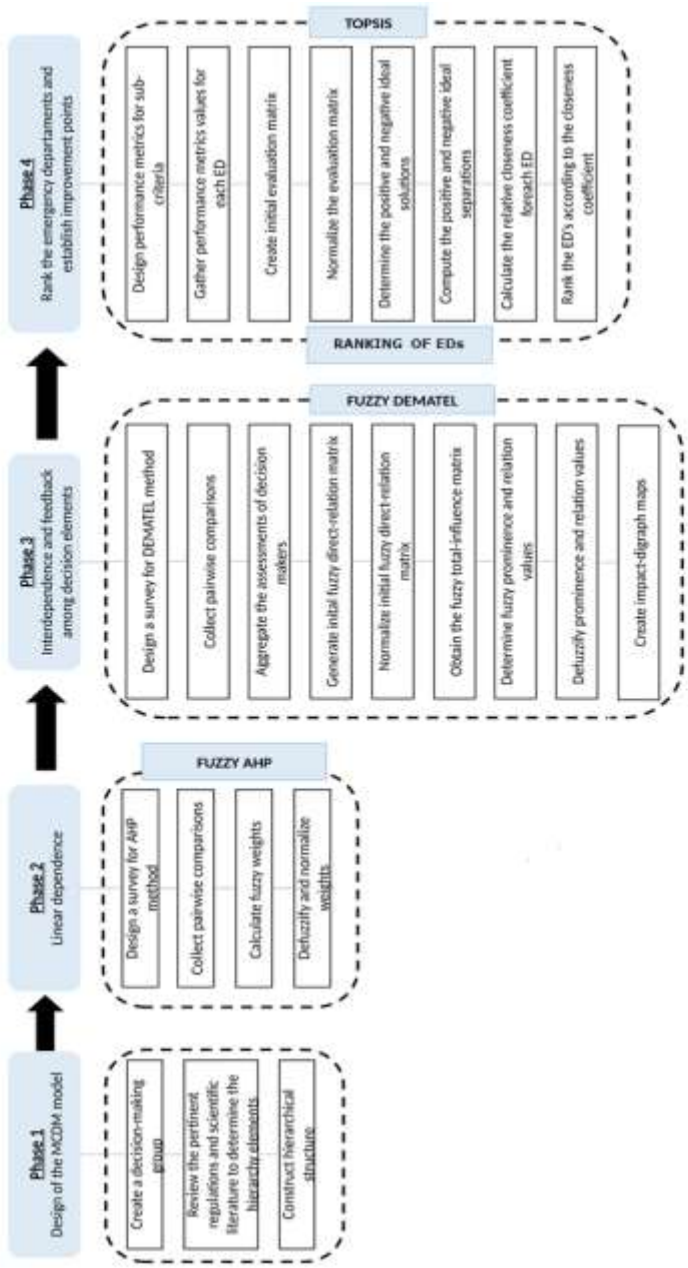


Figure 1. Proposed methodology for ranking the ED's in accordance with their overall performance

2.3.3.1 Fuzzy Analytic Hierarchy Process (FAHP)

In accordance with the reported literature, AHP does not take into account the vagueness derived from human judgments (Jing et al., 2018). Hence, fuzzy sets were introduced to deal with this problem (Gou et al., 2019) (as presented in pairwise comparisons). In this respect, AHP can be "fuzzified" by generalizing the concept of crisp data to a fuzzy set with blurred boundaries (Awasthi et al., 2018). With this modification, AHP, now FAHP, can be more realistic and is, therefore, more precise to solve real-world MCDM problems which inexorably entails some degree of noise in their variables (Izquierdo et al., 2018). The comparisons are described by triangular numbers M which are represented by (a,b,c) and the membership function is defined as follows:

$$\mu_{\tilde{M}}(x)=\begin{cases}\dfrac{x-a}{b-a}, & a\le x\le b\\ \dfrac{c-x}{c-b}, & b\le x\le c\\ 0, & otherwise\end{cases}$$

Here, $-\infty<a\le b\le c<\infty$ additionally, the strongest grade is represented by parameter b whilst, a and c are the lower and upper bounds. The fuzzy triangular numbers to be used in FAHP are enlisted in Table 2 where can be easily matched with the AHP scale. Also, a reduced version of the Saaty natural scale with only three points is adopted to facilitate the engagement of unskilled respondents and then reduce inconsistencies in the decision-making process.

Table 2. Fuzzy triangular numbers used in FAHP (taken from ref. 98)

Reduced AHP scale	Definition	Fuzzy triangular number
1	Equally important	[1,1,1]
3	More important	[2,3,4]
5	Much more important	[4,5,6]
1/3	Less important	[1/4,1/3,1/2]
1/5	Much less important	[1/6,1/5,1/4]

The FAHP algorithm can be summarized as follows (Ortíz-Barrios et al., 2018):

Step 1: Perform paired judgments between decision elements by using the fuzzy triangular numbers described in Table 2. With this information, a fuzzy judgment matrix $\tilde{A}^k\left(a_{ij}\right)$ can be obtained as defined below in Eq. 1:

$$A^k=\begin{bmatrix} d_{11}^k & d_{12}^k & \dots & d_{1n}^k\\ d_{21}^k & d_{22}^k & \dots & d_{2n}^k\\ \dots & \dots & \dots & \dots\\ d_{n1}^k & d_{n2}^k & \dots & d_{nn}^k\end{bmatrix} \quad (1)$$

$\tilde{d}_{ij}^{k}$ Denotes the kth decision-maker’s preference of ith element over jth element via fuzzy triangular numbers.

Step 2: In the case of an expert group, the comparisons are averaged in accordance with Eq. 2, where K represents the number of decision-makers involved in the process. Afterwards, the fuzzy judgment matrix is updated as presented in Eq. 3.

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{K} \tilde{d}_{ij}^{k}}{K} \tag{2}$$

$$\tilde{A} = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \cdots & \tilde{d}_{nn} \end{bmatrix} \tag{3}$$

Step 3: Determine the geometric mean of fuzzy judgments $(\tilde{r}_i)$ for each decision element via applying Eq. 4.

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{d}_{ij} \right)^{1/n}, i = 1, 2, \ldots, n \tag{4}$$

Step 4: Calculate the fuzzy weights of each decision element $(\tilde{w}_i)$ by using Eq.5.

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n \right)^{-1} = \left(lw_i, mw_i, uw_i \right) \tag{5}$$

Step 5: Defuzzify $(\tilde{w}_i)$ by implementing the Centre of Area method (Gul et al., 2019) by applying Eq. 6. M_i is a non-fuzzy number. Finally, normalize M_i by using Eq. 7.

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \tag{6}$$

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{7}$$

2.3.3.2 Fuzzy Decision Making Trial and Evaluation Laboratory (FDEMATEL)

DEMATEL is a potent method that has been widely used to evaluate the interdependence between decision elements (i.e. criteria and sub-criteria) and identify causal relationships in a complex MCDM model (Barrios et al., 2014). This method uses digraphs to categorize criteria and sub-criteria into cause group and effect group effectively. Whereas the pairwise judgments provided by experts are crisp values, it is necessary to incorporate fuzzy logic to represent the vagueness contained in real-world problems and deal with the imprecision of human comparisons (Kazancoglu et al., 2018). Although Fuzzy ANP (FANP) can also assess dependency and feedback, the disadvantages mentioned in Section 2.3.2 and the assumption of equal weight for each cluster to achieve a weighted supermatrix in this method does not make its application reasonable for practical situations (Liu et al., 2014; Kou et al., 2014).

Table 3. Fuzzy triangular numbers used in FDEMATEL (taken from Ref. 99).

DEMATEL scale	Definition	Fuzzy triangular number
0	No influence	[0,0,0.25]
1	Low influence	[0,0.25,0.5]
2	Medium influence	[0.25,0.5,0.75]
3	High influence	[0.5,0.75,1]
4	Very high influence	[0.75,1,1]

To effectively apply the conventional DEMATEL technique for group decision-making in a fuzzy environment the following steps must be considered (Ortíz et al., 2015).

Step 1: Create the Fuzzy linguistic scale: To cope with the ambiguities of human judgments (expert opinion) five linguistic qualifications are used to represent the “influence” variable. This is expressed as a fuzzy triangular number $(l_{ij}^k, m_{ij}^k, r_{ij}^k)$ which denotes the kth decision-maker’s preference of ith element over jth, as shown in Table 3.

When there is an expert group, the preferences are averaged based on Eq. 8-10, where K indicates the number of specialists.

$$l_{ij} = \frac{\sum_{k=1}^{K} l_{ij}^k}{K} \quad (8)$$

$$m_{ij} = \frac{\sum_{k=1}^{K} m_{ij}^k}{K} \quad (9)$$

$$r_{ij} = \frac{\sum_{k=1}^{K} r_{ij}^{k}}{K} \quad (10)$$

Step 2: Determine the fuzzy direct-influence matrix: Considering the experts' opinion expressed through the linguistic scale the fuzzy direct-influence matrix $\tilde{\boldsymbol{D}}$ can be calculated by using Eq. 11.

$$\tilde{\boldsymbol{D}} = \left[\tilde{d}_{ij}\right]_{n\,x\,m}, \quad \text{where } \tilde{d}_{ij} = \left(d_{ij}^{l}, d_{ij}^{m}, d_{ij}^{r}\right) \quad (11)$$

Step 3: Normalize the fuzzy direct-influence matrix: the normalized fuzzy direct-relation matrix $\tilde{N}$ is obtained through the fuzzy direct-influence matrix $\tilde{\boldsymbol{D}}$ by applying Eq. 12.

$$\tilde{\boldsymbol{N}} = \tilde{\boldsymbol{D}} / u, \text{ where } u = \max_{ij}\left\{\max_{i}\sum_{j=1}^{n} d_{ij},\ \max_{j}\sum_{i=1}^{n} d_{ij}\right\},\ i, j \in \{1, 2, \ldots, n\} \quad (12)$$

$$\tilde{\boldsymbol{N}} = \left[\tilde{e}_{ij}\right]_{n\,x\,n}, \tilde{e}_{ij} = \left(e_{ij}^{l}, e_{ij}^{m}, e_{ij}^{r}\right).$$

Step 4: Reach the fuzzy total-influence matrix: After calculating the normalized fuzzy direct-influence matrix. $\tilde{\boldsymbol{N}} = \left(N^{l}, N^{m}, N^{r}\right)$ where $\boldsymbol{N}^{l} = \left[e_{ij}^{l}\right]_{n\,x\,n}$, $\boldsymbol{N}^{m} = \left[e_{ij}^{m}\right]_{n\,x\,n}$, $and\ \boldsymbol{N}^{r} = \left[e_{ij}^{r}\right]_{n\,x\,n}$, the fuzzy total-influence matrix $\tilde{\boldsymbol{T}}$ can be obtained by Eq. 13. Here, the $\boldsymbol{I}$ indicates the identity matrix.

$$\tilde{\boldsymbol{T}} = \left[\tilde{t}_{ij}\right]_{n\,x\,n},\ where\ \tilde{t}_{ij} = \left(t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{r}\right) \quad (13)$$

$$\text{Where } \boldsymbol{T}^{l} = \left[t_{ij}^{l}\right]_{n\,x\,n} = \boldsymbol{N}^{l}\left(\boldsymbol{I} - \boldsymbol{N}^{l}\right)^{-1}, \boldsymbol{T}^{m} = \left[t_{ij}^{m}\right]_{n\,x\,n} = \boldsymbol{N}^{m}\left(\boldsymbol{I} - \boldsymbol{N}^{m}\right)^{-1}.$$

$$and\ \ \boldsymbol{T}^{r} = \left[t_{ij}^{r}\right]_{n\,x\,n} = \boldsymbol{N}^{r}\left(\boldsymbol{I} - \boldsymbol{N}^{r}\right)^{-1}$$

The triangular fuzzy numbers in fuzzy total-influence matrix $\tilde{\boldsymbol{T}}$ are divided into $\boldsymbol{T}^{l} = \left[t_{ij}^{l}\right]_{n\,x\,n}$, $\boldsymbol{T}^{m} = \left[t_{ij}^{m}\right]_{n\,x\,n}$, $\boldsymbol{T}^{m} = \left[t_{ij}^{m}\right]_{n\,x\,n}$, when $e_{ij}^{l} < e_{ij}^{m} < e_{ij}^{r}$ for any $i, j \in \{1, 2, \ldots, n\}$.

Step 5: Compute the threshold value p to then determine the structural model through the causal diagram (refer to Eq. 14).

$$p = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} t_{ij}}{n^{2}} \quad (14)$$

The sum of rows and columns are indicated as separate vectors $\tilde{C}_i$ and $\tilde{R}_i$ respectively, where *i* = *j.* The horizontal axis vector called “Prominence” is achieved by adding this vectors $\left(\tilde{C}_i + \tilde{R}_i\right)$.This relationship represents the influence of each sub-criterion *i* (*i* = 1, 2,…, *s*) whereas the prominence of criterion *k* (*k* = 1, 2, …, *m*) is denoted by $\left(\tilde{C}_k + \tilde{R}_k\right)$. Here, *m* represents the total number of criteria while *s* denotes the total number of sub-criteria considered in the performance assessment model.

Similarly, the vertical axis $\left(\tilde{C}_i - \tilde{R}_i\right)$ called “Relation” separates the sub-criteria into a cause group and effect group. When $\left(\tilde{C}_i - \tilde{R}_j\right)$ is negative, the criterion belongs to the receiver group; otherwise, it is categorized as a dispatcher. This is also applicable for criteria where relation parameter is symbolized by $\left(\tilde{C}_k - \tilde{R}_k\right)$.

Applying the CFCS method indicated in Eq. 15-23, the fuzzy vectors $\left(\tilde{C}_i + \tilde{R}_j\right)$ and $\left(\tilde{C}_i - \tilde{R}_j\right)$ are defuzzified into crisp values. Then, the causal diagram can be obtained by mapping the dataset $\left(\left(\tilde{C}_i + \tilde{R}_j\right)^{def}, \left(C_i - \tilde{R}_j\right)^{def}\right)$.

(1) Normalization

$$xl_{ij}^k = \left(l_{ij}^k - min\, l_{ij}^k\right) / \Delta_{min}^{max} \tag{15}$$

$$xm_{ij}^k = \left(m_{ij}^k - min\, l_{ij}^k\right) / \Delta_{min}^{max} \tag{16}$$

$$xr_{ij}^k = \left(r_{ij}^k - min\, l_{ij}^k\right) / \Delta_{min}^{max} \tag{17}$$

Where $$\Delta_{min}^{max} = max\, r_{ij}^k - min\, l_{ij}^k \tag{18}$$

(2) Compute left (ls) and right (rs) normalized value:

$$xls_{ij}^k = xm_{ij}^k \,/ \left(1 + xm_{ij}^k - xl_{ij}^k\right) \tag{19}$$

$$xrs_{ij}^k = xr_{ij}^k \,/ \left(1 + xr_{ij}^k - xm_{ij}^k\right) \tag{20}$$

(3) Compute total normalized crisp value:

$$x_{ij}^k = \left[xls_{ij}^k \left(1 - xls_{ij}^k\right) + xrs_{ij}^k xrs_{ij}^k \right] / \left[1 - xls_{ij}^k + xrs_{ij}^k\right] \quad (21)$$

(4) Compute crisp value:

$$z_{ij}^k = \min l_{ij}^k + x_{ij}^k \Delta_{min}^{max} \quad (22)$$

(5) Integrate crisp values:

$$z_{ij} = \frac{1}{K}\left(z_{ij}^1 + z_{ij}^2 + \ldots + z_{ij}^K\right) \quad (23)$$

2.3.3.3 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a ranking technique aiming at selecting alternatives with the shortest distance from the positive ideal solution (PIS) and the farthest distance from negative ideal solution – NIS simultaneously (sun et al., 2018). In this respect, PIS considers the best value $\left(A^+\right)$ of each criterion/sub-criterion whilst NIS represents the worst scenario $\left(A^-\right)$. TOPSIS then uses an aggregating function denoting the closeness (Euclidean distance) to the reference points as stated by Zyoud and Fuchs-Hanusch (Zyoud and Fuchs-Hanusch, 2017). The result is an index called as *closeness coefficient* which helps to identify the best alternative quickly. Although fuzzy TOPSIS, gray TOPSIS, and interval-valued intuitionistic fuzzy TOPSIS can be also proposed for this particular aim, its use is discarded due to the presence of indicators defined by crisp values (as those often stated by health institutions), in addition to the complex computational processing and data collection (Keshavarz Ghorabaee et al., 2017). On a different tack, the Weighted Aggregated Sum Product Assessment (WASPAS) (Deveci et al., 2018) is not preferred over TOPSIS because it does not provide a contribution measure of each criterion/sub-criterion to the overall performance, which does not facilitate the identification of weaknesses and the subsequent design of focused improvement strategies. On the other hand, the Complex Proportional Assessment (COPRAS) (Roy et al., 2019) is not considered in this context since it may be less stable compared to TOPSIS in case of data variation, a situation often expected in the ED framework. Other methods that could be proposed for this particular aim are: Evaluation Based on Distance from Average Solution (EDAS) (Ghorabaee et al., 2017) and the Combinative distance-based assessment (CODAS) (Keshavarz Ghorabaee et al., 2015). However, they do not allow identifying how far each alternative is from the desired performance in each criterion/sub-criterion, an aspect that is widely addressed by TOPSIS. This is of extreme importance considering that managers and decision-makers need to determine which criteria/sub-criteria should be prioritized for ED performance improvement. Crisp TOPSIS then responds to the current healthcare monitoring system of Colombia and facilitates the implementation of the evaluation model in EDs where the performance measurement culture is at the earlier stages. The TOPSIS method is easy to understand and implement for unskilled decision-makers. A simplified version of the TOPSIS procedure is presented below (Barrios et al., 2016):

Step 1: Set a decision matrix X with "e" emergency departments and "n" sub-criteria Xij represents the value of the sub-criterion (i = 1, 2,…, n) in each emergency department ED_r (r = 1, 2,…, s).

$$X = \begin{array}{c} ED_1 \\ ED_2 \\ ED_3 \\ . \\ . \\ ED_s \end{array} \begin{bmatrix} SC_1 & SC_2 & \dots & SC_n \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ x_{31} & x_{32} & \dots & x_{3n} \\ \vdots & \vdots & \dots & \vdots \\ x_{y1} & x_{y2} & \dots & x_{ys} \end{bmatrix} \tag{24}$$

Step 2: Compute the normalized decision matrix R via applying Eq. 25. Let n_{ij} be the norm used by TOPSIS method (Refer to Eq. 26). Furthermore, r_{ij} denotes an element of this matrix.

$$R = X \cdot n_{ij} \tag{25}$$

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{y} x_{ij}^2}} \tag{26}$$

Step 3: Obtain the weighted normalized decision matrix V (Refer to Eq. 27). The set of global sub-criteria contributions GW_i (i = 1, 2,…, s) arises from the FAHP method.

$$V = \left[GW_i r_{ij} \right] = \left[v_{ij} \right] \qquad (27)$$

Step 4: Determine the PIS A⁺ and NIS A⁻ in accordance with Eq. 28-29 respectively:

$$A^{+} = \left\{ \left({}^{max}_{i} a_{ij} \mid \mathrm{j} \in J \right), \left({}^{min}_{i} a \mid \mathrm{j} \in J' \right) \, for\, i = 1, 2, \ldots, m \right\} = \left\{ a_1^{+}, a, \ldots, a, \ldots, a \right\} \qquad (28)$$

$$A^{-} = \left\{ \left({}^{min}_{i} a_{ij} \mid \mathrm{j} \in J \right), \left({}^{max}_{i} a_{ij} \mid \mathrm{j} \in J' \right) \, for\, i = 1, 2, \ldots, m \right\} = \left\{ a_1^{-}, a, \ldots, a_j^{-}, \ldots, a_n^{-} \right\} \qquad (29)$$

Here:

$J = \{ j = 1, 2, \ldots, n | j\ associated\ with\ the\ benefit\ sub-criterion / criterion \}$ ·

$J' = \{ j = 1, 2, \ldots, n | j\ associated\ with\ the\ cost\ sub-criterion / criterion \}$ ·

Step 5: Estimate the separation values of each emergency department to the PIS and NIS via applying Euclidean distance as detailed in Eq. 30-31.

Separation from PIS.

$$d_i^{+} = \sqrt{\sum_{j=1}^{n} \left(a_{ij} - a_j^{+} \right)^2} \qquad i = 1, 2, \ldots, m \qquad (30)$$

Separation from NIS

$$d_i^{-} = \sqrt{\sum_{j=1}^{n} \left(a_{ij} - a_j^{-} \right)^2} \qquad i = 1, 2, \ldots, m \qquad (31)$$

Step 6: Calculate the closeness coefficient R_i by using Eq. 32. If $R_i = 1$, the emergency department operates in accordance with d_i^{+}.Hence, high *Ri* measures denote satisfactory overall performances.

$$R_i = \frac{d_i^{+}}{\left(d_i^{+} + d_i^{-} \right)}, \quad 0 < R_i < 1, \quad i = 1, 2, \ldots, m \qquad (32)$$

Step 7: Rank the emergency departments in accordance with the preference order of *Ri*.

2.3.4 Model verification and phases

2.3.4.1 Phase 1: design of the MCDM model

The main motivation of this research lies on the need of providing safety, satisfaction and high quality of care to the patients asking for ED services in a region of Colombia. Particularly, its patient satisfaction level continues to decrease and the likelihood of waiting for more than the upper specification limit (30 minutes/patient) is about 93.13%. Therefore, it is necessary to perform high-effective interventions on ED's to avoid increased mortality rates, augmented readmission rates and patient dissatisfaction. In an effort to address this problem, three decrees were created by the government: Decree N°1761 of 1990 and Decree N°4747 of 2007. The first regulation establishes specific guidelines and protocols governing the emergency services in Colombia; on the other side, the Decree N°4747 of 2007 regulates the financial relations between healthcare insurance companies and hospitals/clinics. However, in spite of this legal framework, there is still a gap between theory and practice which can be further evidenced by the fact that ED's continue to be full of inefficiencies and medical errors.

Looking into the root causes of the problem, it was concluded that there was not a complete and understandable approach to effectively measure the overall performance of these departments. Without this model, analysis and decision-making processes performed by the healthcare cluster managers could not be fully supported and the resulting action plans were then poorly focused and less effective. Therefore, an MCDM framework was proposed to be designed and implemented in the healthcare public sector of this region as a response to the aforementioned need. In this respect, three ED's (ED1, ED2, and ED3) were invited to participate in this study. These departments are part of the regional network of emergency services whose primary targets are patients coming from small towns located in the surroundings.

Considering the above mentioned panorama, this proposal was presented to the ethics committee of each ED. However, no formal approval was required since it did not involve patient participation. In addition, this project was discussed with the ED managers who gave informed consent and legal permission to contribute to this research. After this, the decision-making group was formed based on a selection scheme carefully considering particular expert profiles aiming to diminish inconsistencies of the FAHP and FDEMATEL matrixes. In this respect, three types of professionals were concluded to be appropriate for the decision-making process: healthcare inspectors, ED managers and researchers (academic sector).

Particularly, the *Healthcare inspectors* were invited to be part of the expert group since they have extensive knowledge and experience on the patient flow, system failures and criteria to be considered when assessing the effectiveness of EDs from the public sector; hence, their judgments on the importance and influence of different criteria and sub-criteria can be deemed as highly relevant for the hierarchical model proposed in this study. On the other hand, the *ED managers* were asked to participate in this process due to their wide comprehension and experience concerning the metrics, aims and requirements established by both health insurance companies and the Ministry of Health and Social Protection. This is important to design a Multicriteria decision-making model responding to the current regulations and needs of EDs from the public sector. Additionally, it contributes to reducing the current gap between theory and practice resulting in poor analysis and decision-making. Finally, the *researchers* designed the hierarchical structure with the aid of the expert committee and gathered the paired judgments for both FAHP and FDEMATEL techniques. Each participant had to demonstrate a wide experience in analysing and evaluating emergency departments from the public healthcare industry (>12 years). In addition, the expert had to be directly or indirectly associated with the ED's from this sector. Based on these conditions, an exploratory assessment of up-to-date curriculum vitae was carried out to finally select the experts participating in the decision-making process.

The chosen expert team is presented below:

- *Three ED managers*: All of them associated with hospitals from the public sector. Furthermore, they have an extensive experience (more than 15 years) and knowledge concerning the administration, planning and supervision of emergency room operations.

- *Two healthcare inspectors*: Both have performed audits in different EDs linked to the municipal healthcare network. During their careers, they have aggressively propelled sweeping changes in order to provide better emergency care. With their experience (12 and 20 years respectively) and understanding of the government policies, can also help non-profit and inefficient EDs develop improvement programs.

- *Two researchers*: Both currently working on the academic sector and taking part in projects related to the healthcare industry. They are experts on the implementation of MCDM techniques for the performance evaluation and identification of potential improvement points. Additionally, they have been working with the healthcare cluster and therefore fully know the strategic plans derived from the current needs of emergency services.

The group of experts incorporated a total of **8 criteria** and **35 sub-criteria** to assess the overall performance of emergency departments from the public sector. The decision elements were defined with basis on the personal experience of each decision maker and the performance metrics defined by the Ministry of Health and Social Protection of Colombia through Resolution No. 0256 of 2016 (Quality Information System and Indicators for Healthcare Quality Monitoring), Resolution No. 5596 of 2015 (Technical Criteria for the System of Selection and Classification of Patients in Emergency Departments – Triage) and Decree No. 903 of 2014 (Single Accreditation System on Healthcare) which provide a solid and realistic foundation for the creation and implementation of performance evaluation models in emergency departments. The resulting multicriteria model was then reviewed during several sessions with the experts' group to verify if it was useful and easy-to-understand. The final version of the hierarchy is presented in Figure 2. Each criterion and sub-criterion is labelled and described in Table 4. Finally, the experts involved in the decision-making team judged on the importance and influence of criteria and sub-criteria after a careful explanation of FAHP and FDEMATEL methods.

Table 4. Description of criteria and sub-criteria

Criterion	Sub-criteria	Criterion description
Infrastructure (C1)	Physical condition (SC1) Ventilation and lighting (SC2) Toilet facilities (SC3) Delimitation of ED areas (SC4)	Represents the set of space, design, power, water, hygiene, sanitation and equipment requirements that are

	Physical capacity (SC5)	necessary to deliver high-quality emergency care (Scholz et al., 2015).
Medical equipment (C2)	Availability of medical equipment (SC6) Suitability of medical equipment (SC7) State of medical equipment (SC8)	Refers to the availability, suitability and state conditions of the devices that are used in the prevention, diagnosis or treatment of diseases in EDs aiming to detect, measure, restore, correct or modify the structure or function of the body for some health purpose (Ivlev et al., 2015; Barrios et al., 2016).
Procedures and protocols (C3)	Presence of healthcare procedures (SC9) Dissemination of procedures and protocols (SC10) Adherence of healthcare protocols and procedures (SC11)	Encompasses the activities performed for the implementation of the statements developed to assist practitioners, doctors and patient decisions about suitable ED care for particular circumstances (Kovacs et al., 2018).
Supporting processes (C4)	Effectiveness of radiology process (SC12) Effectiveness of clinical lab (SC13) Effectiveness of hospitalization process (SC14) Effectiveness of pharmaceutical service (SC15) Transportation effectiveness (SC16) Effectiveness of sterilization process (SC17) Effectiveness of non-core activities (SC18)	Denotes a group of processes co-ordinately assisting emergency care. These processes contribute to the effective communication for both fast and appropriate decision-making (Morley et al., 2018).
Human resources (C5)	Availability of specialists (SC19) Availability of general practitioners (SC20) ALS certification (SC21) Availability of nurses (SC22)	Symbolizes the availability and skills of the medical staff for Advanced Life Support in emergency departments (Hermann et al., 2019).
Supplies, medicines and accessories (C6)	Availability of accessories and instrumentation (SC23) Availability of supplies (SC24) Availability of medicines (SC25) Availability of beds (SC26)	Represents the availability of the supplies, accessories, instrumentation, medicines and beds that are used for the prevention, diagnosis or treatment of patients' illnesses during ED healthcare (Hawley et al., 2016).
Quality (C7)	Average physician waiting time (SC27) Patient satisfaction level (SC28) Average length of stay (SC29) Readmission rate (SC30) Waiting time for triage classification (SC31)	Defines the degree to which the healthcare provided by the EDs increase the likelihood of desired health outcomes and is consistent with current professional knowledge in terms of effectiveness, efficiency, equity, patient-centeredness and timeliness (Stang et al., 2015).
Patient safety (C8)	Hospital-acquired infections (SC32) Medication errors (SC33) Errors of clinical diagnosis (SC34) Patient misidentification (SC35)	Patient safety is the cornerstone of high-quality ED care.[60] In this regard, this criterion denotes how well these departments prevent

		errors and adverse effects to patients associated with health care (Farup, 2015; Carter et al., 2014).

Below is an explanation of each sub-element of the model. First, “INFRASTRUCTURE” criterion is comprised of five sub-criteria: PHYSICAL CONDITION (SC1), VENTILATION AND LIGHTING (SC2), TOILET FACILITIES (SC3), DELIMITATION OF ED AREAS (SC4) and PHYSICAL CAPACITY (SC5).

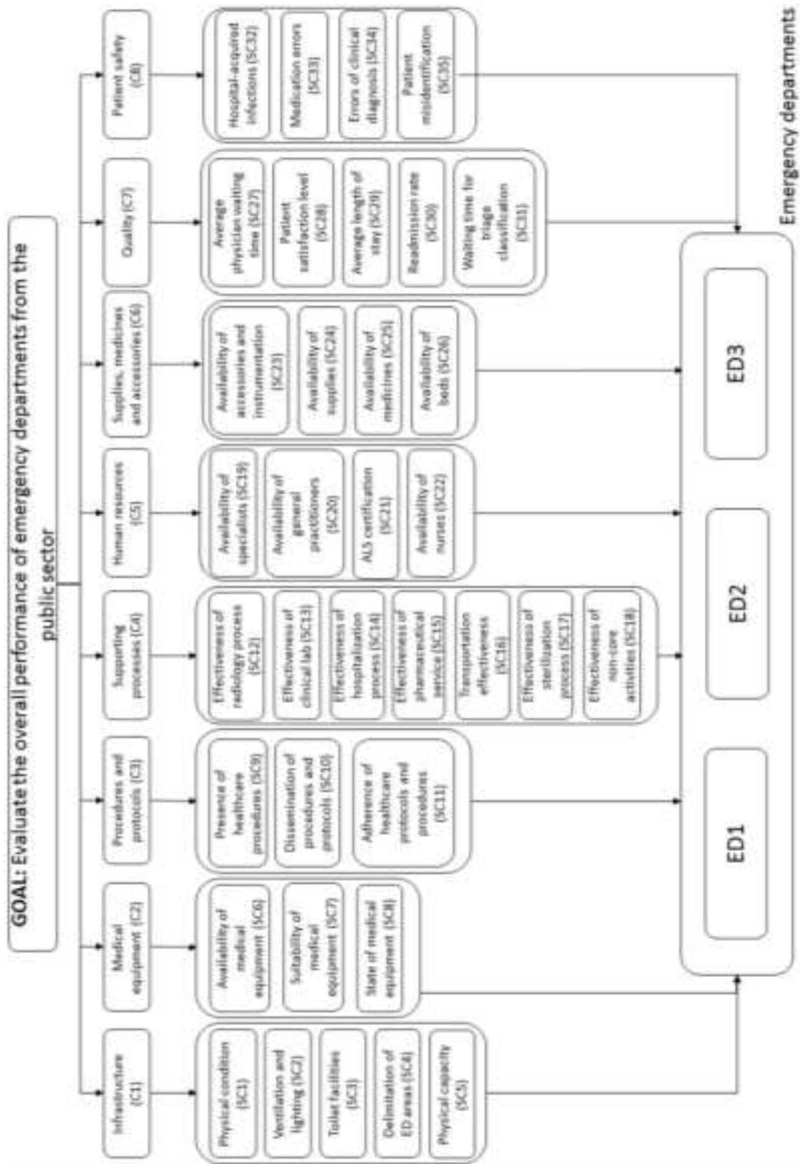


Figure 2. Decision-making model to evaluate the overall performance of emergency departments from the public sector.

Particularly, PHYSICAL CONDITION represents the current status of the ED facilities in terms of functionality, safety and comfort. On the other hand, VENTILATION AND LIGHTING considers how well the emergency department meets the air supply and illumination standards. Another aspect of interest is TOILET FACILITIES which denotes the availability of cleaning areas in the emergency department. The next in order is DELIMITATION OF ED AREAS which assesses whether the major (i.e. triage, resuscitation room, immediate care unit, space for minor emergencies, room for minor surgeries, paediatric emergencies, computed tomography and critical observer) and minor areas of the emergency departments are fully identified and marked with proper signs. Another decision element considered in this cluster is PHYSICAL CAPACITY which establishes the number of available beds in a particular ED.

The second criterion considered in the hierarchical model is “MEDICAL EQUIPMENT”. Medical devices used in EDs are included in the information technology area given their ability to store, retrieve, transmit, and manipulate data (through computer hardware and software) derived from patients and emergency care processes. Herein, three decision elements can be found: AVAILABILITY OF MEDICAL EQUIPMENT (SC6), SUITABILITY OF MEDICAL EQUIPMENT (SC7) and STATE OF MEDICAL EQUIPMENT (SC8). Specifically, AVAILABILITY OF MEDICAL EQUIPMENT represents the percentage of medical devices that is fully or partially functional to be used by the medical staff during ED care. The second criterion is SUITABILITY OF MEDICAL EQUIPMENT which determines whether the medical devices are pertinent to both ED needs and patient expectations. The third decision element within “Medical equipment” cluster is STATE OF MEDICAL EQUIPMENT which evaluates the current technical conditions of the medical devices that are used during prevention, treatment, rehabilitation and diagnosis activities performed by EDs. The proposed hybrid model can then provide meaningful insights on these information technology sub-criteria for further monitoring and improvement. For example, poor performance in “Suitability of medical equipment” may lead to a better selection of health information technology (HIT).

Concerning “PROCEDURES AND PROTOCOLS” criterion, three sub-elements are also deemed: PRESENCE OF HEALTHCARE PROCEDURES (SC9), DISSEMINATION OF PROCEDURES AND PROTOCOLS (SC10) and ADHERENCE OF HEALTHCARE PROTOCOLS (SC11). The first sub-criterion assesses if the standard operation procedures (SOP) have been documented and included in the quality management system (QMS) of the emergency departments (Ebben et al., 2018). On the other hand, DISSEMINATION OF PROCEDURES AND

PROTOCOLS determines whether the SOPs have been fully known and understood by the medical and administrative staff involved. Apart from these sub-criteria, we also considered the ADHERENCE OF HEALTHCARE PROTOCOLS. Particularly, this sub-element establishes how well the EDs comply with the protocols, regulations and international standards documented in the QMS.

In “SUPPORTING PROCESSES” factor, seven decision elements have been taken into account: EFFECTIVENESS OF RADIOLOGY PROCESS (SC12), EFFECTIVENESS OF CLINICAL LAB (SC13), EFFECTIVENESS OF HOSPITALIZATION PROCESS (SC14), EFFECTIVENESS OF PHARMACEUTICAL SERVICE (SC15), TRANSPORTATION EFFECTIVENESS (SC16), EFFECTIVENESS OF STERILIZATION PROCESS (SC17) and EFFECTIVENESS OF NON-CORE SERVICES (SC18). The first sub-element evaluates the rapidness of radiology units to provide diagnostic imaging to EDs. Likewise, EFFECTIVENESS OF CLINICAL LAB examines the turnaround time (TAT) for laboratory results. On the other hand, EFFECTIVENESS OF HOSPITALIZATION PROCESS measures the average waiting time between the request for a bed and the time in which the ED patient is transferred to it. Another aspect considered in the regulations was the EFFECTIVENESS OF PHARMACEUTICAL SERVICE. This sub-factor represents the time in which the medication orders are dispensed in accordance with the need established by the ED physicians. In addition to the aforementioned decision sub-elements, the group of experts recommended assessing the TRANSPORTATION EFFECTIVENESS. Specifically, this aspect determines whether the ED has ambulances satisfying the government standards and regulations. Another sub-criterion of interest in this cluster is EFFECTIVENESS OF STERILIZATION PROCESS. Particularly, this sub-factor seeks to define if the EDs apply disinfection and sterilization protocols in healthcare settings. Government laws also evaluate the EFFECTIVENESS OF NON-CORE SERVICES to support ED operations. This domain encompasses the Maintenance, cooking, laundry and surveillance activities performed in ED settings. Their contribution is relevant to assist a service subject to patient turnover and even overcrowding (Innes et al., 2019).

Up to this point, we have explained the aspects related to the infrastructure, medical equipment, supporting processes and protocols assisting ED operations. Yet, other elements cannot be discarded from this study. In this regard, “HUMAN RESOURCES” has been also included in the decision hierarchy containing four sub-criteria: AVAILABILITY OF SPECIALISTS (SC19), AVAILABILITY OF GENERAL PRACTITIONERS (SC20), ALS CERTIFICATION (SC21) and AVAILABILITY OF NURSES (SC22). Frequently, the AVAILABILITY OF SPECIALISTS has been associated with ED overcrowding (Chan et al., 2015; Yarmohammadian et al., 2017; Di Somma et al., 2015). This sub-factor represents the number of full-time and part-time specialists that is intended to respond to the risen demand for advanced emergency care. It is also necessary to verify the availability of both general practitioners (GPs) and nurses. The AVAILABILITY OF GENERAL PRACTITIONERS focuses on how many GPs have been employed by the ED in order to provide care for patients with less urgent clinical problems (Uthman et al., 2018). On the other hand, the AVAILABILITY OF NURSES refers to the number of nursing professionals directly associated with attending patients during the ED service. In addition to the above-mentioned sub-elements, it was considered essential to evaluate ALS CERTIFICATION in EDs. This sub-criterion establishes the percentage of nursing and medical staff certified in Advanced Life Support (ALS).

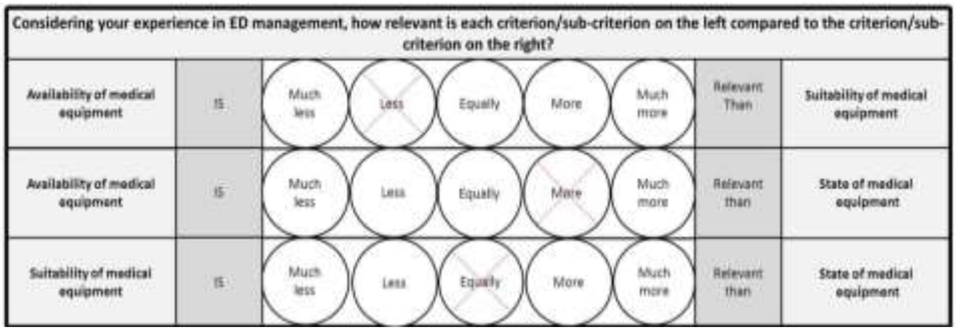
We also assessed the SUPPLIES, MEDICINES AND ACCESSORIES criterion which is defined by four decision elements: AVAILABILITY OF ACCESSORIES AND INSTRUMENTATION (SC23), AVAILABILITY OF SUPPLIES (SC24), AVAILABILITY OF MEDICINES (SC25) and AVAILABILITY OF BEDS (SC26). The presence of “AVAILABILITY OF ACCESSORIES AND INSTRUMENTATION” sub-criterion allows decision-makers to determine if the EDs pose the medical instruments necessary to stabilize patients who are found to have an emergency medical condition (Razzak et al., 2015). Regarding AVAILABILITY OF SUPPLIES, the reported literature has evidenced its influence on ED efficiency (Dart et al., 2018; Mkoka et al., 2014). In this respect, the scarcity of medical supplies may contribute to poor quality emergency service and increased mortality rate. Thus, policymakers should evaluate the governance of the delivery system and focus on stakeholders’ performance. On the other hand, AVAILABILITY OF MEDICINES sets whether the service level provided by the inventory of drugs is enough to satisfactorily respond to the emergency services demand. Another aspect of concern in EDs is the AVAILABILITY OF BEDS. Deficiencies in bed capacity generate the boarding of admitted patients in EDs (Beck et al., 2016). In this sense, the patients are placed in hallways and storage rooms resulting in ED congestion and poor healthcare outcomes.

The performance of EDs is also influenced by QUALITY. To well define this domain, five sub-elements were considered: AVERAGE PHYSICIAN WAITING TIME (SC27), PATIENT SATISFACTION LEVEL (SC28), AVERAGE LENGTH OF STAY (SC29), READMISSION RATE (SC30) and WAITING TIME FOR TRIAGE CLASSIFICATION (SC31). Special attention has been paid to timely clinical care in EDs. Prolonged PHYSICIAN WAITING TIME augments patient dissatisfaction, causes delayed admissions of new patients and interferes with providing effective medical care (Oliveira et al., 2018). In this sense, it is therefore important to continuously measure and control this performance metric in order to improve the efficacy of emergency departments. The second aspect is a significant mediator for a range of outcomes in EDs (i.e. quality of care and service delivery). Satisfied patients have a meaningful impact on the public view of emergency care in general. To a great extent, ED managers must use satisfaction data to analyse overtime, study improvement strategies, evaluate physician’s performance and design incentive programs (Vermeulen et al., 2016). Another element of importance in this cluster is AVERAGE LENGTH OF STAY (ALOS) which refers to the time elapsed between patient registration and departure. In the decision-making model, READMISSION RATE was also considered as a potential determinant of ED overall performance. Readmissions are costly and interventions are then necessary to alleviate the subsequent burden faced by EDs (Singh et al., 2015). Thus, it should be continuously monitored as a purported measure of quality (Venkatesh et al., 2018). Another measure under consideration is WAITING TIME FOR TRIAGE CLASSIFICATION. Triage systems have been designed to rapidly discriminate critical ill patients in EDs and have contributed to improved patient satisfaction and diminished waiting times (Oliveira et al., 2018); although, if it is not well implemented and administrated, it may increase the waiting time interval and subsequently influences patient morbidity and nurses dissatisfaction indirectly.

Considering the goal of assessing the overall performance of EDs, PATIENT SAFETY criterion was also taken into account in this study. With regard to this area, four decision elements were identified: HOSPITAL-ACQUIRED INFECTIONS (SC32), MEDICATION ERRORS (SC33), ERRORS OF CLINICAL DIAGNOSIS (SC34) and PATIENT MISIDENTIFICATION (SC35). First, SC32 denote the infections acquired in healthcare facilities and may result in increased morbidity, mortality and costs. In turn, MEDICATION ERRORS have been defined as "*any preventable event that may cause or lead to inappropriate medication use or patient harm while medication is in the control of the healthcare professional, patient or consumer*" (Källberg et al., 2015; Riga et al., 2015). Another aspect of interest is ERRORS OF CLINICAL DIAGNOSIS. These are described as the inaccurate and delayed diagnosis which may lead to serious harm or treatment changes (Norman et al., 2017). Whilst, PATIENT MISIDENTIFICATION is the failure to correctly identify patients which results in medication errors, testing errors and disruptive care.

2.3.4.2 Phase 2: final criteria and sub-criteria weights

This phase initially presents the data-collection instrument implemented for gathering all the pairwise comparisons in the FAHP method. The main objective is to propose an easy-to-understand and effective way to introduce FAHP to the decision makers who are untrained in complex mathematics (e.g. medical and administrative staff). Thereby, inconsistency can be meaningfully diminished so that reliability of the decision-making process can be significantly augmented. In this regard, a survey (refer to Fig. 3) was created and used during a 20-minute session led by the researchers. For each pairwise comparison, it was asked: *Considering your experience in ED management how relevant is each criterion/sub-criterion on the left compared to the criterion/sub-criterion on the right?* The experts considered in Sub-section 2.3.4.1 filled out the survey by using the aforementioned three-level scale stated in Section 2.3.3.1. This procedure was then repeated until completing all the judgments. Particularly, the survey layout and the shorter version of Saaty's scale greatly helps to diminish intransitive comparisons during the process.



Considering your experience in ED management, how relevant is each criterion/sub-criterion on the left compared to the criterion/sub-criterion on the right?								
Availability of medical equipment	IS	Much less	Less	Equally	More	Much more	Relevant Than	Suitability of medical equipment
Availability of medical equipment	IS	Much less	Less	Equally	More	Much more	Relevant than	State of medical equipment
Suitability of medical equipment	IS	Much less	Less	Equally	More	Much more	Relevant than	State of medical equipment

Figure 3. Data-collection instrument for FAHP comparisons

The collected data were then aggregated and arranged using Eq. 1-3. An example of a fuzzy judgment matrix is presented in Table 5. After this, by using Eq. 4, the geometric means of fuzzy judgments were estimated for each decision element. An illustration of these results is described in Table 6. Furthermore, by applying Eq. 5-7, the normalized weight values of criteria and sub-criteria were achieved (refer to Table 7). The fuzzy and non-fuzzy global criterion (k = 1, 2, …, m) weight GW_k, local sub-criterion (i = 1, 2, …, s) weight LW_i^k, and global sub-criterion (i = 1, 2, …, s) priorities GW_i^k were enlisted in Table 8 to present the outcomes of the FAHP method.

Table 5. Fuzzy judgment matrix for "criteria"

	C1	C2	C3	C4	C5	C6	C7	C8
C1	[1.000,1.000, 1.000]	[2.167,2.667 ,3.167]	[1.708,2.2 22,2.750]	[2.167,2.667 ,3.167]	[1.542,1.8 88,2.250]	[1.125,1.332 ,1.583]	[1.833,2.3 33,2.833]	[2.500,3.3 33,4.167]
C2	[0.595,0.622, 0.667]	[1.000,1.000 ,1.000]	[1.500,2.0 00,2.500]	[1.375,1.888 ,2.417]	[1.083,1.4 43,1.833]	[0.875,0.888 ,0.917]	[1.333,1.6 67,2.000]	[0.875,0.8 88,0.917]
C3	[0.777,0.977, 1.208]	[0.625,0.665 ,0.750]	[1.000,1.0 00,1.000]	[1.333,1.667 ,2.000]	[1.542,2.2 22,2.917]	[1.208,1.555 ,1.917]	[1.500,2.0 00.2.500]	[1.000,1.0 00,1.000]
C4	[0.595,0.622, 0.667]	[0.792,0.998 ,1.250]	[0.750,0.7 77,0.833]	[1.000,1.000 ,1.000]	[1.667,2.3 33,3.000]	[0.750,0.777 ,0.833]	[1.333,1.6 67,2.000]	[0.917,1.1 10,1.333]
C5	[0.902,1.088, 1.292]	[1.083,1.443 ,1.833]	[0.667,0.8 87,1.167]	[0.500,0.553 ,0.667]	[1.000,1.0 00,1.000]	[1.333,1.667 ,2.000]	[1.375,1.5 55,1.750]	[1.833,2.3 33,2.833]
C6	[1.360,1.867, 2.375]	[1.167,1.333 ,1.500]	[0.917,1.1 10,1.333]	[1.333,1.667 ,2.000]	[0.750,0.7 77,0.833]	[1.000,1.000 ,1.000]	[1.333,1.6 67,2.000]	[0.875,0.8 88,0.917]
C7	[0.610,0.643, 0.708]	[0.750,0.777 ,0.833]	[0.625,0.6 65,0.750]	[0.750,0.777 ,0.833]	[1.027,1.2 00,1.375]	[0.750,0.777 ,0.833]	[1.000,1.0 00,1.000]	[1.333,1.6 67,2.000]
C8	[0.345,0.398, 0.500]	[1.167,1.333 ,1.500]	[1.000,1.0 00,1.000]	[1.208,1.555 ,1.917]	[0.610,0.6 43,0.708]	[1.167,1.333 ,1.500]	[0.750,0.7 77,0.833]	[1.000,1.0 00,1.000]

Table 6. Geometric means of fuzzy comparisons for "factors" cluster

Criterion	Geometric mean of fuzzy comparisons
C1	[1.810, 2.268, 2.740]

C2	[1.045, 1.238, 1.433]
C3	[1.088, 1.333, 1.587]
C4	[0.916, 1.071, 1.245]
C5	[1.013, 1.246, 1.514]
C6	[1.246, 1.448, 1.620]
C7	[1.042, 1.076, 1.104]
C8	[0.850, 0.930, 1.000]

Table 7. Normalized fuzzy global weights for “criteria”

Fuzzy weight				**Non-fuzzy weight**	**Normalized weight**
C1	0.148	0.214	0.304	0.222	0.215
C2	0.085	0.117	0.159	0.120	0.117
C3	0.089	0.126	0.176	0.130	0.126
C4	0.075	0.101	0.138	0.105	0.101
C5	0.083	0.117	0.168	0.123	0.119
C6	0.102	0.103	0.180	0.139	0.135
C7	0.085	0.101	0.123	0.103	0.100
C8	0.069	0.088	0.111	0.089	0.087
Total				1.032	1

Table 8. Local and global weights of criteria and sub-criteria by using FAHP

Criterion-sub criterion	**Local weight**	**Global weight**
Infrastructure (C1)		0.215
Physical condition (SC1)	0.256	0.055
Ventilation and lighting (SC2)	0.126	0.027
Toilet facilities (SC3)	0.160	0.034
Delimitation of ED areas (SC4)	0.290	0.062
Physical capacity (SC5)	0.168	0.036
Medical equipment (C2)		0.117
Availability of medical equipment (SC6)	0.423	0.049
Suitability of medical equipment (SC7)	0.365	0.043
State of medical equipment(SC8)	0.212	0.025
Procedures and protocols (C3)		0.126
Presence of healthcare procedures (SC9)	0.333	0.042
Dissemination of procedures and protocols (SC10)	0.333	0.042
Adherence of healthcare protocols and procedures (SC11)	0.333	0.042
Supporting processes (C4)		0.101
Effectiveness of radiology process (SC12)	0.198	0.020
Effectiveness of clinical lab (SC13)	0.209	0.021
Effectiveness of hospitalization process (SC14)	0.130	0.013
Effectiveness of pharmaceutical service (SC15)	0.167	0.017
Transportation effectiveness (SC16)	0.124	0.013
Effectiveness of sterilization process (SC17)	0.115	0.012
Effectiveness of non-core activities (SC18)	0.058	0.006
Human resources (SC5)		0.119
Availability of specialists (SC19)	0.345	0.041

Availability of general practitioners (SC20)	0.364	0.043
ALC certification (SC21)	0.224	0.027
Availability of nurses (SC22)	0.067	0.008
Supplies, medicines and accessories (C6)		0.135
Availability of accessories and instrumentation (SC23)	0.307	0.041
Availability of supplies (SC24)	0.276	0.037
Availability of medicines (SC25)	0.270	0.036
Availability of beds (SC26)	0.148	0.020
Quality (C7)		0.100
Average physician waiting time (SC27)	0.149	0.015
Patient satisfaction level (SC28)	0.280	0.028
Average length of stay (SC29)	0.145	0.015
Readmission rate (SC30)	0.332	0.033
Waiting time for triage classification (SC31)	0.092	0.009
Patient safety (C8)		0.087
Hospital-acquired infections (SC32)	0.280	0.024
Medication errors (SC33)	0.262	0.023
Errors of clinical diagnosis (SC34)	0.203	0.018
Patient misidentification (SC35)	0.255	0.022

Infrastructure was the criterion with the highest priority level (GW = 21.5%) while *Supplies, medicines and accessories* was ranked in the second place (GW = 13.50%) (Fig. 4). However, the difference between *C6* (2nd place) and *C8* (8th place) is not significant (4.8%). This evidences that multidimensional improvement strategies should be designed with a huge focus on *Infrastructure* so that the overall ED performance can be continuously and significantly augmented. ED managers should then convert these outcomes into new management policies coping with the rapid changes addressed by emergency services in terms of increasing patient numbers and limited resources. On the other hand, given the multifactorial nature of the strategies, it is important to ensure the participation and commitment of all the departments involved in the ED core operations both directly and indirectly. This is to avoid quality-related problems such as overcrowding, patients leaving without their care being finished, adverse events, high mortality rate, and increased readmission. Indeed, similar studies as those presented by Mohammadi et al. (2016), Zhao and Paul (2012), and Pan et al. (2016) have highlighted the need for continuously monitoring these measures in EDs in order to provide satisfactory emergency care to patients.

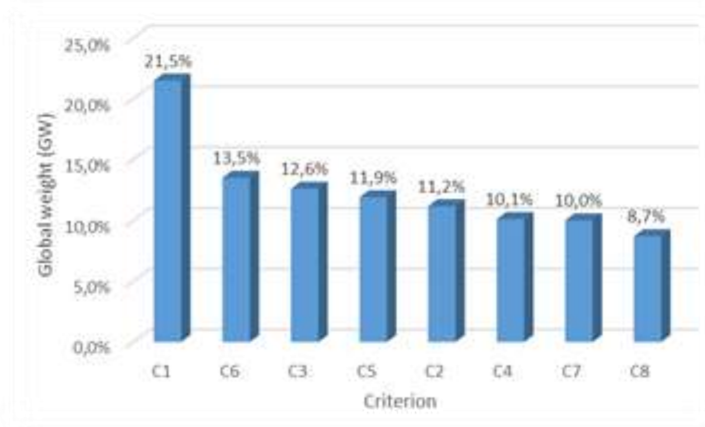


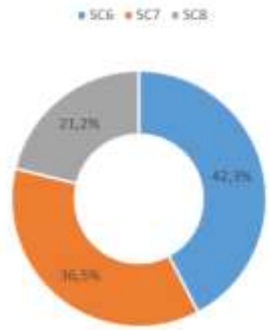
Figure 4. Global criteria weights derived from the FAHP method

Local weights were also analysed after performing FAHP calculations (Eq. 1-7). Particularly, in *Infrastructure* cluster (Figure 5a), the most important sub-criterion was *Delimitation of areas – SC1* (29.0%). In this regard, several studies have concluded that proper demarcation facilitates patient flow within EDs. If this is not well implemented, negative effects can be expected regarding the length of stay and patient safety. In fact, this has to be considered as a major requirement for future ED architectural designs in order to avoid patients' stress and ensure timely physician assessment. Moreover, this aspect is also regulated by control agencies during accreditation visits and should be therefore further prioritized by the ED managers for continuous monitoring and intervention.

In *Medical equipment* cluster (Figure 5b), the most relevant decision element was *Availability of medical equipment – SC6* (42.3%). Constant management efforts should be then directed towards the monitoring and evaluation of stock-outs and equipment breakdowns as well as service contracts and local repair capabilities. This facilitates the effective procurement and stock management, activities of great importance for defining rapid interventions and underpinning ED core operations. These considerations have to be also inserted into the planning processes of EDs to ensure budget availability and timely maintenance interventions. Similarly to *Physical condition*, deficiencies in equipment availability may result in poor patient outcomes and reduced quality of care. Furthermore, as slight difference was detected between this sub-criterion and *Suitability of medical equipment - SC7*

(5.8%), *SC7* is also called to be considered within the improvement strategies created in this domain.

(a)



(b)

Figure 5. Local contributions in **a)** Infrastructure cluster **b)** Medical equipment cluster

In *Procedures and protocols* cluster (Figure 6a), the sub-criteria were found equally important (33.3%). This result bears out the importance of correctly translating the ED guidelines to the stakeholders in order to ensure that they are recognized and well understood prior to implementation. Such intervention helps to reduce the gap between the protocols and clinical practice which results in a lessened number of patients not receiving appropriate care. In addition, the correct dissemination of protocols enables nurses to initiate diagnostic tests on-time so that length of patient stay can be diminished while improving the bedtime availability. This finding confirms the urgent need for appropriately creating, disseminating and adhering to ED protocols and procedures as a path towards the decline of adverse events and patient dissatisfaction within ED settings. As explained by Yamani et al. (2012), this is propelled by the effective interaction between ED physicians and nurses, a space where their communicational skills should be often converge for providing well and efficient care.

In *Supporting processes* criterion (Figure 6b), the most important sub-criterion was *Effectiveness of clinical lab - SC13* (20.9%). Laboratory testing has been found to have a significant influence on patients' length of stay in emergency departments (Georgiou et al., 2015). In this regard, clinical laboratories have to be effectively managed in order to reduce ED overcrowding. Interventions may include controlling the laboratory service performance through increasing lab resources and staffing after-hours. Aside from clinical lab, 5 more supporting processes (*SC12, SC14, SC15, SC16,* and *SC17*) were found to have non-significant gaps with respect to the leading sub-criterion and should be hence considered to be inserted into future improvement~~s~~ programs.

(a) (b)

Figure 6. Local contributions in a) Procedures and Protocols cluster b) Supporting processes cluster

In *Human resources* cluster (Figure 7a), the most relevant decision element was *Availability of general practitioners - SC20* (36.4%). General practitioners (GPs) play a crucial role in EDs since they provide primary care to patients. In fact, GPs are a response to the increased number of non-urgent patients, one of the main causes of ED overcrowding and extended waiting times. Additionally, it has been proved that GPs tend to make fewer referrals to other specialists, order fewer tests and work under ED standards which is beneficial to reduce the financial burden faced by policymakers (Uthman et al., 2018). However, the GPs are advised to work together with specialists in order to ensure high quality of care. This could be an explanation of why *Availability of specialists – SC19* (34.5%) was ranked second in *Human resources* criterion. These findings are consistent with Gul et al. (2016), Yeh and Cheng (2016) and Ketabi et al. (2018) whose DEA models qualified "number of staff" as a critical input in EDs. Regarding *Supplies, medicines and accessories* cluster (Figure 7b), *Availability of accessories and instrumentation - SC23* was ranked in the first place. Being aware of its importance, *World Health Organization (WHO)* (2004) has established a list of essential supplies for providing a basic emergency care. Policymakers must then ensure high fill rate of these material resources to meet priority health needs while saving in acquisition costs. This is even more important in the developing world where resources are largely limited. It is therefore necessary to properly promote collaborations between suppliers and policymakers for allocating financial resources properly.

(a) (b)

Figure 7. Local contributions in a) Human resources cluster b) Supplies, medicines and accessories cluster

In *Quality* cluster (Figure 8a), the most relevant sub-criterion was *Readmission rate – SC30* (33.2%). Today's emergency departments have to focus on reducing readmission rates in order to restore patient's confidence, diminish unnecessary overcrowding, and minimize the cost of medical care (Telem et al., 2016). It is then relevant to find the factors associated with patients' return by studying the pre-discharge, ED care, and post-discharge processes to subsequently establish targeted interventions addressing this problem. To this particular aim, discharge planning, outpatient monitoring, and education can be implemented. It is also good to highlight the importance of *patient satisfaction level* (28.0%) which was ranked second according to the FAHP results. In this regard, the DEA model developed by Ketabi et al. (2018) found that the number of patients' complaints is an aspect of extreme consideration in emergency care services. In fact, the selection of EDs is strongly influenced by the quality perception of patients as also stated by Yamani et al. (2012) through their 360 degree evaluation. Another significant finding is the accumulated sum of relative weights corresponding to the waiting times (24.1%). The increasing attention on this indicator is consistent with the focus of several performance evaluation models as those designed by Mohammadi et al. (2016), Yamani et al (2012), and Ketabi et al. (2018). On the contrary, despite its inclusion in the performance model proposed by Pan et al (2016) length of stay was not considered as highly important in this study (14.5%). Regarding *Patient safety* criterion (Figure 8b), the most significant element was *Hospital-acquired infections – SC32* (28.0%). However, little difference (7.7%) was found between this sub-criterion and *Errors of clinical diagnosis*. This is an evidence of the multidimensional nature of patient safety, which demands multifactorial strategies (including the aspects described in this cluster) to reduce the negative impact on patients' health. In this respect, it is important to better characterize the adverse events occurring in ED settings and their causes (e.g. multiple transitions in care and ED overcrowding). Furthermore, system failure prevention must be a priority for ED directors and quality managers considering that EDs are prone to patient safety incidents and demands for emergency services continue to rise (Rigobello et al., 2017).

(a) (b)

Figure 8. Local contributions in a) Quality cluster b) Patient safety cluster

The consistency ratios (CR) were also computed (refer to Table 9). Since CR values are not greater than 10%, the calculated weights can be used to establish the priority ranking of EDs. In this regard, the experts were neither inconsistent nor random when making the comparisons. Therefore, the evaluation process can be considered as satisfactory and both reduced FAHP scale and survey layout can be effectively replicated in real-world scenarios.

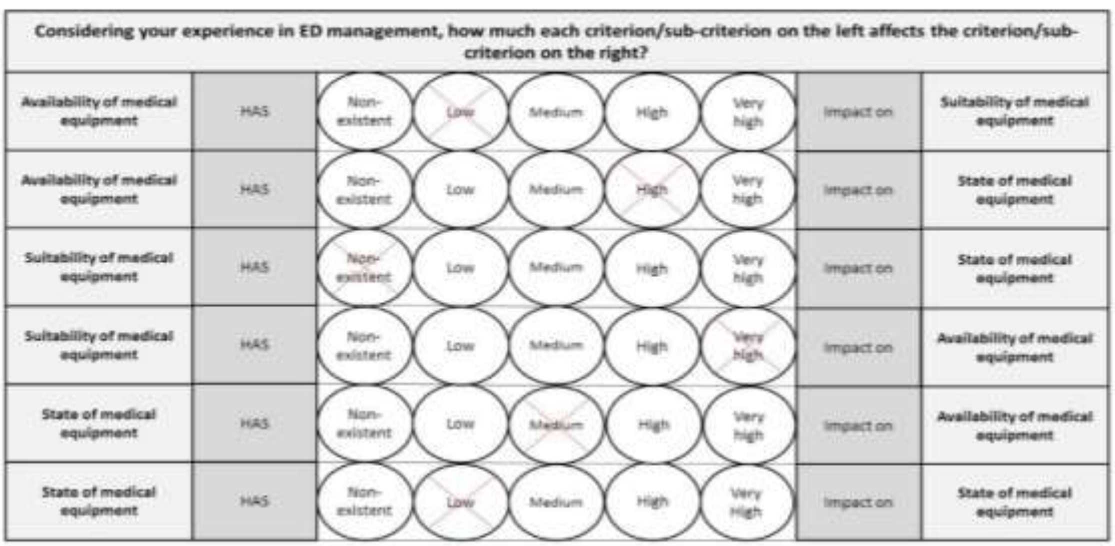
Table 9. Consistency ratios for fuzzy judgment matrixes

Matrix	Consistency ratio (CR)
Criteria	0.058
Infrastructure	0.046
Medical equipment	0.024
Procedures and protocols	0.003
Supporting processes	0.046
Human resources	0.062

Supplies, medicines and accessories	0.057
Quality	0.097
Patient safety	0.020

2.3.4.3 Phase 3: Interdependence and feedback among decision elements

Similar to the FAHP method, a survey was designed for collecting FDEMATEL comparisons (refer to Figure 9) which will evidence the interdependence and feedback among criteria/sub-sub-criteria. For each judgment, it was asked: *Considering your experience in ED management, how much each criterion/sub-criterion on the left affects the criterion/sub-criterion on the right?* The decision-makers considered in Sub-section 2.3.4.1 answered in accordance with the five-point scale presented in Table 3. The evaluation process was also repeated until completing all the comparisons.



Considering your experience in ED management, how much each criterion/sub-criterion on the left affects the criterion/sub-criterion on the right?								
Availability of medical equipment	HAS	Non-existent	Low	Medium	High	Very high	Impact on	Suitability of medical equipment
Availability of medical equipment	HAS	Non-existent	Low	Medium	High	Very high	Impact on	State of medical equipment
Suitability of medical equipment	HAS	Non-existent	Low	Medium	High	Very high	Impact on	State of medical equipment
Suitability of medical equipment	HAS	Non-existent	Low	Medium	High	Very high	Impact on	Availability of medical equipment
State of medical equipment	HAS	Non-existent	Low	Medium	High	Very high	Impact on	Availability of medical equipment
State of medical equipment	HAS	Non-existent	Low	Medium	High	Very High	Impact on	State of medical equipment

Figure 9. Data-collection instrument for FDEMATEL comparisons.

The pairwise fuzzy judgments were then aggregated by applying Eq. 8-11. An example of a fuzzy direct-influence matrix $\tilde{\boldsymbol{D}}$ is presented in Table 10. Then, via using Eq. 12, the normalized fuzzy direct-relation matrix $\tilde{N}$ is obtained (refer to Table 11). After this, the fuzzy total-influence matrix is computed by implementing Eq. 13. An illustration of this matrix is described in Table 12.

Table 10. Fuzzy direct-influence matrix for "Patient safety" cluster

	SC32	SC33	SC34	SC35
SC32	[0.000,0.000,0.000]	[0.542,0.792,0.917]	[0.292,0.500,0.750]	[0.375,0.625,0.792]
SC33	[0.500,0.750,0.958]	[0.000,0.000,0.000]	[0.500,0.750,0.958]	[0.250,0.458,0.708]
SC34	[0.417,0.667,0.875]	[0.542,0.792,0.958]	[0.000,0.000,0.000]	[0.250,0.458,0.708]
SC35	[0.333,0.583,0.792]	[0.542,0.792,0.958]	[0.542,0.792,0.958]	[0.000,0.000,0.000]

Table 11. Fuzzy normalized direct-influence matrix for "Patient safety" cluster

	SC32	SC33	SC34	SC35
SC32	[0.000,0.000,0.000]	[0.200,0.292,0.338]	[0.108,0.185,0.277]	[0.138,0.231,0.292]
SC33	[0.158,0.277,0.354]	[0.000,0.000,0.000]	[0.158,0.277,0.354]	[0.092,0.169,0.262]
SC34	[0.154,0.246,0.323]	[0.200,0.292,0.353]	[0.000,0.000,0.000]	[0.092,0.169,0.262]
SC35	[0.123,0.215,0.292]	[0.200,0.292,0.354]	[0.200,0.292,0.354]	[0.000,0.000,0.000]

$\tilde{C}_i$ and $\tilde{R}_j$ values were calculated to finally obtain prominence $\left(\tilde{C}_i+\tilde{R}_j\right)$ and relation $\left(\tilde{C}_i-\tilde{R}_j\right)$ measures (refer to Table 13). The *dispatchers* and *receivers* were then identified and indicated in Table 13. The results reveal that *Patient safety (C8)* has the highest positive *C* + *R* value (12.771) is then considered as the most influencing factor when assessing the overall performance of emergency departments. Hence, *Patient safety (C8)* should be greatly prioritized for continuous improvement in these institutions.

Table 12. Fuzzy total-influence matrix for "Patient safety" cluster

	SC32	SC33	SC34	SC35	R
SC32	[0.015,0.530,4.750]	[0.307,0.827,5.258]	[0.271,0.690,4.996]	[0.203,0.610,4.363]	[0.842,2.657,19.367]
SC33	[0.274,0.754,5.240]	[0.143,0.608,5.245]	[0.274,0.752,5.268]	[0.169,0.573,4.543]	[0.861,2.687,20.295]
SC34	[0.249,0.726,5.109]	[0.306,0.824,5.387]	[0.116,0.528,4.893]	[0.166,0.565,4.444]	[0.837,2.643,19.832]
SC35	[0.242,0.762,5.343]	[0.328,0.889,5.653]	[0.305,0.815,5.410]	[0.092,0.464,4.455]	[0.966,2.930,20.860]
C	[0.088,2.772,20.441]	[1.084,3.148,21.542]	[0.913,2.784,20.568]	[0.629,2.213,17.804]	

Additionally, the high prominence values (*C* + *R* > *10*) evidence the existence of strong correlations between criteria which confirms the interactive nature of emergency care processes. There is also a good chance that *Patient safety (C8)* would be influenced by the rest of the criteria. In this regard, Lisbon et al. (2016) revealed that failure to engage in teamwork behaviours may cause adverse events. Thus, it is important that EDs endeavour to implement formal teamwork training with the goal of reducing medical errors affecting patients of each complexity level. On a different tack, it is necessary to ensure that online decision support tools and medical equipment (C2) are smoothly integrated into all process management systems so that reliable clinical data can be obtained and efficiently analysed for risk management in EDs.

Also, potential dangers of overcrowding should be carefully deemed and addressed as a future *Infrastructure (C1)* challenge. In this respect, physical capacity and facilities of EDs should be adapted to the expected growing demand and required patient safety conditions as highlighted by Gul et al. (2016). On the other hand, the DEMATEL outcomes evidence the influence of *Human resources (C5)* and the corresponding shift patterns in the generation of hazardous conditions within EDs. In fact, the probability of making medical errors and the occurrence of accidents may increase three times with longer work hours. Additionally, errors may occur when the ED staff is stressed and overloaded. Thus, staff scheduling and working conditions should be carefully reviewed in order to diminish both the risk of adverse events and absenteeism. Special attention should be also paid on any deviation from *Procedures and protocols (C3)* which could result in patient deterioration. Indeed, standard operating procedures have been concluded to be in their infancy and ED managers must, therefore, propose solutions aiming to reduce such errors and proactively prevent negative impact on patients' health.

Inefficiencies concerning *Supporting processes (C4)* also appear to contribute to patient safety problems. Actually, delay in ED diagnoses, testing or treatment has been identified to be a risk factor for in-hospital infections and other negative patient outcomes. It is hence necessary to alleviate the burden faced by both patients and EDs through the implementation of improvement projects considering interactions between ED and supporting processes while targeting higher efficiency rates. Likewise, *Supplies, medicines and accessories (C6)* are a vital component for ensuring the effective deployment of patient safety programs. Inappropriate resource management may cause adverse events, especially when combined with already existing problems related to the aforementioned criteria. There is then a need to effectively implement inventory management systems providing satisfactory fill rates of supplies, medicines and accessories with a high turnover rate. Furthermore, it is relevant to purchase items fulfilling patient safety standards so that events such as falls and bloodstream infections can be prevented. Another aspect to be considered in this discussion is *Quality (C7)* which was found to be the dispatcher with the highest prominence (C + R = 12.368). This is explained by the presence of multiple agents as well as the interactions amidst complex diagnostic, healthcare, and logistics processes.

A multidisciplinary system-wide approach is then required to increase the overall performance of EDs. ED managers should thus consider all the criteria when designing effective improvement strategies addressing the current challenges of emergency services including collaboration practices and increased demand.

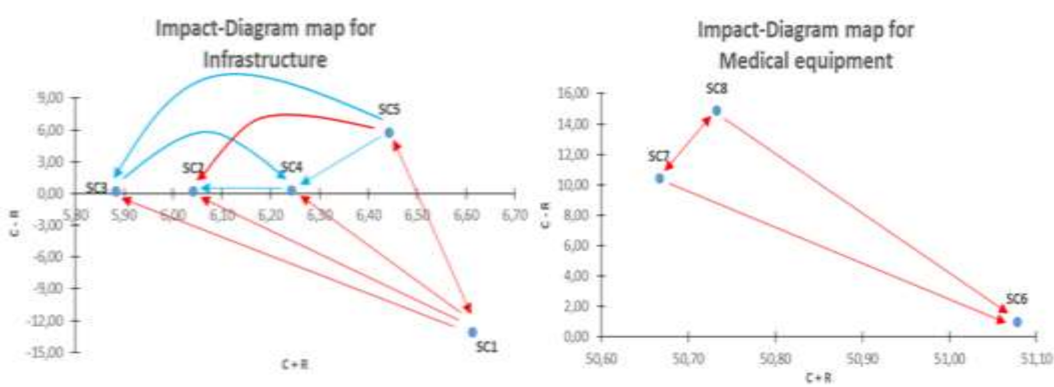
Table 13. Dispatchers and receivers in the decision-making model

Criterion/Sub-criterion	Prominence (C + R)	Relation (C– R)	Dispatcher	Receiver
Infrastructure (C1)	11.470	-0.095		✓
Physical condition (SC1)	6.614	-13.074		✓
Ventilation and lighting (SC2)	6.042	0.244	✓	
Toilet facilities (SC3)	5.883	0.183	✓	
Delimitation of ED areas (SC4)	6.243	0.303	✓	
Physical capacity (SC5)	6.443	5.784	✓	
Medical equipment (C2)	11.778	0.348	✓	
Availability of medical equipment (SC6)	51.078	0.997	✓	
Suitability of medical equipment (SC7)	50.667	10.406	✓	
State of medical equipment (SC8)	50.733	14.854	✓	
Procedures and protocols (C3)	12.146	-0.040		✓
Presence of healthcare procedures (SC9)	16.509	-0.237		✓
Dissemination of procedures and protocols (SC10)	16.386	-12.689		✓
Adherence of healthcare protocols and procedures (SC11)	16.212	0.399	✓	
Supporting processes (C4)	11.711	-4.974		✓
Effectiveness of radiology process (SC12)	7.471	-0.037		✓
Effectiveness of clinical lab (SC13)	7.464	0.104	✓	
Effectiveness of hospitalization process (SC14)	8.371	4.535	✓	
Effectiveness of pharmaceutical service (SC15)	7.342	4.423	✓	
Transportation effectiveness (SC16)	7.125	4.385	✓	
Effectiveness of sterilization process (SC17)	7.000	4.414	✓	
Effectiveness of non-core activities (SC18)	7.203	0.105	✓	
Human resources (C5)	11.704	-0.030		✓
Availability of specialists (SC19)	12.404	-0.041		✓

Availability of general practitioners (SC20)	12.476	2.707	✓	
ALS certification (SC21)	12.037	0.050	✓	
Availability of nurses (SC22)	12.042	0.190	✓	
Supplies, medicines and accessories (C6)	11.763	0.016		✓
Availability of accessories and instrumentation (SC23)	13.106	-1.965		✓
Availability of supplies (SC24)	12.846	-1.385		✓
Availability of medicines (SC25)	12.796	- 1.781		✓
Availability of beds (SC26)	12.633	-2.146		✓
Quality (C7)	12.368	0.382		✓
Average physician waiting time (SC27)	18.225	0.360	✓	
Patient satisfaction level (SC28)	17.820	0.226	✓	
Average length of stay (SC29)	18.216	1.153	✓	
Readmission rate (SC30)	18.052	0.624	✓	
Waiting time for triage classification (SC31)	17.707	0.327	✓	
Patient safety (C8)	12.771	0.120	✓	
Hospital-acquired infections (SC32)	11.250	0.288	✓	
Medication errors (SC33)	11.866	0.555	✓	
Errors of clinical diagnosis (SC34)	11.336	0.253	✓	
Patient misidentification (SC35)	10.852	3.706	✓	

Correlations among sub-criteria of each cluster were later analysed by adopting impact-relation maps - IRM (Figure 10a, 10b). IRMs for *Infrastructure* and *Medical equipment* are provided to give an overview of the DEMATEL application. First, the influence diagram for *Infrastructure* is presented (Figure 10a). The threshold value was set as $p = 15{,}646 / 5^2 = 0{,}626$ after defuzzifying the corresponding fuzzy total-influence matrix. It can be mentioned that *Ventilation and lighting (SC2), Toilet facilities (SC3), Delimitation of ED areas (SC4),* and *Physical capacity (SC5)* are the *dispatchers* while *Physical condition (SC1)* is the receiver. According to the graph, the dispatchers have similar prominence values and therefore, multifactorial improvement strategies considering these sub-criteria have to be performed in order to satisfy the expected ED requirements and effectively underpin the core operations of emergency care. While FAHP evidenced that Delimitation of ED areas – SC4 (LW = 29.0%) is the most important sub-criterion within the Infrastructure (C1) cluster, Physical condition – SC1 was identified as the most influential element (C + R = 6.614) in the fuzzy DEMATEL method. These results are consistent with the fact that the physical condition of emergency care rooms, waiting spaces, and other units within the ED gets deteriorated in the long term whilst the delimitation of ED areas is an aspect of strict control by healthcare authorities. In spite of Delimitation of ED areas – SC4 was not ranked first in the FDEMATEL method, its C + R (6.243) is close to that obtained in SC1; thereby indicating a critical sub-criterion for continuous monitoring in EDs.

An influence diagram was also drawn for *Medical equipment* sub-criteria (Figure 10b). The established threshold value was established as $p = 76{,}541/3^2 = 8{,}505$. In this case, *Availability of medical equipment (SC6), Suitability of medical equipment (SC7),* and *State of medical equipment (SC8)* were categorized as dispatchers. Additionally, a feedback relationship is observed between *Suitability of medical equipment (SC7)* and *State of medical equipment (SC8)*. Given the fact that all the sub-criteria were qualified as dispatchers, ED managers are advised to design multidimensional strategies to ensure the effective incorporation and functioning of the medical equipment during the ED care. In this case, Availability of medical equipment (SC6) was found as both the most important sub-criterion in the FAHP method (LW = 42.3%) and the most influential element (C + R = 51.078) in the medical equipment domain by the fuzzy DEMATEL technique. Such a finding is supported by the fact that the number of available medical equipment should be congruous with the current (short-term period) and projected increased demand (long-term period), especially in disaster situations such as the Covid-19 (World Health Organization, 2020).



(a) (b)

Figure 10. Impact-relation map for a) Infrastructure b) Medical equipment

2.3.4.4 Phase 4: TOPSIS method

To complete implementation of the proposed approach, the EDs were ranked according to their overall performance by using the TOPSIS method. Initially, a set of metrics was defined for each sub-criterion (refer to Table 14) considering the current regulations set by the Ministry of Health and Social Protection. The mathematical formulas of these indicators were also enlisted in Table 14.

Table 14. Key performance metrics for sub-criteria

Sub-criterion	Metric	Formula
Physical condition (SC1)	% of ED rooms with adequate infrastructure conditions	$\frac{\text{Number of ED rooms with adequate infrastructure conditions}}{\text{Total of rooms in ED}} * 100$.
Ventilation and lighting (SC2)	% of ED rooms without appropriate lighting, cleaning and noise conditions	$\frac{\text{Number of ED rooms without appropriate lighting, cleaning and noise conditions}}{\text{Total of rooms in ED}} * 100$
Toilet facilities (SC3)	Availability of toilet facilities	If available (1), otherwise (0)
Delimitation of ED areas (SC4)	Delimitation of ED areas	If delimited (1), otherwise (0)
Physical capacity (SC5)	Floor area	Floor area in m^2
Availability of medical equipment (SC6)	% of available medical equipment	$\frac{\text{Number of available medical equipment}}{\text{Total of medical equipment}} * 100$.
Suitability of medical equipment (SC7)	% of medical equipment with high quality standards	$\frac{\text{Number of medical equipment with high quality standards}}{\text{Total of medical equipment}} * 100$.
State of medical equipment (SC8)	% of damaged medical equipment	$\frac{\text{Number of damaged medical equipment}}{\text{Total of medical equipment}} * 100$.
Presence of healthcare procedures (SC9)	Presence of healthcare procedures	If present (1), otherwise (0)
Dissemination of procedures and protocols (SC10)	% of disseminated procedures and protocols	$\frac{\text{Number of disseminated procedures and protocols}}{\text{Total of procedures and protocols}} * 100$.
Adherence of healthcare protocols and procedures (SC11)	Proportion of monitored adverse events in ED	$\frac{\text{Number of monitored adverse events}}{\text{Total of adverse events}} * 100$.
Effectiveness of radiology process (SC12)	Average waiting time for radiology results	$\sum_{i=1}^{n} \frac{DD_i - RD_i}{n}$.

		Where: n : $number\ of\ radiology\ tests\ in\ a\ year$. DD_i : $delivery\ date\ of\ radiology\ order\ i$. RD_i : $request\ date\ of\ radiology\ order\ i$.
Effectiveness of clinical lab (SC13)	Average waiting time for laboratory test results	$\sum_{j=1}^{n} \frac{DD_j - RD_j}{n}$. Where: n : $number\ of\ laboratory\ tests\ in\ a\ year$. DD_j : $delivery\ date\ of\ laboratory\ test\ order\ j$. RD_j : $request\ date\ of\ laboratory\ test\ order\ j$
Effectiveness of hospitalization process (SC14)	Average transfer time from the ED to inpatient bed	$\sum_{k=1}^{n} \frac{RTD_k - STD_k}{n}$. Where: n : $number\ of\ transferred\ patients\ in\ a\ year$. RTD_k : $real\ transfer\ date\ for\ patient\ k$. STD_k : $scheduled\ transfer\ date\ for\ patient\ k$.
Effectiveness of pharmaceutical service (SC15)	Average waiting time for drug delivery	$\sum_{l=1}^{n} \frac{DD_l - RD_l}{n}$. Where: n : $number\ of\ drug\ orders\ in\ a\ year$. DD_l : $delivery\ date\ of\ drug\ order\ l$. RD_l : $request\ date\ of\ drug\ order\ l$.
Transportation effectiveness (SC16)	Availability of ambulances according to the standards	If available (1), otherwise (0)
Effectiveness of sterilization process (SC17)	Application of sterilization protocols in ED	If available (1), otherwise (0)
Effectiveness of non-core activities (SC18)	Number of non-core activities	Number of non-core activities supporting ED operations
Availability of specialists (SC19)	Number of vacant positions for ED specialists	Number of specialists needed in ED for covering the current demand
Availability of general practitioners (SC20)	Number of vacant positions for ED general practitioners	Number of general practitioners needed in ED for covering the current demand
ALS certification (SC21)	Percentage of physicians and nurses with ALS certification	$\frac{Number\ of\ physicians\ and\ nurses\ with\ ALS\ certification}{Total\ of\ adverse\ events} * 100$.
Availability of nurses (SC22)	Number of vacant positions for ED nurses	Number of nurses needed in ED for covering the current demand
Availability of accessories and instrumentation (SC23)	Availability of accessories and instrumentation	Number of medical devices and instruments needed for covering the current demand
Availability of supplies (SC24)	Fill rate (medical supplies)	$\frac{Number\ of\ satisfied\ orders}{Total\ of\ required\ orders} * 100$.

Availability of medicines (SC25)	Fill rate (Medicines)	$\frac{Number\ of\ satisfied\ orders}{Total\ of\ required\ orders} * 100$.
Availability of beds (SC26)	Bed-occupancy rate	$\frac{Number\ of\ occupied\ beds\ in\ ED}{Total\ of\ beds\ in\ ED} * 100$.
Average physician waiting time (SC27)	Average physician waiting time	$\sum_{k=1}^{n} \frac{AT_k - CT_k}{n}$ Where: $n : number\ of\ patients\ in\ a\ year$. $AT_k : arrival\ time\ for\ patient\ k$. $CT_k : consultation\ time\ for\ patient\ k$.
Patient satisfaction level (SC28)	Patient satisfaction level	$\frac{Number\ of\ satisfied\ patients}{Number\ of\ patients\ received\ in\ ED} * 100$.
Average length of stay (SC29)	Average length of stay	$\frac{Total\ length\ of\ stay\ in\ ED}{Number\ of\ patients\ received\ in\ ED}$.
Readmission rate (SC30)	Readmission rate	$\frac{Number\ of\ readmitted\ patients\ within\ a\ 72\text{-}hour\ period\ due\ to\ the\ same\ cause}{Number\ of\ patients\ received\ in\ ED} * 100$
Waiting time for triage classification (SC31)	Average waiting time for triage classification	$\sum_{k=1}^{n} \frac{AT_k - TCT_k}{n}$. Where: $AT_k : arrival\ time\ for\ patient\ k$ $TCT_k : triage\ classification\ time\ for\ patient\ k$ $n : number\ of\ patients\ in\ a\ year$.
Hospital-acquired infections (SC32)	Average number of hospital-acquired infections per month	$\frac{Total\ of\ hospital-acquired\ infections\ in\ a\ year}{12}$.
Medication errors (SC33)	Average number of medication errors per month	$\frac{Total\ of\ medication\ errors\ in\ a\ year}{12}$
Errors of clinical diagnosis (SC34)	Average number of clinical diagnosis errors per month	$\frac{Total\ of\ clinical\ diagnosis\ errors\ in\ a\ year}{12}$.
Patient misidentification (SC35)	Average number of patient misidentification errors per month	$\frac{Total\ of\ patient\ misidentification\ errors\ in\ a\ year}{12}$.

Tables 15a-15b depicted the TOPSIS decision matrix *X* (Eq. 24) where emergency departments (ED1, ED2, and ED3) were matched to the above-mentioned sub-criteria. KPIs values were then introduced in this table considering the description presented in Table 14. The positive A^+ and negative A^- ideal scenarios were also established in this table. Additionally, the sub-criterion global weights were derived from the FAHP method using Eq. 1-7. On the other hand, Tables 16a-16b show the normalized decision matrix *R* in accordance with Eq. 25 and Eq. 26. Tables 17a-17b present the weighted normalized decision matrix *V* (Eq.27) while Table 18 evidences the distance of each ED from the positive ideal solution d_i^+. Table 18 also provides the contribution of each sub-criterion to the total PIS separation. Lately, Table 19 describes the distance of each ED from the negative ideal scenario d_i^- and the influence of each decision element on this distance.

Table 15a. TOPSIS decision matrix X (SC1 – SC18)

	ED1	ED2	ED3	A+	A-	W	Norm
SC1	1.000	0.950	1.000	1.000	0.950	0.055	1.704
SC2	0.900	0.800	0.930	0.930	0.800	0.027	1.521
SC3	1.000	1.000	1.000	1.000	1.000	0.034	1.732
SC4	1.000	1.000	1.000	1.000	1.000	0.062	1.732
SC5	690.000	580.000	420.000	690.000	420.000	0.036	994.435
SC6	0.950	0.880	0.900	0.950	0.880	0.049	1.577
SC7	0.850	0.780	0.750	0.850	0.750	0.043	1.376
SC8	0.930	0.850	0.880	0.930	0.850	0.025	1.537
SC9	1.000	1.000	1.000	1.000	1.000	0.042	1.732
SC10	1.000	1.000	0.900	1.000	0.900	0.042	1.676
SC11	1.000	1.000	1.000	1.000	1.000	0.042	1.732
SC12	1.500	1.000	1.500	1.000	1.500	0.020	2.345
SC13	1.000	1.000	1.000	1.000	1.000	0.021	1.732
SC14	25.000	25.000	30.000	25.000	30.000	0.013	46.368
SC15	1.500	3.500	3.000	1.500	3.500	0.017	4.848
SC16	1.000	1.000	1.000	1.000	1.000	0.013	1.732
SC17	1.000	1.000	1.000	1.000	1.000	0.012	1.732
SC18	4.000	3.000	3.000	4.000	3.000	0.006	5.831

Table 15b. TOPSIS decision matrix X (SC19 – SC35)

	ED1	ED2	ED3	A+	A-	W	Norm
SC19	0.000	1.000	2.000	0.000	2.000	0.041	2.236
SC20	1.000	1.000	1.000	1.000	1.000	0.043	1.732
SC21	0.850	0.900	0.850	0.900	0.850	0.027	1.502
SC22	1.000	1.000	1.000	1.000	1.000	0.008	1.732
SC23	1.000	1.000	1.000	1.000	1.000	0.041	1.732
SC24	0.850	0.800	0.830	0.850	0.800	0.037	1.432
SC25	0.900	0.850	0.900	0.900	0.850	0.036	1.531
SC26	0.200	0.200	0.150	0.200	0.150	0.020	0.320

SC27	35.000	45.000	40.000	35.000	45.000	0.015	69.642
SC28	0.950	0.900	0.900	0.950	0.900	0.028	1.588
SC29	1.500	2.000	1.500	1.500	2.000	0.015	2.915
SC30	0.150	0.200	0.350	0.150	0.350	0.033	0.430
SC31	30.000	25.000	25.000	25.000	30.000	0.009	46.368
SC32	2.000	1.000	0.000	0.000	2.000	0.024	2.236
SC33	2.000	1.000	3.000	1.000	3.000	0.023	3.742
SC34	3.000	2.000	3.000	2.000	3.000	0.018	4.690
SC35	1.000	0.000	2.000	0.000	2.000	0.022	2.236

Table 16a. Normalized decision matrix R for emergency departments (SC1 – SC18)

	ED1	ED2	ED3	A+	A-	W
SC1	0.587	0.558	0.587	0.587	0.558	0.055
SC2	0.592	0.526	0.611	0.611	0.526	0.027
SC3	0.577	0.577	0.577	0.577	0.577	0.034
SC4	0.577	0.577	0.577	0.577	0.577	0.062
SC5	0.694	0.583	0.422	0.694	0.422	0.036
SC6	0.602	0.558	0.571	0.602	0.558	0.049
SC7	0.618	0.567	0.545	0.618	0.545	0.043
SC8	0.605	0.553	0.573	0.605	0.553	0.025
SC9	0.577	0.577	0.577	0.577	0.577	0.042
SC10	0.597	0.597	0.537	0.597	0.537	0.042
SC11	0.577	0.577	0.577	0.577	0.577	0.042
SC12	0.640	0.426	0.640	0.426	0.640	0.020
SC13	0.577	0.577	0.577	0.577	0.577	0.021
SC14	0.539	0.539	0.647	0.539	0.647	0.013
SC15	0.309	0.722	0.619	0.309	0.722	0.017
SC16	0.577	0.577	0.577	0.577	0.577	0.013
SC17	0.577	0.577	0.577	0.577	0.577	0.012
SC18	0.686	0.514	0.514	0.686	0.514	0.006

Table 16b. Normalized decision matrix R for emergency departments (SC19 – SC35)

	ED1	ED2	ED3	A+	A-	W
SC19	0.000	0.447	0.894	0.000	0.894	0.041
SC20	0.577	0.577	0.577	0.577	0.577	0.043
SC21	0.566	0.599	0.566	0.599	0.566	0.027
SC22	0.577	0.577	0.577	0.577	0.577	0.008
SC23	0.577	0.577	0.577	0.577	0.577	0.041
SC24	0.593	0.559	0.579	0.593	0.559	0.037
SC25	0.588	0.555	0.588	0.588	0.555	0.036
SC26	0.625	0.625	0.469	0.625	0.469	0.020

SC27	0.503	0.646	0.574	0.503	0.646	0.015
SC28	0.598	0.567	0.567	0.598	0.567	0.028
SC29	0.514	0.686	0.514	0.514	0.686	0.015
SC30	0.349	0.465	0.814	0.349	0.814	0.033
SC31	0.647	0.539	0.539	0.539	0.647	0.009
SC32	0.894	0.447	0.000	0.000	0.894	0.024
SC33	0.535	0.267	0.802	0.267	0.802	0.023
SC34	0.640	0.426	0.640	0.426	0.640	0.018
SC35	0.447	0.000	0.894	0.000	0.894	0.022

Table 17a. Weighted normalized decision matrix V for emergency departments (SC1 – SC18)

	ED1	**ED2**	**ED3**	**A+**	**A-**
SC1	0.032	0.030	0.032	0.032	0.030
SC2	0.016	0.014	0.016	0.016	0.014
SC3	0.019	0.019	0.019	0.019	0.019
SC4	0.035	0.035	0.035	0.035	0.035
SC5	0.025	0.021	0.015	0.025	0.015
SC6	0.029	0.027	0.028	0.029	0.027
SC7	0.026	0.024	0.023	0.026	0.023
SC8	0.015	0.014	0.014	0.015	0.014
SC9	0.024	0.024	0.024	0.024	0.024
SC10	0.025	0.025	0.022	0.025	0.022
SC11	0.024	0.024	0.024	0.024	0.024
SC12	0.013	0.008	0.013	0.008	0.013
SC13	0.012	0.012	0.012	0.012	0.012
SC14	0.007	0.007	0.008	0.007	0.008
SC15	0.005	0.012	0.010	0.005	0.012
SC16	0.008	0.008	0.008	0.008	0.008
SC17	0.007	0.007	0.007	0.007	0.007
SC18	0.004	0.003	0.003	0.004	0.003

Table 17b. Weighted normalized decision matrix V for emergency departments (SC19 – SC35)

	ED1	**ED2**	**ED3**	**A+**	**A-**
SC19	0.000	0.018	0.036	0.000	0.036
SC20	0.025	0.025	0.025	0.025	0.025
SC21	0.015	0.016	0.015	0.016	0.015
SC22	0.004	0.004	0.004	0.004	0.004
SC23	0.024	0.024	0.024	0.024	0.024
SC24	0.022	0.020	0.021	0.022	0.020
SC25	0.021	0.020	0.021	0.021	0.020
SC26	0.012	0.012	0.009	0.012	0.009

SC27	0.007	0.009	0.008	0.007	0.009
SC28	0.017	0.016	0.016	0.017	0.016
SC29	0.007	0.010	0.007	0.007	0.010
SC30	0.011	0.015	0.027	0.011	0.027
SC31	0.006	0.005	0.005	0.005	0.006
SC32	0.021	0.011	0.000	0.000	0.022
SC33	0.013	0.006	0.018	0.006	0.018
SC34	0.012	0.008	0.012	0.008	0.012
SC35	0.010	0.000	0.019	0.000	0.019

Table 18. Separation measures from PIS

Sub-criterion	ED1	ED2	ED3
SC1	0.0000000	0.0000026	0.0000000
SC2	0.0000003	0.0000053	0.0000000
SC3	0.0000000	0.0000000	0.0000000
SC4	0.0000000	0.0000000	0.0000000
SC5	0.0000000	0.0000159	0.0000955
SC6	0.0000000	0.0000047	0.0000024
SC7	0.0000000	0.0000048	0.0000098
SC8	0.0000000	0.0000017	0.0000007
SC9	0.0000000	0.0000000	0.0000000
SC10	0.0000000	0.0000000	0.0000063
SC11	0.0000000	0.0000000	0.0000000
SC12	0.0000175	0.0000000	0.0000175
SC13	0.0000000	0.0000000	0.0000000
SC14	0.0000000	0.0000000	0.0000020
SC15	0.0000000	0.0000492	0.0000277
SC16	0.0000000	0.0000000	0.0000000
SC17	0.0000000	0.0000000	0.0000000
SC18	0.0000000	0.0000009	0.0000009
SC19	0.0000000	0.0003362	0.0013448
SC20	0.0000000	0.0000000	0.0000000
SC21	0.0000008	0.0000000	0.0000008
SC22	0.0000000	0.0000000	0.0000000
SC23	0.0000000	0.0000000	0.0000000
SC24	0.0000000	0.0000017	0.0000003
SC25	0.0000000	0.0000014	0.0000000
SC26	0.0000000	0.0000000	0.0000098
SC27	0.0000000	0.0000045	0.0000011
SC28	0.0000000	0.0000008	0.0000008
SC29	0.0000000	0.0000066	0.0000000
SC30	0.0000000	0.0000147	0.0002355
SC31	0.0000009	0.0000000	0.0000000
SC32	0.0004608	0.0001152	0.0000000
SC33	0.0000378	0.0000000	0.0001511

SC34	0.0000147	0.0000000	0.0000147
SC35	0.0000968	0.0000000	0.0003872
S_i^+	0.0250930	.0237937	0.0480495

Table 19. Separation measures from NIS

Sub-criterion	ED1	ED2	ED3
SC1	0.0000026	0.0000000	0.0000026
SC2	0.0000031	0.0000000	0.0000053
SC3	0.0000000	0.0000000	0.0000000
SC4	0.0000000	0.0000000	0.0000000
SC5	0.0000955	0.0000336	0.0000000
SC6	0.0000047	0.0000000	0.0000004
SC7	0.0000098	0.0000009	0.0000000
SC8	0.0000017	0.0000000	0.0000002
SC9	0.0000000	0.0000000	0.0000000
SC10	0.0000063	0.0000063	0.0000000
SC11	0.0000000	0.0000000	0.0000000
SC12	0.0000000	0.0000175	0.0000000
SC13	0.0000000	0.0000000	0.0000000
SC14	0.0000020	0.0000020	0.0000000
SC15	0.0000492	0.0000000	0.0000031
SC16	0.0000000	0.0000000	0.0000000
SC17	0.0000000	0.0000000	0.0000000
SC18	0.0000009	0.0000000	0.0000000
SC19	0.0013448	0.0003362	0.0000000
SC20	0.0000000	0.0000000	0.0000000
SC21	0.0000000	0.0000008	0.0000000
SC22	0.0000000	0.0000000	0.0000000
SC23	0.0000000	0.0000000	0.0000000
SC24	0.0000017	0.0000000	0.0000006
SC25	0.0000014	0.0000000	0.0000014
SC26	0.0000098	0.0000098	0.0000000
SC27	0.0000045	0.0000000	0.0000011
SC28	0.0000008	0.0000000	0.0000000
SC29	0.0000066	0.0000000	0.0000066
SC30	0.0002355	0.0001324	0.0000000
SC31	0.0000000	0.0000009	0.0000009
SC32	0.0000000	0.0001152	0.0004608
SC33	0.0000378	0.0001511	0.0000000
SC34	0.0000000	0.0000147	0.0000000
SC35	0.0000968	0.0003872	0.0000000
S_i^-	0.0437648	0.0347650	0.0219795

The closeness coefficients R_i and final ranking of EDs are detailed in Figure 11. These metrics were computed by implementing Eq. 32. In contrast to the measure proposed by Pan et al. (2016), the closeness coefficient can better represent the entire context of ED performance which is advantageous for supporting government stimulation programs and measuring the effectiveness of interventions. The outcomes obtained from TOPSIS method reveals that ED1 was ranked first with 0.6356 whilst ED3 achieved the lowest score (0.3139). Additionally, a little difference was found between the performance measures of the first-ranked and second-ranked departments (0.0419). Such outcomes are an evidence of the regular and poor performance of these EDs in the wild. A similar finding was presented by Yeh and Cheng (2016) who detected that 60% of national Taiwanese hospitals ran an inefficient performance. It is then important to further seek the reasons explaining the aforementioned results. To this aim, Fig. 12 and Fig. 13 were derived. In particular, ***Hospital-acquired infections "SC32"*** (2 cases/month - Separation = 0.0004608), ***Patient misidentification "SC35"*** (1 case/month - Separation = 0.0000968), ***Medication errors "SC33"*** (2 cases/month - Separation = 0.0000378), ***Errors of clinical diagnosis "SC34"*** (3 cases/month - Separation = 0.0000147), and ***Effectiveness of radiology process "SC12"*** (1.5 weeks - Separation = 0.0000175) were found as the most significant contributors to the total separation from positive ideal solution. This demonstrates that ED1 has to mainly focus on *Patient Safety* to augment its overall performance score and then benefit both patient care and ED sustainability. In this sense, ED1 has to emphasize on i) preventing errors ii) identifying lessons learned from errors and iii) providing an overarching umbrella of safety involving healthcare managers, medical staff, patients, and policymakers. Furthermore, ED1 should examine the causes of inefficiencies in radiology process. Specifically, healthcare managers should evaluate whether its radiology department is able to respond to the increased demand for emergency services. A gap between capacity and demand may cause extended waiting times for radiology results, and therefore lead to prolonged ED stay and increased costs. Such capacity could be slackened by delays related to preliminary reporting and transportation as well as ineffective job scheduling.

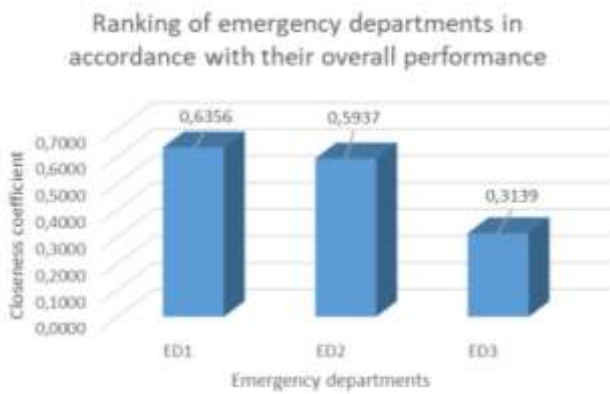


Figure 11. Final ranking of emergency departments

Likewise, meaningful effects on the separation from ideal solutions in ED2 were also noted (refer to Fig 12, 13). In this department, ***Availability of specialists "SC19"*** (1 vacant position - Separation = 0.0003362), ***Hospital-acquired infections "SC32"*** (1 case/month - Separation = 0.0001152), and ***Effectiveness of pharmaceutical service "SC15"*** (3.5 days/order – Separation = 0.0000492) were concluded to be the main sources of this distance. Hence, improvement strategies must be primarily focused on *supporting processes*, *human resources,* and *patient safety* domains. Regarding the *availability of specialists*, ED2 should secure partnership agreements with international universities to address the lack of these medical personnel in the local market. In addition, incentive programs should be fostered to keep specialists motivated while new specialization programs can be set in local universities. In relation to *Hospital-acquired infections*, ED2 must search for infection prevention practices to avoid meaningful clinical consequences for both patients and medical staff. Furthermore, ED2 should focus on minimizing the infection risk associated with emergency services and the transmission of infectious diseases to both ED staff and patients. On the other hand, the average waiting time for drug delivery has to be significantly diminished in this emergency department. In this regard, it is suggested to implement a decision support system (DSS) for the correct and fast procurement of drugs. The DSS can help managers to monitor and prioritize the prescription orders in accordance with the triage category reported by the ED physicians. It is also recommended to collaborate with physicians to promote safe an effective medication use in ED2, and thereby ensuring the timely provision of drugs and continuity of emergency care.

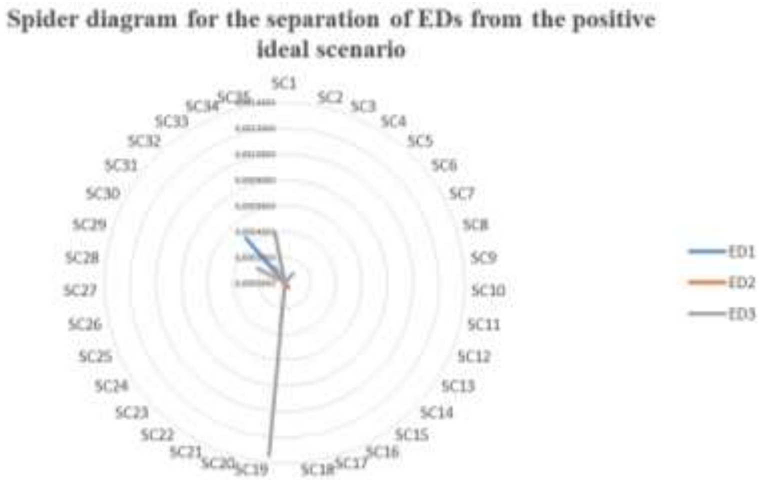


Figure 12. Spider diagram for positive ideal scenario

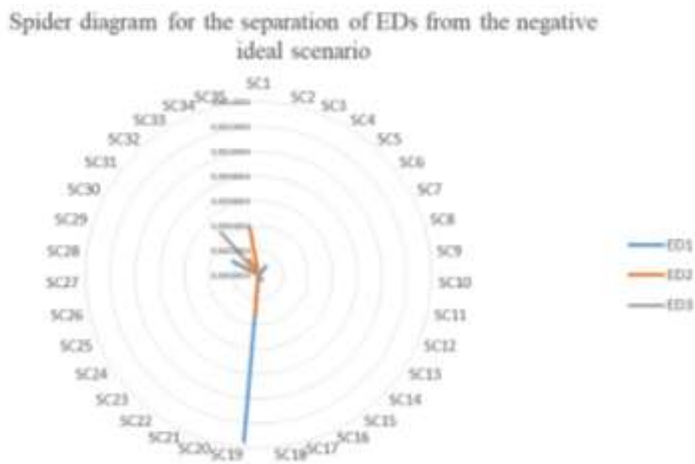


Figure 13. Spider diagram for negative ideal scenario

An analysis was also carried out to determine the root causes of poor performance in ED3. In this sense, the following decision elements were concluded to be the highest contributors: ***Availability of specialists "SC19"*** (two vacant positions - Separation = 0.0013448), ***Patient misidentification "SC35"*** (two cases/month – Separation = 0.0003872), and ***Readmission rate "SC30"*** (35% - Separation = 0.0002355). ED3 should then prioritize interventions related to *Human resources, patient safety, and quality* domains. In relation to the *availability of specialists*, the same strategies recommended for ED2 should be followed by ED3. Another aspect of concern in ED3 was the *patient misidentification*. In this respect, nurses have recognized that the most important factors causing the problem are: desire not to undermine patients' trust, time pressure, and confidence in their ability to informally identify patients (Farmer, 2016). Therefore, it is necessary to adopt technologies (e.g. ID wristband, barcodes) supporting the fast identification and tracking of patients while staying in ED3. Such technologies will help managers to avoid other errors related to clinical diagnosis and treatment.

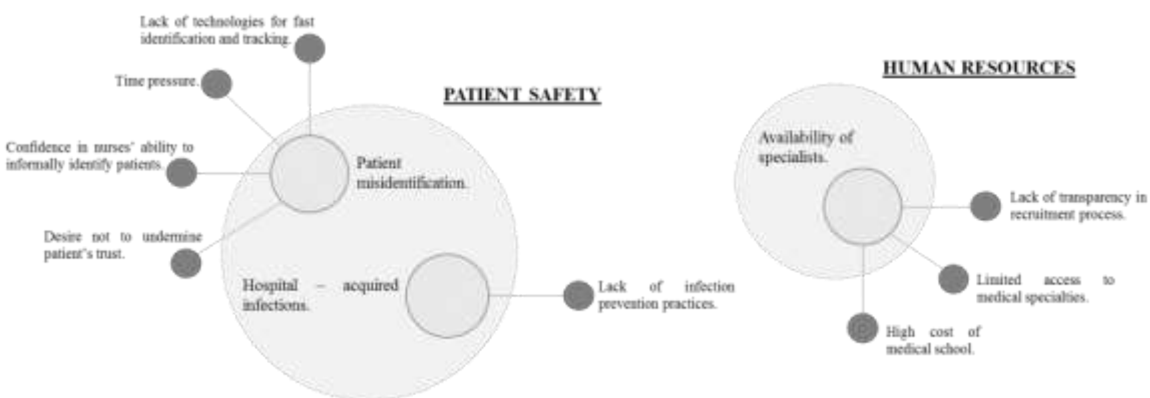


Figure 14. Map of performance improvement interventions to be undertaken within ED cluster

From a general perspective, the commonest and most critical criterion in this group of emergency departments is *Patient safety.* For this purpose, government authorities and managers of healthcare clusters should work together with EDs for supporting the creation of improvement strategies addressing this problem immediately. This motivates the revision of the medical care resources allocation in the public health sector as also proposed by Yeh and Cheng (2016) who suggested the Taiwanese government reconsider the budget distribution between urban and non-urban hospitals. Additionally, *patient misidentification* and *hospital-acquired infections* should be measured and monitored progressively since they have been identified as common symptoms in most of the departments. Finally, the Ministry of Education, Ministry of Health and Social Protection and EDs should jointly define actions propelling the constant production of specialist physicians. In this respect, three barriers have to be overcome: i) the high cost of medical school, ii) the limited access to medical specialties, and iii) the lack of transparency in the recruitment process. By addressing these weaknesses (Fig. 14), the overall performance of emergency departments can be meaningfully augmented. Thereby, healthcare costs can be diminished while outcomes for patients requiring emergency care may be improved. This is consistent with Yamani et al. (2012) who mentioned that the identification of strengths and weaknesses leads to better planning process and subsequent increased performance in EDs. In parallel, as also recommended by Yeh and Cheng (2016), ED performance can be regarded as a prerequisite for government incentives; thereby, performance improvement and self-efficiency operation can be effectively fostered within the public EDs.

2.3.5 Sensitivity analysis

A sensitivity analysis was undertaken to show the effects of changing the global sub-criterion weights on the final TOPSIS scores and ranking of EDs. The results of this analysis are depicted in Table 20 and Fig. 15. In this case, we considered the effects of varying the GW_1 (Δ_1 = 0.055) values which represents changes in the global weights of the other sub-criteria {GW_1, GW_2,…,GWn} in accordance with the approach depicted in Alinezhad and Amini (2011). For example, if GW_1 = 0.220, the set of weights will be {0.220, 0.022, 0.028, 0.051, 0.030, 0.040, 0.035, 0.021, 0.035, 0.035, 0.035, 0.016, 0.017, 0.011, 0.014, 0.011, 0.010, 0.005, 0.034, 0.035, 0.022, 0.007 , 0.034, 0.031, 0.030, 0.017, 0.012, 0.023, 0.012, 0.027, 0.007, 0.020, 0.019, 0.015, 0.018}.

Table 20. Sensitivity analysis results

GW1	Closeness coefficient (CCi)			Ranking		
	ED1	ED2	ED3	ED1	ED2	ED3
0.000	0.6354	0.5942	0.3133	1	2	3
0.055	0.6356	0.5937	0.3139	1	2	3
0.110	0.6361	0.5917	0.3159	1	2	3
0.165	0.6372	0.5880	0.3198	1	2	3
0.220	0.6391	0.5817	0.3263	1	2	3
0.275	0.6419	0.5724	0.3360	1	2	3
0.330	0.6461	0.5593	0.3496	1	2	3
0.385	0.6522	0.5417	0.3679	1	2	3
0.440	0.6607	0.5190	0.3915	1	2	3
0.495	0.6724	0.4906	0.4209	1	2	3
0.550	0.6880	0.4565	0.4566	1	3	2
0.605	0.7084	0.4167	0.4987	1	3	2
0.660	0.7343	0.3714	0.5475	1	3	2
0.715	0.7661	0.3211	0.6029	1	3	2
0.770	0.8035	0.2662	0.6650	1	3	2
0.825	0.8460	0.2074	0.7340	1	3	2

0.880	0.8924	0.1451	0.8098	1	3	2
0.935	0.9412	0.0800	0.8926	1	3	2
0.990	0.9909	0.0125	0.9828	1	3	2

In summary, 19 combinations of sub-criteria were analysed. For each set of weights, the closeness coefficients and ranking of EDs were established. According to Table 20, ED_1 will have the best performance ($CC_1 = 0.909$) when $GW_1 = 0.990$, while the lowest score ($CC_1 = 0.6354$) will be reached in $GW_1 = 0$. Regarding ED_2, the highest closeness coefficient ($CC_2 = 0.5942$) will be obtained when $GW_1 = 0$ whilst the worst score ($CC_2 = 0.0125$) can be expected if $GW_1 = 0.990$. Concerning ED_3, the major performance ($CC_3 = 0.9828$) will be achieved when $GW_1 = 0.990$ whereas the poorest qualification ($CC_3 = 03133$) can be foreseen when $0 \leq GW_1 \leq 0.055$. Based on Fig. 15, ED_2 (the second ranked alternative), under the current conditions (expressed through the KPIs), will maintain this place if $0 \leq GW_1 < 0.550$. Then, as GW_1 increases, its overall performance continues falling. Specifically, when $0.550 \leq GW_1 < 0.990$, ED_2 is expected to be placed "third". The opposite behaviour is observed in ED_1 and ED_3 whose closeness coefficient rises as the GW_1 increases.

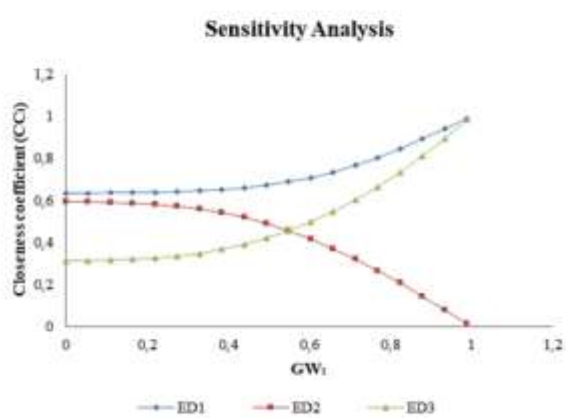


Figure 15. Sensitivity analysis of ED TOPSIS scores

2.3.6 Managerial and practical implications

The aforedescribed model provides meaningful insights to decision-makers, practitioners, cluster managers, and researchers involved in ED-related interventions. One of the major contributions is the identification of weaknesses and strengths in ED performance. In particular, the detection of shortcomings facilitates the design of focused interventions and the correct resource allocation during improvement process. Thereby, investments can be made on projects targeting an increased performance of EDs, an aspect of extreme importance in the public sector where the budget is highly constrained. In the cited example, *patient misidentification* and *hospital-acquired infections* were found to be the weakest points of ED cluster and special attention should be therefore paid to these sub-criteria for further improvement. On the other hand, as strengths are pointed out, cluster managers can replicate the good practices in EDs with similar deficiencies. For instance, a deepest exploration on maintenance plans can be undertaken on ED1 in order to understand the causes behind the high *availability of medical equipment* and widespread their adoption in the other EDs. As demands on emergency services continue to widen in the future, such strategies become the foundation that will propel the development of cost-effective collaborative structures providing highly satisfactory care.

From a cluster perspective, the approach here described can support the implementation of before-and-after analysis that enables decision-makers to assess the effectiveness of the applied strategies. Furthermore, such framework serves as a solid foundation for deploying incentive programs rewarding high-performance EDs. In this respect, it is also necessary to count on a mature performance measurement system continuously supplying high-quality data to the model. As such system is at the earlier stages and faces increasing criticism, it is advisable that cluster managers offer the appropriate endorsement through the path from data collection to reporting. In addition, adaptive measurement systems can be adopted for tackling the administrative and financial burden often addressed by EDs when administering their data.

On a different tack, the FAHP and FDEMATEL results underpin the effective creation and deployment of long-term plans through the identification of *dispatcher* criteria and sub-criteria. Development plans can be then centred on these elements for propelling multi-factorial interventions that respond to the multi-causality and interactive nature of ED context. For example, in the afore-detailed application, *suitability of medical equipment* and *state of medical equipment* can be prioritized in long-range planning for increasing the *availability of medical equipment* within EDs.

The above-mentioned implications end up affecting the patients' perceptions regarding the care received at ED settings. Patients are increasingly becoming aware of EDs' performance and their expectations are constantly evolving towards more challenging and complex scenarios. In fact, the selection of emergency care providers has been greatly influenced by the experience of others. Such considerations then confirm the relevant role that our proposed approach can play in a decision-making context where both patient care and financial sustainability often converge.

2.3.7 Conclusions

EDs are an important component of healthcare systems since they are responsible for providing timely and high-quality emergency care to patients with major injuries and life-threatening medical conditions. In this regard, multiple agents, factors, and processes should effectively interact to face the increased demand for emergency services while reducing operational costs. It is then essential to establish appropriate methods for progressively monitoring and assessing the overall performance of EDs.

Although performance evaluation has become a critical task for supporting the continuous development and improvement of EDs, the studies concentrating on deploying methodological frameworks addressing this problem are largely limited. In addition, the approaches presented in these studies do not represent the entire ED performance context since several important domains (e.g. medical equipment, human resources and infrastructure) have not been included in the assessment models. On the other hand, interrelations among criteria have not been studied which is a relevant aspect when considering the presence of interactions in emergency services and the need for creating long-term development plans. Another aspect of concern lies in the fact that poor effort has been made to represent the vagueness in performance evaluation models which limits their effectiveness in practical scenarios. The present paper bridged the aforementioned gaps through a novel MCDM hybrid model based on FAHP, FDEMATEL, and TOPSIS techniques. This approach provides more robust results, overcomes the limitations of single methods, and deals with the vagueness derived from human judgments. Hence, our proposed method is useful to provide decision support to policymakers, healthcare managers, government authorities, cluster directors, and practitioners when making managerial decisions targeting improved patient safety, satisfaction level, and quality of care.

The proposed approach is also a guide to evaluate the response of EDs when facing a rising number of patients, which facilitates the development of more efficient planning processes. This specific aspect is even more critical in the public sector where the financial resources are greatly limited and should be hence assigned properly. In the present study, 8 domains, 35 sub-criteria, and 3 public emergency departments were considered with the basis on the current healthcare regulations, reported literature, and experts' opinion. The outcome is a multi-criteria model evaluating the overall performance of emergency departments which is relevant when targeting i) decreased readmission rate, ii) increased patient satisfaction, iii) reduced mortality rate, and iv) decreased healthcare costs.

From the managerial perspective, the aforesaid model provides significant support to decision-makers, practitioners, cluster managers, and researchers involved in emergency care services. The contributions are summarized as follows: i) Identification of weaknesses and strengths in ED performance ii) Implementation of before-and-after analysis that enables decision-makers to assess the effectiveness of the applied strategies, and iii) Identification of *dispatcher* criteria and sub-criteria for supporting the creation of short-term and long-term development plans.

In relation to the scenario under study, the results show that ED1 $(R_1 = 0.6356)$ is the emergency department with the highest overall performance. In addition, considering the FAHP results, *Infrastructure* was the parameter with the highest importance (GW = 21.50%). However, given the little difference found between the second and last criterion, it is recommended to deploy multifactorial improvement strategies with a primary focus on *Infrastructure*. On a different tack, *Patient safety* obtained the highest positive $C + R$ value (12.771) and it is therefore considered as the main generator of effects in emergency departments. Hence, it should be highly prioritized for continuous monitoring and intervention. *Patient safety* was also concluded to be the weakest aspect in the cited set of emergency departments. Such finding calls for the rapid intervention of the local government and healthcare cluster in order to avoid poor clinical outcomes in admitted ED patients and the associated cost overruns as established by Zhao and Paul (2012) through their MAPQC approach. The *availability of specialists* was also found to be a primary intervention point in the ED cluster. The cluster manager should thus secure partnership agreements with international universities to address the lack of these medical personnel in the local market. Moreover, barriers such as: high cost of medical school, limited access to medical specialties, and lack of transparency in the recruitment process have to be tackled to ensure the constant provision of specialists that face the projected increased demand on emergency care services. Lately, the sensitivity analysis revealed that, under current conditions, ED_2 will be ranked second if $0 \leq GW_1 < 0.550$. In addition, its overall performance will fall as GW_1 increases, which is opposite to the behaviour observed in ED_1 and ED_3.

The robustness of the results presented in this paper is limited to the consulted experts and may thus vary in other contexts. Therefore, complementary to this approach, future studies may consider financial and environmental domains to better assist ED managers and policymakers in decision-making processes. Thereby, the tactical-operational processes and the most strategic level of the EDs can be further integrated for better resource allocation and emergency care. The proposed approach can be also adapted for measuring the performance of EDs when addressing pandemics outbreaks such as the current Covid-19 (Ortíz-Barrios et al., 2020; World Health Organization, 2020). Furthermore, it is envisioned to incorporate interval data in TOPSIS method in order to represent the variation of KPIs, upgrade the maturity of the ED performance measurement system, and subsequently provide deepest insights for future interventions. This is, of course, subject to the adoption of interval-valued indicators supporting the effective application of interval TOPSIS in the wild. Finally, it is intended to contrast our hybrid approach with other vagueness-based methods (i.e. Intuitionistic fuzzy set theory and Neutrosophic set theory) so that similarities and differences regarding the criteria/sub-criteria weights, robustness, and final rankings can be identified.

2.3.8 References

Abdel-Basset M, Manogaran G, Gamal A, Smarandache F. A hybrid approach of neutrosophic sets and DEMATEL method for developing supplier selection criteria. Des Autom Embedded Syst 2018;22(3):257-278.

Abdullah L, Zulkifli N. Integration of fuzzy AHP and interval type-2 fuzzy DEMATEL: An application to human resource management. Expert Syst Appl 2015;42(9):4397-4409.

Aires RFDF, Ferreira L. A new approach to avoid rank reversal cases in the TOPSIS method. Comput Ind Eng 2019;132:84-97.

Al Salem AA, Awasthi A. Investigating rank reversal in reciprocal fuzzy preference relation based on additive consistency: Causes and solutions. Comput Ind Eng 2018;115:573-581.

Alinezhad A, Amini A. Sensitivity analysis of TOPSIS technique: the results of change in the weight of one attribute on the final ranking of alternatives. Journal of Optimization in Industrial Engineering 2011;4(7):23-28.

Arya A, Yadav SP. Development of FDEA Models to Measure the Performance Efficiencies of DMUs. Int J Fuzzy Syst 2018;20(1):163-173.

Ashtiani M, Azgomi MA. A hesitant fuzzy model of computational trust considering hesitancy, vagueness and uncertainty. Appl Soft Comput J 2016;42:18-37.

Awasthi A, Govindan K, Gold S. Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach. Int J Prod Econ 2018;195:106-117.

Barrios MAO, Caballero JE, Sánchez FS. A methodology for the creation of integrated service networks in outpatient internal medicine. Lect Notes Comput Sci 2015;9456:247-257.

Barrios MAO, De Felice F, Negrete KP, Romero BA, Arenas AY, Petrillo A. An AHP-topsis integrated model for selecting the most appropriate tomography equipment. Int J Inf Technol Decis Mak 2016;15(4):861-885.

Beck MJ, Okerblom D, Kumar A, Bandyopadhyay S, Scalzi LV. Lean intervention improves patient discharge times, improves emergency department throughput and reduces congestion. Hosp Pract (1995) 2016;44(5):252-259.

Bergeron BP. Performance Management In Healthcare: From key performance indicators to balanced scorecard. RAE 2019;59(5):370-371.

Brenna M. Farmer MD. Patient safety in the emergency department. [Internet]. [Extracted 16 de jul 2020]. Retrieved from: https://mdedge-files-live.s3.us-east-2.amazonaws.com/files/s3fs-public/issues/articles/em048090396.pdf

Carter EJ, Pouch SM, Larson EL. The relationship between emergency department crowding and patient outcomes: A systematic review. J Nurs Scholarsh 2014;46(2):106-115.

Chan SSW, Cheung NK, Graham CA, Rainer TH. Strategies and solutions to alleviate access block and overcrowding in emergency departments. Hong Kong Med J 2015;21(4):345-352.

Chanamool N, Naenna T. Fuzzy FMEA application to improve decision-making process in an emergency department. Appl Soft Comput J 2016;43:441-453.

Chang K-, Chang Y-, Lee Y-. Integrating TOPSIS and DEMATEL methods to rank the risk of failure of FMEA. Int J Inf Technol Decis Mak 2014;13(6):1229-1257.

Chen M-, Tzeng G-, Tang T-. Fuzzy MCDM approach for evaluation of expatriate assignments. Int J Inf Technol Decis Mak 2005;4(2):277-296.

Chen T-. An interactive signed distance approach for multiple criteria group decision-making based on simple additive weighting method with incomplete preference information defined by interval type-2 fuzzy sets. Int J Inf Technol Decis Mak 2014;13(5):979-1012.

Chen Z, Ming X, Zhang X, Yin D, Sun Z. A rough-fuzzy DEMATEL-ANP method for evaluating sustainable value requirement of product service system. J Clean Prod 2019;228:485-508.

Dargi A, Anjomshoae A, Galankashi MR, Memari A, Tap MBM. Supplier selection: A fuzzy-ANP approach. Procedia Comput Sci 2014;31:691-700.

Dart RC, Goldfrank LR, Erstad BL, Huang DT, Todd KH, Weitz J, et al. Expert Consensus Guidelines for Stocking of Antidotes in Hospitals That Provide Emergency Care. Ann Emerg Med 2018;71(3):314-325.e1.

de Almeida Filho AT, Clemente TRN, Morais DC, de Almeida AT. Preference modeling experiments with surrogate weighting procedures for the PROMETHEE method. Eur J Oper Res 2018;264(2):453-461.

Deveci M, Canıtez F, Gökaşar I. WASPAS and TOPSIS based interval type-2 fuzzy MCDM method for a selection of a car sharing station. Sustainable Cities Soc 2018;41:777-791.

Di Somma S, Paladino L, Vaughan L, Lalle I, Magrini L, Magnanti M. Overcrowding in emergency department: an international issue. Intern Emerg Med 2015;10(2):171-175.

Ebben RHA, Siqeca F, Madsen UR, Vloet LCM, Van Achterberg T. Effectiveness of implementation strategies for the improvement of guideline and protocol adherence in emergency care: A systematic review. BMJ Open 2018;8(11).

Emrouznejad A, Yang G-. A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. Socio-Econ Plann Sci 2018;61:4-8.

Farokhi S, Roghanian E. Determining quantitative targets for performance measures in the balanced scorecard method using response surface methodology. Manage Decis 2018;56(9):2006-2037.

Farup PG. Are measurements of patient safety culture and adverse events valid and reliable? Results from a cross sectional study. BMC Health Serv Res 2015;15(1).

Frazão TDC, Camilo DGG, Cabral ELS, Souza RP. Multicriteria decision analysis (MCDA) in health care: A systematic review of the main characteristics and methodological steps. BMC Med Informatics Decis Mak 2018;18(1).

Ghorabaee MK, Amiri M, Zavadskas EK, Antucheviciene J. Supplier evaluation and selection in fuzzy environments: A review of MADM approaches. Economic Res Ekon Istraz 2017;30(1):1073-1118.

Ghorabaee MK, Zavadskas EK, Olfat L, Turskis Z. Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS). Informatica 2015;26(3):435-451.

Gou X, Xu Z, Liao H. Hesitant Fuzzy Linguistic Possibility Degree-Based Linear Assignment Method for Multiple Criteria Decision-Making. Int J Inf Technol Decis Mak 2019;18(1):365-387.

Govindan K, Khodaverdi R, Vafadarnikjoo A. Intuitionistic fuzzy based DEMATEL method for developing green practices and performances in a green supply chain. Expert Sys Appl 2015;42(20):7207-7220.

Gul M, Celik E, Gumus AT, Guneri AF. Emergency department performance evaluation by an integrated simulation and interval type-2 fuzzy MCDM-based scenario analysis. European Journal of Industrial Engineering 2016;10(2):196-223.

Gul M, Guneri AF, Nasirli SM. A fuzzy-based model for risk assessment of routes in oil transportation. Int J Environ Sci Technol 2019;16(8):4671-4686.

Hawley KL, Mazer-Amirshahi M, Zocchi MS, Fox ER, Pines JM. Longitudinal trends in US drug shortages for medications used in emergency departments (2001–2014). Acad Emerg Med 2016;23(1):63-69.

Hermann RM, Long E, Trotta RL. Improving Patients' Experiences Communicating With Nurses and Providers in the Emergency Department. J Emerg Nurs 2019; 45(5):523-530.

Ho W, Ma X. The state-of-the-art integrations and applications of the analytic hierarchy process. Eur J Oper Res 2018;267(2):399-414.

Ho W, Ma X. The state-of-the-art integrations and applications of the analytic hierarchy process. Eur J Oper Res 2018;267(2):399-414.

Hosseini S, Khaled AA. A hybrid ensemble and AHP approach for resilient supplier selection. J Intell Manuf 2019;30(1):207-228.

Hsiao B, Chen L-. Performance Evaluation for Taiwanese Hospitals by Multi-Activity Network Data Envelopment Analysis. Int J Inf Technol Decis Mak 2019;18(3):1009-1043.

Innes GD, Sivilotti MLA, Ovens H, McLelland K, Dukelow A, Kwok E, et al. Emergency overcrowding and access block: A smaller problem than we think. Can J Emerg Med 2019;21(2):177-185.

Ivlev I, Vacek J, Kneppo P. Multi-criteria decision analysis for supporting the selection of medical devices under uncertainty. Eur J Oper Res 2015;247(1):216-228.

Izquierdo NV, Lezama OBP, Dorta RG, Viloria A, Deras I, Hernández-Fernández L. Fuzzy logic applied to the performance evaluation. Honduran coffee sector case. Lect Notes Comput Sci 2018;10942 LNCS:164-173.

Jing M, Jie Y, Shou-yi L, Lu W. Application of fuzzy analytic hierarchy process in the risk assessment of dangerous small-sized reservoirs. Int J Mach Learn Cyb 2018;9(1):113-123.

Jovčić S, Pruša P, Dobrodolac M, Švadlenka L. A proposal for a decision-making tool in third-party logistics (3PL) provider selection based on multi-criteria analysis and the fuzzy approach. Sustainability 2019;11(15).

Jumaah FM, Zadain AA, Zaidan BB, Hamzah AK, Bahbibi R. Decision-making solution based multi-measurement design parameter for optimization of GPS receiver tracking channels in static and dynamic real-time positioning multipath environment. Meas J Int Meas Confed 2018;118:83-95.

Kahraman C, Onar SC, Oztaysi B. Fuzzy Multicriteria Decision-Making: A Literature Review. Int J Comput Intell Syst 2015;8(4):637-666.

Kaliszewski I, Podkopaev D. Simple additive weighting - A metamodel for multiple criteria decision analysis methods. Expert Sys Appl 2016;54:155-161.

Källberg A-, Göransson KE, Florin J, Östergren J, Brixey JJ, Ehrenberg A. Contributing factors to errors in Swedish emergency departments. Int Emerg Nurs 2015;23(2):156-161.

Kazancoglu Y, Kazancoglu I, Sagnak M. Fuzzy DEMATEL-based green supply chain management performance: Application in cement industry. Ind Manage Data Sys 2018;118(2):412-431.

Keshavarz Ghorabaee M, Amiri M, Zavadskas EK, Turskis Z, Antucheviciene J. A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. Comput Ind Eng 2017;112:156-174.

Ketabi S, Teymouri E, Ketabi M. Efficiency measurement of emergency departments in Isfahan, Iran. International Journal of Process Management and Benchmarking 2018;8(2):142-155.

Kou G, Ergu D, Shang J. Enhancing data consistency in decision matrix: Adapting Hadamard model to mitigate judgment contradiction. Eur J Oper Res 2014;236(1):261-271.

Kou G, Ergu D, Shang J. Enhancing data consistency in decision matrix: Adapting Hadamard model to mitigate judgment contradiction. Eur J Oper Res 2014;236(1):261-271.

Kou G, Lin C. A cosine maximization method for the priority vector derivation in AHP. Eur J Oper Res 2014;235(1):225-232.

Kovacs E, Strobl R, Phillips A, Stephan A-, Müller M, Gensichen J, et al. Systematic Review and Meta-analysis of the Effectiveness of Implementation Strategies for Non-communicable Disease Guidelines in Primary Health Care. J Gen Intern Med 2018;33(7):1142-1154.

Labib A, Read M. A hybrid model for learning from failures: The Hurricane Katrina disaster. Expert Sys Appl 2015;42(21):7869-7881.

Lee K-, Tsai W-, Yang C-, Lin Y-. An MCDM approach for selecting green aviation fleet program management strategies under multi-resource limitations. J Air Transp Manage 2018;68:76-85.

Li L, Georgiou A, Vecellio E, Eigenstetter A, Toouli G, Wilson R, et al. The effect of laboratory testing on emergency department length of stay: A multihospital longitudinal study applying a cross-classified random-effect modeling approach. Acad Emerg Med 2015;22(1):38-46.

Lin C, Kou G, Peng Y, Alsaadi FE. Aggregation of the nearest consistency matrices with the acceptable consensus in AHP-GDM. Ann Oper Res 2020;1-17

Lisbon D, Allin D, Cleek C, Roop L, Brimacombe M, Downes C, et al. Improved Knowledge, Attitudes, and Behaviors After Implementation of TeamSTEPPS Training in an Academic Emergency Department: A Pilot Report. Am J Med Qual 2016;31(1):86-90.

Liu H-, You J-, Zhen L, Fan X-. A novel hybrid multiple criteria decision making model for material selection with target-based criteria. Mater Des 2014;60:380-390.

Lolli F, Balugani E, Ishizaka A, Gamberini R, Butturi MA, Marinello S, et al. On the elicitation of criteria weights in PROMETHEE-based ranking methods for a mobile application. Expert Sys Appl 2019;120:217-227.

Lord K, Parwani V, Ulrich A, Finn EB, Rothenberg C, Emerson B, et al. Emergency department boarding and adverse hospitalization outcomes among patients admitted to a general medical service. Am J Emerg Med 2018;36(7):1246-1248.

Mkoka DA, Goicolea I, Kiwara A, Mwangu M, Hurtig A-. Availability of drugs and medical supplies for emergency obstetric care: Experience of health facility managers in a rural District of Tanzania. BMC Pregnancy Childbirth 2014;14(1).

Mohammadi E, Zaebi Y, Mousavi SH, Mahboubi M, Mohammadi M, Zangeneh A, et al. Emergency department performance evaluation indicators in pre and post-health care reform in kermanshah public hospitals. Res J Med Sci 2016;10(2):54-59.

Morley C, Unwin M, Peterson GM, Stankovich J, Kinsman L. Emergency department crowding: A systematic review of causes, consequences and solutions. PLoS ONE 2018;13(8).

Mousavi-Nasab SH, Sotoudeh-Anvari A. A new multi-criteria decision making approach for sustainable material selection problem: A critical study on rank reversal problem. J Clean Prod 2018;182:466-484.

Mufazzal S, Muzakkir SM. A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals. Comput Ind Eng 2018;119:427-438.

Norman GR, Monteiro SD, Sherbino J, Ilgen JS, Schmidt HG, Mamede S. The Causes of Errors in Clinical Reasoning: Cognitive Biases, Knowledge Deficits, and Dual Process Thinking. Acad Med 2017;92(1):23-30.

Oliveira MM, Marti C, Ramlawi M, Sarasin FP, Grosgurin O, Poletti P-, et al. Impact of a patient-flow physician coordinator on waiting times and length of stay in an emergency department: A before-after cohort study. PLoS ONE 2018;13(12).

Ortiz Barrios M, Felizzola Jimï¿½nez H, Nieto Isaza S. Comparative analysis between ANP and ANP-DEMATEL for six sigma project selection process in a healthcare provider. Lect Notes Comput Sci 2014;8868:413-416.

Ortiz Barrios MA, Felizzola Jiménez H. Use of Six Sigma Methodology to Reduce Appointment Lead-Time in Obstetrics Outpatient Department. J Med Syst 2016;40(10).

Ortíz MA, Felizzola HA, Isaza SN. A contrast between DEMATEL-ANP and ANP methods for six sigma project selection: A case study in healthcare industry. BMC Med Informatics Decis Mak 2015;15(3).

Ortiz-Barrios M, Gul M, López-Meza P, Yucesan M, Navarro-Jiménez E. Evaluation of hospital disaster preparedness by a multi-criteria decision making approach: The case of Turkish hospitals. Int J Disaster Risk Reduct 2020;49.

Ortíz-Barrios M, Neira-Rodado D, Jiménez-Delgado G, Hernández-Palma H. Using fahp-vikor for operation selection in the flexible job-shop scheduling problem: A case study in textile industry. Lect Notes Comput Sci 2018;10942 LNCS:189-201.

Ortiz-Barrios MA, Herrera-Fontalvo Z, Rúa-Muñoz J, Ojeda-Gutiérrez S, De Felice F, Petrillo A. An integrated approach to evaluate the risk of adverse events in hospital sector: From theory to practice. Manage Decis 2018;56(10):2187-2224.

Otay İ, Oztaysi B, Cevik Onar S, Kahraman C. Multi-expert performance evaluation of healthcare institutions using an integrated intuitionistic fuzzy AHP&DEA methodology. Knowl Based Syst 2017;133:90-106.

Pan C-, Chang C-, Chiu C-, Chi C-, Tian Z, Wen J-, et al. What can emergency medicine learn from kinetics: Introducing an alternative evaluation and a universal criterion standard for emergency department performance. Medicine 2016;95(11).

Razzak JA, Baqir SM, Khan UR, Heller D, Bhatti J, Hyder AA. Emergency and trauma care in Pakistan: A cross-sectional study of healthcare levels. Emerg Med J 2015;32(3):207-213.

Riga M, Vozikis A, Pollalis Y, Souliotis K. MERIS (Medical Error Reporting Information System) as an innovative patient safety intervention: A health policy perspective. Health Policy 2015;119(4):539-548.

Rigobello MCG, Carvalho REFLD, Guerreiro JM, Motta APG, Atila E, Gimenes FRE. The perception of the patient safety climate by professionals of the emergency department. Int Emerg Nurs 2017;33:1-6.

Roy J, Sharma HK, Kar S, Zavadskas EK, Saparauskas J. An extended COPRAS model for multi-criteria decision-making problems and its application in web-based hotel evaluation and selection. Economic Res Ekon Istraz 2019;32(1):219-253.

Saaty TL, Ergu D. When is a decision-making method trustworthy? Criteria for evaluating multi-criteria decision-making methods. Int J Inf Technol Decis Mak 2015;14(6):1171-1187.

Saaty TL, Vargas LG. Models, methods, concepts & applications of the analytic hierarchy process. 2nd. Ed. Pittsburgh USA: Springer Science & Business Media; 2012.

Saksrisathaporn K, Bouras A, Reeveerakul N, Charles A. Application of a decision model by using an integration of AHP and TOPSIS approaches within humanitarian operation life cycle. Int J Inf Technol Decis Mak 2016;15(4):887-918.

Samanlioglu F, Taskaya YE, Gulen UC, Cokcan O. A Fuzzy AHP–TOPSIS-Based Group Decision-Making Approach to IT Personnel Selection. Int J Fuzzy Syst 2018;20(5):1576-1591.

Santos SP, Belton V, Howick S, Pilkington M. Measuring organisational performance using a mix of OR methods. Technol Forecast Soc Change 2018;131:18-30.

Scholz S, Ngoli B, Flessa S. Rapid assessment of infrastructure of primary health care facilities - A relevant instrument for health care systems management. BMC Health Serv Res 2015;15(1).

Singh A, Prasher A. Measuring healthcare service quality from patients' perspective: using Fuzzy AHP application. Total Qual Manage Bus Excellence 2019;30(3-4):284-300.

Singh S, Lin Y-, Nattinger AB, Kuo Y-, Goodwin JS. Variation in readmission rates by emergency departments and emergency department providers caring for patients after discharge. J Hosp Med 2015;10(11):705-710.

Sørup CM, Jacobsen P, Forberg JL. Evaluation of emergency department performance - a systematic review on recommended performance and quality-in-care measures. Scand J Trauma Resusc Emerg Med 2013;21(1).

Stang AS, Crotts J, Johnson DW, Hartling L, Guttmann A. Crowding measures associated with the quality of emergency department care: A systematic review. Acad Emerg Med 2015;22(6):643-656.

Sun G, Guan X, Yi X, Zhou Z. An innovative TOPSIS approach based on hesitant fuzzy correlation coefficient and its applications. Appl Soft Comput J 2018;68:249-267.

Sunder VM, Ganesh LS, Marathe RR. A morphological analysis of research literature on Lean Six Sigma for services. Int J Oper Prod Manage 2018;38(1):149-182.

Telem DA, Yang J, Altieri M, Patterson W, Peoples B, Chen H, et al. Rates and risk factors for unplanned emergency department utilization and hospital readmission following bariatric surgery. Ann Surg 2016;263(5):956-960.

Uthman OA, Walker C, Lahiri S, Jenkinson D, Adekanmbi V, Robertson W, et al. General practitioners providing non-urgent care in emergency department: A natural experiment. BMJ Open 2018;8(5).

Uthman OA, Walker C, Lahiri S, Jenkinson D, Adekanmbi V, Robertson W, et al. General practitioners providing non-urgent care in emergency department: A natural experiment. BMJ Open 2018;8(5).

Vargas LG. Voting with intensity of preferences. Int J Inf Technol Decis Mak 2016;15(4):839-859.

Venkatesh AK, Wang C, Wang Y, Altaf F, Bernheim SM, Horwitz L. Association Between Postdischarge Emergency Department Visitation and Readmission Rates. J Hosp Med 2018;13(9):589-594.

Vermeulen MJ, Stukel TA, Boozary AS, Guttmann A, Schull MJ. The Effect of Pay for Performance in the Emergency Department on Patient Waiting Times and Quality of Care in Ontario, Canada: A Difference-in-Differences Analysis. Ann Emerg Med 2016;67(4):496-505.e7.

Wang H, Kou G, Peng Y. Multi-class misclassification cost matrix for credit ratings in peer-to-peer lending. J Oper Res Soc 2020;1-12.

Wong TW. The role of the emergency department: Beyond gatekeeping. Hong Kong Med J 2010;16(1):4-5.

World Health Organization Coronavirus disease 2019 (COVID-19) situation report–182. [Internet]. [Extracted 16 de jul 2020]. Retrieved from: https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200720-covid-19-sitrep-182.pdf?sfvrsn=60aabc5c_2 (2020)

World Health Organization WHO. Generic essential emergency equipment list. [Internet]. [Extracted 16 de jul 2020]. Retrieved from: https://www.who.int/surgery/publications/EEEGenericListFormatted%2006.pdf?ua=1

Yamani N, Moosavi SA, Alizadeh M, Khorvash F, Ghiasi M. A 360-degree performance evaluation of emergency medicine ward in Alzahra Hospital. J Pak Med Assoc 2012;62(3 Suppl 2):S13-17.

Yarmohammadian MH, Rezaei F, Haghshenas A, Tavakoli N. Overcrowding in emergency departments: A review of strategies to decrease future challenges. J Res Med Sci 2017;22(1).

Yeh D-, Cheng C-. Performance Management of Taiwan's National Hospitals. Int J Inf Technol Decis Mak 2016;15(1):187-213.

Yeh T-, Huang Y-. Factors in determining wind farm location: Integrating GQM, fuzzyDEMATEL, and ANP. Renew Energy 2014;66:159-169.

Zavadskas EK, Govindan K, Antucheviciene J, Turskis Z. Hybrid multiple criteria decision-making methods: A review of applications for sustainability issues. Economic Res Ekon Istraz 2016;29(1):857-887.

Zhao R, Paul III DP. Performance evaluation of hospitals' emergency departments using a modified american productivity and quality center approach. Int J Soc Ecol Sustainable Dev 2012;3(4):34-47.

Zyoud SH, Fuchs-Hanusch D. A bibliometric-based survey on AHP and TOPSIS techniques. Expert Sys Appl 2017;78:158-181.

3 GENERAL DISCUSSION OF RESULTS

The first part of this research evidenced a significant increase in the number of articles reporting process improvement approaches focused on tackling the main ED problems (Overcrowding, Extended LOS, Excessive patient flow time, High LWBS, and Prolonged WT). This trend, initiated by 2011 (84.23% of the total related contribution) denotes the urgent need for upgrading the emergency care provided to patients. This is congruous with the recent efforts made by several countries seeking for lessening delays, mortality rates, cost overruns, health complications, and adverse events.

Among the wide variety of methodological approaches used to address the abovecited problems, the reported evidence revealed a slide into high-intensity application of simulation techniques. Several reasons support the use of this approach in the emergency care context: i) it can faithfully represent the pathways and multiple care options of patients within the EDs; thereby better administering the interactions with satellite services and stakeholders, ii) it collects data regarding the patient experience in the ED so that focused improvement strategies can be further implemented, iii) it provides an animated visualization of the process which supports engagement with ED administrators and policy makers, and iv) it allows decision makers to evaluate improvement strategies before implementation in EDs. It is also good to highlight the frequent use of lean manufacturing (LM) for addressing the main ED problems. The main reasons explaining this trend includes: i) the identification of non-value activities (delays, cost overruns) along the ED patient journey, ii) the promotion of collaborative work between the different agents of emergency care, and iii) the creation of standard operating procedures reducing the service time in each station of the emergeny care unit. The advantages evidenced by both simulation and LM can be further combined with data-driven approaches and other OR methods for achieving a sustainable lessening of patient flow time, behavioral changes, and high throughput in public emergency care units where healthcare is often provided under constrained resources. There is then much room for the implementation of hybrid approaches in the emergency care context. Such contributions will also prepare EDs to face peak demands as those experienced during the current Covid-19 pandemics. On a different note, the multifaceted nature of these techniques is attractive for ED administrators and decision makers searching for methodological frameworks capable of tackling different operational problems simultaneously. In fact, decisions involving the administration of medical staff, the construction of new observation rooms, and the acquisition of new medical equipment can be properly evaluated using these approaches.

More specifically, 48 techniques have been implemented by authors for reducing the waiting time problem in EDs. Most of contributions have been skewed to the application of OR methods as revealed in interventions targeting reduced LOS. Indeed, four OR methods were ranked among the six most popular approaches: simulation (*n* = 46 articles; 48.4%), optimization (*n* = 11 articles; 11.6%), integer programming (*n* = 10 articles; 10.5%), and queuing theory (*n* = 6 articles; 6.3%). There are, however, very few studies exposing the application of hybrid methods for this particular aim. These approaches can properly address an operational context comprised of multiple transient stages, interactions with other healthcare services (radiology, lab, etc.) treatment options, and outcomes. Thereby, ED administrators may better predict the potential effects of demand changes and ED configurations on average waiting time and other metrics of interest. A concern, however, is the availability of sufficient and suitable data for providing a good representation of patient pathways directly affecting ED waiting times. ED administrators should then define strategies for granting proper data gathering supporting the effective implementation of combined approaches. Apart from these considerations, there is no research addressing this problem in emergency care networks. Future efforts in this research field should be hence directed towards the above-mentioned lines with a special focus on developing countries where the financial budget is highly restricted and the waiting problem has reached devastating proportions.

Our findings are also congruous with the WHO document entitled as “Delivering quality health services: A global imperative for universal health coverage” which calls for improving the collaboration flows among emergency care units, academic partners, and government institutions for tackling the waiting time problem. The approaches here exposed will serve as a basis for short-term and long-term interventions targeting improved timeliness of emergency care while maintaining financial sustainability as pursued by WHO. In this regard, it is important to address some general methodological limitations that became evident from the review. For example, the application of hybrid approaches and multi-objective interventions are at the earlier stages and more contributions are then expected to increase the evidence base.

After deeply scanning the related literature, a methodology composed by 9 steps with the inclusion of simulation, LSS, and collateral payment models was proposed to design in-time and economically sustainable emergency care networks (2^{nd} part of this research). From the initial diagnosis, it can be observed that H2 is the node with the highest average and variable demand per semester (μ = 65,908.5 patients; σ^2 = 41,137). Besides, H2 evidenced the minimum waiting time (μ = 3.71 minutes; σ^2 = 0.31) and then reflected an effective response to the current demand. On a different note, patients admitted in H1 and POCs are expected to wait for more than the threshold (30 minutes). In fact, the short-term sigma level (-2.10) also revealed that the process is catastrophic and needs urgent intervention. In other words, it is estimated that 985,306.3 in every 1,000,000 patients will experience waiting times over 30 min. ED administrators and policy makers should then focus on upgrading the timeliness of such nodes to shorten the operational inefficiencies (i.e. high risk of mortality, development of more severe health complications, and cost overruns) that may appear during the ECN operation.

Being aware of this situation, LSS was applied to reduce the ED waiting time. Although a slight improvement was achieved (PPM = 921,329; σ_S = -1.41; Efficiency = 7.87%), the process is not yet capable of satisfying the threshold. Indeed, some nodes (POC1, POC2, POC3, POC4, and H1) still evidence a catastrophic process (PPM > 800,000; short-term sigma level < 0). Some other interventions are thus necessary to shorten the patients' stay in waiting rooms. In this regard, the main proposal of this research was to propel the deployment of emergency care networks

(ECNs) so that an estimated number of 1,315,283 patients can be timely served. This approach, of course, is also useful for increasing the response of EDs against the current Covid-19 pandemics.

Upon analyzing the potential risks through FMEA, it was found that the most critical failures (wrong triage classification and delay to triage; RPN = 450**) are related to *higher mortality rate*, no controls and frequent potential causes (misjudgment of the physical symptoms/signs and delay during triage classification). Such findings revealed that triage processes are the major highest-risk sources within the ECN. It is therefore necessary to train doctors to classify patients suitably, use p control charts to monitor the percentage of correctly triaged patients, and employ LM tools for minimizing the non-value activities during the triage process.

On a different note, the Mann-Whitney test provided enough support to establish that the proposed ECN is satisfactory for shortening the ED waiting time (p-value = 0; W = 17,791,765.5; 95%D[-9.08; -6.71]). In other words, if the ECN is implemented, the patients may experience a faster emergency care with an expected reduction of waiting times ranging from 6.71 min and 9.08 min. In a similar vein, a paired t-test confirmed that hospitals and POCs would have resource utilization rates (p-value = 0; T = 5.85; 95%D [8.06%; 18.21%]) ranging from 8.06% and 18.21% increase (Confidence level = 95%) if the proposed network design is adopted. Based on the above results, the proposed methodology cen be hence regarded as effective for ensuring not only the timeliness of the ECN here studied but the resource usage within each node. This statement is also underpinned from the financial perspective. The results evidenced that H2 and POC8 were found to be the nodes with the highest total gain within the network (US$212,142 and US$77,064 correspondingly). It is good to note that the significant total profit difference observed between H2 and the rest of nodes is explained by the high number of patients transferred to this hospital $(31{,}810)$ and the increased waiting time derived from the collaboration ($WT_2 = 4.19$; $\sigma^2 = 0.35$). To sum up, all nodes obtained financial benefits (μ = US$58,152/node) whereas ensuring the earliest possible emergency care to patients.

The third part of this dissertation focused on designing a model for evaluating the overall performance of EDs within ECNs. In particular, the FAHP results revealed that *Infrastructure* was the criterion with the highest importance (GW = 21.5%) while *Supplies, medicines and accessories* was ranked in the second place (GW = 13.50%). Nevertheless, the gap between *C6* (2nd place) and *C8* (8th place) is not significant (4.8%) reason why multidimensional improvement interventions with a huge focus on *Infrastructure* should be deployed for augmenting the overall ED performance. On a different tack, the fuzzy DEMATEL results revealed that *Patient safety (C8)* has the highest prominence (C + R = 12.771) and is then regarded as the most influencing factor in the overall performance of EDs. Therefore, *Patient safety (C8)* programs should be greatly prioritized by ED administrators and policy makers when designing long-term improvement plans. Besides, the high prominence values ($C + R > 10$) evidenced the presence of strong correlations between criteria which verifies the interactive nature of emergency care processes. It is also necessary to ensure that online decision support tools and medical equipment (C2) are smoothly integrated into all process management systems so that suitable clinical data can be extracted and efficiently analysed for risk management in EDs whereas high availability of medical equipment (LW = 42.3%; C + R = 51.078; C – R = 0.997) is guaranteed to address the current and future demands. Apart from the aforementioned results, the TOPSIS method showed that ED1 performed the best (CC = 0.6356) whilst ED3 achieved the lowest score (CC = 0.3139). These outcomes are an evidence of the regular and poor performance frequently reported in these EDs as well as the need for urgent interventions targeting timely care at reasonable costs.

In this respect, one of the major contributions was the detection of shortcomings which facilitates the deployment of focused interventions and the effective resource allocation during the improvement process. Thereby, investments can be made on interventions targeting an increased performance of EDs, an aspect of extreme relevance in the public sector where the budget is highly limited. In the cited case, *patient misidentification* and *hospital-acquired infections* were categorized as the weakest points of ED cluster and urgent attention should be thus paid to these sub-criteria for further improvement. On a different note, as strengths are further identified, ED administrators and policy makers can replicate the good practices in EDs with similar deficiencies. For example, a deepest exploration on maintenance plans can be performed on ED1 to understand the causes explaining the high *availability of medical equipment* and widespread their application in other EDs. As demands on emergency services continue to widen in the future, such strategies will become the foundation fostering the development of cost-effective collaborative structures providing highly satisfactory care. From a cluster point of view, the methodology here exposed can support the implementation of before-and-after analysis that enables decision-makers to evaluate the effectiveness of the proposed strategies. In addition, such framework serves as a solid platform for deploying incentive programs rewarding high-performance EDs. On a different tack, the FDEMATEL results revealed that *suitability of medical equipment* and *state of medical equipment* can be prioritized in long-range planning for increasing the *availability of medical equipment* within EDs. Also, *Patient safety* was concluded as the commonest and weakest aspect in the selected group of EDs. It is then crucial that government authorities and managers of healthcare clusters work together with EDs for underpinning the creation of intervention addressing this problem urgently. In parallel, *patient misidentification* and *hospital-acquired infections* should be measured and regulated progressively since they have been identified as common problems in most of the departments. Aside from these strategies, the Ministry of Education, Ministry of Health, and EDs should jointly define actions fostering the constant production of specialist physicians. In this regard, three barriers need to be overcome: i) the high cost of medical school, ii) the restricted access to medical specialties, and iii) the lack of transparency in the recruitment process.

The above implications end up influencing on the patients' perceptions regarding the care received at EDs. Indeed, patients are aware of EDs' performance and their expectations are constantly evolving towards more challenging and complex scenarios. These considerations thus confirm the key role that our proposed methodology can play in a decision-making context where both patient care and financial sustainability often converge. In a similar vein, the multifactorial nature of the required interventions need for the involvement and commitment of all the departments directly or indirectly related to the ED core operations. Considering above, it is evident that a multidisciplinary and multisectoral system-wide approach is then needed for increasing the overall performance of EDs.

4 CONCLUSIONS

4.1 Contribution

ECNs are projected to be the main strategy of goverments and stakeholders against the ever-increasing waiting times experienced by patients in ED settings. It is however evident that methodological approaches supporting the design of in-time and economically sustainable ECNs are highly limited and poorly developed throughout the reported literature.

In order to lay groundwork for devising, creating, and validating an approach bridging the aforementioned gap, this research provided a comprehensive literature review where the most prominent process-improvement approaches used for tackling the main ED deficiencies (including extended waiting time) were finally identified. Besides, it was concluded that a combination of Operations Research (OR) methods, quality-based techniques, and data-driven approaches is able to cope up with the complexity of emergency care operations, the interactions with other services, and the continued increased demand as expected in the real-life scenario of emergency care. By fully exploiting the advantages of each method, it is possible to effectively underpin ED operations within ECNs so that optimized emergency care can be delivered under reasonable costs and profits.

Based on the above considerations, the main contribution of this research has been the creation of a 9-step methodology initiating by the characterization and preparation of ECN nodes through lean six-sigma; followed by the design of the ECN considering the legal framework, network's target population, strategic platform, governance arrangements, service protocols, policies, and risks; whereas the ECN configuration is defined through simulation and payments derived from the collaboration are calculated based on collateral models.

From the managerial perspective, the proposed approach is useful for providing decision support to policymakers, ED administrators, and stakeholders when facing the following scenarios: i) deciding whether a patient should be transferred to another node, ii) defining the node offering the most timely emergency care considering transfer times, iii) evaluating the balance between the network capacity and demand, iv) appraising staffing policies, v) calculating ambulance service requirements based on transferring needs, and vi) efficiently distributing profits among participant ECN nodes.

Finally, it is also necessary to evaluate the performance of EDs integrating the public ECNs so that we can ensure that emergency care services are provided with efficiency, high quality, and safety. Nevertheless, the studies concentrating on deploying methodological frameworks addressing this problem are largely limited. Besides, the approaches presented in the related studies do not represent the entire ED performance context since several important criteria (e.g. medical equipment, human resources and infrastructure) have not been incorporated into the assessment models. On a different tack, interrelations among criteria have not been studied which is a relevant aspect when considering the interactive nature of emergency services and the need for creating long-term development plans. Also, poor effort has been made to include the vagueness of human judgments into the performance evaluation models which limits their effectiveness in practical scenarios. This research also bridged the aforementioned gaps through a novel integration of FAHP, FDEMATEL, and TOPSIS methods which operationalizes a performance model comprising of 8 domains and 35 sub-criteria. From the managerial perspective, the aforecited model provides significant support to decision-makers, cluster managers, and researchers involved in emergency care services. The main contributions are summarized as follows: i) Identification of weaknesses and strengths in ED performance ii) Application of before-and-after analysis enabling policy makers to appraise the effectiveness of the improvement interventions, iii) Identification of *dispatcher* criteria and sub-criteria for underpinning the design of short-term and long-term development plans, and iv) Ranking of EDs and performance comparative analysis against standards.

4.2 Future Works

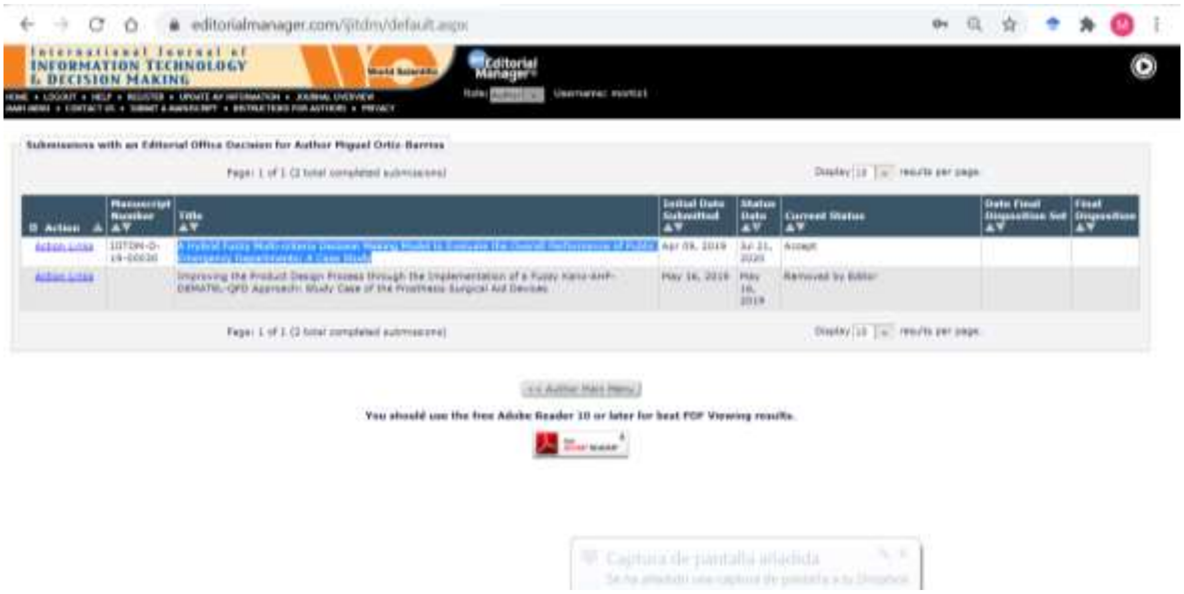
A wide range of future works were identified from the application of the research objectives within this thesis. For instance, the following research lines became evident from the systematic literature review: (i) more studies integrating simulation and lean manufacturing, (ii) contributions combining optimization, CQI, lean manufacturing, simulation, and regression are widely needed, (iii) interventions based on data-driven approaches and behavioral aspects of emergency care services, (iv) application of process improvement approaches underpinning emergency care networks, (v) more projects addressing different emergency department deficiencies simultaneously, (vi) interventions addressing overcrowding and high left-without-being-seen rates, (vii) the design and implementation of new modelling frameworks considering patient heterogeneity, interactions, and multiple care alternatives for supporting the deployment of strategic plans within emergency care and its associated services, viii) the promotion of international collaboration to undertake comparative studies among countries, (ix) propel the widespread application of the identified approaches in developing countries where financial budget is largely limited, (x) foster closest collaborations among EDs, government, and academic partners for creating scale-up and sustainable improvement interventions in emergency care, (xi) review the research progress related to interventions tackling non-urgent ED admissions considering the high waste of resources reported by public hospitals especially on weekends, and (xii) review the literature concerning improvement strategies based on clinical-related interventions, personnel training, the ABCDE of emergency care, and triage which have not been covered in this research.

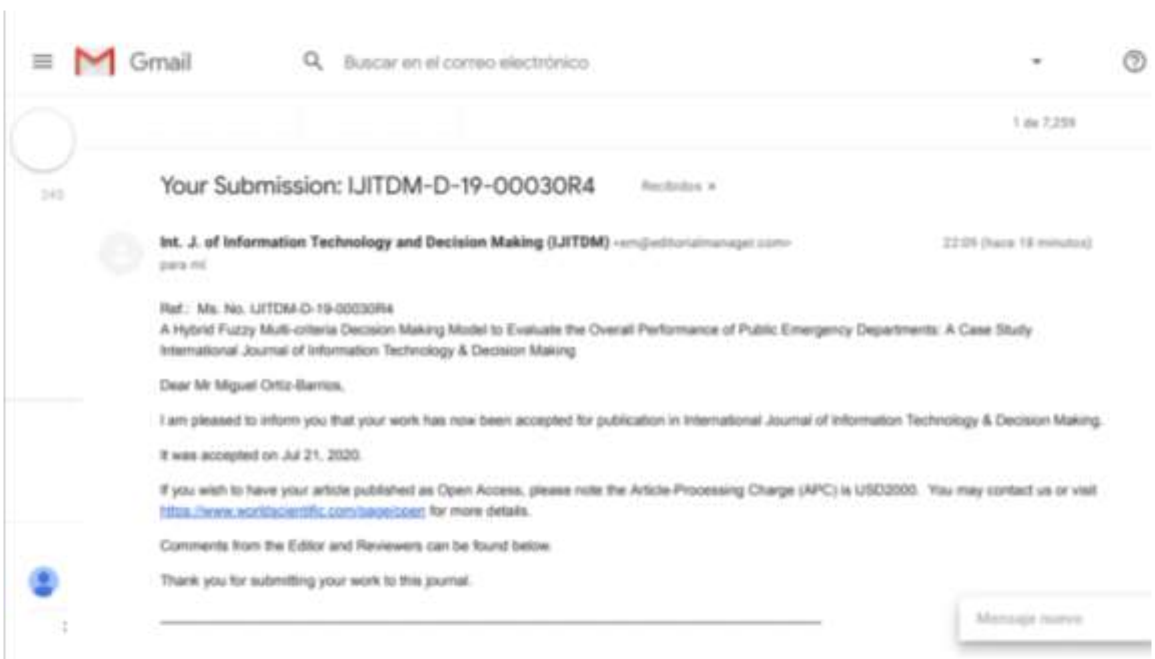
On the other hand, given the considerable potential of this approach, we plan in the future to incorporate transferring costs and ambulance routing optimization models for increasing the ECN competitiveness.Thereby, more informative and detailed models can be provided for evaluating more complex decisions. It is also aimed to compare our modified collateral payment scheme with other utility distribution models to improve the profit allocation efficiency within the ECN.

Lately, future studies related to ED performace evaluation may incorporate financial and environmental criteria to better support ED administrators and policymakers in decision-making processes. The proposed methodology can be also adapted for assessing the performance of EDs when facing disaster situations such as the current Covid-19. It is additionally envisioned to use interval TOPSIS method to incorporate the variation of KPIs, upgrade the ED performance measurement system, and consequently provide significant inputs for future interventions. From the theoretical perspective, it is pursued to compare our hybrid MCDM method with other vagueness-based techniques (i.e. intuitionistic fuzzy set theory and Neutrosophic set theory) for establishing similarities and differences concerning the criteria/sub-criteria weights, interdependence evaluation, and final ranking of alternatives.

5 ATTACHMENTS

Justification of the paper in the status ‘accepted’: “A Hybrid Fuzzy Multi-Criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study”





International Journal of Information Technology & Decision Making | VOL. 0, NO. ja

A Hybrid Fuzzy Multi-criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study

Miguel Ortiz-Barrios and Juan-Jose Alfaro-Saiz

https://doi.org/10.1142/S0219622020500364

Accepted manuscript to appear in IJITDM

Accepted Manuscript

International Journal of Information Technology & Decision Making

Article Title:	A Hybrid Fuzzy Multi-criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study
Author(s):	Miguel Ortiz-Barrios, Juan-Jose Alfaro-Saiz
DOI:	10.1142/S0219622020500364
Received:	09 April 2019
Accepted:	21 July 2020
To be cited as:	Miguel Ortiz-Barrios, Juan-Jose Alfaro-Saiz, A Hybrid Fuzzy Multi-criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study, *International Journal of Information Technology & Decision Making*, doi: 10.1142/S0219622020500364
Link to final version:	https://doi.org/10.1142/S0219622020500364

International Journal of Information Technology & Decision Making | VOL. 0, NO. ja

A Hybrid Fuzzy Multi-criteria Decision Making Model to Evaluate the Overall Performance of Public Emergency Departments: A Case Study

Miguel Ortiz-Barrios and Juan-Jose Alfaro-Saiz

https://doi.org/10.1142/S0219622020500364

Accepted manuscript to appear in IJITDM