



Discrete Event Simulation In The Optimization Of Emergency Departments

Palacios-Alvarado Wlamyr^{a 1}, Luna-Pereira, Henry Orlando^b, Caicedo-Rolon, Alvaro Junior^c

^aPhD in Business Administration, productivity and competitiveness research group, Orcid: <https://orcid.org/0000-0002-0953-7598>, E-mail: wlamyrpalacios@ufps.edu.co, Universidad Francisco de Paula Santander, Cúcuta – Colombia.

^b PhD in Business Administration, Director Director of investigación & Desarrollo Regional IDR Group, Orcid: <https://orcid.org/0000-0003-2741-9170>, Email: henryorlandop@ufps.edu.co, Universidad Francisco de Paula Santander.

^c Doctor in Engineering, emphasis in Industrial Engineering, Director of productivity and competitiveness research group, Orcid: <https://orcid.org/0000-0002-3651-3364>, E-mail: alvarojuniorcr@ufps.edu.co, Universidad Francisco de Paula Santander, Cúcuta, Colombia.

APA Citation:

Wlamyr, P.A., Orlando, L.P.H., Junior, C.R.A., (2022). Discrete Event Simulation In The Optimization Of Emergency Departments, *Journal of Language and Linguistic Studies*, 16(4), 194-203.

Submission Date: 20/08/2022

Acceptance Date: 18/10/2022

Abstract

Emergency departments are the most important units of the hospital network, which present daily problems in their system due to inefficient resource management. The objective of this research is to study the various problems presented by emergency departments and how they have been solved using optimization and simulation models. Based on the implemented methodology, 52 publications (books and articles) were collected, which allowed the investigation of the problems generated in the emergency departments and the models that helped to reduce or improve these problems. The most applied quantitative methodology is the simulation of discrete events and the most used software is the Arena simulator. Finally, the performance indicators used in the modeling of the system are the length of stay, arrival at the provider's door (doctor's door), rate of patients leaving without being attended and total waiting times. It is concluded that the application of the different models helps to improve the ED system, such as decreasing waiting times and reducing overcrowding.

Keywords: Discrete events, Patient flow, Overcrowding, Emergency department, Simulation.

1. Introduction

Emergency departments are units belonging to hospital centers, responsible for providing medical care to patients whose pathologies or situation requires immediate care at any time (Lopez & Fernandez, 2017). These services reflect the policy of universal coverage, in particular the obligation to provide health care, regardless of the economic capacity of the users (Elalouf & Wachtel, 2015). Emergency services around the world are showing a substantial increase in the demand for the service, including in countries with a strong health care network and coverage (Humberto, Jaen-Posada, Espinal Piedrahita, & Zapata Florez, 2018). This increase is due to different factors such as: older adults, high numbers of patients with chronic diseases, and behavioral changes related to the way people choose to access health services, i.e., people with primary care problems using emergency and urgent

¹ Corresponding author.

E-mail address: wlamyrpalacios@ufps.edu.co

care services to access medical care (Evan Berg, 2020). This situation is leading to increased total costs (Mason, Mountain, Turner, Arain, & Weber, 2014), shortage of bed availability, occupancy rates exceeding 85% of the maximum efficiency level, and increased overcrowding (Gardner, y otros, 2018). This last problem is generating multiple consequences on system performance such as: reduced hospital service quality, low performance standards, adverse health outcomes such as mortality (Joanne E Coster, 2017); increased waiting time and length of stay (Jimenez-Barragan, y otros, 2021).

The events that are occurring in emergency departments have led managers to implement strategies and management models for risk minimization in decision making, optimization of healthcare resources in the patient care process and exploration of new opportunities for improvement in the system (Burns, 2017). These strategies arise with the purpose of making healthcare institutions autonomous, highly sustainable and improving the quality of service and, in turn, satisfying the needs of users (Varney, Weiland, & Jelinek, 2014).

The following are literature reviews that studied the problems presented by hospital emergency departments and the development of operational research models that allowed the improvement of management (Velásquez-Restrepo, Rodríguez-Quintero, & Jaén-Posada, 2011). One of the reviews identified the problems and areas for improvement in the ED, in order to design a strategic plan with needs and resources analysis involving a better distribution and utilization of healthcare resources (WaleedAbo-Hamad & AmrArisha, 2012). Green and Liu (2015) use queuing theory to study the capacity of an obstetric unit in New York City. They conclude that a large fraction of obstetric units could probably reduce their bed capacity without sacrificing timely access to care. Noyes (2008) develops a simulation model that represents the activities in the emergency department at Deaconess Israel Beth Medical Center, a Harvard teaching hospital, with the goal of evaluating patient flow. With the application of the model, new policies are proposed to improve service times such as: increasing the number of beds, reducing downtime between patients, among others (Pérez-Ciordia, F, C, Fernández-Martínez, & Aguinaga). Finally, mixed methods study identifying the factors that cause bottlenecks in patient flow and prolonged ED stays (Farzane Asgaria, 2021).

2. Background

Lean Manufacturing, is known as lean, which refers to productive improvement and optimization, whose focus is to make them more efficient, reduce costs and waste (Orozco, Cuervo and Bolaños, 2016). This term was initially used by "...John Krafcik", when explaining that "lean" refers to concrete, precise or lean production, because it uses fewer resources, comparing it to mass or large-scale production (Vargas, Muratalla, & Jiménez, 2018, p.5).

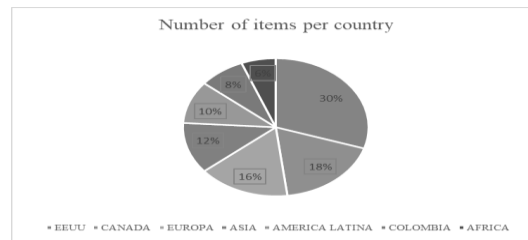
In the vicinity of the twentieth century it was evident the development in various sectors of the economy, the concept of mass production, conceived and developed in the automotive sector, which found in Taylorism and Fordism, its maximum exposure. But this not only referred to the manufacture of products in large volumes, but also encompassed a fairly broad system of markets, technologies, economies of mass production or scale and inflexible rules. Taylorism, according to Bounine, was the proponent of the scientific method of division of labor, chain production, and the elimination of control or autonomy that the worker had over how to develop his work, but that, in the long run, did not get the expected sales because it increased production cycles and inventories.

3. Method

As a search strategy, articles were selected that met the following criteria: 1) those that address the problems presented by emergency departments based on the application of operations research methodologies; 2) those that implement simulation and optimization models (qualitative and quantitative) in the search for optimal solutions; and 3) those whose publication date does not exceed 10 years. The databases Scielo, Science Direct, Redalyc, Dialnet, PubMed and Google Scholar were consulted using keywords such as Discrete Events, Patient Flow, Overcrowding, Emergency Department, Simulation. Finally, the selection was made by reviewing the title, abstract and conclusions of the articles.

Finally, 52 publications were selected, research and review articles (92%) and books (8%). Graph 1 lists the articles according to the country where they were published.

Figure 1. Number of articles by country of publication.



4. Results

The search for information made it possible to identify the problems to which emergency departments are constantly exposed (Pryce, Unwin, Kinsman, & McCann, 2021). These problems, in general, have been associated with the absence of timely intervention in the management of services, and have an impact on different factors such as timeliness, continuity, quality and costs (Estrada-Atehortúa & Zuluaga-Gómez, 2020) .

The research articles that provided optimal solutions for the improvement of service delivery considered the following objectives: 1) To analyze the benefits of the application of quality improvement methods in emergency departments (Paloma Martínez & Cavazos, 2015); 2) To design a model for decision making in the presence of changes in the system [19]; 2) To design a model for decision making in the presence of changes in the system (A.Hussein, F.Abdelmaguid, S.Tawfik, & G.S.Ahmed, 2017). The objectives made it possible to consider certain decisions for the improvement of the emergency department, such as the incorporation of medical personnel when a certain number of patients are reached during peak demand hours, an increase in the number of beds in the observation area, the creation of a priority policy for care, and the elimination of activities that generated reprocessing.

As for the performance indicators (Kpis) (Chinchilla, Oliveros, & Forero, 2017), it is observed in Table 1, those most frequently used to evaluate the system were: length of stay (LoS), total waiting time (TWT), arrival time at the doctor's door (ATP), degree of congestion (NEDOCS) and highest rate of patients leaving without being seen by a medical professional physician (LWBS), etc (Konrad, y otros, 2017).

Table 1. Performance indicators used to evaluate the emergency department system.

Indicador	Reference	%
Degree of congestion (NEDOCS)	[18]	7%
Length of stay (LoS)	[18], [21], [22], [24]	27%
Arrival at provider's time ("door to doctor") (APT)	[20], [22]	13%
Loss of accumulated time (processes)	[21]	7%
Rate of patients leaving without being seen (LWBS)	[21], [25]	13%
Number of concurrent patients (WP)	[21]	7%
Variability of the length of stay of patients	[22]	7%
Total waiting time (TWT)	[26], [27]	13%
Adequacy of bed management	[27]	7%

Table 2 below shows the models used for solving emergency department problems.

Table 2. Optimization and simulation models

Modelo	Referencia	%
Discrete event simulation	[13], [19]–[21][28]–[34]	46%
Queuing theory	[35]	4%
Cumulative priority queue	[24]	4%
Mixed integer programming	[36]	4%
Pragmatic and cluster randomized trial.	[37]	4%
Process facilitators	[25]	4%
Descriptive statistics	[38]	4%
Lean manufacturing	[17]	4%
Six sigma	[18]	4%
Retrospective analysis	[27], [39], [40]	13%
Genetic algorithm	[41], [42]	8%

Table 3 shows the software used in the optimization, simulation, statistical and mathematical modeling models. Although several software tools were used, the Arena software is presented in greater frequency.

Table 3. Software used in the models

Software		Referencia	%	% Total
Optimización	IBM ILOG CPLEX	[36]	6,25%	6,25%
Simulación	ARENA	[17], [20]–[22], [24], [28]–[30], [35]	56,25%	75,00%
	SIMIO	[19]	6,25%	
	SIMUL8	[18]	6,25%	
	Microsoft Excel	[38]	6,25%	
Estadístico	IBM SPSS Statistics	[25]	6,25%	18,75%
	STATA	[40]	6,25%	
	SAS (Statistical Analysis System)	[39]	6,25%	

5. Discussion

Discrete-event simulation occurs when the equipment, modification in scheduling policies, process design, distribution redesign, and the impact of changes in demand (Oh, y otros, 2016). Applications of discrete event simulation Chongsun Oh et al (2016), applied discrete event simulation to decrease length of stay to less than 3 hours for 80% or more of patients, maximize productivity, and reduce operating costs. Simulation modeling allowed ED managers to make decisions about operational changes using quantitative information on the impact of hypothetical scenarios on key performance measures (Yang, WeiLam, M.W.Low, & HockOng, 2016) David Hernandez, Camacho & Duarte (2017), implemented a discrete event simulation model that will represent the system and its variables (patient arrival, length of stay, delays in care and required staffing), based on a new population segmentation (days of stay and pathology); This allowed a better causal analysis of the days of stay in the system, achieving a 14%

improvement in length of stay and a decrease in queue waiting time (Ratnovsky, Rozenes, Bloch, & Halpern, 2021). System variables change value instantaneously, corresponding to the occurrence of an event that generates alternation in the state of the model (Cildo, Ibarra, & Mallor, 2019).

The simulation considers the variability in the time of the system in the analysis, the randomness of the possible events that may occur in the progress of the simulation and the ability to animate the movement of the entities (patient or staff) that flow within the model, which allows studying the behavior of the system during the course of the simulation period (Taype-Huamaní, Chucas-Ascencio, Cruz-Rojas, & Amado-Tineo, 2019). Also, the model is shaped by rules that govern the movement of the entities, the processing activity of the resources and the state variables collected by the user, allowing to capture the uncertainty related to the arrivals to the system and the interactions between the human resource and equipment (Stanford, Taylor, & Ziedins, 2013). Several researchers have implemented discrete event simulation in emergency departments to model patient flow. Their goal is to identify problems that cause long waiting times or customer dissatisfaction, in order to improve the quality of service (Antoni Juan, y otros, 2010). The improvement changes that are commonly made to emergency services with the application of discrete event simulation are: addition of staff, beds or Delgado & Mejía (2010), developed a simulation model in which the types of patients admitted to the emergency department were identified; after several analyses, the best alternative obtained was the modification of the physicians' schedule of care to reduce the patient's length of stay (Allyson M Best 1, Kelton, Lindsell, & 5, 2014).

Queuing theory makes basic assumptions about a system to perform mathematical formulations describing the flow of service in order to predict waiting times. A central tenet of this model is that variability in the arrival process is unpredictable or predictable but unmanageable. Arrivals are generally assumed to be "Markovian" or random, so they do not probabilistically affect future arrival patterns; the arrival pattern is also assumed to be constant, although the actual realization of arrival times can be highly variable. The system is designed based on queuing disciplines (priorities) that describe the order in which service is provided. Some commonly used disciplines include first come, first served (FCFS), where patients are stratified and patients are stratified and the highest priority class that has been waiting the longest (Palomera, Ángeles, & León, 2010). Some research articles show that queuing model can be used efficiently in healthcare. Where emergency department performance (patient flow) and available resources can be studied. This model considers the emergency medical system as a network of queues and different types of servers where patients arrive, wait for a service, receive outcome and then go home or are admitted to a hospital unit (Encina & Puente, 2011).

Rodriguez et al (2017), proposed a strategy that allows understanding the relationship that exists between service demand, number of physicians and patient care priority. Applying queuing theory allowed calculating the minimum number of physicians needed to satisfy the current and future service demand, with the same service times and the same service discipline.

Priority queuing in systems has been used under the assumption that customer classes have fixed priorities, that no customer of a given class is admitted to service as long as there are customers present from higher priority classes. However, this logic does not work for all systems, hence comes the cumulative priority queuing theory, where users accumulate priority as a linear function of their time in the queue: the greater the urgency of the client class, the greater the rate at which that client accumulates priority. When the server becomes free, the client with the highest accumulated priority at that time is the one selected for service (Blake, Carter, & Richardson, 2016).

Cildo, Ibarra & Mallor (2019), because the established objectives were not being met when overcrowding was present, decided to implement cumulative priority queue management policies in the emergency department. In which four priority rules were proposed: PR-1C, (prioritizes the first consultation) PR-2C (prioritizes the second consultation) PR-AI (prioritizes patients according to their disease acuity index, and within each priority prioritizes the first consultation over the second) and PR-HN (combines PR-AI for high priority patients with PR- 2C for medium and low priority. The results showed that for emergency departments with low demand, the PR.2C policy works better than the other rules and for higher demand, the PR.2C policy works better than the PR.2C policy rest of the other rules and for higher congestion the PR-1C policy.

Lean manufacturing studies the process for the elimination or reduction of agents that do not generate value (waste). Thus, Lean principles are divided into value-added and non-value-added activity; the former contribute to satisfy the user's needs and the other takes time, space or resources that does not meet the customer's requirements (Luo, y otros, 2018). In healthcare 95% of operations are non-value-added and only 5% are value-added. The eight wastes that can occur in this service are the following: Defect: time spent looking for something missing in the supply room; overcrowding: unnecessary diagnostic procedures or too much laboratory testing; transport: unnecessary movement of patients, specimens or materials throughout a system, often as a result of poor design; Wait for service; inventory: excess inventory, storage, movement, spoilage or waste all have a cost: movement: moving: moving employees from one room to another; Excessive processing. Describes work not valued by patients or caused by rules that are not aligned with patients' needs; and Human potential: employees are not engaged due to physical exhaustion from long workdays.

Martinez et al. (2015), To improve patient care time, Lean manufacturing was applied, First, the current state of the processes is established and subsequently the factors that generate delays are identified. The results of the improvement proposal show a 54% decrease in the cycle time, 96% improvement in the generation of the output order and 20% improvement in the admission to consultation. Lean becomes a viable and low-cost practice in emergency departments.

Six Sigma is a management system that seeks to improve the efficiency of processes, reducing defects to achieve improved quality and customer satisfaction. Its philosophy is based on reducing variation and activities (without added value) that result in long cycle times, high cost and poor results. Six Sigma uses the "Define, Measure, Analyze, Improve and Control" improvement cycle of traditional continuous quality improvement techniques. Of traditional continuous quality improvement techniques in order to achieve variance reduction objectives. A process operating under true Six Sigma levels produces acceptable quality levels more than 99.99% of the time.

The development of this model in emergency departments has achieved optimal results such as reduced errors and cycle times, improved quality of service and patient flow, and decreased costs. Hussein et al. (2017), used six sigma methodology to improve emergency department performance by reducing the degree of congestion and patient length of stay. Software was used to analyze and evaluate the impact of the suggested system redesign implementations on ED performance. The results indicate that the Six Sigma-Simulation presented has proven to be versatile in providing guidelines, developing and evaluating different improvement scenarios. It provides a more systematic improvement methodology rather than relying on personal intuition and judgment in proposing improvement scenarios and evaluating their results through simulation experiments. This approach can also be used to improve the performance of other healthcare management systems, taking advantage of their potential to substantially improve and develop medical services, particularly considering their low investment cost

The retrospective analysis study is a type of study in which researchers search for patients and collect information about their medical history. In this study, the researcher uses historical data to analyze patient outcomes and review whether they have suffered from any disease, also observing the current health status of individuals.

Chaou et al. (2016) To collect the requested data are extracted by the administrative staff of the emergency rooms, where there is a database control. On the other hand, the arrival time of the physicians is divided into 8-hour shifts, leading to not generate idle time among the medical staff and that all patients can be attended in their entirety. In addition, the triage classification triage classification for a better coverage of patients by level.

In the retrospective study, analyses are performed using statistical methods such as standard deviation and mean. Through these methods it can be observed that most patients can be discharged from the emergency department, because they do not have a serious illness to move to the next phase, which is hospitalization. Finally, it is considered that the retrospective analysis study is extremely important to

identify patients who need more advanced care in order to reduce overcrowding in the emergency room and to discharge patients who do not have a chronic disease .

Daldoul et al (2018), to cope with the remains of the emergency department, proposed an approach to optimize human and material resources and minimize patient waiting times. A mixed-integer programming model is planned, which can be solved using a sample mean approximation approach. sample approximation. For this purpose, the ILOG CPLEX Optimization Studio software was used. The performance obtained from the optimization model was compared with what currently exists in the ED. The results of the experimental study show that the proposal improves the average patient waiting time by up to 23.24% .

The genetic algorithm is an adaptive method that can be used to solve optimization problems and works to determine the allocation of resources in emergency rooms. On the other hand, the genetic algorithm is capable of creating solutions to everyday problems. This method has 16 variables, which it can effectively recognize and identify the optimal allocation of resources. These algorithms have as their starting point a set of random solutions.

Azadeh et al (2014), patient scheduling is required in emergency laboratories according to the priority of treatment in order to minimize the total waiting time, genetic algorithm (GA) was proposed to provide a solution to this problem, response surface was applied to adjust the GA parameters. In order to demonstrate the superiority In order to demonstrate the superiority of the proposed approach, it has been applied to a real emergency in the department. A full computer simulation of the application case has been performed. Simulation experiments reveal that the proposed approach improves the performance of patient scheduling in the emergency department and makes efficient use of available resources.

6. Conclusions

Several researchers are interested in improving the performance of the emergency department in the United States, Canada and Europe, where the largest number of studies is evident. The articles show that the most common problems affecting the emergency department system are: overcrowding, long waiting and stay times, lack of bed availability and inadequate management of resources; factors that generate poor quality of service and user dissatisfaction.

To counteract the aforementioned problems, different optimization and simulation models have been applied, the most predominant of which is the discrete event simulation model with 46%, since it adjusts to the system variables, which change instantaneously due to the occurrence of an event (higher demand, high staffing, limited resources, etc.). This model has made it possible to study the behavior of the system, allowing managers to make appropriate decisions in the management and control of the service.

During the modeling of the system, simulation (75%), statistical (18.75%) and optimization (6.25%) software was used, considering that the most widely used was the Arena simulator. In addition, performance indicators that allow evaluating the evolution of the system were taken into account in this modeling, such as length of stay (26%), arrival at the provider's door (doctor's door) (13%), rate of patients leaving without being attended (13%) and total waiting times (13%).

With the application of the different models, optimal results were obtained that allowed improving the performance of the emergency system, reducing waiting and stay times, and optimizing resources, in order to provide a quality service that meets the objectives and organizational policies of the entity.

References

- A.Hussein, N., F.Abdelmaguid, T., S.Tawfik, B., & G.S.Ahmed, N. (2017). Mitigating overcrowding in emergency departments using Six Sigma and simulation: A case study in Egypt. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S221169231630100X>

- Allyson M Best 1, C. A., Kelton, W. D., Lindsell, C. J., & 5, M. J. (2014). Using discrete event computer simulation to improve patient flow in a Ghanaian acute care hospital. *Am J Emerg Med*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/24953788/>
- Antoni Juan, E. E., Valgañón, C. V., Fortea, C. G., Juan Castellanos, J. R., Milán, J. M., Luis Lores, J. U., . . . Cé, M. (2010). Impacto de implementación de medidas de gestión hospitalaria para aumentar la eficiencia en la gestión de camas y disminuir la saturación del servicio de urgencias. *Dialnet*. Obtenido de <https://dialnet.unirioja.es/servlet/articulo?codigo=3262918>
- Blake, J. T., Carter, M. W., & Richardson, S. (2016). An Analysis Of Emergency Room Wait Time Issues Via Computer Simulation. *Taylor Francis Online*. Obtenido de <https://www.tandfonline.com/doi/abs/10.1080/03155986.1996.11732308?cookieSet=1>
- Burns, T. R. (2017). Contributing factors of frequent use of the emergency department: A synthesis. *Int Emerg Nurs*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/28676296/>
- Chinchilla, D. H., Oliveros, M. Á., & Forero, E. L. (2017). Análisis del flujo de pacientes en el servicio de urgencias del Hospital Universitario la Samaritana a través de simulación discreta. *Avances Investigación En Ingeniería*. Obtenido de <https://revistas.unilibre.edu.co/index.php/avances/article/view/1289>
- Cildo, M., Ibarra, A., & Mallor, F. (2019). Accumulating priority queues versus pure priority queues for managing patients in emergency departments. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/pii/S2211692318301309>
- Elalouf, A., & Wachtel, G. (2015). An alternative scheduling approach for improving patient-flow in emergency departments. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S2211692314200592>
- Encina, K. D., & Puente, M. M. (2011). Aplicación de la simulación discreta para proponer mejoras en los procesos de atención en el área de emergencia de un hospital público. *Revista de la Facultad de Ingeniería Industrial*. Obtenido de <https://www.redalyc.org/pdf/816/81622582008.pdf>
- Estrada-Atehortúa, A. F., & Zuluaga-Gómez, M. (2020). Estrategias para la medición y el manejo de la sobreocupación de los servicios de urgencias de adultos en instituciones de alta complejidad con altos volúmenes de consulta. *IATREIA*. Obtenido de <http://www.scielo.org.co/pdf/iat/v33n1/0121-0793-iat-33-01-68.pdf>
- Evan Berg, A. T. (2020). Emergency Department Operations II: Patient Flow. *National Center for Biotechnology information*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/32336328/>
- Farzaneh Asgaria, S. (2021). Addressing artificial variability in patient flow. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S2211692321000047>
- Gardner, G., Gardner, A., Middleton, S., Considine, J., Fitzgerald, G., Christofis, L., . . . O'Connell, J. (2018). Mapping workforce configuration and operational models in Australian emergency departments: a national survey. *Aust Health Rev*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/28514641/>
- Humberto, R.-Z. J., Jaen-Posada, J. S., Espinal Piedrahita, J. J., & Zapata Florez, P. A. (2018). Emergency Department Overcrowding: A Four-Hospital Analysis in Medellín and a Strategy Simulation. *Revista Gerencia y Políticas de Salud*. Obtenido de http://www.scielo.org.co/scielo.php?script=sci_abstract&pid=S1657-70272018000100130&lng=es&nrm=is&tlng=en
- Jimenez-Barragan, M., Rodriguez-Oliva, M., Sanchez-Mora, C., Navarro-Bustos, C., Fuentes-Cantero, S., Martin-Perez, S., . . . An. (2021). Emergency severity level-3 patient flow based on point-of-care testing improves patient outcomes. *Clin Chim Acta*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/34537218/>

- Joanne E Coster, J. K. (2017). Why Do People Choose Emergency and Urgent Care Services? A Rapid Review Utilizing a Systematic Literature Search and Narrative Synthesis. *Acad Emerg Med*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/28493626/>
- Konrad, R., Sotto, K. D., Grocela, A., McAuley, P., Wang, J., Lyons, J., & Bruin, M. (2017). Modeling the impact of changing patient flow processes in an emergency department: Insights from a computer simulation study. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S2211692313000052>
- Lopez, F. R., & Fernandez, F. J. (2017). *Ciencia Administrativa Y Gestión Sanitaria*. La casa del libro. Obtenido de <https://latam.casadellibro.com/ebook-ciencia-administrativa-y-gestion-sanitaria-ebook/9788416956517/5082272>
- Luo, L., Zhang, Y., Qing, F., Ding, H., Shi, Y., & Guo, H. (2018). A discrete event simulation approach for reserving capacity for emergency patients in the radiology department. *BMC Health*. Obtenido de <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6003191/>
- Mason, S., Mountain, G., Turner, J., Arain, M., & Weber, E. R. (2014). Innovations to reduce demand and crowding in emergency care; a review study. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*. Obtenido de <https://sjtrem.biomedcentral.com/articles/10.1186/s13049-014-0055-1>
- Oh, C., M. Novotny, A., L. Carter, a., K. Ready, R., D. Campbell, D., & C. Leckie, M. (2016). Use of a simulation-based decision support tool to improve emergency department throughput. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S2211692314200579>
- Paloma Martínez, J. M., & Cavazos, P. N. (2015). Mejora en el Tiempo de Atención al Paciente en una Unidad de Urgencias Mediante la Aplicación de Manufactura Esbelta. *Información tecnológica*. Obtenido de https://www.scielo.cl/scielo.php?script=sci_arttext&pid=S0718-07642015000600019
- Palomera, A. M., Ángeles, Á. G., & León, S. V. (2010). Reducir tiempos de espera de pacientes en el departamento de emergencias de un hospital utilizando simulación. *evistas científicas de Acceso*. Obtenido de <https://www.redalyc.org/articulo.oa?id=81619989010>
- Pérez-Ciordia, I., F. A. B., C. G.-G., Fernández-Martínez, & Aguinaga, I. (s.f.). Identificación de problemas y propuestas para mejorar la atención de las urgencias extrahospitalarias en Navarra: un estudio Delphi. *Anales del Sistema Sanitario de Navarra*. Obtenido de https://scielo.isciii.es/scielo.php?script=sci_arttext&pid=S1137-66272011000300006
- Pryce, A., Unwin, M., Kinsman, L., & McCann, D. (2021). Delayed flow is a risk to patient safety: A mixed method analysis of emergency department patient flow. *Int Emerg Nurs*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/33360361/>
- Ratnovsky, A., Rozenes, S., Bloch, E., & Halpern, P. (2021). Statistical learning methodologies and admission prediction in an emergency department. *Australasian Emergency Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S2588994X20301147>
- Stanford, D. A., Taylor, P., & Ziedins, I. (2013). Waiting time distributions in the accumulating priority queue. *Queueing Systems*. Obtenido de <https://link.springer.com/article/10.1007/s11134-013-9382-6>
- Taype-Huamaní, W., Chucas-Ascencio, L., Cruz-Rojas, L. D., & Amado-Tineo, J. (2019). Tiempo de espera para atención médica urgente en un hospital terciario después de implementar un programa de mejora de procesos. *Anales de la Facultad de Medicina*. Obtenido de http://www.scielo.org.pe/scielo.php?script=sci_arttext&pid=S1025-55832019000400005
- Varney, J., Weiland, T. J., & Jelinek, G. (2014). Efficacy of hospital in the home services providing care for patients admitted from emergency departments: an integrative review. *Int J Evid Based Healthc*. Obtenido de <https://pubmed.ncbi.nlm.nih.gov/24945961/>

- Velásquez-Restrepo, P. A., Rodríguez-Quintero, A. K., & Jaén-Posada, J. S. (2011). Quantitative methodology for emergency service optimization: a review of past literature. Obtenido de <http://www.scielo.org.co/pdf/rgps/v10n21/v10n21a12.pdf>
- WaleedAbo-Hamad, & AmrArisha. (2012). Simulation-based framework to improve patient experience in an emergency department. *European Journal of Operational Research*. Obtenido de <https://www.sciencedirect.com/science/article/pii/S0377221712005693>
- Yang, K. K., WeiLam, S. S., M.W.Low, J., & HockOng, M. E. (2016). Managing emergency department crowding through improved triaging and resource allocation. *Operations Research for Health Care*. Obtenido de <https://www.sciencedirect.com/science/article/abs/pii/S221169231420035X>

Appendix A. An example appendix

Authors including an appendix section should do so after References section. Multiple appendices should all have headings in the style used above. They will automatically be ordered A, B, C etc.

A.1. Example of a sub-heading within an appendix

There is also the option to include a subheading within the Appendix if you wish.

Makalenin Türkçe başlığı buraya yazılır....

Özet

Türkçe özet.

Anahtar sözcükler: anahtar sözcükler1; anahtar sözcükler2; anahtar sözcükler3

AUTHOR BIODATA

Insert here author biodata.