Universitat Autònoma de Barcelona

Simulation for Investigating Impact of Dependent and Independent Factors on Emergency Department System Using High Performance Computing and Agent-based Modeling

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Thesis submitted by Elham Shojaei for the degree of Doctor of Philosophy by the Universitat Autònoma de Barcelona, under the supervising of Dr. Emilio Luque Fadón and Dr. Francisco Epelde done at the Computer Architecture and Operating Systems Department, PhD. in Computer Science.

Bellaterra, June 2020

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acknowledgment

First and most, I would like to express my sincere gratitude to my advisor Emilio Luque for the continuous support of my Ph.D. study and related research, for his patience, motivation, and immense knowledge, all the support and encouragement. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my Ph.D. study. He has been a great person to work and socialize with for the last three years.

Many thanks also to doctor Francisco Epelde of the Emergency Department of the Hospital Universitari Parc Taulì that I should pursue my doctoral degree and who made it possible for me to obtain the meetings and information provided for the preparation of this research.

My deep appreciation for Dr. Dolores Rexachs for the support received through the collaborative work, her scientific advice and knowledge, and many insightful discussions and suggestions during the entirety of my work.

I am also very grateful for Gemma Roque, Daniel Ruíz Molina and all the staff at the Computer Architecture and Operating Systems Department, and the High-Performance Computing for Efficient Applications and Simulation Research Group, especially to, Remo Suppi (former colleague).

I am incredibly fortunate to have so many friends and colleagues, without whom I may never have completed this thesis.

A very special thank to Alvaro Wong and Cecilia Jaramillo, their kindness made me feel at home. All of these are the precondition for the fulfillment of my research. Last but not least, I would like to THANK my parents, my Aunt Nahid Talebi, my brother Iman Shojaei and my boyfriend Norbert Marek, for their deep support, patience, wisdom, example, care, love.

This research has been submitted in May. 2020. This research has been supported by the MICINN/MINECO Spain under contract TIN2014-53172-P and also by the Agencia Estatal de Investigación (AEI), Spain and the Fondo Europeo de Desarrollo Regional (FEDER) UE, under contract TIN2017-84875-P and partially funded by a research collaboration agreement with the Fundacion Escuelas Universitarias Gimbernat (EUG).

Elham Shojaei

Abstract

Increased life expediency and population aging in Spain, along with their corresponding health conditions such as non-communicable diseases (NCDs), have been suggested to contribute to higher demands on the Emergency Department (ED). Spain is one of such countries which an ED is occupied by a very high burden of patients with NCDs. They very often need to access healthcare systems and many of them need to be readmitted even though they are not in an emergency or dangerous situations.

Furthermore many NCDs are a consequence of lifestyle choices that can be controllable. Usually, the living conditions of each chronic patient affect health variables and change the quantity of these health variables, so they can change the stability situation of the patients with NCDs to instability and its resultant will be visiting ED. In this study, a new method for the prediction of future performance and demand in the emergency department (ED) in Spain is presented. Prediction and quantification of the behavior of ED are, however, challenging as ED is one of the most complex parts of hospitals. Future years of Spain's ED behavior was predicted by the use of detailed computational approaches integrated with clinical data. First, statistical models were developed to predict how the population and age distribution of patients with non-communicable diseases change in Spain in future years. Then, an agent-based modeling approach was used for simulation of the emergency department to predict impacts of the changes in population and age distribution of patients with NCDs on the performance of ED, reflected in hospital LoS, between years 2019 and 2039. Then in another part of this study, we propose a model that helps to analyze the behavior of chronic disease patients with a focus on heart failure patients based on their lifestyle. We consider how living conditions affect the signs and symptoms of chronic disease and, accordingly, how these signs and symptoms affect chronic disease stability. We use an agent-based model, a state machine, and a fuzzy logic system to develop the model. Specifically, we model the required 'living condition' parameters that can influence the required medical variables. These variables determine the stability class of chronic disease.

This thesis also investigates the impacts of Tele-ED on behavior, time, and efficiency of ED and hospital utilization. Then we propose a model for Tele-ED which delivers the medical services online. Simulation and Agent-based modeling are powerful tools

that allow us to model and predict the behavior of ED as a complex system for a given set of desired inputs. Each agent based on a set of rules responds to its environment and other agents. This thesis can answer several questions in regards to the demand and performance of ED in the future and provides health care providers with quantitative information on economic impact, affordability, required staff, and physical resources. Prediction of the behavior of patients with NCDs can also be beneficial for health policy to plan for increasing health education in the community, reduce risky behavior, and teaching to make healthy decisions in a lifetime. Prediction of behavior of Spain's ED in future years can help care providers for decision-makers to improve health care management.

Resumen

Se ha sugerido que el aumento de la vida útil y el envejecimiento de la población en España, junto con sus condiciones de salud correspondientes, como las Enfermedades No Transmisibles (ENT), contribuyen a una mayor demanda en el Servicio de Urgencias Hospitalarias (SUH). España es uno de esos países donde los SUH soportan una carga muy alta de pacientes con ENT. Estos pacientes a menudo necesitan acceder a los sistemas de salud y muchos de ellos deben ser readmitidos, aunque no se encuentren en una situación de emergencia o peligrosa. Además, muchas ENT son consecuencia de elecciones de estilo de vida que pueden ser controlables. Por lo general, las condiciones de vida de cada paciente crónico afectan las variables de salud y modifican los valores de estas variables, por lo que pueden cambiar la situación de estabilidad de los pacientes con ENT, a la de inestabilidad y su consiguiente visita al Servicio de Urgencias. En este estudio, se presenta un nuevo método para la predicción del futuro rendimiento y la demanda en el Servicio de Urgencias Hospitalarias (SUH) en España. Esta predicción y cuantificación del comportamiento del SUH son todo un desafío, ya que el SUH es una de las partes más complejas de los hospitales. El futuro del comportamiento del SUH en España se predice mediante el uso de enfoques computacionales detallados, integrados con datos clínicos. En primer lugar se desarrollaron modelos estadísticos para predecir cómo, la distribución de la población y la edad de los pacientes con enfermedades no transmisibles (ENT), cambiarían en España en los próximos años. A continuación, se usó un enfoque de modelado basado en agentes, para la simulación del Servicio de Urgencias Hospitalarias (SUH), con el objetivo de predecir los impactos que los cambios en la distribución de la población y la edad de los pacientes con ENT, tendrían en el rendimiento del SUH, reflejado en el indicador LoS (Tiempo de estancia del paciente) del SUH, entre los años 2019 y 2039. Otra parte de este estudio, es la propuesta de un modelo que ayuda a analizar el comportamiento de los pacientes con enfermedades crónicas (ENT), con un enfoque específico en pacientes con insuficiencia cardíaca, en función de su estilo de vida. Consideramos cómo las condiciones de vida afectan los signos y síntomas de las enfermedades crónicas y, en consecuencia, cómo acaban afectando la estabilidad de estas enfermedades crónicas. Utilizamos el modelado basado en agentes, máquinas de estados y un sistema de lógica difusa para desarrollar nuestro modelo. Específicamente, modelizamos los parámetros requeridos de çondición de vida”que pueden influir

en las variables médicas requeridas. Estas variables determinan la clase de estabilidad de la enfermedad crónica. Esta tesis también investiga los impactos del Tele-SUH en el comportamiento, el tiempo de atención y la eficiencia del SUH y la utilización del hospital. También se propone un modelo para el Tele-SUH, que proporciona servicios médicos de atención "en línea". La simulación y el modelizado basado en agentes son herramientas poderosas que nos permiten modelizar y predecir el comportamiento del SUH, como un sistema complejo, para el conjunto de entradas deseadas. Cada agente, basado en un conjunto de reglas, interacciona con su entorno y con el resto de los agentes.

Esta tesis puede responder a varias preguntas con respecto a la demanda y el rendimiento del SUH en el futuro y proporciona a los proveedores de atención médica información cuantitativa sobre el impacto económico, la asequibilidad, el personal requerido y los recursos físicos necesarios. La predicción del comportamiento de los pacientes con ENT también puede ser beneficiosa, para que la política de salud planifique el incremento de la educación sanitaria en la comunidad, reduzca los comportamientos arriesgados y enseñe a tomar decisiones de vida saludables. La predicción del comportamiento del Servicio de Urgencias Hospitalarias en España en los años venideros, puede ayudar, en la toma de decisiones, a los proveedores de atención sanitaria en la mejora de la gestión de la atención médica.

Resum

S’ha suggerit que l’augment de la vida útil i l’envelliment de la població a Espanya, juntament amb les seves condicions de salut corresponents, com les Malalties No Transmissibles (ENT), contribueixen a una major demanda en els Serveis d’Urgències Hospitalàries (SUH). Espanya és un d’aquests països on els SUH suporta una càrrega molt alta de pacients amb ENT. Aquests pacients sovint necessiten accedir als sistemes de salut i molts d’ells han de ser readmesos, encara que no es trobin en una situació d’emergència o perillosa.

A més, moltes ENT són conseqüència de l’elecció de l’estil de vida que poden ser controlables. En general, les condicions de vida de cada pacient crònic afecten a les variables de salut i modifiquen els valors d’aquestes variables, per la qual cosa poden canviar la situació d’estabilitat dels pacients amb ENT, a la d’inestabilitat i la seva conseqüent visita al Servei d’Urgències. En aquest estudi, es presenta un nou mètode per a preveure el futur rendiment i la demanda als Serveis d’Urgències Hospitalàries (SUH) a Espanya. Aquesta predicció i quantificació del comportament dels SUH són tot un desafiament, ja que els SUH són una de les parts més complexes dels hospitals. El futur del comportament dels SUH a Espanya es preveu mitjançant l’ús d’enfocaments computacionals detallats, integrats amb dades clíniques. En primer lloc es van desenvolupar models estadístics per a preveure com, la distribució de la població i l’edat dels pacients amb malalties no transmissibles (ENT), variarien a Espanya en els pròxims anys. Seguidament, es va usar un enfocament de modelatge basat en agents, per a la simulació dels Serveis d’Urgències Hospitalàries (SUH), amb l’objectiu de predir els impactes que els canvis en la distribució de la població i l’edat dels pacients amb ENT, tindrien en el rendiment als SUH, reflectit en l’indicador del (Temps d’estada del pacient) al SUH, entre els anys 2019 i 2039.

Una altra part d’aquest estudi, és la proposta d’un model que ajuda a analitzar el comportament dels pacients amb malalties cròniques (ENT), amb un enfocament específic en pacients amb insuficiència cardíaca, en funció del seu estil de vida. Considerem que les condicions de vida afecten els signes i símptomes de les malalties cròniques i, en conseqüència, com aquestes acaben afectant a l’estabilitat de les malalties cròniques. Utilitzem el modelatge basat en agents, màquines d’estats i un sistema de lògica difusa per a desenvolupar el nostre model. Específicament, modelem els paràmetres requerits de çondició de vida”que poden influir en les variables

mèdiques requerides. Aquestes variables determinen la classe d'estabilitat de la malaltia crònica.

Aquesta tesi també investiga els impactes del Tele-SUH en el comportament, el temps d'atenció i l'eficiència dels SUH i el fet de fer ús dels hospitals. També es proposa un model pel Tele-SUH, que proporciona serveis mèdics d'atenció "en línia". La simulació i el modelatge basat en agents són eines poderoses que ens permeten modelitzar i preveure el comportament dels SUH, com un sistema complex, pel conjunt d'entrades desitjades. Cada agent, fonamentat en un conjunt de regles, interacciona amb el seu entorn i amb la resta dels agents.

Així mateix, aquesta tesi pot respondre a diverses qüestions al respecte de la demanda i el rendiment dels SUH en un futur i proporciona als proveïdors d'atenció mèdica informació quantitativa sobre l'impacte econòmic, l'assequibilitat, el personal requerit i els recursos físics necessaris. La predicció del comportament dels pacients amb ENT també pot ser beneficiosa, perquè la política de salut planifiqui l'increment de l'educació sanitària a la comunitat, reduint els comportaments de risc i ensenyant a prendre decisions de vida saludables. La predicció del comportament dels Servei d'Urgències Hospitalàries a Espanya durant els pròxims anys, pot ajudar, en la presa de decisions, als proveïdors d'atenció sanitària a la millora de la gestió de l'atenció mèdica.

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Chapter 1

1. Introduction

Emergency Department (ED) is the major entrance for patients in the healthcare system and should be prepared for 24-hour services, 365 days a year, to people requesting medical demand. An ED always experiences uncertainty; an ED needs sufficient resources to overcome unexpected injuries and diseases. The ED provides nonstop emergency treatment along with the year, so everyone can have proper treatment while they suffering. Overcrowding, and its consequences pressure on ED, is a worldwide issue leading to increased ED waiting times and hence reduce the quality of services, low clinical outcomes, and high patients dissatisfaction [52] and [117]. Lower ED performance reduces the efficiency of the entire health care system and poses a threat to patient safety. Quality of care is often evaluated using the length of stay (LoS), which is the most widely used and accepted index in the literature for the quality and performance of ED services. In particular, longer LoS could be indicative of increased demand for ED and insufficient resources or delay in service provision and inefficient use of resources [11] and [104]. Increased life expediency and population aging, causing health conditions, have been recognized to increase higher demands on ED and healthcare system, leading to a longer LoS. It had been reported that Spain is experiencing the world's oldest country by 2050, with about 30 % of its population being aged over 65 years [53]. As such, mortality and disability have become more linked to NCDS in recent years in Spain as about 90 % of diseases has been NCDs [40] and [70]. Management of ED for timely and appropriate primary care and efficient use of medical resources is vital to provide patients with satisfactory services and achieve the best clinical outcomes in minimum LoS. ED, however, is one of the most complex parts of hospitals to manage as several unpreventable and unpredictable contributing factors are involved in designing the ED managing system [82]. Non- communicable diseases (NCDs)(which are also known as chronic) are the leading cause of disability and death. When determining the global burden of disease, NCDs are categorized as one of the emergency conditions and reasons for visiting the ED and healthcare systems. It has been reported that the incidence of non-communicable diseases increases with age such that aging is a dominant predictor of death for NCDs in rapidly aging regions [18]. In addition to more frequent readmission of the elderly in a healthcare system that causes overcrowding in ED (Fig.1.a), the elderly with NCDs need more medical tests (Fig.1.b) and consultation (Fig.1.c) leading to a higher burden on ED and longer hospital LoS [47][65].

Furthermore, most of the chronic conditions are a consequence of lifestyle, choices, they can be preventable and under our control. The reduction of the unnecessary visits of chronic patients to the healthcare system could help to improve healthcare system efficiency. Usually, each chronic patient has a living condition that affects health variables and changes the quantity of these health variables, so they can change the stable health of a patient to instability and its resultant will be visiting ED. In some part of the study, We analyze the behavior of patients (with a focus on heart failure patients) based on their lifestyle and consider how living conditions affect signs and symptoms of NCDs, accordingly, how these signs and symptoms affect NCDs stability and lead them to visit ED.
Telemedicine and e-health are considered as solutions for remote delivery of health services to care seekers in order to decrease hospital visits for patients with less emergency condition. Incorporating smart devices and health monitoring platforms allows creating electrical follow-up care and medication adherence. The supposed system can have the capacity to save the information of the patients and this information will be updated periodically through Tele-ED by receiving data from current chronic patient's activities and conditions. By collecting data from a patient, plus informa-

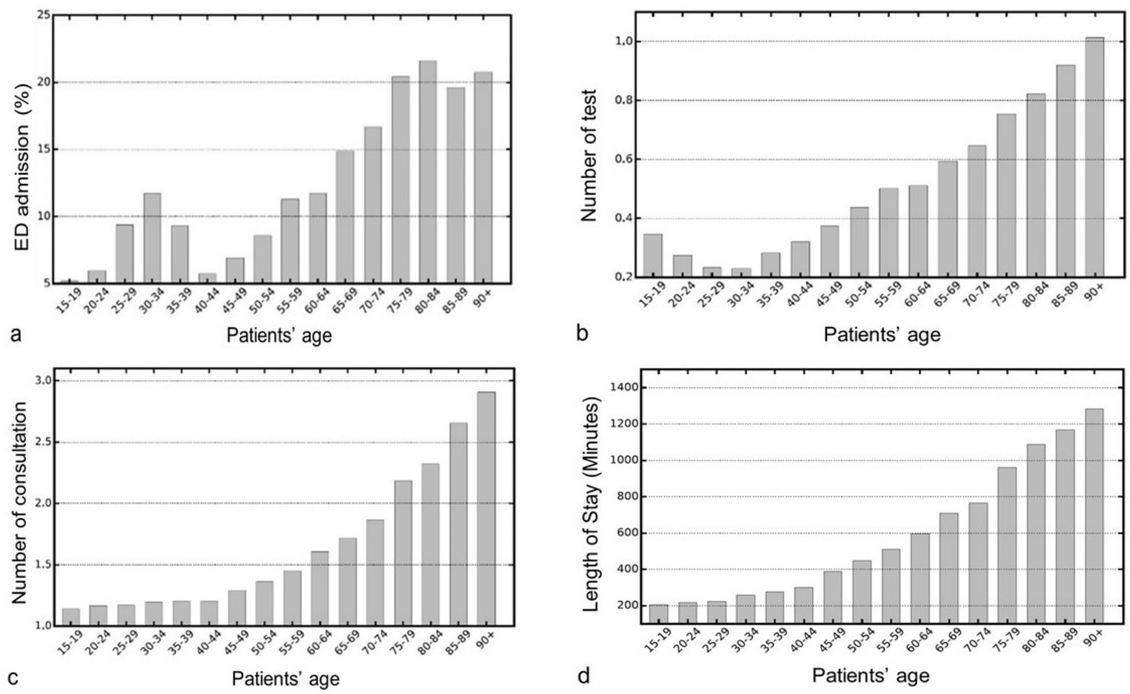


Figura 1-1: Histograms of patients' ages versus: Total hospital admission (a), average medical-tests (b), and average consultations (c) [65]

tion about their existent history, a pattern can be made to estimate and predict the critical condition of a patient along with the critical time of the health care system. A simulation is a powerful tool that allows us to model and predict the behavior of ED as a complex system for a given set of desired inputs. Agent-based modeling and simulation (ABMS) have successfully been used to study the behavior of ED by taking detailed modeling parameters into account. ABMS models systems using a set of independent decision-making entities called agents. Each agent can interact with each other and with their own environment. Each agent based on a set of rules responds to its environment and other agents. Our research group has simulated ED using ABMS wherein patients, ED staff, and hospital physical resources were considered as agents whose actions and interactions were characterized by the ED simulator. ED simulator allows us to analyze the behavior and predict the performance of an

ED under different scenarios. We use the simulation for solving healthcare operations management problems through some designed models such as a model for non-critical patients with less frequent visits or predicting ED behavior in the future according to aging demography. This thesis predicts the behavior of ED in future, it also includes a designed model to predict the behavior of patient before arriving at ED and it investigates the impacts of frequent non-urgent visits of ED on behavior and outcome of ED and quantitative information in the literature on the role of tele-ED in ED performance and evaluates the pressures on ED. Then we propose a model for Tele-ED which delivers the medical services online. The prediction behavior of Ed and investigating the impact of tele-ED on time and efficiency of ED and hospital utilization can answer several questions in regards to the demand and performance of ED in the future and provides health care providers with quantitative information on economic impact, affordability, required staff and physical resources. Prediction of the behavior of patients with NCDs can also be beneficial for health policy to plan for increasing health education in the community, reduce risky behavior, and teaching to make healthy decisions in a lifetime. Prediction, using detailed computational approaches integrated with clinical data behavior of Spain's ED in future years can help care providers for decision-makers to improve health care management.

1.1. Problem Statement

Health care providers talk about improving health care system efficiency when they need to reduce costs and use the minimum resources within a limited time. Furthermore, population aging is caused by an increase in the number of chronic patients and after, a decrease in quality of health care services so it will be perused enhancing the length of stay and a significant discontent of both people who receive or give services. World Health Organization (WHO) shows a high burden of chronic diseases which has been estimated at about 52 million of European in 2030 [41] [83]. Many chronic patients visit the health care system and need to be readmitted while mostly they are not in an urgent situation. A large number of them should wait for a long time to receive medical services and sometimes the system is overcrowded and

some of the patients should leave the care setting without being seen. We admit that some of them are not able to move by themselves even though transportation needs a separate budget. Some of the elderly people are disabled to do some activity in normal time as it should be done naturally, for example, they are slower to wear or remove the clothes or even they may need someone to do it, many of them are not able to sit in a waiting queue and they should lie down on the bed, so all these matters make the health care system more problematic of what ordinarily is imagined.
As we see in figure 1 aging population rise quantities of chronic patients and then more people need to visit care system, they should be transferred, so more ambulance or another transportation services is required then it increases traffic jam beside needs more time and transportation budget. On the other hand, when the care system gets overcrowded, the care environment will face more pressure and it burns out staffs and it enhances the probability of medical error. Increasing length of stay and wait time along with that an increase in patient dissatisfaction will be another complication of population aging. Finally all of that decrease the quality of the health care system.

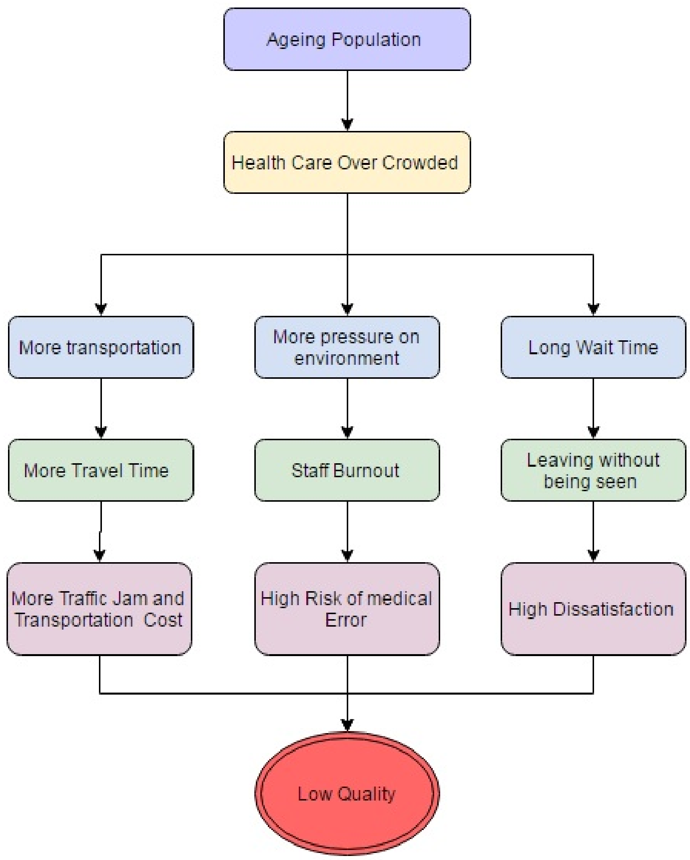


Figura 1-2: Ageing Population Problem

1.2. Objectives

In general, the objective of this studies had been to develop a methodology that improves the quality of care in a Hospital Emergency, the main goal is reducing the length of stay through developing a few models for e-health and online medical services. The general objective is specified in the following specific The General objectives were specified as the following:

- To improve an existing agent-based ED simulator [64] by taking into account patients with NCDs, in addition to regular patients, as inputs into the model.
- To use the ED simulator to investigate and predict the impacts of changes in population and age distribution of patients with NCDs on ED performance through estimations of LoS between the years 2019 and 2039.
- To create a model to investigate the behavior of patients with NCD according to their lifestyle.
- To improve an existing agent-based ED simulator by taking into account varying non-urgent arrival, in addition to entire arrival, as inputs into the model.
- To use the ED simulator to investigate and predict the impacts of potential changes in the number of visits on ED performance through estimations of LoS.
- to create a model for long-distance services into the non-urgent patient to minimize LoS.

The inputs were provided through clinical data (collected from Parc Tauli Hospital in Sabadell/Spain and from GDB, WHO)[64] as well as data from statistical models that we developed to predict how population and age distribution of patients with NCDs changes in Spain in future years.

1.3. Contributions of the Thesis

This research work is talking about an investigation on an integrated health care system which is composed of four submodels. The main contributions of this research work can be summarized :

- Development of a model for Projections of the Emergency Department Behaviour by Non-Communicable Diseases from 2019 to 2039
- Design a model for evaluation of lifestyle effects on chronic disease
- Develop a model to investigate the impact of telemedicine in emergency department
- Designed a model for telemedicine and e-health for distance services.

1.3.1. A General investigation for an agent-based integrated health care system

In general, Discrete Event Simulation (DES), Analytic Queuing Models (AQM), System Dynamics (SD), and Agent-based Modeling (ABM) are the main approaches in the literature for simulating a complex system like ED. All methods have been validated against modeling approaches and Empirical data. DES is a more traditional method that has been used in $\sim 75\,\%$ of earlier ED simulation studies and, compared to AQM and SD, is capable of modeling of more complex non-linear systems [59]. While DES is a powerful method for the process flow, it has limitations on the modeling individual entities and their behavior (e.g., differences in skills of a physician versus a delegate such as a medical student or nurse practitioner) leading to an unrealistic representation of ED care. To overcome such limitations, in recent years ABM has been used to represent people (e.g., physicians, patients), their behavior, and the environment in which they operate actively. In ABM, agents can interact with each other, make self-governing decisions, and indicate proactive behavior based on their goals. As such, the main purpose of using ABM is to simulate at the individual level to be able to capture detailed interaction patterns and emergent behavior [59]. The downside of using ASB is, however, its high computational complexes and the associated cost [59], [102], [14] and [24].

1.3.2. Development of Model through sub-models

The integrated health care system is a complex model and composed of different sub-model. Investigating an integrated health care system needs to consider various aspects associated with 1) emergency department and health care system 2) patients' behavior, lifestyle, and environment 3) impact of telemedicine in emergency department quality and 4) a detailed model for telemedicine. In each model selection step, plots of the data, process knowledge, and assumptions about the process are used to determine the form of the model to be fit the data. It is important to mention that this research has been a collaboration between the HPC4EAS research group and the medical team of the Short Stay Unit of the Parc Taulí Hospital Universitari. Institut d'Investigació I Innovació Parc Taulí I3PT. This collaboration has allowed us to apply computational techniques to the study of phenomena of great interest in the medical field, such as chronic disease, non-urgent patients, and remote medical services. The projects allow us to promote research and generate new knowledge in both the medical and computational fields.

1.4. Simulator Development and Implementation Methodology

As our research is made of different sub-model, we have used two different methodologies for different sub-model.

1.4.1. So-called fourth scientific paradigm

The initial methodological approach of the research which predicts the behavior of ED in the future and behavior of ED under applying of online monitoring and recommendation system is based on the so-called fourth scientific paradigm [36] and [56]. A division between the mining and analysis of data and the creation of theories is one aspect of the Fourth Paradigm. Data-intensive science is considered to be the fourth paradigm of science and consists of three basic activities: capture, curation, and analysis [42]. Data can be found and collected in all scales and shapes, covering; single-laboratory, cross-laboratory, individual observations; large international experiments, and potentially individuals' lives or generated by simulation (Figure1-3). Curation incorporates a diverse set of activities, starting with capturing the right data structures to map into different storage and archiving. The entire set of activities which is covered by data analysis, includes the use of databases, analysis and modeling the data, and finally data visualization. A designed database must be able to answer the key questions of a scientist. The ultimate goal is extracting some information that can generate knowledge based on this information.

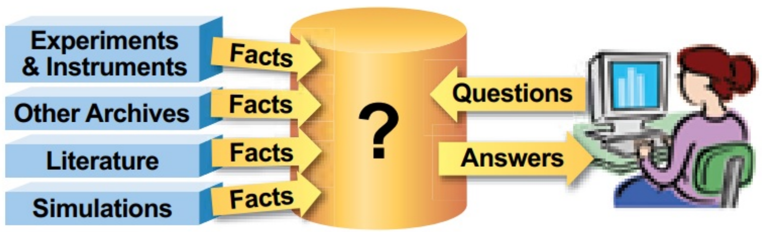


Figura 1-3: Capturing data from different activity

The first part of the data for our study come from the historical data of the parc Tauli Hospital from Sabadell. Based on this data, its result, and data from Our World In data (from the Institute for Health Metrics and Evaluation) and Spain demography a statistical analysis was completed. Through this analysis, we obtain the information related to patient arrival at the service. This analysis indicates a pattern for patient input into ED (average number of patients entering each hour of the day, and each day of a week) Figure1-4.

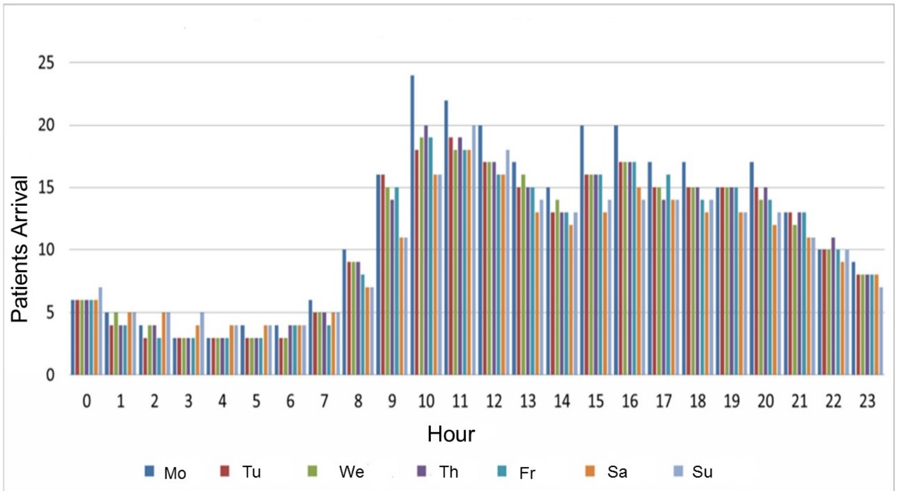


Figura 1-4: Patient arrival [108]

On the other hand, the configuration of the existing ED proves that the number of staff and their level of experience and proficiency and their compositions impact on the efficiency of the system. All these matters are taken into account theoretically to design and simulate ED configuration [108].

The pattern of patient entry and the configuration of medical staff are the parameters that specify a characteristic SUH scenario in the simulator. After these parameters have been determined, we can launch the simulation, and it will generate data related to the simulated scenario. From the analysis of these data we can obtain the desired information and knowledge (Figure 1.5). Thus, the data are generated by the simulation, processed transformed into information. This information is the number of patients with AL4 and ALL5 per hour (which are also known as non-urgent). It has been shown in Figure1-5.

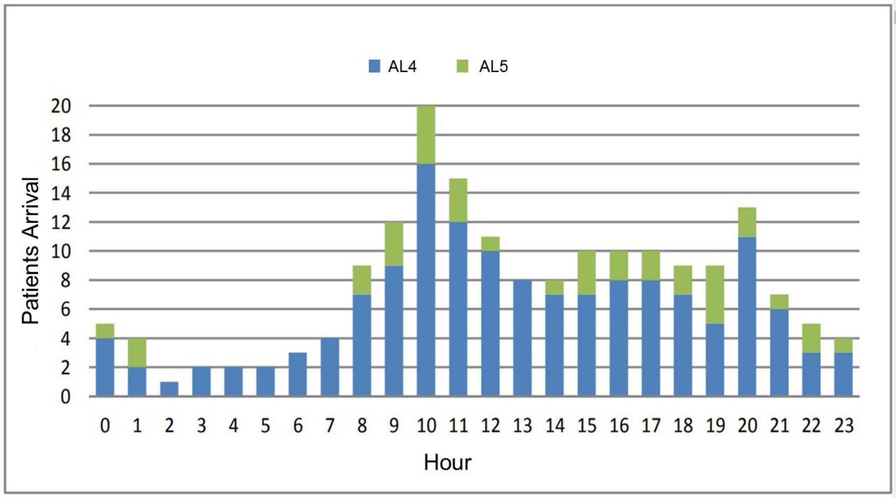


Figura 1-5: Patient arrival hourly per day [108]

The information is called knowledge when it is given to a specific meaning. At the end that knowledge can be specified in a proposal or action to improve the system. In our case, the proposed action has specified the pressure on ED in the future and investigating the impact of online monitoring and recommendation systems on ED. Our Starting hypothesis states that ED will experience more pressure in the future and a decrease in the input of Patients through online monitoring may decrease the length of time in the HUS. The model to carry out this future prediction will be based on the redistribution of age and number of daily arrival patient with NCD and model to carry out the impact of online monitoring and recommendation system is based on redistribution of acuity level and a number of daily and weekly arrival patient into the medical service. The simulation will be used as a predictive tool to indicate the effectiveness of proposed models through the obtained information and at the end the knowledge about the quality of the model. of waiting for patients in the HUS, as an indicator to assess. A large number of executions will be required for each scenario so that results obtained from the simulation data are statistically reliable and significant. The use of High-Performance Computing (HPC) will allow us to facilitate its processing. The potential of the HPC provides us this possibility to generate a large number of data in a reasonable way, store this data, process it, and analyze it to obtain knowledge. Each execution will generate the corresponding data based on the designed model for later analysis. The implementation of this model can improve the quality of care, optimize the perception of quality of provided care and contribute to the sustainability of the system, ensuring better system management. In short, our proposal aims to improve the service provided in hospital emergency services, which are the main entrance of patients in the health system, in relation to access, quality, and satisfaction of patients.

1.4.2. Methodology of the Spiral Model

We use the methodology of the Spiral Model to develop some part of this research work. This methodology has been previously used in our HPC4EAS research group for developing other projects. The base of the spiral model (Figure 1.4.2) is a repetition of 5 phases sequentially which include, system analysis, model design, implementation of simulator, execution, and at the end verification and validation of result. In each new iteration, a new passive and active agents are added, and the new behaviors that make the initial model grow in complexity and allow us to create increasingly complex simulation environments.

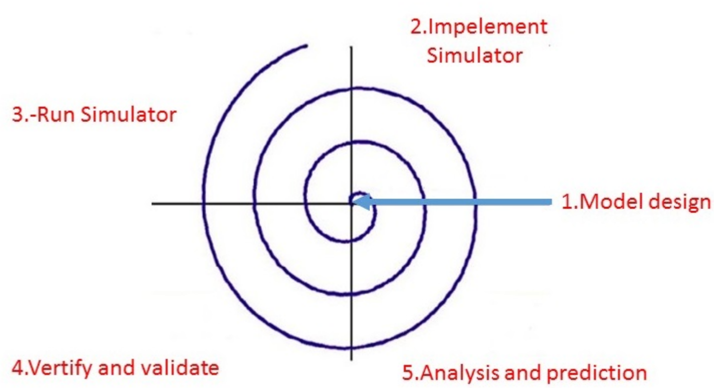


Figura 1-6: Description of the phases in Spiral Model.

Briefly, a description of the different stages of the Spiral model applied to this research was taken as follows:

1. **System Analysis:** This stage starts from the formulation of the problem along with a study of the state of the art and the observation of the real model. For this purpose, the research group was collaborating with a professional team in the ED of the Parc Taulí Hospital Universitari (Sabadell, Spain). The analysis of the system involves the study of the real functioning of ED, the detail of the possible actions, and interactions between the agents and each agent with its environment. It also clarified the behavior and attribute of each agent. This part of the development of the project has been done through meetings with the health personnel of the ED and the visits to their facilities. As a result of this stage, we have been able to identify qualitative and quantitative information that allows us to describe the functionality of the system as a whole and incorporating each element individually, plus the interactions between them.

2. **Model Design:** We have created the conceptual or theoretical models of our research based on the collected information from the previous stage. This stage indicates a set of available information and a formal definition of the environment, agents, interactions, and behaviors. As simulation models are a simple share of the real world incorporating its essential aspects. The creation of a conceptual model was the objective of this stage. The proposed conceptual model must be as simple as possible, and as complex as necessary. As a result of this phase, we have designed the conceptual models of behavior of patients with NCD, the behavior of ED with patients with NCD. The parameters, variables, and behaviors of each type of agent and the possible interactions between them were defined, to collect this information, the real ED model was incorporated. Because the design process is based on the spiral methodology, the obtained models are provisional, approximate, and each phase includes refinement and recently added data is considered.

3. **Simulator Implementation:** In this stage, based on the conceptual model in the previous phase, the implementation of the computational model was improved. An ABMS model can be implemented using the software in general or specifically designed for simulation projects. The interest of using simulation

grows in different areas, there are several programming languages and software packages that enable us to implement simulation models. In addition, depending on what has being studied, the computational model may require a small or medium amount of computational resources and therefore can be developed on a PC or a large computing capacity for high-performance computing. we develop the simulation with the ABMS approach which was continuity with previous investigations of the HPC4EAS research group in Netlogo software with version 5.2.1.

4. **Simulation Execution:** This phase includes quantitative results that are obtained through the execution of simulations in the NCD-simulator. We designed different scenarios in which each scene is characterized by the given values to input. For our experiments, the available HPC system of our department was used. Usually, a simulation using high-performance computing techniques would be evaluated through a large number of scenarios and quantitative repetitions should be performed. In this condition obtained result is statistical validity. On the other hand, it is important to ensure that the results are available in a limited time.

5. **Verification and Validation of Results:** The objective of this phase was to find a mechanism that provides us the certainty about the validity of results, The theory of this model is designed based on the real data available. If the obtained results by simulation are comparable to the actual data, we can conclude that the proposed model has been correctly designed and implemented and that the simulator works properly. In our case, the previous validation process included a model in the calibration phase. The obtained results by simulation were harmonized with those obtained from real sources and the phase was terminated at the time when the simulated results were within the expected ranges.

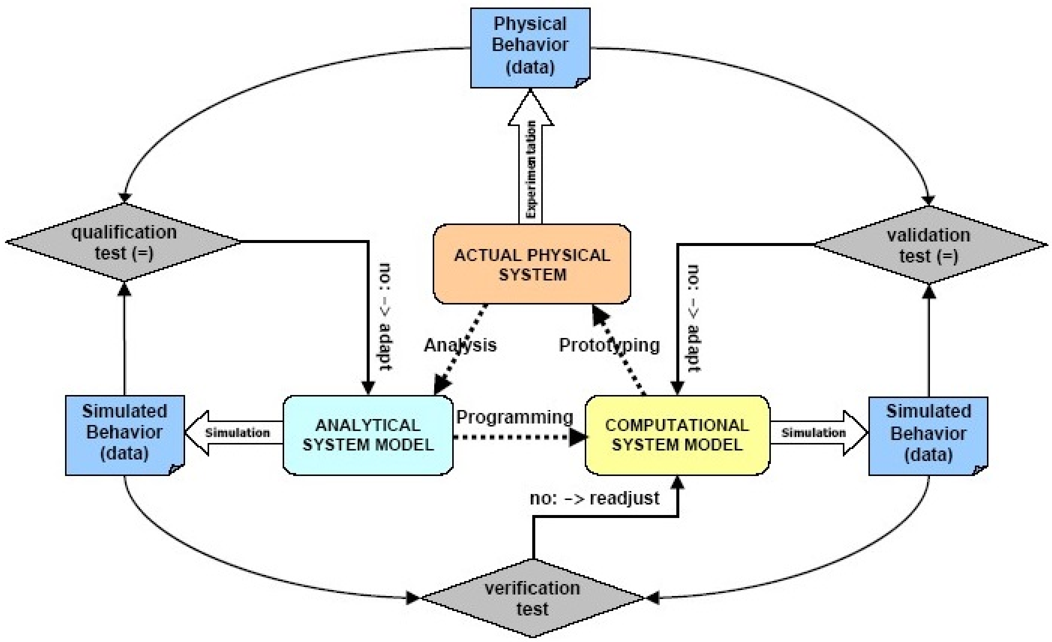


Figura 1-7: Diagram of model driven appraoch Liutesis

In cases where any inconsistency related to an earlier stage was detected, the relevant corrections were made and the process continued. Several complete development cycles were necessary before obtaining the final version of the simulator.

1.5. Thesis outline

This research carries out by the author in the last four years is structured in six chapters. Besides the presented background material, many of the results and ideas in this thesis have been developed through collaboration with various colleagues and former colleagues, in particular my supervisor Dr Emilio Luque. In chapter one, the definition of a general agent-based model for an integrated health care system was discussed and a detailed approach was made to agent-based modeling and simulation techniques. The general and specific objectives, the proposed methodology for the development of the project and the research contributions were also detailed. The content of the remaining chapters is as below.

Chapter2

Chapter two justify the literature review and theoretical framework. it details the basis of research in both medical and computational issues. Briefly, it describes the functioning of ED, the effect of lifestyle on patient health behavior, and online long-distance services. in this chapter, a conference has been presented.

Chapter 3

Chapter three details the behavior of the emergency department through population aging in the future. It predicts the ED situation based on two different scenarios. a journal has been published in this chapter entitled 'A Method for Projections of the Emergency Department Behavior by Non-Communicable Diseases from 2019 to 2039'.

Chapter 4

Chapter three explains two conceptual models in our investigation. The first model tracking the impact of the lifestyle of patients with a non-communicable disease on their medical behavior and quality of their health. This model has been proposed and published in Winter Simulation Conference entitling Evaluation of lifestyle effects on chronic disease management. The second model details the structure of the online monitoring and recommendation system. it talks about the used algorithm and technique behind it. In this part of the study, two journals have been published.

Chapter 5

Chapter five describes the impact of online monitoring and recommendation system on the pressure on the ED. In this chapter, a journal has been published entitling investigating impacts of Tele-medicine on the emergency department through decreasing non-urgent patients.

Chapter 6

Finally, chapter six summarizes the main conclusions, limitations, and possible future work and open lines generated by this research.

Chapter 2

"If you would be a real seeker after truth, it is necessary that at least once in your life you doubt, as far as possible, all things."

- Rene Descarte.

2. Literature review

2.1. State of the art and background

2.1.1. Related works

Generally, the research tried to solve the problem of overcrowding in Hospital of Emergency Department (EDs). Research on addressing the problem of EDs saturation is mainly divided into three categories: descriptive, predictive, and intervention-oriented [84]. Descriptive studies describe the definition of overcrowding [49], investigating and analysing the causes and effects of it [21] and [105] and proposing models to justify the problem [8] and measures to quantify it [12] and [26]. Predictive studies have focused on predicting while an ED will become overcrowded and provide an early warning system for upcoming overcrowding circumstances assuming different recourse, such as reserve personnel and auxiliary treatment bays [26]. The third category of research, intervention-oriented studies, has focused on interventions to resource optimization methods and processes incorporating patient length of stay (LOS) [119] monitoring code red hours, and re-designing processes [100], educating physicians regarding non-ED options for patients and patient flows [7] and [55].

In general, EDs experience overcrowding when the demand for emergency services surpass the ability of medical staff to provide quality care within a reasonable time [98]. The high burden of admitted patients in the ED for prolonged periods of time is the main factor resulting in ED overcrowding. Medical literature reports that some of the other factors that resulting in overcrowding EDH incorporates non-urgent visits [35] and [46], respiratory virus epidemics (flu seasons) [96], insufficient staff [95], and shortage of hospital bed [48], among others.

Other studies state that effects of saturation and the long times of expected from patients in EDs, the increase in the burden of patients who leave the service without being seen by a doctor (Leave Without Being Seen, LWBS) [15], [60], [115], and [91] treatment delays, and increased patient mortality and at the end leading with patient dissatisfaction. The aim of all of this research is to investigate significant challenges in improving the time and resources efficiency of delivering high-quality services through changes in organizations of ED. As soon as a patient enters ED, the length of stay is started to calculate until the time of departure from ED (either admission or discharge). LoS is used as an index in the literature to measure ED efficiency. The Process of reduction of the total length of stay of the patients in the service (LoS), can be implemented by both of the waits time, and some of the other measures such as the so-called fast tracks [23], [33] as well as the referral of non-urgent patients to other care systems [32] and [76]. Fast track is a method to reduce emergency department (ED) crowding. some research determines the implementation of a fast track on ED would improve LoS for low-acuity patients without negatively effecting patients with higher acuity. As non-urgent visit in ED contains a high percentage of visits, many researchers implement the investigation on referral non-urgent patient to another health care level such as primary care and so on. But most of the solutions proposed to address the effects of the saturation of EDs and reduce patient waiting times, going through measures that require an increase in the capacity of the ED resources in human or physical [20]. However, because of economic and budget limitations, most of Hospitals can not provide additional resources. Therefore, they need to concentrate on the optimization of resources and processes [84]. ED is a Complex system, thus we need analysis tools to optimize the processes. Simulation is one of the strongest tools for analysis. It provides us the flexibility to make the tests for various scenarios, hypotheses, or policies of action in healthcare settings and can be used as a research tool, as well as for making decisions [44]. There are many examples of computer simulation models that support decision-making processes in the health sector. Specifically, simulation has been extensively used to investigate the causes of overcrowding in EDs to reduce them. Many contributions show how simulation can be used as a tool to address this problem [20], [74],[118], [10] and [72].

In this study, the EDs are modeled as a stochastic system as the time for arrivals and medical services consider as random variables. Simulation of discrete events [54] is the technique simulation most used in the studies reviewed. A DES models the operation of a system as a discrete sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system. Between consecutive events, no change in the system is assumed to occur; thus the simulation time can directly jump to the occurrence time of the next event [101]. System dynamics is another methodology and mathematical modeling technique used to model, understand, and discuss complex issues and problems of the system,[109] and [89]. The motivation of most studies related to the use of simulation is costs, efficiency, re-engineering, and quality of service [84]. The main objective of most of these studies has been considering the causes of inefficiencies in use of resources [103] and bottlenecks in flows [25], causes of excessive waiting times [103],[57] and performance [6]. We have highlighted those references that use simulation to improve times of patients staying in the EDs through the redesign of the processes and verifying the effectiveness of the proposed measures [10], [6], [112] and [113]. The main causes of crowding related to EDs incorporate population aging and presentations by the elderly, the accessibility of EDs, low-acuity presentations, expectations in hospital care, delay in scheduled care and culture of immediacy, and so on [106], [26], [43], and [45]. It has been reported that almost 70 % of visits in EDs will be classified into non-urgent cases which is called inappropriate use of EDs [16]. Briefly, some self-referred patients with non-urgent conditions could have been referred to other types of services such as primary care, pharmacies or teleservice advice. Inappropriate ED use is defined when a patient who was discharged after ED visit and did not have any of the following criteria: admitted to the hospital, transferred to another hospital, deceased in the ED, diagnostic tests performed, or treatments administered [79].

In this study we have tried to investigate the EDs in diverse dimensions including the factors which change the behavior of patients end up visiting EDs, projection of ED in future causing aging population and at the end proposed model of telemedicine and its resultant on EDs. Same to other highlighted works in this section, this study has used the simulation as a tool to examine the efficiency of the proposed model, through an agent-based model (ABM, Agent-Based Model) [60] and [67]. The proposed framework reduces the time spent by patients in the EDs, and helps the system to unlock the overcrowding situations.

2.2. General Framework

In our study, we have investigated the environment and lifestyle factors that affect non-urgent patients' health stability and leading them to ED, in fact we have tracked the non-urgent patient behavior causing overcrowding of EDs. Overcrowding in EDs through non-urgent patients is a common problem for Spain which called the inappropriate use of ED services. Telemedicine is one of the additional solutions to address the increased ED demand through online monitoring remote medical services. We have designed a general framework which is made of three sub-model for all the highlighted work. Figure2-1 shows how all the sub-models interact with each other. Model1 pursues the behavior of patients according to their lifestyle. When a patient uses the telemedicine system has a different code behavior from when/who does not use it. Model2 shows the healthcare system which is made of ED and hospital. ED is the main entrance of the health care system and any changes in ED impact the quality of service in the entire health care system. Model3 indicates an online monitoring and recommendation system (OMRS) which includes two parts, one is a machine part to monitor patient and another part is an expert person who helps the patient while the machine is disabled to recognize the problem of the patient.

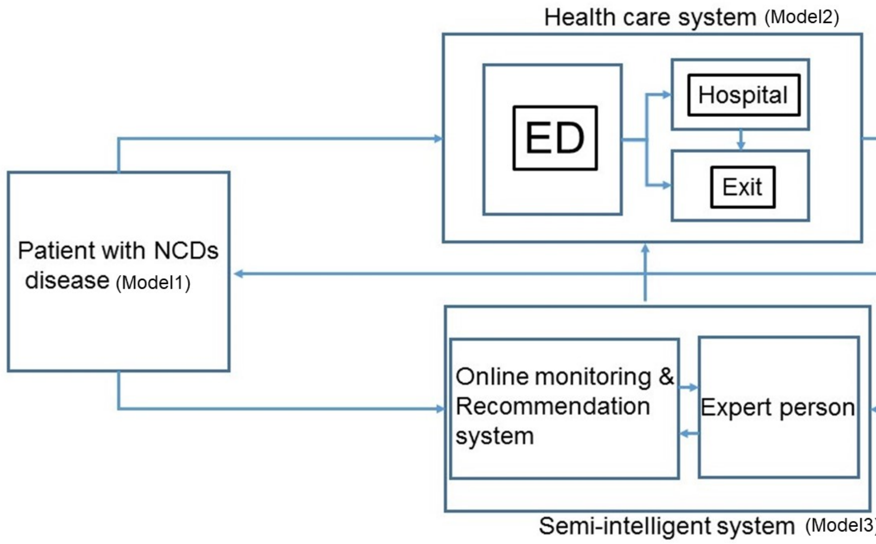


Figura 2-1: Full model of research which is composed of three submodels

Developing an exciting ED simulation enables us to make quantitative analyses of ED behavior and predict the performance of ED under different scenarios. These scenarios are designed according to different assumptive models. Our integrated health care system model is composed of these three sub models. The integrated health care model is highly complex which we try to simplify the model as much as possible and as complex as necessary with respect to all the important component and their interaction which details system behavior.

2.2.1. Chronic patient model (Model 1)

Non- communicable diseases (NCDs) also know as chronic diseases, are not transmissible from one person to another directly. NCDs are responsible for cause of disability and death. According to global burden of disease (GBD) in 2017, NCDs were the main cause of death/disability, corresponding to 92.4 % of all deaths/disabilities

(Fig2-2). They were followed by 4.0 % deaths/disabilities due to communicable diseases and 3.6 % deaths/disabilities due to injuries (Fig2-2). The 5 top specific NCDs causing death were shown in Fig2-3

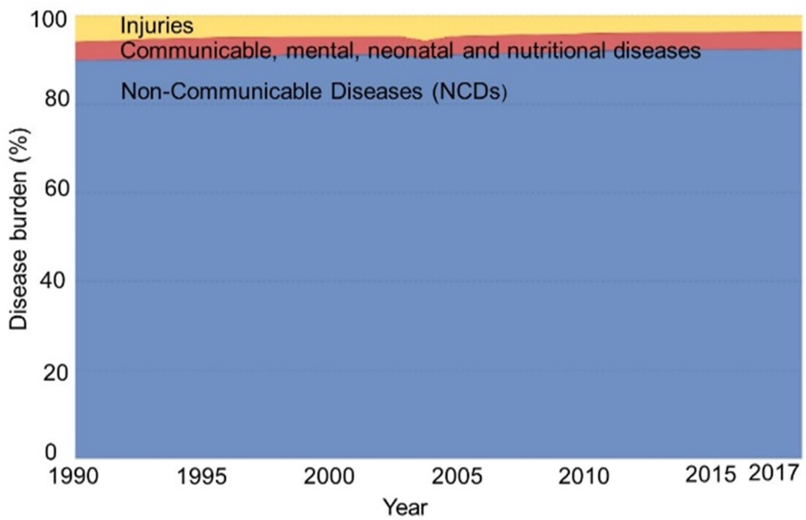


Figura 2-2: Total annual number of death/disability by causes in Spain in 2017. NCD-caused: 92.4 %, communicable disease-caused: 4.0 %, and injury-caused: 3.6 % [70]

In regards to how mortality and disability have increased with increases in NCDs, Fig2-6 indicates the increases in NCDs from 2007 to 2017 (from 85.8 % to 87.8 %), and then from Fig2-7, we can observe the corresponding increases in NCDs-related mortality/disability from 2007 to 2017. (from 91.6 % to 92.4 %).

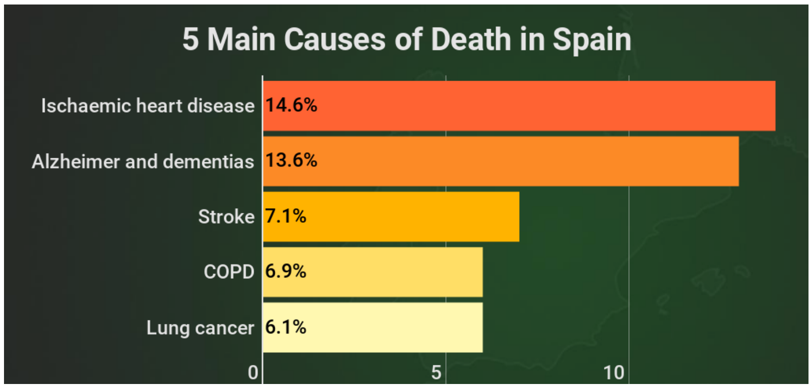


Figura 2-3: 5 top specific NCDs causing death in Spain (2017) according to global burden of disease (GBD)

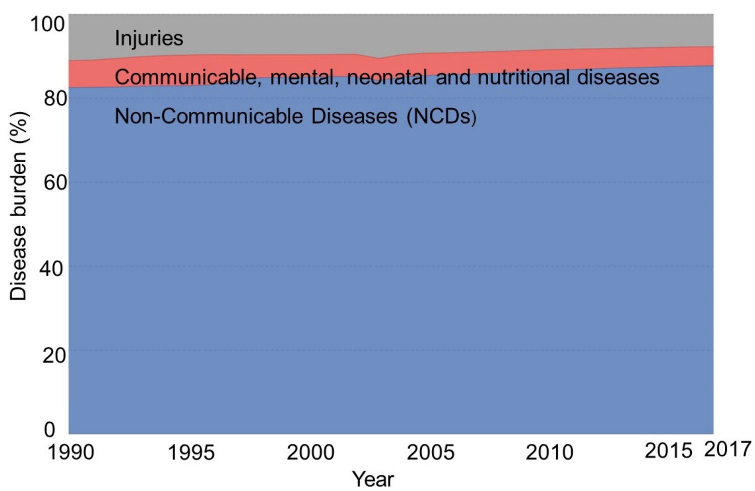


Figura 2-4: Total disease burden by cause, Spain (1990-2017). Total disease burden measured as the number of DALYs (Disability-Adjusted Life Years) per year [70].

The details for 10 top specific NCDs causing death/disability in 2007 and 2017 in Spain and their percent changes from 2007 to 2017 were indicated below.

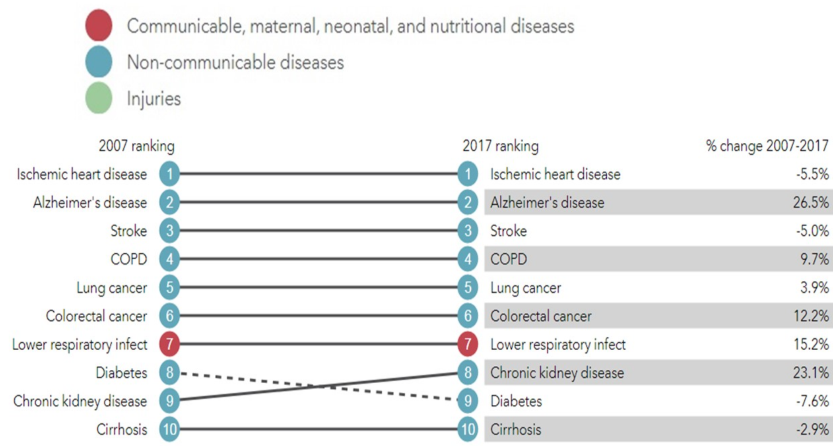


Figura 2-5: 0 top specific NCDs causing death in 2007 and 2017 in Spain and their percent changes from 2007 to 2017. (The Institute for Health Metrics and Evaluation)[70]

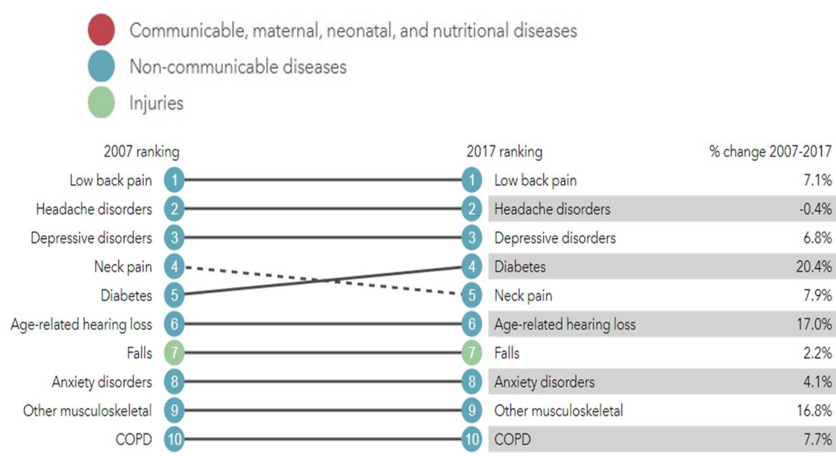


Figura 2-6: 10 top specific NCDs causing disability in 2007 and 2017 in Spain and their percent changes from 2007 to 2017 (The Institute for Health Metrics and Evaluation) [70]

Tracking patient behavior can provide us better information about the consumption of time, resources, and services by the patient with NCDs. Specially this information can manage the factors associated with inappropriate use of EDs. Lifestyle is defined to the way, day to day behaviors, and functions of individuals in job, activities, fun, and diet by people. Recently, lifestyle is fast becoming a debated issue as an important factor of health by researchers. The relationship between lifestyle and health is significant such as according to WHO, 60 % of related factors to individual health are associated with lifestyle [28]. An unhealthy lifestyle causes illness, disability such as metabolic cardio-vascular diseases, hypertension, overweight, violence, and so on. Malnutrition, unhealthy diet, inactivity, smoking, alcohol consumption, drug abuse, and so on, presents a dominant form of lifestyle which threatens the physical and mental health of the human being. Changing lifestyle can impact on some chronic conditions. A model to presents the behavior of patients based on lifestyle can predict or prevent them before arriving ED.

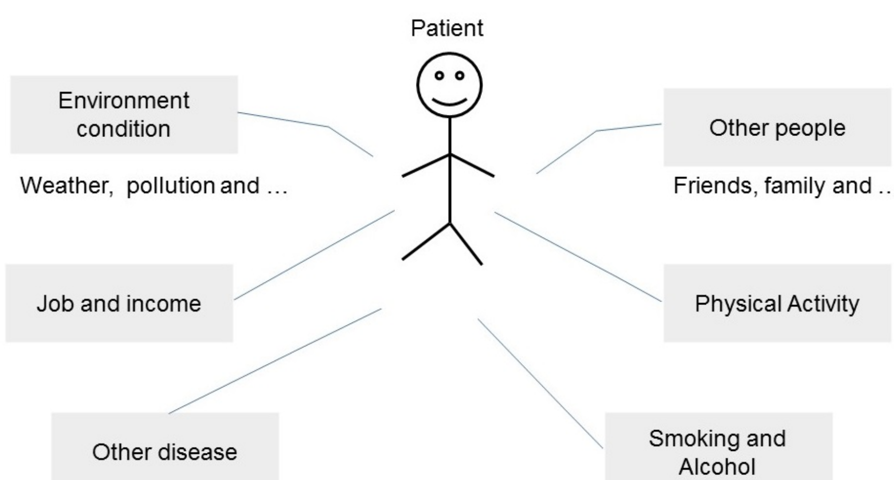


Figura 2-7: Impacting Factors of chronic patient behavior

2.2.2. Health Care System (Model2)

Health care system (HCS) is an organization of people, institutions, and resources that deliver medical services to healthcare seekers. According to WHO, three main goals of healthcare systems' are good health for the citizens, responsiveness to the expectations of the population, and fair means of funding operations. Some dimensions to evaluate it include quality, efficiency, acceptability, and equity [81]. The health care system in Spain is a combination of an Emergency Department with a hospital. ED is the major entry of the health care system which any impact of ED changes the evaluation parameter of the Health care system.

1. Operation of the Emergency Department
   Agent-based modeling and ED simulation were accomplished by using NetLogo [114]. NetLogo provide a natural and simple technique for modeling which is easily understood by programmer [5]. Validation of simulator has been done, as a result of prior work of our research group [64] and [65], it was implemented based on the real data of the Sabadell Hospital. After validation, we use the simulator as a platform to study the behavior of the ED. Each study can be done based on designed models, scenarios using different configurations. Each configuration is identified by the input parameters of simulator including the number and level of experience of each type of personnel and its distribution in each phase, the number of arrival patients in each hour of the week, their age and acuity level, whereas the behavior of the system emerges from their interactions. The output reports data in an excel file showing the time of attention and length of stay for each patient in each phase through the service and etc. This data can be visualized and provide us some information. The simulator enables us to make a prediction based on collected information in different situations. It can be helpful for decision-makers before changing or implementing the real system.

2. The simulator in previous works
   Emergency Department of the hospital (EDs) is the units that as a key part of the health care system provide immediate attention to all type of illness or injury that requires medical services. The urgency has different definitions, according to the World Health Organization (WHO), urgency can be defined

as any activity that causes a divers problem that generates awareness of an imminent need for attention. another definition says when a condition is not life-threatening and fatal but requires care within 24 hours to avoid major complications.

An emergency is an urgent situation that the patient is in the risk of life or limb. It is the case that with the lack of assistance, it would lead to death or loss of organs in minutes. ED care is provided with the highest level of availability and accessibility, 24 hours a day, 7 days a week, and 365 days a year, and without any limitation for who can access the service. They are usually the main gate of hospital admission and a key component of the entire health care system. Our research group collaborating with staff from the Sabadell Hospital, we have made a brief description of the operation of the EDs, and its different phases or from the moment that patients arrive at the service until they are discharged and leave the ED service.

3. Admission phases in Emergency Department
Diseases or injuries can happen suddenly without any warning. ED provides urgent care to patients who have a traumatic injury, major diseases, or any issues that need immediate treatment for unscheduled demand. Patient in ED has to follow five steps in which each step has been explained as follows:

   - Admissions Step The admission process is important because it lets the ED staff collect and record information of the patient. They make the query about personal data (address and data personal), the medical history of a patient, and billing information.
   - Triage Phase In the triage process, healthcare professionals (triage nurses) identify the level of the severity of a patient's condition. Patients with a higher acuity level are emphasized to receive immediate treatment. The triage process assigns the patient a priority level based on their medical history and current condition according to the following scale: 1)Resuscitation (immediate life-saving intervention), 2) Emergency, 3) Urgent, 4) Semi-urgent, 5) Non-urgent.
   - Diagnostic and Treatment Phase In this step, healthcare staff (doctors and nurses) try to determine the reason for the patient's illness, and possibly,

find the solution for it.

In the first contact, the patient visits an initial doctor. The doctor question and examine the patient to perform the diagnoses for their pathology. Some patients can be required to do diagnostic tests or a complimentary test or be sent to treatment administration which is tracked in the treatment process under the control of nurses and doctors.

The medical team in this phase is specific to each zone:

a) Zone1 (or Area A): It is the area of care for patients with most urgent acuity level (1, 2, and 3).

b) Zone2 (or Area B): It is the area of care for patients with less urgent acuity level (4 and 5)

- Discharge
  When patients finish the treatment will have four possible destinations He can get back home, he can be admitted to the hospital, He can be transferred to another hospital or can be death.

4. Emergency Department: Performance and Basic Model
   Agent-based modeling is one class of the microscale computational models that simulate operations, actions, and interactions of multiple independent entities (i.e., agents). This model tries to regenerate and project the behavior of a complex phenomenon/system as a whole. Our research team has developed a simulator using an agent-based design of a system and validate it to predict the behavior and performance of ED. Various types of variables can be received by the simulator. The inputs need clinical data set collection and analyses, statistical models, etc. Specifically, in the current study, we needed to define a set of Environment Configuration Parameters in our model as particular inputs of non-urgent arrival patients to the service. In this section, we first elaborate on methods used to obtain information on non-urgent arrival patients and their ALs and then introduce our agent-based model and the way it works in detail [64]. Each agent possesses a set of attributes and behaviors, individually assesses its own situation, and makes decisions based on a set of rules [13]. Attributes and behavior of each agent are a function of agent type and interactions between agents (Fig2-9) [64]. Patients in the model are divided into 5 acuity levels (ALs) [34], [37], according to Spanish triage system [92]. Incoming patients have

different priorities based on their ALs. Those who cannot wait to be seen (based on the patient's condition and resource needs) classified as a patient with higher priority. Patients with a higher AL (level I, II, or III) receive treatment and/or use physical resources of ED. The triage results of a patient also determine their treatment area in the ED. As such, in our model ED is divided into zones A and B (Fig. 2)[64], where urgent patients are hospitalized/treated in zone A and stay in their own care-box during all diagnosis and treatment processes whereas non-urgent patients are hospitalized/treated in zone B. For all patents, admission, and triage phases are conducted by same nurses and healthcare staff. After triage, in diagnoses and treatment stages, different doctors and assistant nurses serve at each zone while sharing the same test service resources such as X-Ray, laboratory test, etc.

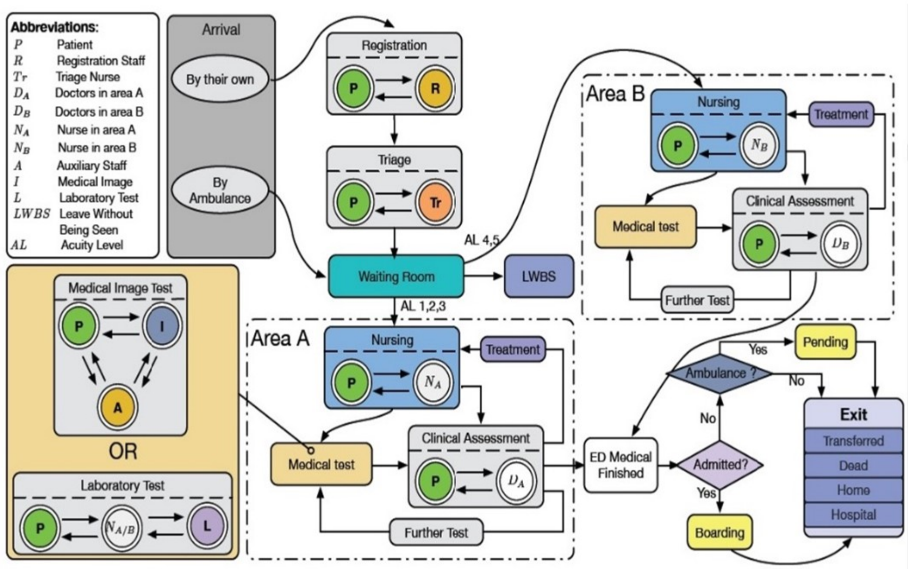


Figura 2-8: General workflow of ABM simulator wherein patients, ED staff, and hospital physical resources were considered as agents. NCDs and age distribution were attributed to the patients, and actions and interactions between the agents were modeled in the ED simulator. LoS of ED, as an index of health care quality, was directly obtained from the simulator [64].

The non-linear behavior of agents in our model has been contacted by if-then rules based on signals the agents receive: If [signal vector x is present], Then [execute act y]. If an agent is busy with an interaction when a signal is received, the signal will be sent to its task queue. Table2-1 shows an example of an if-then rule for the patient's agent. Usually, patients in ED are directed by the information systems (IS). IS is a system that staff, patients, and test room can communicate and coordinate with each other. Patients enter to receive treatment/service if they are notified otherwise stay in their current place. During the process in ED, patients alternate between two states: waiting (e.g., for a doctor, nurse, medical testing service/result, etc. or receiving treatment/service **??** and **??**.

Tabla 2-1: An example of an if-then rule for patient's agent ??

IF	THEN
Notified by IS (before entering treatment area)	Go to the corresponding place as notified
No requests from IS (before entering treatment area)	Keep staying in waiting room
Notified by IS (in area B)	Go to diagnosis room or medical image test-room as notified

The distributions and the probabilities of transition between the states (agents) determining their interactions were done by actual data analysis. (collected from the Sabadell Hospital). Later, these dates were used for validation of the model in developed simulation.

2.2.3. Online Monitoring and and Recommendation System (mode3)

Telehealth is the distribution of health care services and information technologies that allows long-distance patient and clinician contact, care, advice, reminders, education, intervention, monitoring, and remote admissions [97] and [68]. Telemedicine or telehealth is sometimes used as a synonym or is used in a more limited sense to describe remote medical services, such as diagnosis and monitoring. The patient monitoring system is defined as an online health monitoring system that is used to measure a patient's body vital signs by using embedded technology. Using telemedicine can achieve numerous benefits incorporating lower healthcare costs, drive up efficiency and quality of health care system, provide the patients better access to healthcare services which leading to ultimately happier and more satisfied and healthier patients.

When patients go directly to the emergency department, we do not receive any feedback from them to evaluate or fed back compared to their input. This system is called an open-loop system (non-feedback system) that has no information about its output to correct errors. Generally, a system called closed-loop control system, or feedback control system, if it is able to assess, monitor, and control a process to precisely measure the output and the feedback section, compare it to the actual output and Reduce errors. Telemedicine is a closed-loop system in which referring to feedback easily means that part of the recovery output is returned to the input to improve part of the systems. Telemedicine is a closed-loop system in which the reference to feedback easily means that part of the output is returned "back"to the input to improve part of the systems.

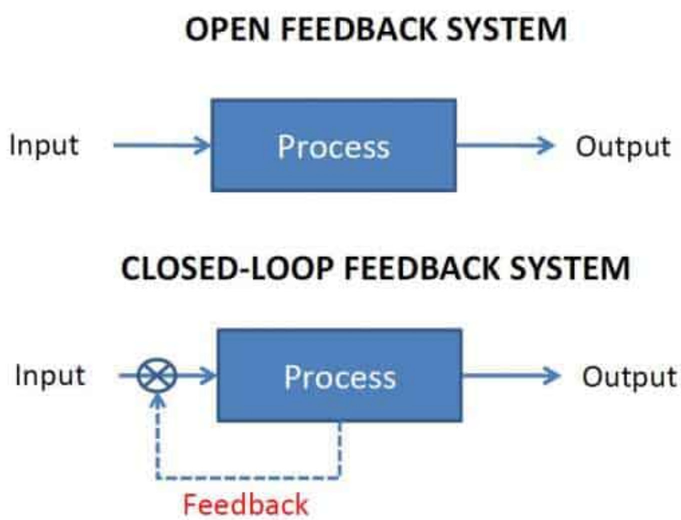


Figura 2-9: Open loop system Vs Closed loop system

ED is the major entrance of the health care system which any impact on ED can directly affect health care system efficiency. The connection of ED to the telemedicine can change the ED behavior.

Chapter 3

"Information is the resolution of uncertainty."

- Claude Shannon

3. Emergency Department Behavior in Future

3.1. Develop a Method to Predict Behavior of ED Caused by Non-Communicable Diseases

ED is the major entry of the healthcare system that provides 24-hour services, in the entire year, for who is experiencing medical conditions, trauma, or injury. Patients usually visit ED without an appointment and are expected to receive services and treatment. The prolonged length of stay (LOS) in the ED, delayed laboratory and imaging tests, delay of consultants, and lack of sufficient inpatient beds are the main reason for overcrowding in the ED. Briefly, overcrowding makes pressure on ED which is leading to an increase in ED waiting times and hence decreased quality of services, poor clinical outcomes, and patients' dissatisfaction [52] and [117] and **??**. Usually, the quality of care is evaluated through the LoS index, which is the most widely used and accepted in the literature to show the quality and performance of the ED. LoS is the time when the patient enters to ED until he/she is discharged. A longer LoS indicates a growth of demand in ED, inadequate resources or delayed service delivery, and ineffective use of resources[104], [11]. As a result of the demography change and population aging, health problems such as the profile of prevalent diseases, chronic noncommunicable diseases (NCD) being the core of attention. All these conditions making the elderly require frequent assessment in an emergency service [27]. The demand in the attention and medical services in ED has been increased in the last years especially because of elderly people. Older people have biological, physiological, and social changes, related to aging and all of which lead to a difficulty for their life quality and health. More frequent readmission of the elderly is also one of the reasons for in saturation in ED as the elderly with NCDs need more medical [47], [65] and [18]. NCDs are one of the emergency conditions leading cause of disability and death. They are the main reason for visiting ED while aging is a dominant factor of increasing incidence of NCDs [18].

3.2. Influence of patients with NCDs on behavior of ED

3.2.1. Simulation of patients with NCDs

In order to investigate the correlation between a number of NCDs visit and saturation of ED, we have tracked the behavior of patients with NCDs in ED and then modeled them when visiting ED. As soon as a patient (i.e., regular or NCD) enters the healthcare system, the simulation starts to run according to the patient flow. In our simulation scenario, the set of Environment Configuration Parameters has not changed apart from specific inputs of patients into the service, therefore, the same staff configuration and physical resources are used for both NCDs and regular patients. The inputs into the model are made of a number of arrival patients and their type of disease (regular or NCD). Each year is calculated based on data in Spanish demography and their age distribution was provided through statistical analysis of data from Our World in Data [70] and Spain demography. In the ED simulator, patients with NCDs follow the same steps for admission, triage, diagnoses, treatment, and finally discharge of patients.

3.3. Projection Scenarios

When it is not possible to see the exact image of the future, scenario analysis as a main form of projection is used to estimate the process of analyzing in future events by comparing it with alternative possible outcomes (sometimes known as 'alternative worlds'). Projections scenario presents several alternatives to develop possible future outcomes. However, all aspects of the scenarios should be reasonable and probable. Although highly discussed, experience has shown that around all scenarios are most appropriate for further discussion and selection. Scenario-building is made to ease decision-making by allowing deep consideration of outcomes and their conclusions. We have designed and model the behavior of patients with NCDs in our ED simulator, now we needed to predict how population changes cause a different age distribution of patients with NCDs in future years. Demographics of Spain (2019 to 2040) show that Spain's population is decreasing with a very gentle slope. If the current demographic trends continue, Spain will encounter a reduction of ~ 0.5 million people in the next from 2019 to 2039 (Fig3-1) [9]. The population may not change significantly but it is aging, and elderly persons have a high burden of comorbidities and functional and cognitive impairments so patients are more likely to have multiple, chronic conditions leading to NCDs. Therefore, gentle decreases in an aging population can result in increases/no changes in the number of patients with NCDs and changes in their age distribution in the health care system. Analyzing data from Parc Tauli Hospital in Sabadell/Spain [63] and [65] shows that the ED had a total number of 137,757 arrival in 2014. We kept this number as the total number of visitors in our simulator and assumed there are trivial variations in the number of patients from year to year. Other data from Parc Tauli hospital used in our model included the number of arrival patients (hourly, daily, and weekly), number of staff, number and type of physical resources, type of interaction and behavior between agents, etc. We have built data analyses and conducted optimistic and pessimistic projection scenarios to estimate upper and lower ends of a percentage of patients with NCDs and their age distribution is from 2019 to 2039. The consequences of each prediction from each scenario were then used as inputs into the ED simulator.

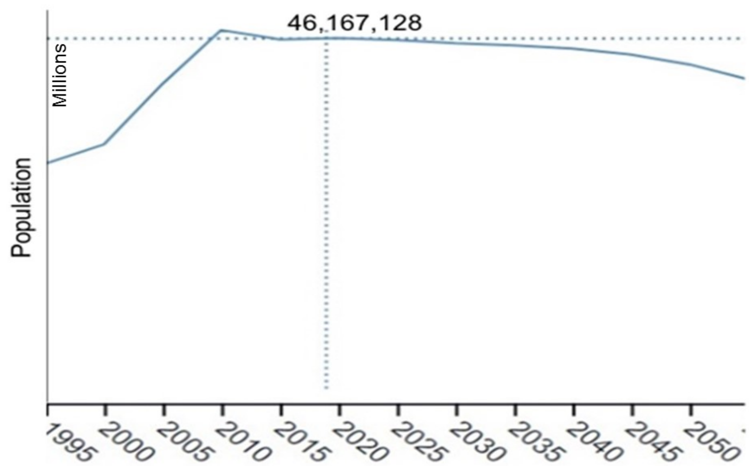


Figura 3-1: Spain demography from 1995 to 2050 which shows Spain population from 2019 to 2039 is decreasing with a gentle gradient [9]

3.3.1. Pessimistic scenario:increases in percentage of patients with NCDs and changes in age distribution

The worst-case scenario is a part of the risk management concept wherein it discusses the possible disasters that can rationally be predicted to occur in a specific situation. It can warn to prepare and minimize the accident that could lead to quality problems or other issues. The worst-case scenario shows the worst result that could happen in a specific matter and resultant in negative consequences. Data from the Our World in Data shows that the number of patients with NCDs has increased from 2010 to 2017 (Fig2-2) [69] and [70]. Using these data and computational methods (see below), it was predicted that the number of patients with NCDs will further increase by 2039. Also, through combining data from Spain demography (Table3-1) [9] and disease burden from non-communicable disease by age (Fig3-2), it was predicted that a number of patient with NCDs in different age categories (collectively called age distribution hereafter) will change from 2019 to 2039 (see below).

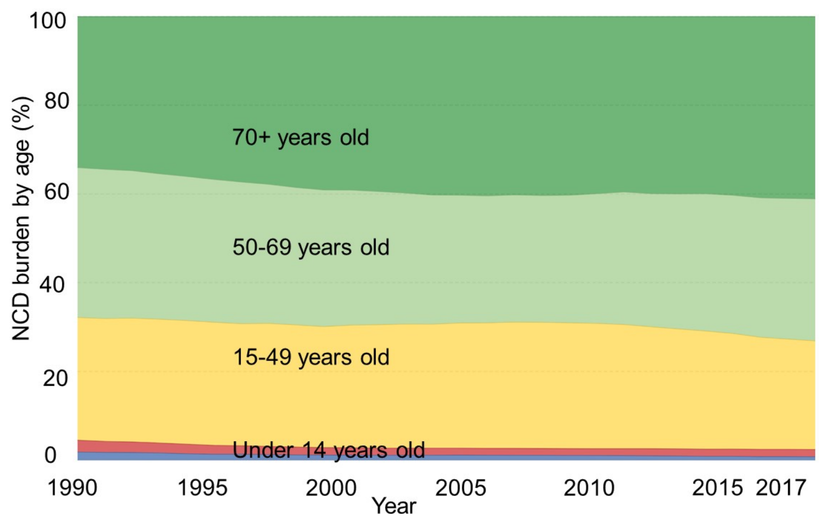


Figura 3-2: Disease burden from non-communicable diseases (NCDs) by age. Disease burden is measured in DALYs (Disability-Adjusted Life Years) [70].

Therefore, a pessimistic scenario with two variables (i.e., more patients with NCDs and changes in age distribution) was considered.

The least-squares method is a standard approach of mathematical regression analysis to predict the line of the best-fitting line for a set of data. This procedure is a simple linear technique that provides a visual demonstration of the relationship between the set of data points. We have used Least Squares Regression to find a line of best fit to data on patients with NCDs from 2010 to 2017 (Fig2-2). This line was then used to predict rate of patients with NCDs for every consequent 5 years from 2019 to 2039 (Fig3-3 **??**).

We used NCDs by age's data (2010 to 2017) from age categories of 0-14, 15-49, 50-69, and above 70 (Fig.3-2) [70] to forecast the same data from 2019 to 2039. In ED,

Tabla 3-1: Spain demography and its projection from 2014 to 2039 for different age intervals. Population pyramid prediction issued by the Spanish National Statistics Institute [9].

	Percentage of population in each year						
age	2014	2017	2019	2024	2029	2034	2039
-19	4.5	4.7	4.9	5.3	4.6	4.5	4.2
20-24	4.9	4.7	4.5	4.9	5.5	5.1	4.7
25-29	5.5	5.1	5.0	4.7	5.1	5.7	5.3
30-34	7.1	6.0	5.6	5.1	4.9	5.3	5.9
35-39	8.6	7.8	7.0	5.6	5.2	4.9	5.4
40-44	8.6	8.7	4.5	7.0	7.0	5.2	5.1
45-49	7.9	8.3	4.5	8.3	8.5	5.8	5.3
50-54	7.6	7.8	7.9	8.4	8.3	7.0	5.8
55-59	6.5	7.1	7.4	7.8	8.3	8.4	7.0
60-64	5.4	6.0	6.4	7.3	7.6	8.2	8.4
65-69	4.8	5.2	5.3	6.2	7.0	7.4	8
70-74	4.2	4.5	4.7	5.0	5.9	6.7	7.1
75-79	3.5	3.6	3.8	4.3	4.6	5.5	6.3
80-84	3.1	3.0	2.9	3.1	3.6	4.0	4.7
85-89	1.7	2.0	2.2	2.1	2.3	2.8	3
90-94	0.7	0.9	0.9	1.2	1.2	1.4	1.7
95-100	0.1	0.3	0.3	o.4	0.	0.4	0.6
100+	0.0	0.0	0.0	0.0	0.0	0.0	0.0

children separately are treated in a different department so they are not considered in hour age category, it means we need data for only patients above 15 years in our model. To estimate the disease burden from NCDs by age for each age categories (Fig.3-2 and Table 3-1) by using Least Squares Regression methods. However, since in our ED simulator, and consistent with Spain demography, we had age categories of 5-year intervals, we accordingly mapped the predicted NCDs by age data to these intervals. Briefly, the following steps were taken **??**:

- In our ED simulator, and consistent with Spain demography, an age range

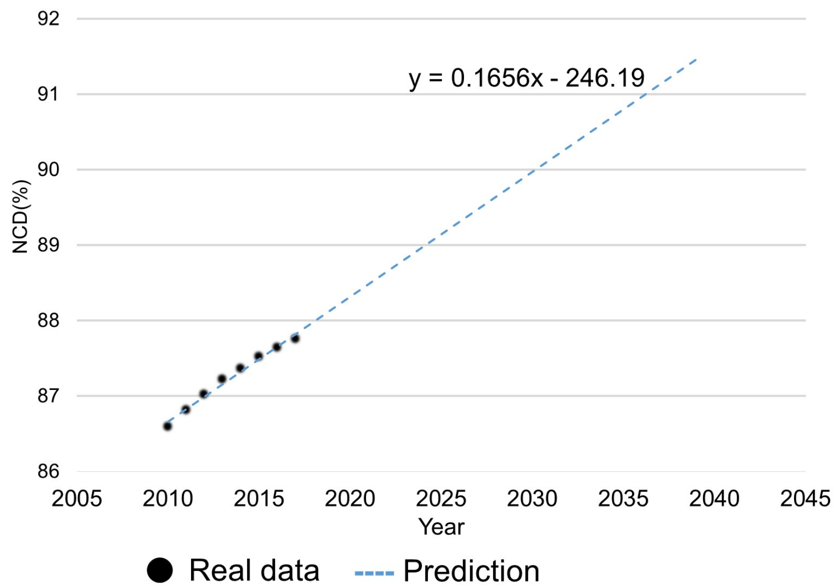


Figura 3-3: Projection of percentage of patients with NCDs from 2019 to 2039 in Pessimistic scenario. Least Squares Regression is used to find a line of best fit to data on patients with NCDs from 2010 to 2017 **??**

between 0 to 100 years was assumed. The age range was then classified into 20 age categories of 5-year intervals.

- An index for each age distribution was defined ($i = 1 : 20$). For instance, the index for age category of $[0 - 4]$ is equal to 1. Because we only studied adults older than 15 years, i started from 4.

- If $P(i)$ is population of Spain for category index i, according to Spain demography (Table 1), the population from 15 to 49, 50 to 69, and above 70 is respectively calculated through$Pop_{15-49} = \sum_{i=4}^{i=10} P(i)$, $Pop_{50-69} = \sum_{i=11}^{i=14} P(i)$, and $Pop_{+70} = \sum_{i=15}^{i=20} P(i)$ for each year.

Tabla 3-2: Predicted values for percentage of patients with NCDs from 2019 to 2039 for pessimistic scenario. The line of best fit to data on patients with NCDs from 2010 to 2017 ($y = 0{,}1656x - 246{,}19$) was used for predictions.

age	2019	2024	2029	2034	2039
NCDs(%)	88.15	89.98	89.81	90.64	91.47

- An index for each age category was defined ($j = 1 : 4$). For instance, the index for age category of $[0 - 14]$ is equal to 1. For our study, j started from 2 so that $Pop(j = 2)$ means Pop_{15-49}.

- Consider the total number of patients with NCDs in age category j as $Pop(jNCD)$ (known from Fig. 7 and Table 3), and number of patients with NCDs in age category i as $P(incd)$ (to be calculated). Then we can approximate$P(incd)$from 2019 to 2039 through $\frac{P(i)}{Pop(j)} = \frac{Pop(incd)}{(Pop(jncd)}$ or equally $P(incd) = \frac{Pop(i)*pop(jncd)}{Pop(j)}$ (Table 4) where P(i) and Pop(j) for each year are known from Table 1 and third bullet point above.

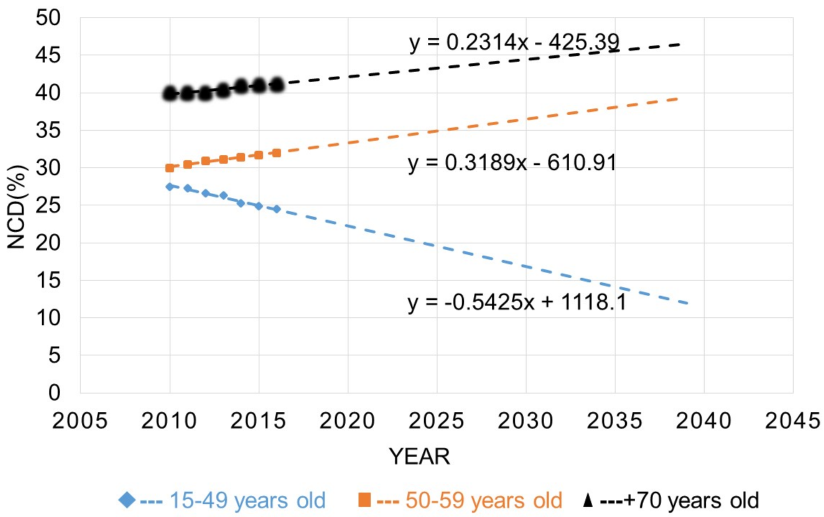


Figura 3-4: Projection of percentage of patients with NCDs by age from 2019 to 2039. NCDs by age's data (2010 to 2017) from age categories of 0-14, 15-49, 50-69, and above 70 were used to predict same data in future (2019 to 2039). Using Least Squares Regression methods, we estimated the disease burden from NCDs by age for each age categories.

Tabla 3-3: Percentage of patients with NCDs for each age category from 2019 to 2039 evaluated from equations in Figure8.

	NCD(%)		
YearAge	15-49	50-69	+70
9	22.79	32.95	41.80
2024	20.08	34.547	42.96
2029	17.37	36.14	44.12
2034	14.6	37.73	45.28
2039	11.94	39.33	46.43

We use the predictions from percentage of patients with NCDs (Fig3-3, Table3-2) and their age distribution (Table 3-4) as inputs into the ED simulator. We did not changed the value for the rest of input parameters including staff configuration (number of staff in each shift) and various physical resources.

Tabla 3-4: The predicted NCDs by age for 5-year intervals

	NCDs by age: $P(incd)$				
age	2019	2024	2029	2034	2039
15-19	3.1 0	2.60	2.22	1.80	1.39
20-24	2.85	2.40	2.50	2.04	1.56
25-29	3.16	2.30	2.32	2.29	1.76
30-34	3.54	2.50	2.22	2.12	1.96
35-39	2.85	3.43	2.54	2.08	1.72
45-49	2.85	4.07	3.18	2.33	1.76
50-54	9.64	9.77	9.78	8.52	7.63
55-59	9.03	9.07	9.55	10.22	9.20
60-64	7.81	8.49	8.74	9.98	11.05
65-69	6.46	7.21	8.05	9.00	10.52
70-74	13.27	13.42	14.46	14.51	14.03
75-79	10.73	11.54	11.27	11.91	12.45
80-84	8.19	8.32	8.82	8.66	9.28
85-89	6.21	5.63	5.63	6.06	5.92
90-94	2.54	3.22	2.94	3.03	3.35
95-100	0.84	0.80	0.98	0.86	1.18
100+				0.21	0.19

3.3.2. Optimistic scenario: Constant percentage of patients with NCDs and changes in age distribution

A best-case scenario is a made-up situation or problem using real-life constraints and affects in order to discuss and predict how the best situation could occur in the real world. Spain demography demonstrates that the population of Spain, from 2010 to 2017, is approximately unaltered but it is aging. Therefore, we considered an optimistic scenario under two conditions 1) a steady percentage of patients with

NCDs and 2) a changing age distribution. Specifically, we consider that percentage of patients with NCDs for each year from 2019 to 2939 is the same as that of 2017. For disease burden from NCDs by ages, we used the same results we obtained from the pessimistic scenario (P(incd)) in the ED simulator.

3.4. Result for future of ED

When decision-maker can not effectively plan for different future possibilities, the result of projection scenarios is able to utilize 'what if' analyses to anticipate the most likely future situations they will need to manage, and then plan accordingly. What-if analysis is a data-intensive simulation whose goal is to inspect the behavior of a complex system, such as ED, under some given hypotheses called scenarios.
The what-if scenario analysis is used as a project management process that measures various scenarios to approximate their effects (both positive and negative) on the project objectives. This is one of the modeling techniques used in the Develop Schedule process. These assessments can be used to test the amount of risk present within a given situation as related to a different potential event, ranging from highly probable to highly improbable. Depending on the results of the analysis, would be determined if the level of risk present falls within the comfort zone. Both likely and unlikely events can be tested relying on computer simulations.
As mentioned, an ED simulator can have various outcomes including interaction information of patients, healthcare staff, and physical resources. One of such interaction information is the patient's LoS that is an objective indicator of the quality of care. We have quantified and predicted LoS from 2019 to 2039 for the two projection scenarios we considered.
Both results from projection scenarios prove that Spain would have an increase in LoS (sum of LoS among all age intervals for one year) from 5.7 million hours in 2019 to 6.2 million hours in 2039 if they use the same configuration setting and resources. It has been shown in Fig.3-5. The constant increase in total LoS for optimistic scenario (constant NCDs) (Fig.3-5) indicates that the changes in age distribution alone play a key role in the increase of total LoS. Increases in NCDs in addition to changes in the age distribution (i.e., pessimistic scenario) exacerbate the total LoS by 1.58 % on average from 2019 to 2039 when compared to the optimistic scenario. However, we

observed smaller differences in total LoS between pessimistic and optimistic scenarios for years 2019, 2024, and 2039 ($< 0{,}31\,\%$) and a larger difference between the scenarios for years 2029 and 2034 ($> 3{,}1\,\%$) (Fig.3-5). Such behavior indicates that there are interactions between the two variables (i.e., NCDs and age distribution).

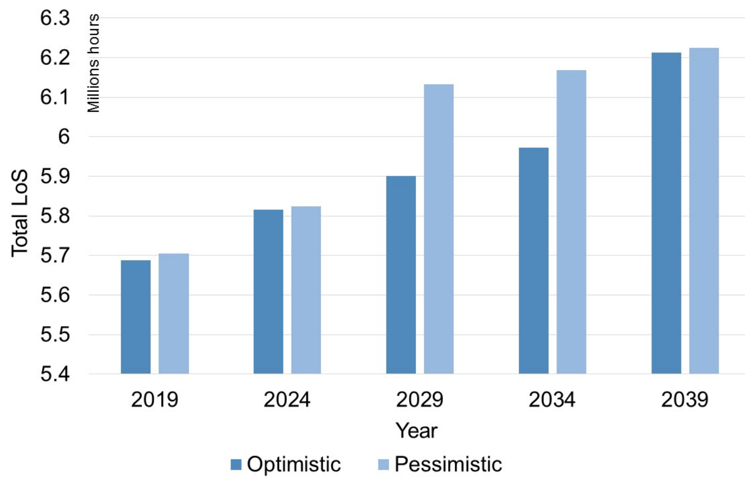


Figura 3-5: Total LoS for optimistic versus pessimistic scenarios from 2019 to 2039

Significant increases in LoS started after age 50 with the maximum values of LoS being observed in 70-74 and 75-79 age intervals (Fig. 3-6 and Fig. 3-7). Comparison of four marginal conditions (i.e., optimistic 2019, pessimistic 2019, optimistic 2039, and pessimistic 2039) indicated that, due to changes in age distribution, LoS in elderly people is increasing along the time for both optimistic and pessimistic scenarios (Fig.3-8).

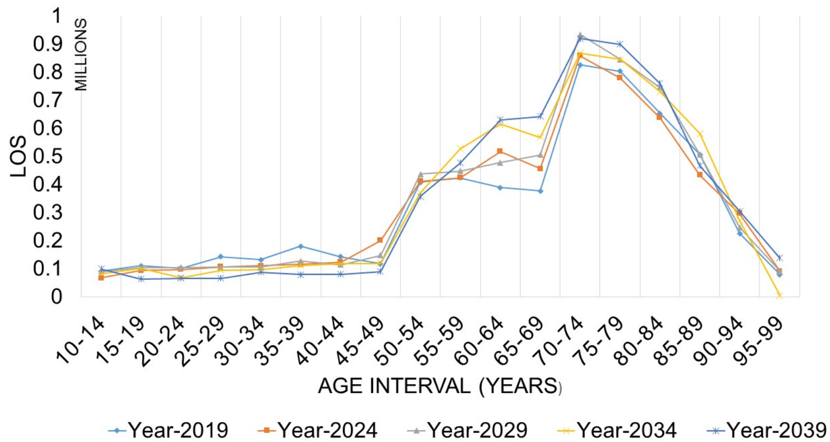


Figura 3-6: Contribution of each age interval into the LoS from 2019 to 2039 for pessimistic scenario

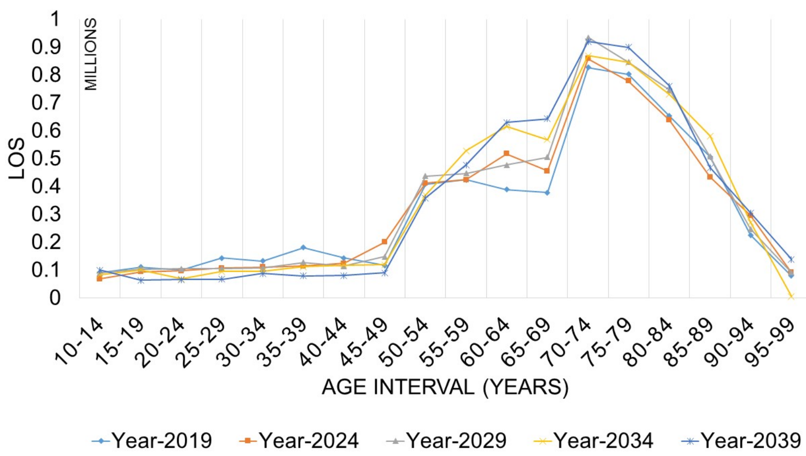


Figura 3-7: Contribution of each age interval into the LoS from 2019 to 2039 for optimistic scenario

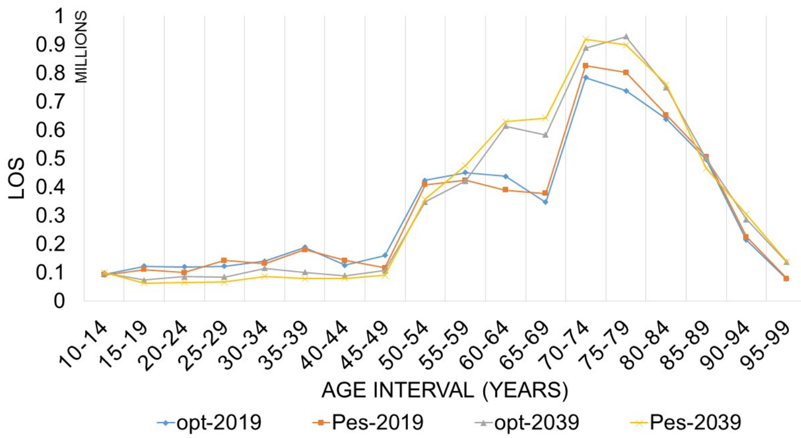


Figura 3-8: Comparison of LoS between four marginal conditions for different age intervals

Chapter 4

"Essentially, all models are wrong, but some are useful."

- George E. P. Box

4. Computational Models

4.1. Computational Mode1: Effect of Lifestyle on Behavior of Patient with NCDs

4.1.1. Increase of Burden of NCDs Associated with Lifestyle

WHO has been reported NCD is the cause of almost 70 % of all deaths worldwide incorporating cancer, heart disease, diabetes, stroke, and chronic lung disease. However, most chronic diseases could be preventable or predictable as many chronic conditions are a result of a wrong lifestyle that is modifiable. Four primary risk factors are responsible for the rise of NCD: exposure to tobacco smoke, physical inactivity, the harmful use of alcohol, and unhealthy diets. Reducing these major risk factors can lead to the exclusion of NCDs. WHO says NCDs are preventable and it reports approximately 80 percent of heart disease, stroke, and type 2 diabetes and more than one-third of cancers could be prevented by omitting the main risk factors. Mostly, NCDs are rising by the rapid globalization of unhealthy lifestyles, unplanned urbanization, and population aging. Usually, unhealthy diets and a lack of physical activity raise blood pressure, increased blood glucose, elevated blood lipids, and obesity. These are known as metabolic risk factors that can end to cardiovascular disease, the leading NCD in terms of premature deaths. Most of the risk factors associated with these diseases are modifiable whereas the focus on the reduction of the risk factors can control NCDs. A healthy lifestyle is one which low-cost solution to keep and improve people's health and well-being. The ways of being healthy to include healthy eating, physical activities, weight management, and stress management. Chronic patients often need to access healthcare systems while many of them need to be readmitted even though they are not in an emergency or dangerous situations. Reducing unnecessary attendance of chronic patients to the healthcare system and controlling their time of visit could be an important solution to improving healthcare system efficiency. When chronic patients are aged people, usually they need different attention from other patients. Tracking the behavior of chronic patients individually inform us how much time, resources and services are consumed by the chronic patient and how reducing the number of chronic patients can affect the efficiency of the healthcare system.

4.1.2. Demonstration of Changes in Lifestyle Risk Factors through State Machine

We need different parameters and conditions for the prediction of chronic patient behavior. These parameters and conditions include the physical environment, lifestyle risk factor, and other considerations which affect health parameter. The different parameter value makes each chronic patient behave differently from others. As mentioned, each living condition changes health variables, and these changes can affect the quantity of these health variables, so the stability situation of the chronic patient can differ to instability or vice versa, they can also go from unstable to stable. Each chronic patient is classified into different classes based on their symptoms and signs, it is supposed there is a state machine to present the movement between different states. As shown in Figure 4-1, each transition from one state to another indicates the behavior of each patient and transition occurs when the health variables are changed, which means that the living condition of the patient is changed.

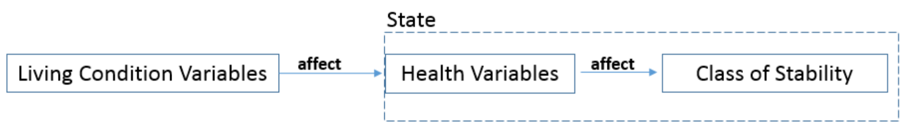


Figura 4-1: Influence of living condition on state.

The set of states is an indicator of the stability of the patient's different level which, is composed of the classes of chronic disease and medically related variables. Any transition from one class to another is presented in a diagram to show the patient's behavior, which can be seen in Figure 4-2 that is the extended shape of Figure 4-1. It shows our inputs are life condition parameters in a specific time and these transitions happen between classes according to the number of state variables in a particular time, and all the modifications throughout time are displayed in the diagram.

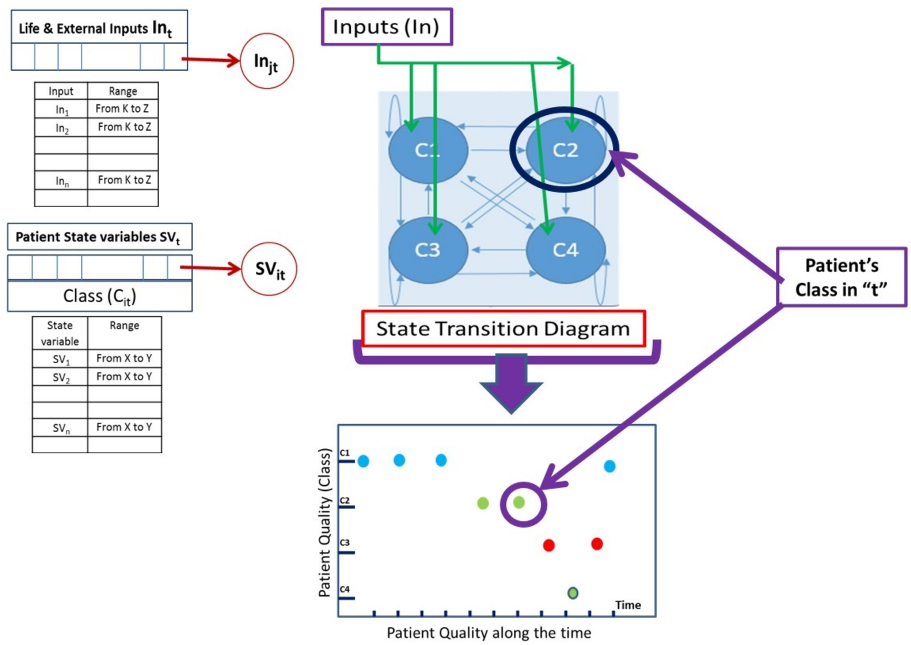


Figura 4-2: Extended shape of influence of living is shown condition on State.

4.2. FORMAL MODELS AND APPROACH

Medical variable and risk factors values are usually in natural language and computing based on the degree of truth rather than the Boolean principle (binary truth). In other words, it's complicated to translate this type of variable into an absolute term of one or zero. Because of our variables (Living condition Parameter and health variables (state variable)) are mostly in a vague language therefor we use the fuzzy logic system [110]. In this model, We use fuzzy logic twice. Firstly, for the classification of each medical health variable (state variable) where inputs are the living conditions parameters and, secondly, we classify the chronic disease quality (classes of stability), where the inputs are the medical health variables. The steps for the algorithm of the proposed model are taken as follows (Figure 4-3):

- At the beginning, it holds the current state (the class of stability of the patient and its related health variables)
- Checks whether the living conditions of the patient are changed, if nothing is changed it means that the patient is in the same situation, then the state won't be changed, If the life condition is changed it means it could affect state variables, so it goes to a Fuzzy logic system and gains the new health variables
- By using new state variables it goes to the fuzzy logic system to find the new class, then it moves to a new state.

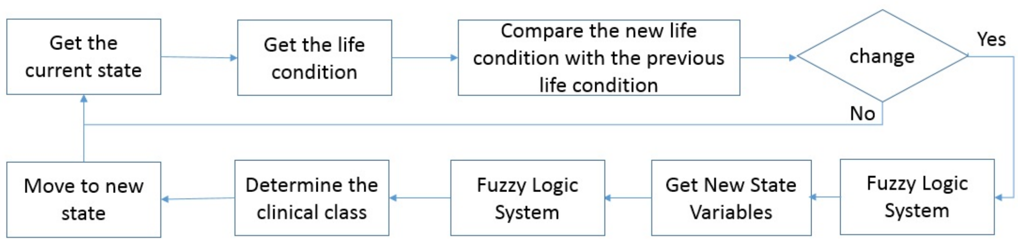


Figura 4-3: General model of chronic patient's behavior according to living condition.

Basically, the model is constructed based on an agent-based model including two sub-models: 1) a state machine model and 2) a fuzzy logic model. Each patient is considered as an agent. Based on a set of rules, the state machine indicates this agent action and movement. These rules are identified by the use of Fuzzy logic.

4.2.1. Fuzzy Logic

Human has a unique skill to make a decision in an environment with uncertain information. Fuzzy Logic (FL) is a mathematical form of logic for simulating human reasoning. The first time, the term fuzzy logic was presented by Lotfi Zadeh with the 1965 proposal of the fuzzy set theory. He found out that, as opposed to a computer that only understands the language of yes and no, human decision making has a range of possibilities between true and False. Therefore the approach of inventing FL was to resemble the way of decision making in humans in the form of mathematics such as Definitely, Possibly, I don't know, NO.

4.2.2. Fuzzy Logic Systems Architecture

As a projection of a chronic patient's behavior model is an unpredictable, dynamic and complicated model and given that we will have a massive amount of data in the health variables as well as life and medical conditions, then we should formulate this data by a fuzzy system and generate an output, and that is why we have decided to use fuzzy logic system [116]. The fuzzy logic works on the levels of possibilities of input to achieve a definite output. Each Fuzzy system design incorporates the determination of three steps: input variables, output variables, and Fuzzy Inference, which is the main application of fuzzy logic. The major approach of fuzzy inference is taking input variables through a mechanism which is comprised of parallel If-Then rules and fuzzy logical operations and after generating the output

1. Input and Output Variables:
   In this part of the study, fuzzy logic is used as a main for both sub-models. In the first step, the inputs into the model are living conditions contributing to generate health variables as output and, the health variables are used as input for classifying the chronic disease (patient quality) as output. These inputs and their range are used to define the membership functions of input variables. Equations (1), (2), and (3), are used to create its membership for each language expression as follows. Figure 4-4 indicates the graph of membership function of the variable [2] and [4]. The first stage in this system shows, the output variables are the state variables and then, the next step, shows the output is the class of chronic disease. These outputs also should be specified with equation 1, so we consider a different output variable which is divided into the fuzzy set (State1, State2, State3 and etc). **??**.

$$\mu_{\text{Low}}(x) = \begin{cases} 1 & x < a \\ \frac{b-x}{b-a} & a \leq x < b \end{cases} \tag{1}$$

$$\mu_{\text{Normal}}(x) = \begin{cases} \frac{x-a}{b-a} & a \leq x < b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c \leq x < d \end{cases} \tag{2}$$

$$\mu_{\text{High}}(x) = \begin{cases} \frac{x-c}{d-c} & c \leq x < d \\ \\ 1 & x \geq d \end{cases} \tag{3}$$

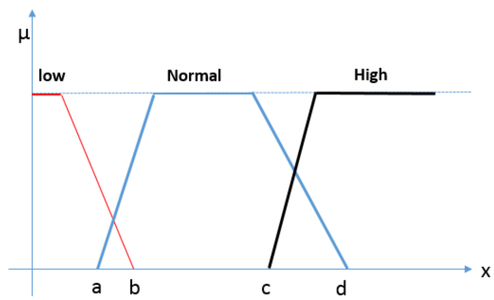


Figura 4-4: Membership graphic

2. Fuzzy Rules Base
When we define the input and output variables and membership function, we create the rule base composed of expert IF-THEN rules [110]. A fuzzy rule-based is made, where fuzzy sets and fuzzy logic are used as tools for showing up different forms of knowledge about the problem plus for modeling the interactions and relationships existing between its variables. These rules transform the input variables to an output. The following steps are taken:

   - First step: These rules are made based on living conditions inputs and give us the modification of the amount of state variables. In Figure4-5, we can see a different combination of living conditions. These compositions help us to make the IF-THEN rules. Figure4-6 shows the definition of rules based on a living conditions. In this figure, we can see how we apply the fuzzy logic system to gain the state variables.
   - Second step: Now the essential rules are created, so we use the rules to determine the future state variable in time $t + 1$ from the current state variable in time t. This means SV_t is an input and SV_{t+1} is an output. This is indicated in Figure4-7.

Living condition 1	Living condition 2	...	Living Condition n	State Variable1	State Variable2	....	State variable n
high	high	high	high	(↓/↑/=/≈...)			
high	high	high	moderate	(↓/↑/=/≈...)			
high	high	high	Low	(↓/↑/=/≈...)			
...	....	...	....	(↓/↑/=/≈...)			
low	low	low	low	(↓/↑/=/≈...)			

Figura 4-5: The different combination of living conditions.

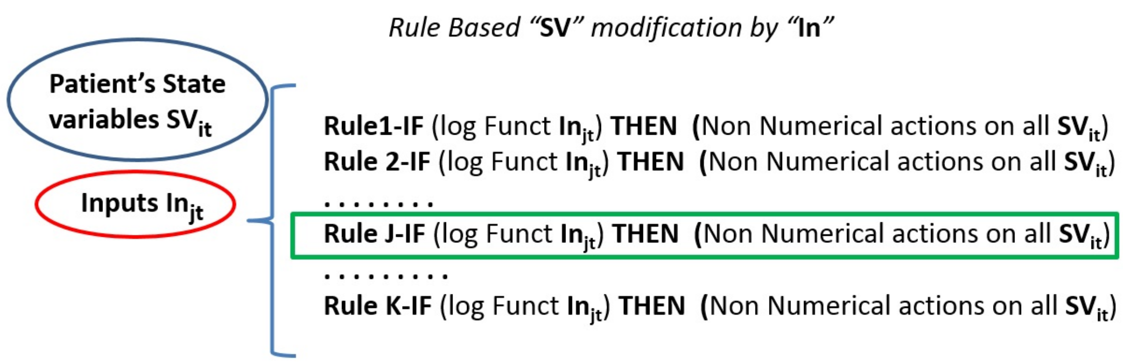


Figura 4-6: Obtaining state variable based on modification of living conditions

- Third step: A different composition of state variables makes IF-THEN rules to obtain the various classification of chronic disease (patient quality). Figure4-8 shows a table that includes all possible combinations of state value, so we can select some of these combinations based on probability of occurrence to make the rules.
  Rule1: IF (Function SV_{t+1}) THEN Select $class(C_{it+1})$
  While rules are made, we can make the chronic disease classifications based on state variables. This is shown in Figure4-9.

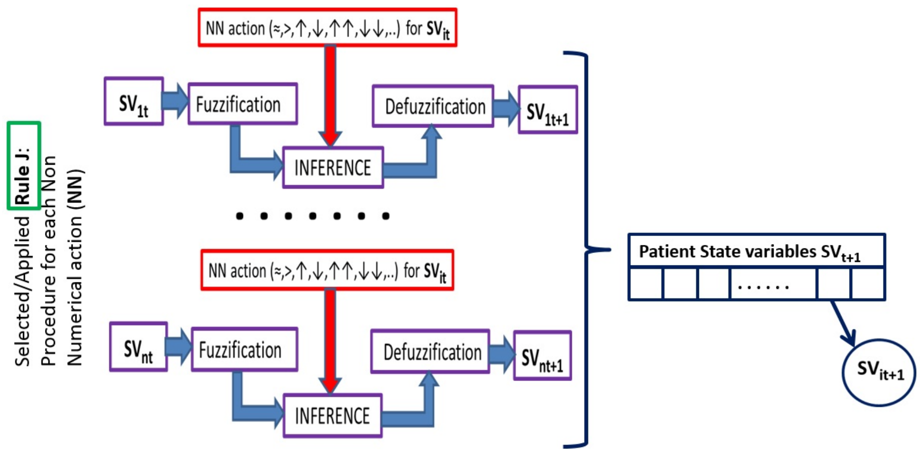


Figura 4-7: Obtaining state variable based on modification of living conditions for time t+1.

State Variable1	state variable2	....	State variable n	Class i	Class i+1
↑	↑	↑	↑	I	(I or II or III,....)
↑	↑	↑	↑	II	(I or II or III,....)
...	...	...	...	...	(I or II or III,....)
↑	↑	↑	↓	I	(I or II or III,....)
...	...	...	...	...	(I or II or III,....)
↓	↓	↓	↓	IV	(I or II or III,....)

Figura 4-8: Table of obtaining class for time i+1 based on modification of state variables and class in time i.

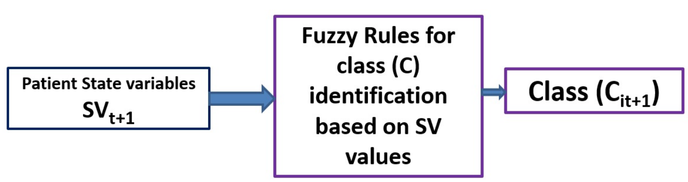


Figura 4-9: Obtaining state variable based on modification of living conditions for time t+1.

3. Defuzzification
   The process of creating a quantifiable result in Crisp logic is defined as Defuzzification, with given fuzzy sets and associate membership degrees. The defuzzification process maps a fuzzy set to a crisp set. The suggested model can use the inference system, whose output membership function is a fuzzy set. Among various methods for defuzzification, we select the center of gravity whose is most widespread in the defuzzification technique. This crisp set is an integer number. Equation (4) display the method's center of gravity [93] and [110] as follows:

$$D^* = \frac{\int D.\mu_M(D)dD}{\int \mu_M(D)dD} \tag{4}$$

4.2.3. Integration of Entire Model

In Figure4-10, the merge of the state machine model and the fuzzy logic models is shown. It shows the integration of model which we have discussed in this section. The arrows on the figure direct the steps of the integrated model.

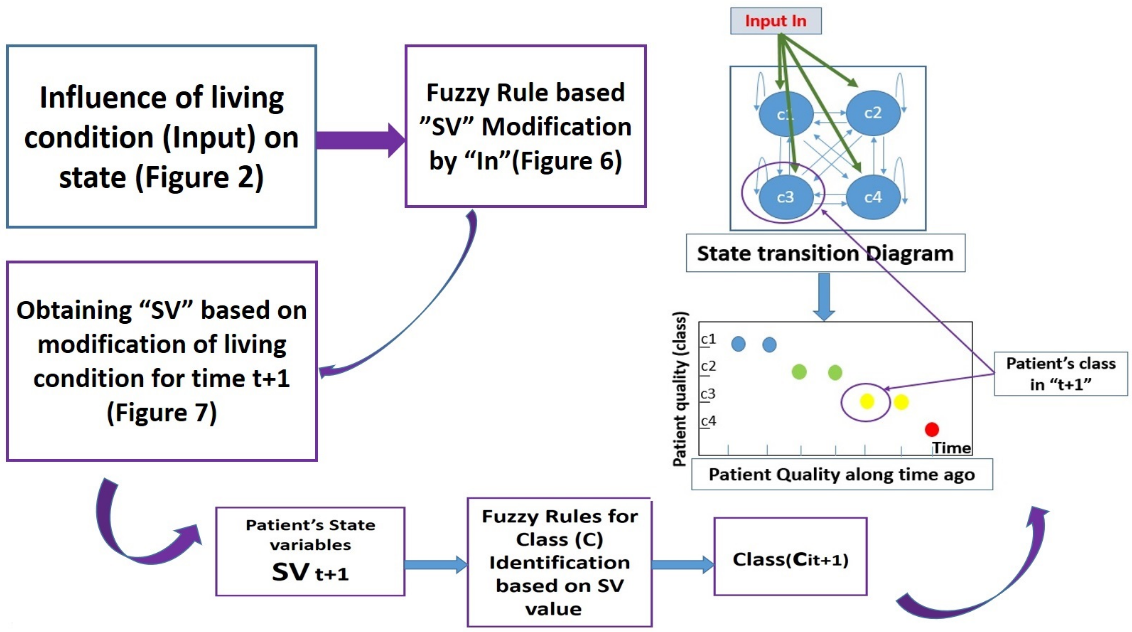


Figura 4-10: Integrated model.

4.2.4. Classification of Heart Failure

Chronic heart failure (CHF) is a global condition, which destroys the quality of life of patients and even can cause premature death. It had been highly debated as problematic, costly, disabling, and deadly illness. CHF merges a wide prevalence with an unspeakable burden of symptoms and morbidity [71]. some literature shows, in developed countries, the prevalence of heart failure among adults is 1-3 % whereas it escalates about 10 % for the people over 70 years old [94]. That is why heart failure disease was the first choice to work on.

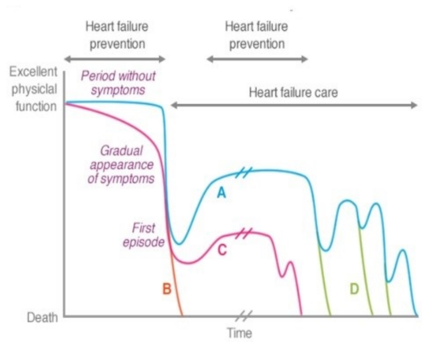
Patients with heart failure are classified into four classes by physicians and doctors based on the severity of their symptoms [86]. In the progression of acute heart failure in Figure4-11 (left side), A indicates a good recovery after the first acute episode, and then the patient experiences a stable period. B displays that the first episode is not recovered. C indicates poor recovery and subsequent deterioration. D indicates persistent deterioration with intermittent acute episodes and an unpredictable death spot [80] **??**. Figure4-11 (right side) demonstrates the progression of heart failure in the simulation.

4.2.5. Heart Failure Signs and Symptoms

Some of the main CHF Signs and Symptoms include:
Edema, obesity, heart rate, heartbeat, blood pressure, a saturation of Oxygen and body temperature.
We define these items as state variables. Any change in these signs and symptoms can impact the heart failure classes and shift it from one class to another one (Figure4-11).

4.2.6. Life Style and Risk Factors

For heart failure disease all these parameters hold a binary value, so in this step, we did not use fuzzy logic for classifying state variables. These parameters are mentioned as follow:
Not following the adherence of the treatment, having an infection, bad nutrition (amount of salt, and if a percentage of water in the body has increased more than two kg per week), drinking alcohol, smoking.



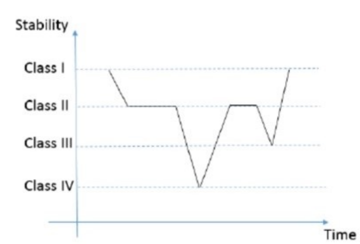


Figura 4-11: Progression of acute heart failure (left side). In simulation of progression of chronic heart failure (right side), we can see the graph that shows the transitions between classes.

1. Various composition of Living Conditions for Generating Fuzzy Rules for Heart Failure Classification:
   The lifestyle of each person can change their health behavior. The important conditions for a patient with heart failure incorporate if they follow their adherence of treatment, if they have an infection, if the amount of salt in their body is high, if the amount of water increases more than two kg per week, if they smoke and if they drink alcohol. Figure4-12 shows some parts of the living and medical conditions composition and the influences of these on heart failure variables. We have six conditions where each condition is a binary variable, so in total, we will have $2^6 = 64$ combinations of different living conditions. According to Figure4-12, we generate the rule IF-THEN for heart failure symptom variables.
   IF Adherence=yes and infection=yes and salt=yes and water =yes and alcohol=yes and smoking=yes THEN oedema=increase.

Adherence	Infection	Salt	Increasing water>2kg	Alcohol	Smoking	Edema	Obesity	Heart Rate	...
Yes	Yes	Yes	Yes	Yes	Yes				
Yes	Yes	Yes	Yes	Yes	No				
...	...	...	...	...	...				
No	No	No	No	No	Yes				
No	No	No	No	No	No				

Figura 4-12: The combinations of different living and medical conditions influence on heart failure variables.

2. Different Combinations of State Variables for Making Rules for Heart Failure Classification:
   After collecting the range of the different living conditions variables, we can build the various compositions of state variables in order to make the If-THEN rules for classification of heart failure. Some parts of these rules are shown in Figure4-13. These rules are driven by a different combination of state variables.
   Rule 1: IF OEDEMA = Yes and Obesity = Yes and Heart Rate = High and Blood Pressure = High and Saturation of Oxygen = High and Temperature = High Then the State of Patient = CIV [93].

Rule No	OEDEMA	Obesity	Heart Rate	Heart Beat	Blood Pressure	Saturation of Oxygen	Temperature
Rule1	Yes	Yes	High	Reg	High	High	High
...							
Rule38	Yes	Yes	Normal	Non-Reg	High	High	High
...							
Rule289	No	No	Low	Non-Reg	Low	Normal	Normal

Figura 4-13: Fuzzy rules to gain heart failure classes.

4.2.7. Heart failure State Variables Classification and Fuzzy Model for Heart Failure Classification

Figure4-14 shows a model where living conditions are our input and based on the rules in Figure4-13, we receive the patient's state variables

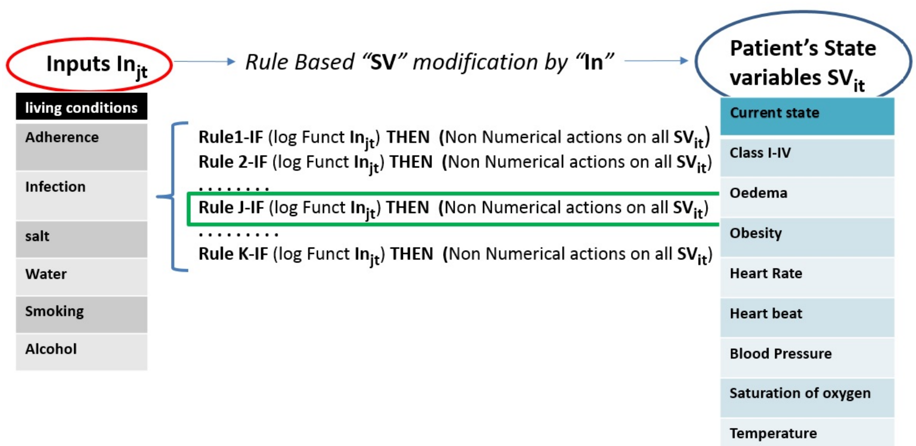


Figura 4-14: Making patient's state variable.

For HF classification, we use fuzzy logic, where health variables are our inputs and states of chronic disease are our outputs [39]. This is shown in Figure4-15. The

Structure of heart failure state fuzzy model consists of three main parts, including inputs, inference engine and output (Figure4-15) [39], [2].

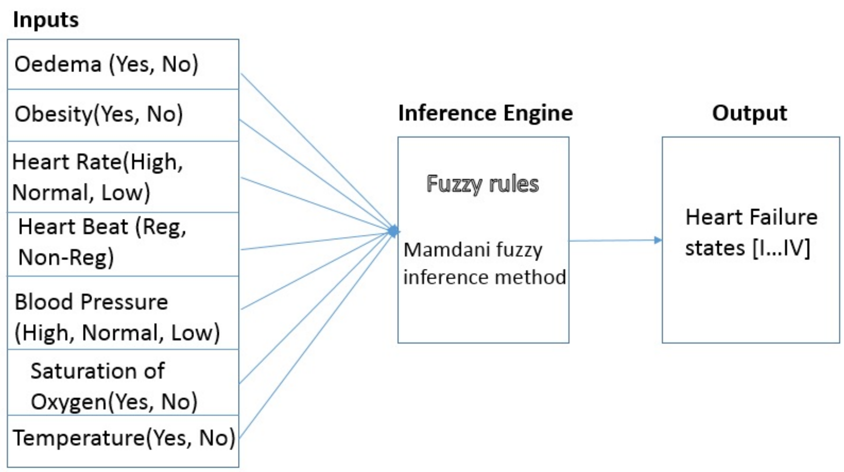


Figura 4-15: Heart Failure Fuzzy Model.

4.2.8. Capability of the Proposed Model

To decrease the influence of chronic conditions on society, we need a complete approach covering all perspectives, incorporating health, finance, education, transport, agriculture, planning, and so on, contribute to minimizing the risks linked with NCDs, prevent and control them. Better management of NCDs requires diagnosing, monitoring and treating the patients with this type of disease, and providing access to palliative care for those in demand. Substantial NCD interventions can be delivered through primary or long-distance health care setting to reinforce early diagnosis and timely treatment. It has been reported that interventions, consider brilliant investments because they can decrease the need for costly treatment if provided timely to the patient. Early detection gives families more time to learn about the disease, develop realistic expectations, plan for their future together, and teach them how to decelerate it. Mostly, all of this leads to less stress and delays in the disease process. The lifetime health and economic burden of NCDs to both individuals and society are dependent on the severity of the diseases; thus, both the timing of the NCDs detecting and subsequent management of the condition could significantly impact this burden. WHO has been reported Early diagnosis generally increases the chance for successful treatment by focusing. Delays in care access cause to lower likelihood of survival, greater morbidity of treatment, and higher costs of care. The designed model contributes to tracking the impact of living conditions on clinical parameters of chronic disease, and it explains how any changes in clinical parameters can swap the class of the health and the quality of care system. Simulation of this model can guide us about the strengths and weaknesses points of the designed model, assess various visions and perspectives of the structure model. So, simulation enables us to empower the proposed model more secure [51]. To simulate this framework model, Matlab and Netlogo can be used. The proposed model can be developed to other types of chronic diseases separately. Two types of data can be used to evaluate the model real data or virtual data which is driven by real data. A patient can have different behavior in the healthcare system according to the preferred lifestyle. simulation provides us the possibility to monitor and compare the quality of life of that patient under different conditions. We also can compare the behavior of a patient with another patient. Monitoring progress and trends of NCDs and their risk is important for guiding policy and priorities for achieving the global target of reduction in the risk of mortality from NCDs. Accessibility and applying advanced analytics to data empower decision-makers to predict the patient's behavior and improve insight into risk, resources, time, and cost [50]. When a patient with a disease can receive information and recommendations, the quantity of unnecessary attendance in the healthcare facilities can be reduced. Also, a non-urgent patient can follow a different schedule and plan visit hospital with the appointment for a sensible time of care system. Such information also helps the health care stuff be aware of likely critical scheduling of the healthcare system. All this knowledge can improve care management, reduce the related cost, assure better use of resources, and deliver patient and staff satisfaction.

4.3. Computational Model2: Tele-medicine System

Telemedicine has few definitions, but according to WHO, telemedicine is "the delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for the diagnosis, treatment, and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers, all in the interests of advancing the health of individuals and their communities"[19]. From the above definition by WHO, we can discover the relevance of telemedicine. Whenever distance ruins the care delivery to a patient, telemedicine can be a good solution. Distance may have a negative impact on the delivery of the medical services, both in time or/and quality. Both developed and developing countries may experience that any delay from disease detection to the starting of the treatment, can influence the final result of the care itself. For instance, When a rural area transmits the weak resolution of a medical diagnostic image to the hospital, some lesions or anatomical districts influenced by the disease or injury may go unnoticed, again compromising the final result of care. Briefly, all countries can take advantage of telemedicine. In recent decades, telemedicine and e-Health have been a hotly debated solution directed at supporting the health care system for chronic and dependent patients. Telemedicine and e-Health system can monitor patients with chronic health conditions such as hypertension, cardiac insufficiency, chronic pulmonary obstruction, asthma, diabetes, cancer, dementia, and other ailments [78]. Telehealth can change the health outcome inaccessibility and cost-effective way. Thus long-distance patients can receive clinical services easier. More patients can obtain care services. Remote hospitals can provide emergency medical services. Remote monitoring decreases the readmission. By performing follow up visits remotely, medical practices can take better control of their schedules, waiting room, and visits. It increases patient satisfaction when patients are looking for convenience. As an example, many of them, the least they drive to medical practice, find a baby sitter and wait in the waiting room. Conducting more effective health care models avoid everyday serious problems and resort to admitting ED. Tele-medicine is a complex and interdependent system which coexist with traditional health care system and technology such as e-health, mobile-health, self-care, and so on.

4.3.1. Health Monitoring and and Recommendation System (mode4)

Telemedicine and e-health are used as solutions for long-distance delivery of medical services to care seekers in order to reduce hospital visits for patients with less emergency condition. Incorporating smart devices and health monitoring platforms allows creating electronic follow-up care and medication adherence such that the care seeker could receive medical services without a need to visit ED. Intelligent health care system focus on clinical parameters related to the patient's clinical condition to treat a chronic patient by the health-care organizer. The data is gained through real-time monitoring or entering by the patient (online) and is used for part of treatment and sometimes diagnose of the patient's condition [30],[17]. Real-time (data) monitoring is the streaming of continuously updated zero-to-low latency information. Intelligent health care system focus on clinical parameters related to the patient's clinical condition to treat a chronic patient by the health-care organizer. The data is gained through real-time monitoring or entering by the patient (online) and is used for part of treatment and sometimes diagnose of the patient's condition [30],[17]. Real-time (data) Real-time monitoring is used in many areas to enable rapid response to instantaneous events. Real-time monitoring is used in different areas to react rapidly to momentary events. Real-time monitoring delivers steady information to keep decision-makers updated and observe trends progressing. In the health care system, real-time data will be collected through some wearable sensors and smart devices from patients to the clinic central. Wearable sensors can be used for persistent monitoring, storing, and sending medical data to healthcare givers over distance. But online monitoring means that there is some kind of interactivity between patient and clinical center involved, but doesn't enforce limits in latency so the patient can measure the parameter and send them to the clinical center. We have proposed a model shown in figure 5, in the model of intelligent health care system after patient succeeds to connect to a system, his/her data will be considered and the problem will be analyzed, if a patient is in danger situation (Al1,2, and 3) an urgent appointment and services are made for him/her otherwise according to patient condition and available data if it is possible system make a recommendation for a patient, if not, the patient should connect to an online doctor or an expert person who can help personally. This model helps patients to recover from a chronic illness [50][90] [87].

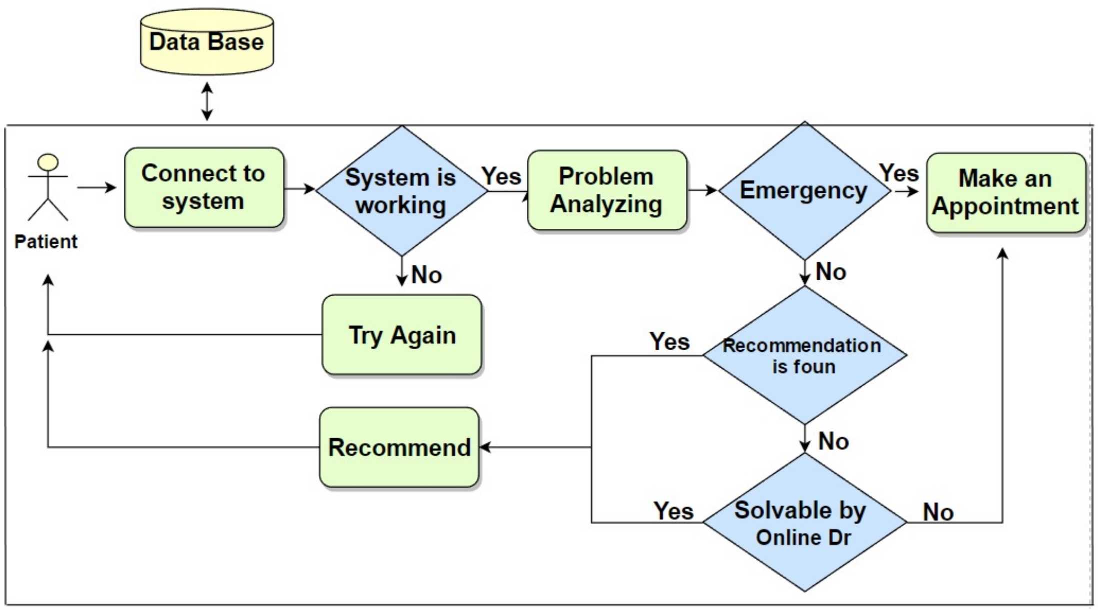


Figura 4-16: Semi-intelligent health care model .

4.3.2. Intelligent Triage and Classification Techniques

In our proposed model regarding the intelligent tracing of chronic diseases, we need to know the acuity level of each patient. Clinical historical data and intelligent techniques provide us this possibility to determine the severity of the illness of each patient. Intelligent techniques can develop clinical decision support systems(CDSS) through some prediction algorithms that provide clinicians, staff, and patients with knowledge, information and recommendations [29]. Thus, objective criteria are provided to health professionals [29]. In order to clarify the AL, we need to run some classifier algorithms through historical clinical data. Each algorithm has its own accuracy, advantage, and disadvantage. The most classifier algorithm used to develop e-triage is shown in Figure4-17.

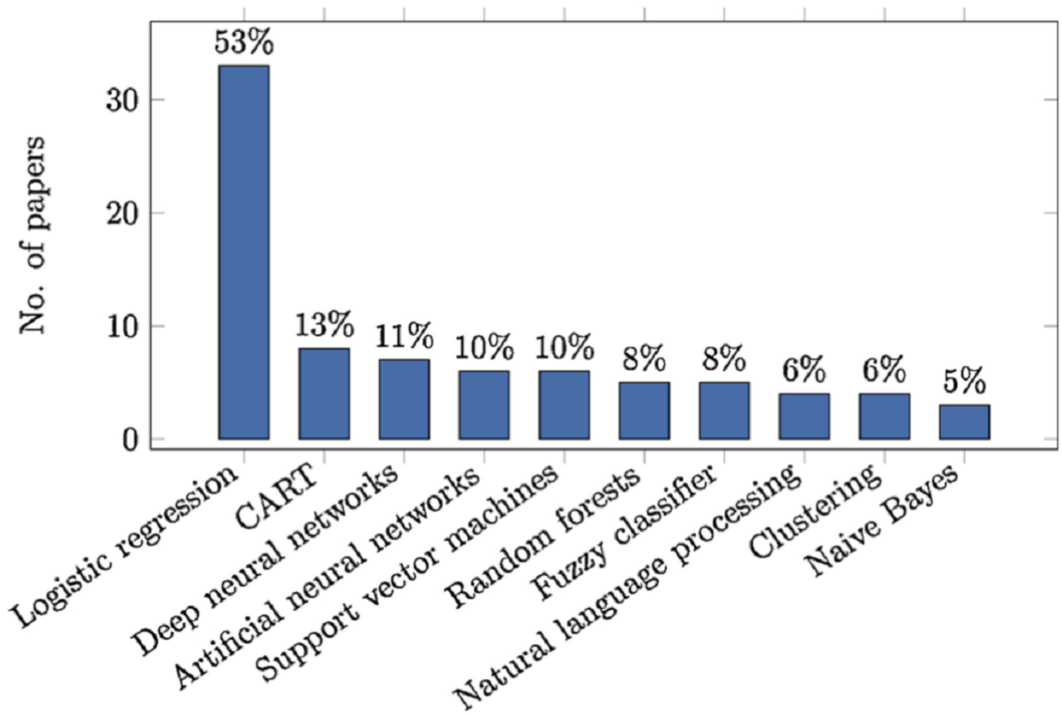


Figura 4-17: Most used Classifier algorithm in literature to develop e-triage [29]

The best way for choosing the desired algorithm for our e-triage model is:

- Read the Data.
- Split the Data into Training and Testing sets.
- Train our Model for different Classification Algorithms such as Fuzzy logic, Decision Tree, Support Vector Machine Classifier, Artificial Neural Network, Naive Bayes, and Logistic Regression, and so on.
- Select the most suitable algorithm.

Because of uncompleted data, we had to go through literature for our investigation. A recent study has been reported the accuracy of each algorithm for different propose. The result has been indicated in 4-18

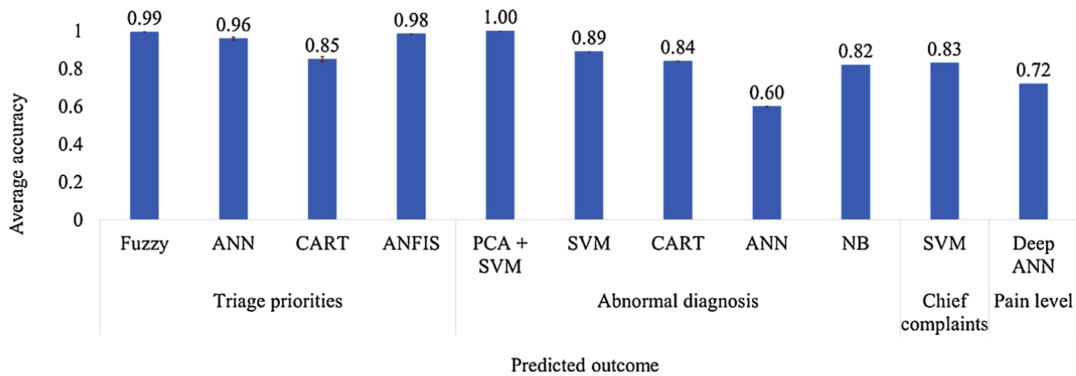


Figura 4-18: The average accuracy achieved in the performance of each test and technique with a different prediction goal. in the papers where the measure of accuracy was presented.ANN-Artificial neural networks, CART-Classification And Regression Trees, ANFIS-Adaptive Neuro-Fuzzy Inference System, PCA-Principal Component Analysis, SVM-Support Vector Machines [29]

In the following, we briefly describe the most used machine learning techniques plus those with higher performance. Advantage and disadvantage of each technique have been described:

1. Logistic Regression
   Logistic regression (LR) is a general statistical model to conduct when the dependent variable is binary. Like all regression analyses, logistic regression is a predictive analysis. LR is can describe data and the relationship between one dependent binary variable and a real number. It is used to map the probability to a certain class or event existing such as pass/fails, wins/lose, alive/dead, or healthy/sick to a nominal, ordinal, interval, or ratio-level variables [85]. RL model itself easily can model the probability of output according to input, RL

is not a classifier itself but it can be used to make a classifier, for example by picking a cutoff value and classifying inputs with probability greater than the desired cutoff value. Figure 4-19 indicates the LR equation and graph.

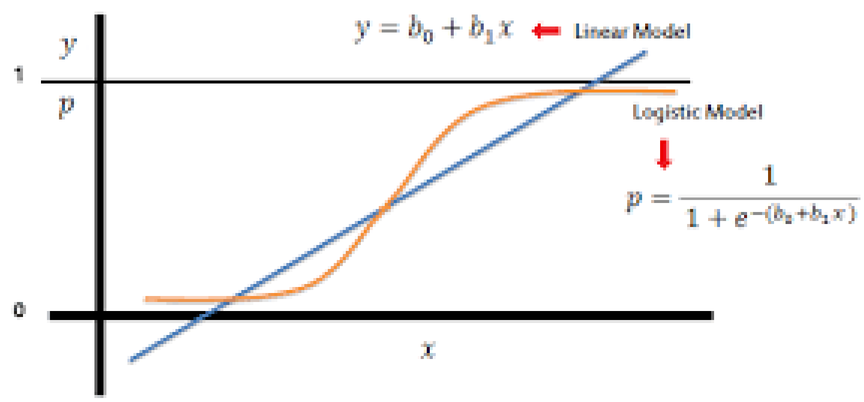


Figura 4-19: Logistic Regression

[29]. Advantages of LR include:

- If a dataset is linear LR technique performs well
- It hardly experiences over-fitting but it can happen in high dimensional datasets. In this case, Regularization (L1 and L2) techniques can be considered.
- Logistic Regression can calculate how relevant a predictor (coefficient size) as well as the direction of association (positive or negative).
- Logistic regression is simple to implement, interpret, and efficient to train.

and the disadvantage of LR are as follow:

- If the number of features is more than the number of observations then Logistic it may lead to overfitting.

- LR is limited to the assumption of linearity between the dependent variable and the independent variables while in the real world, the data is rarely linearly separable, so we can't solve non-linear problems
- LR can only be used to predict discrete functions. Therefore, the dependent variable of Logistic Regression is restricted to the discrete number set.

2. Support Vector Machine
   Support Vector Machine (SVM) is a linear model for classification and regression problems. It is a supervised learning model with associated learning algorithms that can analyze data and solve linear and non-linear problems. The algorithm creates a line or an optimal separating hyperplane for classifying new data points. The hyperplane is in a High-dimensional space that distinctly classifies the data points [38].

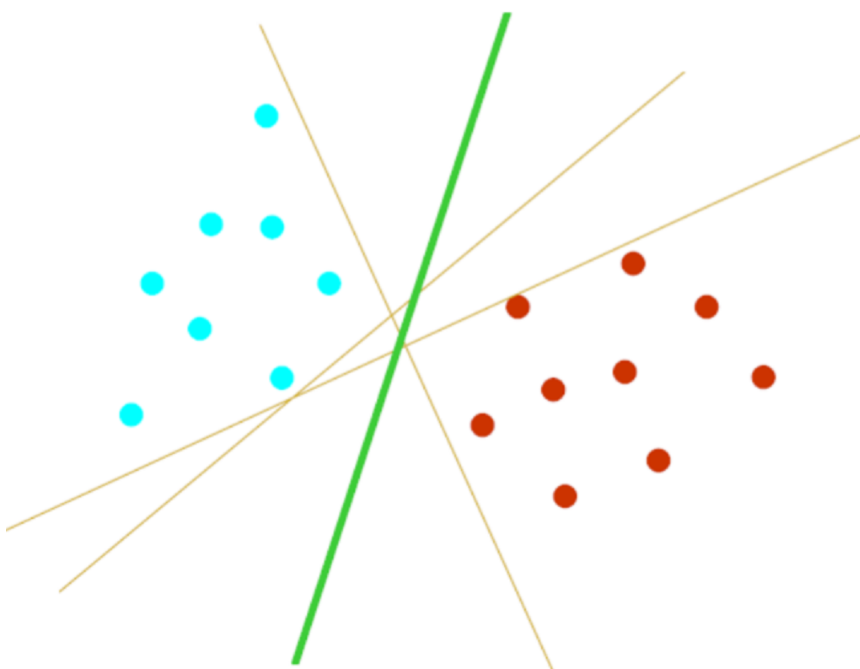


Figura 4-20: Optimal Separating Hyperplane [38]

[38]. Advantage of SVM include:

- SVM works perfectly when there is a clear margin of separation between classes
- SVM is more effective in high dimensional spaces.
- SVM is effective in cases where a number of dimensions are greater than the number of samples
- SVM is relatively memory efficient
- It can be used for even unstructured and semi-structured data such as Text, Images, and trees
- In practical result, the risk of over-fitting is low

Disadvantages of SVM include:

- SVM algorithm does not work well for large data sets
- SVM does not perform good, if the data set has more noise i.e. target classes are overlapping
- In cases where a number of features for each data point exceeds the number of training data samples, the SVM will underperform.
- As the support vector classifier works by putting data points, above and below the classifying hyperplane there is no probabilistic explanation for the classification.
- It is difficult to understand and interpret the final model, variable weights, and individual impact.

3. Naive Bayes
Naive Bayes is one of the most impressive classifiers that can have a precise result with a massive training sample of data. NB is a probabilistic machine learning classifier including a collection of classification algorithms based on Bayes' Theorem. It is simple, but at the same time, impactful and widespread used machine learning classifier. Usually, Naive Bayes classifiers are used and popular mostly for text classification [58]. These classifiers can solve some

problems incorporating Text analysis, spam detection, and medical diagnosis. Naïve Bayes has been used and investigated widely since the 1960s. Figure 4-21 shows the equation and graph of NV algorithm.

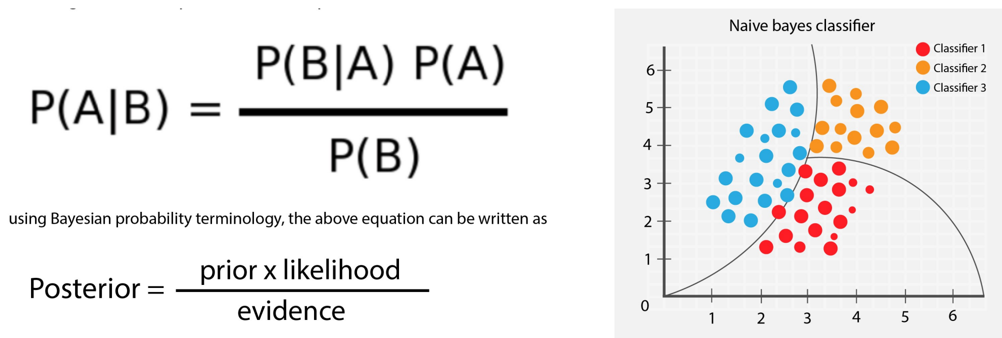


Figura 4-21: Naive Bayes [1]

Advantages of Naive Bayes method include:

- Simple to implement
- A solid mathematical foundation and stable classification efficiency
- A higher speed for large numbers of training and queries
- Good for small-scale data, able to handle multi-category tasks, and suitable for incremental training
- Less sensitive to missing data
- simple and often good for text classification;
- able to explains the results easily.
- it requires few parameters to estimate

Disadvantages of Naïve Bayes include:

- Need to calculate the prior probability;

- There is an error rate in the classification decision;
- Very sensitive to the form of input data;
- due to the assumption of sample attribute independence is used, so if the sample attributes are related, the effect is not good.

4. Fuzzy Logic
   Fuzzy classification, membership function are defined and detailed in section 4.2.1

   Advantage of Fuzzy Logic:

   - similar to human reason
   - based on a linguistic model
   - using simple mathematics for nonlinear, complex and integrated
   - rapid operation 5-high precision
   - reasoning and knowledge of human in and in the shape of membership

   The disadvantage of Fuzzy Logic:

   - for more accuracy needs more fuzzy grade which results in an increase to exponentially the rules
   - lower speed and a longer run time of system
   - lack of real tile respond
   - restricted number of usage of an input variable
   - does not simply capable of receiving feedback for implementation of learning strategy

5. Artificial Neural Network
   Artificial neural network (ANN) is a nonlinear statistical data modeling tools in machine learning. This computing system "learns"to perform the tasks and make decisions in a humanlike manner based on examples. ANN has replicated

biological neurons in brains for example, in image recognition, they could learn to distinguish if an image incorporates a dog, based on the other pictures of dogs that are labeled as a dog manually. These tools are perfect for recognizing patterns with complexity or plentiful for a human to extract and teach the machine to recognize.

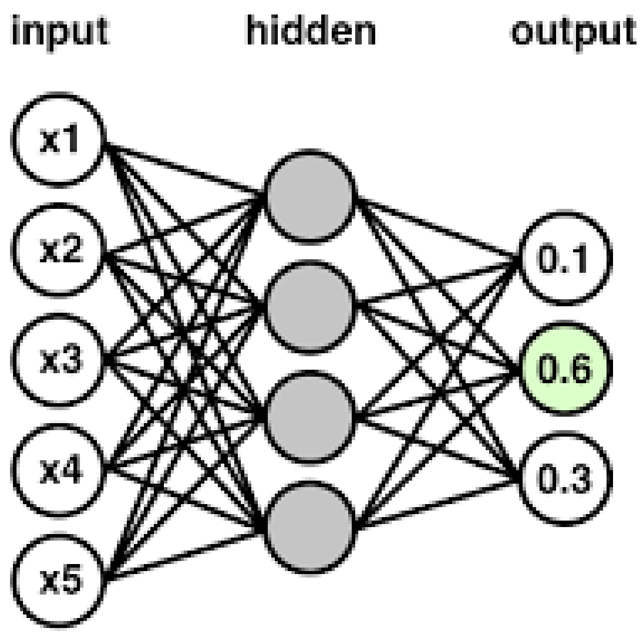


Figura 4-22: Artificial Neural Network

Advantages of Artificial Neural Networks (ANN)

- Storing information on the entire network, not on a database
- Ability to work with incomplete knowledge
- Having fault tolerance i.e. corruption of one or more cells of ANN will not avoid generating output.
- It has a distributed memory: while ANN is learning, it is a must to determine the examples and to teach the network according to the desired

output by showing these examples to the network. The network's success is directly proportional to the selected instances, and if the event can not be shown to the network in all its aspects, the network can produce false output

- The network problem does not immediately corrode immediately because it slows over time
- Artificial neural networks learn events and make decisions by commenting on similar events so in this way enable a machine to learn.
- able to Parallel processing

Disadvantages of Artificial Neural Networks (ANN)

- Because of the needs of a processor with parallel processing power, the realization of the equipment is dependent.
- the main problem of ANN is the Unexplained behavior of the network, It does not clarify why and how produces a probing solution.
- There is no characteristic rule for defining the structure of ANN.
- It is Difficult to show the problem to the network.

6. Decision Tree Learning
   A Decision Tree is a simple and supervised machine learning technique and predictive model for classification and regression. It split the data continuously based on a specific parameter. It makes a model and predicts the value of a target variable by learning simple decision rules.

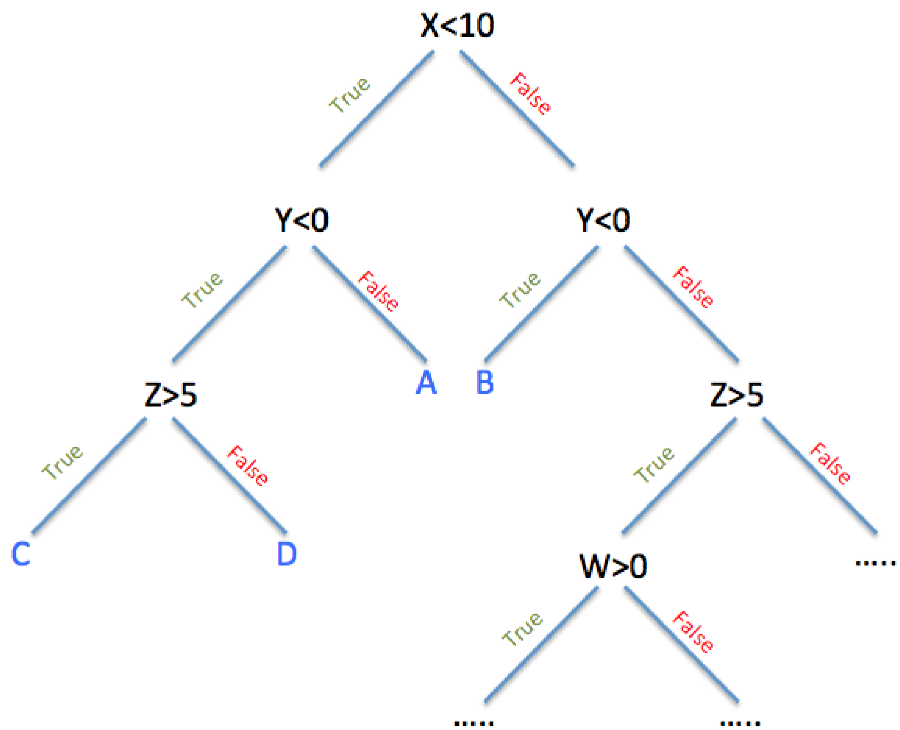


Figura 4-23: Decision Tree

Advantages of Decision Tree:

- Easy to implement and understand and intuitive
- Compared to other algorithms decision trees require less effort for data preparation during pre-processing.
- A decision tree does not require the normalization of data.
- A decision tree does not require scaling of data.
- Missing values in the data also does NOT affect the process of building a decision tree to any considerable extent.

Disadvantage:

- They are fickle, or in another word, any small change in the data can impact a massive change in the structure of the optimal decision tree causing instability. It has been reported some of the other predictors perform more accurately with similar data.
- For a Decision tree sometimes calculation can go far more complex compared to other algorithms.
- Decision tree often involves higher time to train the model.
- Decision tree training is relatively expensive and takes more time.
- Decision Tree algorithm is inadequate for applying regression and predicting continuous values.
- Sometimes calculation can be more complex compare with other algorithms.

4.3.3. Cloud structure and data storage , cloud and telemedicine

Cloud computing has many definitions but mostly accepted one is defined by Mell and Grance at [73]. It has defined cloud computing as "a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly supplied and released with minimal management effort or service provider interaction". Practically, cloud computing often is an Internet-based development that uses computing technology. The applications and data are accessible everywhere through any type of device that can have an internet connection. Using the cloud allows the user to use the application without installation. This technology provides more efficient computing by centralizing data storage, processing, and bandwidth.

Some characteristic of cloud computing incorporates:

- On-demand self-service: Cloud computing resources could be supplied as self-services without the necessity of human interaction from the service provider. These services include storage space, virtual machine instances, database instances, and so on.

- Broad network access: Services are available over the network such internet and are accessible through diverse devices such as phones, tablets, laptops, and workstations.

- Resource pooling: It allows multiple customers to share a collecting a group of resources while retaining privacy and security over their information plus maximize the advantage or minimize the risk to the users.

- Rapid elasticity: It is able to scale services up or down depends on user demand which can be unlimited and suited in any quantity at any time.

- Measured service: Resource utilization can be optimized by leveraging charge-per-use capabilities which means the user is charged according to usage.

Architecture in cloud computing is consist of component and sub-component These components typically include 1)A front-end platform that can include fat clients, thin clients, and mobile devices 2)Back-end platforms, such as servers and storage 3)Cloud-based delivery 3)A network (internet, intranet) In another definition cloud computing architecture is composed of three layers: resource, platform, and application. The resource layer is the infrastructure layer which includes physical and virtualized computing, storage, and networking resources [20]. The platform layer includes components such as web server, application server [20]. service bus [20]. The application layer serves the user and is mainly used for transaction processing and interaction. The application layer serves the user and is mainly used for transaction processing and transaction [20].

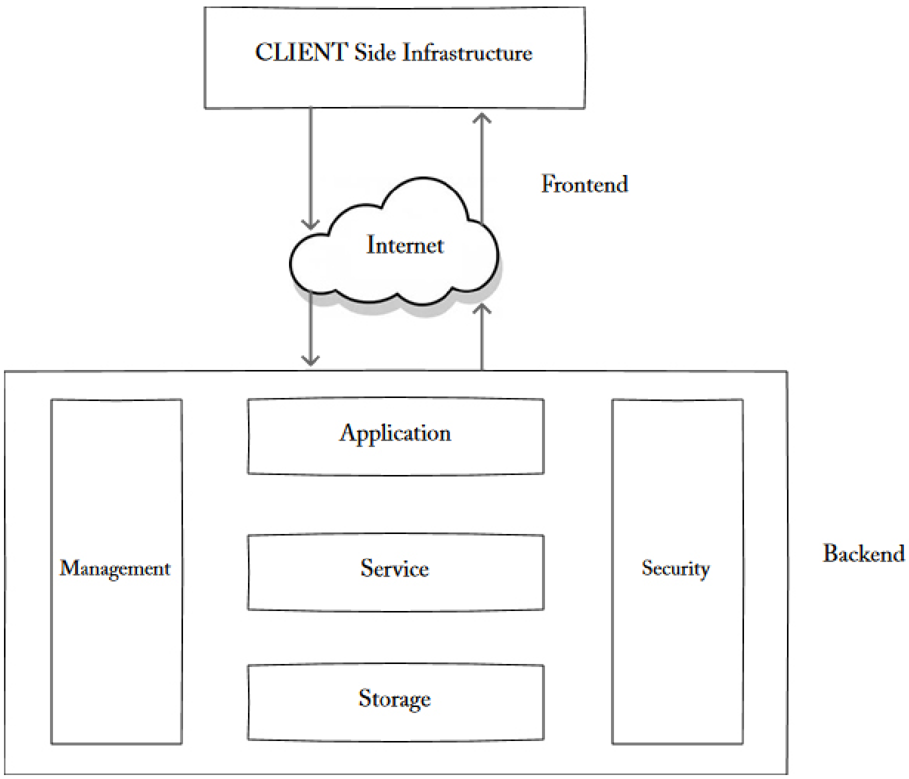


Figura 4-24: Cloud Computing Architecture

According to Mell and Grance, cloud computing includes three main models:

1. Software as a Service (SaaS); In this model, The consumer is able to use an application to meet his or her specific needs but they don't have control over the operating system, hardware, or network infrastructure on which the application is running.

2. Platform as a Service (PaaS) The consumer uses a hosting environment for application development. The consumer has control over the applications and possibly partial control over the hosting environment. The capability provided to the consumer is to deploy onto the cloud.

3. Infrastructure as a Service (IaaS) The consumer has greater access to computing resources including processing power, storage, networking components, and middleware. In general, the consumer has control over the operating system, storage, deployed applications, and possibly networking components. The consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, and deployed applications; and possibly limited control of select networking components (e.g., host firewalls) [73], [111], and [3].

4.3.4. The required components of cloud to establish the e-health model

We have investigated creating an e-health care system on the cloud. In the proposed model, the healthcare staff and the patient can connect to the cloud over the internet and use the proposed application. The patient can send clinical data and receive recommendations or an appointment, concurrently healthcare staff can store and access a patient's data. All of this intercommunication happens in SaaS. PaaS determines how this intercommunication happens. Briefly, each part has been explained as the following:

- Software as a Service (SaaS): in this part of the study, SaaS is considered a Web interface. The details are explained as follows:
  Inputs: Patient into the system, historical data of the patient
  Process: Prediction of patient evolution
  Outputs: Severity classification, online recommendations to the patient and information to the healthcare staff
  SaaS (a user-related service) provides Cloud-based software solutions (e.g. clinical systems) where patients and healthcare providers have access to the software of the cloud [**?**]. E-health care system is trying to supply medical services to focus on required clinical parameters and treat chronic patients by long-distance. Chronic patients need to follow-up their medical and clinical adherence to treatment (compliance with the recommended preventive measures), and to assess changes in their pathology. The data is collected through monitoring or by

being entered by the patient or healthcare staff and can be used for part of the treatment and sometimes for evaluating a diagnosis of the patient's condition [30],[17], [50], [90], and [87].

- Platform as a Service (PaaS): In the PaaS layer, doctors and engineers have possible control over the design, building, testing, updating, and development of online healthcare applications. So this service is used and seen by engineers. The model for sending the recommendation to patients is designed in a PaaS model by use of any machine learning classification algorithm [?].

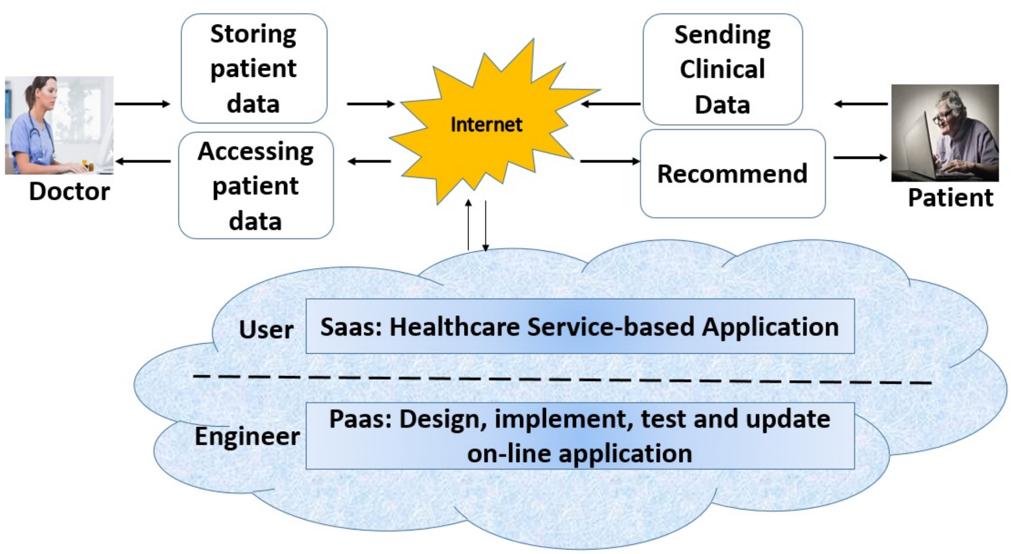


Figura 4-25: Infrastructure of E-health on Cloud computing

Chapter 5

"Errors using inadequate data are much less than those using no data at all."

- Charles Babbage.

5. Investigating Factors Impacting Health Care System Visits

5.1. Lifestyle Factors

Research demonstrates that some lifestyle factors such as tobacco habits, unhealthy diet, and physical inactivity boost the risk of chronic conditions however interventions targeting can decrease the prevalence of a chronic disease or delay the onset of these diseases significantly. We are able to anticipate the rate of mortality and disease burden attributable to risk factors. We can take into account the non-independence of risk factors, thereby providing a more realistic population attributable risk (PAR) estimates for chronic diseases than those obtained using the traditional Levin formula. In addition, We can examine the effect of reducing the relative prevalence of each risk factor by on the future prevalence of the chronic disease. GBD in the year 2016 used the comparative risk assessment framework to approximate attributable deaths, DALYs, and trends in exposure by age group, sex, year, and geography for risks from 1990 to 2016 [77]. Associated with that, we can estimate a new number of arrival (input) to the ED and investigate the impact of controlling risk factors on the efficiency of ED. Ïn epidemiology, an attributable fraction for the population (AFp) is the proportion of incidents in the population that are attributable to the risk factor. Term attributable risk percent for the population is used if the fraction is expressed as a percentage"[**?**]. For estimation of the proportional effects of future risk factors, we used a generalized version of the population attributable fraction (PAF) relationship as follows:

$$PAF_t = \frac{\sum_i^n P_{t,i} RR_{t,i} - \sum_i^n P'_{t,i} RR_{t,i}}{\sum_i^n P_{t,i} RR_{t,i}} \tag{5}$$

$P_{t,i}$ shows the proportion of population in the ith exposure category at time t in one future exposure scenario. $P_{t,i}$ is the proportion of the population in the ith exposure category at time t is an alternative future scenario. $RR_{t,i}$ indicates the relative risk of disease-specific mortality for the ith exposure category at time t and n demonstrates the number of exposure categories.

5.2. Telemedicine Factor

It has been reported that in Spain the incidence of NCDs has increased by ∼90 % (mainly due to the aging population) resulting in more frequent readmission of elderly to ED. Telemedicine usually, is use as solutions for long distance delivery of medical services to people in need in order to reduce hospital saturation for patients with less emergency condition. Including smart devices and health monitoring platforms makes electronic follow-up care and medication adherence such that non-urgent care seekers could have medical services without visiting ED. In recent years several studies were done to investigate the effect of telemedicine framework [61], the difference between online and traditional medical service quality [31] on patient safety and satisfactory for specific diseases such as dementia and chronic conditions [88], and implementation models [107]. However, these studies are scant to explain the impact of telemedicine on time and efficiency of ED and health care system. This study can report quantitative information on the role of telemedicine in ED performance. One of the objectives of this part of the research was to develop an available ED simulator using agent-based modeling[64] by taking into account differing non-urgent arrival, instead of entire arrival, as inputs into the model. The inputs were collected from statistical analysis of clinical data (collected from Parc Tauli Hospital in Sabadell/Spain) [64] that helps us to approximate how telemedicine can change the number of visits in ED. We use the ED simulator to study and speculate the impacts of potential changes in the number of arrival patients on ED output. It was hypothesized that telemedicine would reduce the saturation of ED to improve total LoS in the healthcare system.

5.2.1. Non-urgent arrival patients: clinical data collection and analyses

The ED simulator takes divers types of variables as inputs some of which need clinical data collection and analyses, statistical models, etc. Specifically, in the current study, we needed to define a set of Environment Configuration Parameters in our model as particular inputs of non-urgent arrival patients to the service. In this section, we first elaborate on methods used to obtain information on non-urgent arrival patients and their ALs, and then introduce our agent-based model and the way it works in detail.

We have defined a scenario that characterize the relationship between a number of non-urgent arrival patients and ED saturation by tracking non-urgent patients while visiting ED. Based on a Spanish triage system, patients are classified into 5 acuity levels (ALs) according to their severity indexes [66] where urgent patients classified as ALs 1, 2, and 3 and prioritized to receive treatment and physical resources. Patients with ALs 4 and 5 are considered as non-urgent patients and have less priority to have treatment. Statistical analyses of clinical data collected from Parc Tauli hospital demonstrates that approximately $\sim$ %70 of arrival patients of total ED visits are non-urgent (Table5-1).

Tabla 5-1: Classification of patients visiting ED based on their level of urgency per year (Spanish Triage System)

Acuity Level	Type of Attention	ED Visits	Number of Visit
AL1	I-resuscitation	0.39	530
AL2	II-emergent	4.36	5,905
AL3	III-urgent	25.37	34,394
AL4	IV- less urgent	50.33	68,228
AL5	V-non-urgent	19.55	26,509

Tabla 5-2: ED visits and their frequencies for patients with non-urgent AL (AL4 and 5) relative to all patients visiting ED. (Urgent: U, Non-urgent: NU)

	ED Visits ($\times 10^3$)			ED NU Visits
	U & NU	NU	Unique NU patients	Average per patient
All	135.6	94.5	64.1	1.48
$Frq \geq 2$	86.4	48.0	17.6	2.73
$Frq \geq 3$	54.8	25.9	6.5	3.99

After analyzing the real data, we discovered each non-urgent patient visits ED in average 1.5 times (Table 5-2), furthermore the same information indicates patients who visited ED at least twice (i.e., $Frq \geq 2$) made average of $\sim$ 2.7, in the same way, patients who visited ED at least three times (i.e.,$Frq \geq 3$) made averages of $\sim$ 4.0 visits per patient (Table 5-2). visits per non-urgent patient for arrival are $\sim$ 1.48 visits.

If we assume, we have a tele-ED system that there is an expert person behind it. Non-urgent patients can be connected to the ED and receive some online recommendation and medical advice remotely. A patient can be monitored and receive some clinical services. This semi-intelligent system is able to reduce the number of non-urgent and less urgent visits in Al4 and 5. Unfortunately, literature is scant to provide us sufficient information about e-health users and their possible influence on the frequency of ED visits per patient. That is why we assume a range for the frequency to be able to investigate diverse scenarios. The current frequency was replaced by the

Tabla 5-3: New annual visits of ED for different frequencies of visits per patient.(Frq: Frequency of visit per patient, P: Unique patient, V: No. of visit, % of V: is relative to 135.6)

New variable value into the ED ($\times 10^3$)						
Frq	P-AL4	V-AL4	P-AL5	V-AL5	V	% of V
0	51120	00.0	21115	00.0	040.83	30.11
1	51120	51208	21115	21118	113.15	83.44
2	11169	62377	3619	24736	127.94	94.35
3	3369	65746	1004	25740	132.32	97.58

assumed frequencies to approximate the new annual ED visits as follows:

$$NNV(i) = NP(i) * NFrq \tag{6}$$

where $NNV(i)$ is new number of visit and i is an index for AL (here we use only AL 4 and 5 that means $i = 4$ and5), $NP(i)$ is the number of unique patients with AL 4 and 5, and $NFrq$ is the new frequency per patient.

$$NNV = Numberofurgentvisits + NNV(4) + NNV(5) \tag{7}$$

where NNV is New Number of Visit in ED.

$$Percentageofnewvisits = (NNV * 100)/135{,}6 \times 10^3 \tag{8}$$

where $135{,}6 \times 10^3$ is the existing total number of ED visits per year.

The number of arrival patients into ED is changeable depending on the hour of the day or day of the week. For example, ED receives the most number of arrival patients on Mondays and the least on Saturdays. ED should be prepared to provide services to patients with 24-hour seven days a week. An arrival rate of a patient into ED has been modeled in a table of normalized hourly and daily for all days of a week [62]. To display the number of arrival patient per hour in a day and respectively, per day in a week, we use a matrix with a dimension of 24 x 7 called M

Tabla 5-4: percentage of each AL based on each Frequency in different assumptions

Percentage of each Frequency					
AL	Hospital	FRQ=0	Frq=1	Frq=2	Frq=3
1	0.39	1.30	0.47	0.41	0.40
2	04.36	14.46	5.22	4.62	4.46
3	50.33	0.0	45.25	48.75	49.69
4	3369	65746	1004	25740	132.32
5	19.55	0	18.66	19.33	19.45

Accordingly, our new estimations of ED visits for each frequency was calculated (Table 5-3) to the values in the matrix to be able to update daily/hourly ED visits as well:

$$NM = NPV * M \tag{9}$$

where NM shows the new value of new daily-hourly metrics and NPV is equal to the new percentage of visit and M indicates existing daily-hourly metrics. The New daily-hourly-metrics would be an input into our ED simulator ad the new number of arrival patients. The number of visits for AL1, 2, and 3 stay unchanged and we have the new number of visits for AL4 and 5. As AL values in our ED simulator are calculated in a form of a percentage, the new percentage of visit for each AL (for different frequencies) was computed (Table 5-4):

$$PNV(i) = NNV(i) * 100/NNV \tag{10}$$

where $PNV(i)$ shows Percentage of new visit in $AL(i)$ and i is the index for AL

5.3. result for Impact of Intelligent system on ED

As mentioned earlier, one of such output of ED simulator is the patient's LoS that is an objective indicator of the quality of care. We have evaluated and predicted LoS in ED with less non-urgent arrival according to different assumptions. Results from our assumptions indicated that ED would experience a decrease in total LoS if the same human and physical resources, as well as the same ED configuration, are used. Result for eliminating entire non-urgent visit from ED causes a significant redution (41.14 % equivalent to 1.69 million hours/year) in ED LoS (Fig. 5-1) however, it could be faraway from reality. Setting a limitation of the maximum allowed non-urgent visits to 1, 2, and 3 (i.e., Frq=1, Frq=2, and Frq=3) represents reductions in ED LoS equal to 10.48 % (0.43 million hours/year), 9.12 % (0.37 million hours/year), and 2.11 % (0.087 million hours/year), respectively (Fig. 5-1).

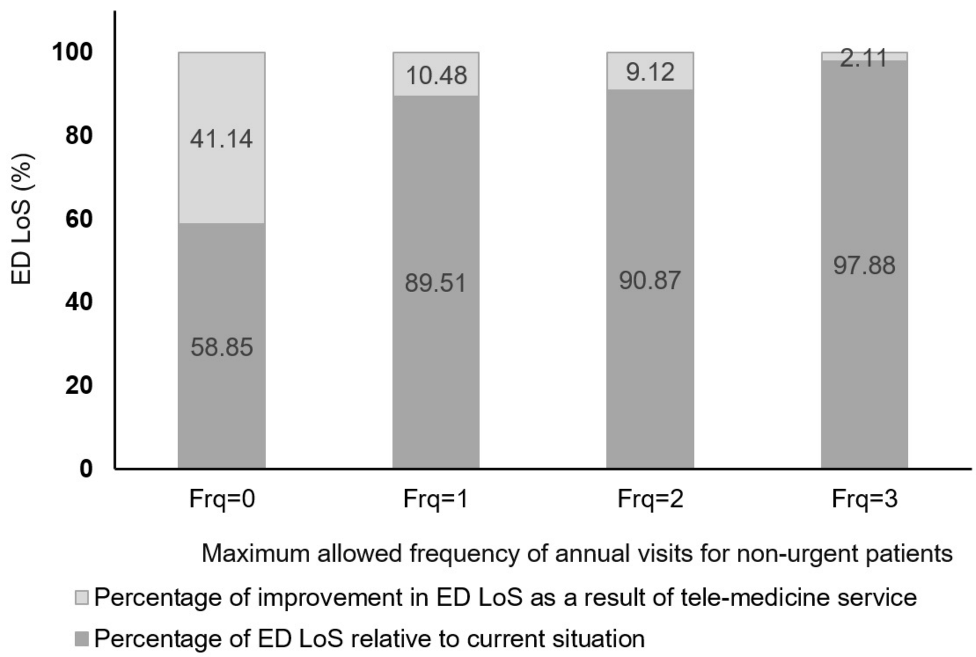


Figura 5-1: Annual ED LoS for different assumed frequencies of visits for non-urgent patients (AL 4 and 5)

Chapter 6

"The proper method for inquiring after the properties of things is to deduce them from experiments."

- Isaac Newton.

6. Conclusion and Discussion

6.1. conclusion

This research includes developing different models and studies, to investigate the influence of dependent and independent components on the emergency department. The main aim of the research was to contribute to the improvement of the quality of provided care in a hospital emergency service, trying to reduce the length of stay. It has investigated different factors that can impact on ED behavior incorporating direct and indirect factors. Direct factors include a number of arrival patients that boosts along with years and can be managed through telemedicine and indirect factor such

as lifestyle that can be controlled especially when it talks about non-urgent patients with chronic diseases.
We have studied how population aging makes more pressure on ED saturation. It can answer diverse questions for the health caregiver concerning the requirement and performance of ED in the future with massive information on desired human and physical resources within the next 20 years. Specifically, we observed, population aging along the time causes ED LoS increases, and ED saturation will occur for both optimistic and pessimistic projection scenarios whether there are neither changes in both staff and physical resources, nor some health care policies, are used. Despite variability in projection scenarios, representing a percentage of patients with NCDs and their age distribution in future years, the effect of the scenarios on ED was fairly certain and consistent.
We also have modeled the behavior evolution of patients with the chronic disease within different conditions. Analyzing the simulation outputs can help the healthcare organizer to explore how chronic patients can cope with different living conditions and health situations. The definition of an analytical model for tracking chronic patients has been a contribution to the investigation. We have designed a model to show how this characterization of behavior, predict the ideal and critical situation of the state system to measure the system performance. This analytical model provides a set of equations for the calculation of a number of patients and known composition of health configuration, with respect to the number of doctors, nurses, admission, and triage staff, at their level of experience and at the type of required attention given.
based on literature, there are some solutions to minimize the overcrowding of ED and enhance its performance. These solutions mentioned as bellows:

1) Enhancing the number of resources (e.g., physicians, nurses, physical Resources such as beds, etc.).

2) Managing arrival patients through redirecting them to different wards.

3) Using operational research methods to get a better efficiency of the resources [22].

4) Using technology and deliver remote medical and clinical services to non-urgent or less urgent patients or who can't have accessibility to the health care system.

The decision-makers with a traditional approach for constant improvement processes use the experience of the decision-makers and trial and error procedures and the experience of the decision-makers. Nevertheless, this approach incorporates some limitations such as the expenses, the amount of time required, and the unclear outcomes. It can go even more problematic when it comes to long-term and future planning. The integration of computational methods and simulations with statistical models, as to introduced in this research, prepare decision-makers with a powerful tool that can let them forecast the results of changes in the ED system or creating various scenarios without really altering the ED. Such results will have implications for optimizing resources, planning and improving the quality of care.

The results obtained by simulation help health care policy-makers to progress modifiable items associating with the need and performance of ED before reaching a critical situation. Since most EDs in Spain has equal structure and configuration, with the same following guidelines from the Spanish triage system (Sistema Español de Triage) [75], the results from our research can be generalized and to predict future of all EDs nationally [24] and [8]. Equivalently, the developed method is able to evaluate and predict the performance and quality of service of EDs in other countries with available required data and information.

This research work has been characterized as an interdisciplinary project that has allowed us to apply computational techniques to the study of phenomena of interest in the medical field, specifically in the field of Non-communicable diseases. This type of project has a special interest in the field of research and knowledge generation because it gives us the possibility of promoting scientific activity among specialists from various areas.

The world of computing in medical science is growing every day to achieve an efficient quality of life that is one of the primary advantages of integrating new innovations into medicine. Medical technologies such as minimally-invasive surgeries, better monitoring systems, and more comfortable scanning equipment are allowing patients to recover faster and enjoying a healthy life for a longer time. Non-urgent patients impose a substantial burden on ED and can be outpatients. Distribution of information via electronic devices allows long-distance patients to receive health-related services. This study can answer some questions to the health care providers and administrators regarding the efficiency of ED using e-health in the future and makes an important contribution to providing information on the quality of care delivery, economic impact, affordability, and required physical resources and staff.

Tracking behavioral of the patients in the ED is already quite challenging. The combination of the two factors like attempting out different assumptions and deep analysis of the studied models must be considered additionally. Establishing a promising system is necessary to empower all the weaknesses of the presented idea in coherence with the literature of the subject, although the process will be costly, time-consuming and not free of the risks. The first step of the implementation will be needed to use a simulation tool performing in the virtual environment. Such a tool can conduct researchers the possibility and capability of the system before going to built. Eventually, additional drivers can be taken into consideration. In the step of validation and measuring the accuracy of such a model will be needed compering the virtual model with real data, which has been historically collected from the different hospitals and similar related various resources.

6.2. Limitations

One of the most common problems in research is Missing data (or missing values). The issue of missing data can affect the conclusions significantly that can be drawn from the data. Therefore, recently, several researchers have focused on managing the missing data, problems caused by missing data, and the methods to minimize prevent such issues in medical studies [99]. Missing data demonstrates diverse issues as bellows

. 1)Insufficient data decreases statistical power, which refers to the probability that the test will reject the null hypothesis when it is false.

2) The lost data can cause bias in the estimation of parameters.

3) It can reduce the representativeness of the samples.

4) It may intricate the analysis of the research.

Each of these issues can destroy the validity of the trials and may cause invalid conclusions. While we are interpreting our findings, we must consider the limitation of the study. First, our predictions of projection and age distribution for ED simulator are created based on the pattern of Spain demography, so needless to say that Spain demography is itself a prediction of projection of long-term so our result depends on the validity of projection of Spain demography. Nevertheless, we have defined two assumptions to decrease uncertainties in our predictions, (i.e., best and worst-case scenario) and to capture extreme conditions. Another limitation was an uncompleted set of data and lack of information for arrival patients with diverse sorts of NCDs which probably, could boost the accuracy of model and result. This also could reduce biased estimates of parameters not restricting our analyses to produce accurate input. More details and information on patients, such as a number of patients in each type of disease, their education level, and the possibility of using smart devices and access to the internet and so on can contribute to a more realistic scenario for prediction of telemedicine impact on ED efficiency.
As it was mentioned before, the clinical data used in our research were collected from only limited resources (i.e., from Parc Tauli Hospital in Sabadell/Spain and from GDB, WHO). Therefore, collecting more data from more healthcare systems and using it as inputs into our models can improve the predictions of projection further. In addition, in our model for prediction of projection (2019 to 2039), we consider the total number of visits as the total patient. Since our regressions and statistical models are based on reports on a number of patients and not the number of visits there was an assumption in our study that the number of visits is proportional to the number of patients.
To project the percentage of patients with NCDs for the next 20 years, we have used linear regression. We emphasize that as to predict the best fit curve to the data point, there were only a few data points available, so, linear regression was likely a rational choice. Nevertheless, by adding more collected data points from next years into the model, we can use curves with higher accuracy to better guesstimate the right relationship for future projection of patients with NCDs.
A significant limitation of the last part of the study (Tracking the behavior on a non-urgent patient) is, using the same environment configuration (number of care

boxes and staff in areas A and B), while the number of a patient with ALs 4 and 5 is reduced in area B (for a non-urgent patient). As simulation can answer the what-if queries, we need a different configuration of staff and physical resources to get the best result for ED efficiency associated with decreasing the number of arrival patients. This model can be designed based on literature and real environment or alternative assumptive configurations.

6.3. Future Work

In this session, we have explained some possible future work. As my research topic is extensive and it can be expanded in different matters. The future works could be continued as follows:

1) Investigating, how changes in modifiable risk factors such as lifestyle can decrease the number of arrival patients with NCDs in the ED and it helps to improve the quality of service and reduce LoS of EDs.

2) Part of the study with modeling of the behavior evolution of patient heart failure, can be developed and extended for another type of chronic disease under different conditions and lifestyles.

3) In the part of the study with tracking NCD patient's behavior in the ED, it can be expanded to a specific type of disease means, a patient with a specific type of disease can be tracked individually.

4) Since it is difficult at this step to completely validate our result, outputs, and conclusions, the prediction of our model can be compared (e.g., NCDs (%) and LoS of ED) with the real data which is collected in coming years (let's say in next 5 years). This helps us firstly, evaluate the performance of our model but and secondly, adjust and update compatibility with the changeable parameters of our model to further improve its performance.

5) Future studies investigating the change of configuration, the impact of distance service for another range of frequency, specific diseases individually, decrease of arrival patients with all AIs on ED. This research can contribute to achieving a comprehensive assessment including cost, affordability of implementation, and quality.

6.4. Publications

Shojaei, E., Luque, E., Rexachs, D., Wong, A., Epelde, F. (2020, April). *A Method for Projections of the Emergency Department Behaviors by Non-Communicable Diseases from 2019 to 2039* In 2020 Journal of Biomedical and Health Informatics. IEEE.

Shojaei, E., Luque, E., Rexachs, D., Wong, A., Epelde, F. (2018, December). *Evaluation of lifestyle effects on chronic disease management.* In 2018 Winter Simulation Conference (WSC) (pp. 1037-1048). IEEE.

Shojaei, E., Luque Fadón, E., Rexachs del Rosario, D., Epelde, F. (2018). *Cloud computing application model for online recommendation through fuzzy logic system.* In VI Jornadas de Cloud Computing Big Data (JCCBD)(La Plata, 2018).

Shojaei, E., Luque, E., Rexachs, D., Epelde, F. (2017). *"Simulation as a tool for evaluating intelligent self-care systems managing chronic disease patients".* International Journal of Integrated Care, 17(5).

Shojaei, E, Rexachs D, Rexachs, D., Luque E y Epelde F. (2018) *"Management of heart failure disease through lifestyle".* (Poster)WomENcourage, BelgeradS, erbia. 2018. Web://womencourage.acm.org

Shojaei, E., Luque, E., Rexachs, D., Epelde, F *How simulation evaluates online monitoring system.* Jornadas de Paralelismo - SARTECO 2014. Málaga-September 2017. Web: http://www.jornadassarteco.org/

6.5. Submitted Journal

Shojaei, E., Luque, E., Rexachs, D., Wong, A., Epelde, F. (2020, June). *Investigating Impacts of Telemedicine on Emergency Department through Decreasing Non-urgent Patients* In 2020 Journal of Biomedical and Health Informatics. IEEE.

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Annexes

ABBREVIATION

AA	Active Agent
ABM	Agent based Modeling
AF	Attributable Fraction
AQM	Analytic Queuing Model
PAF	Population Attributable Fraction
AL	Acuity level
CDSS	Clinical Decision Support System
D	Doctor
ED	Emergency Department
Frq	Frequency
GDB	Global Burden of Diseases
IS	Informatic System
M	Matrix
NCD	Non Communicable Disease
N	Nurse
NM	New Matrix
NNV	New Number of Visit
NV	Number of Visit
NU	Non Urgent
OMRS	Online Monitoring Recommendation System
PA	Passive Agent
PNN	Percentage of New Matrix
RR	Relative Risk
U	Urgent