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Investigating Impacts of Telemedicine on Emergency Department Through Decreasing Non-Urgent Patients in Spain

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ABSTRACT In this paper, a new method is presented to study the impacts of telemedicine on the performance of an emergency department in Spain. Spain's Demographics indicate that this country is experiencing population aging, resulting in overcrowding of emergency departments and significant demand on the healthcare system. However, it has been reported that most patients visiting emergency departments are not in an urgent clinical condition, thus they causing hospital overcrowding, high medical expenses, delays in clinical service delivery and low service efficiency for urgent patients who truly need emergency care. 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 who are in less of an emergency condition. In this study, by using detailed computational modeling and clinical data, we have investigated the impacts of telemedicine on the performance of an emergency department through estimations of Length of Stay as a quantitative index for evaluation of quality of service in the emergency department. Specifically, an agent-based modeling and simulation system was developed and used to study the behavior of the emergency department by taking detailed modeling parameters, including varying the number of non-urgent arrivals as a result of telemedicine, into account as inputs of the model. The inputs were provided through collection and analysis of clinical data that enabled us to predict how telemedicine changes emergency department visits. Our results indicated that emergency departments would experience decreases equal to 41.14% in total Length of Stay if eliminating all non-urgent visits and decreases of up to 10.48% if restricting the non-urgent visits. The developed computational tool in this study and the corresponding results obtained can provide decision makers and health care providers with objective information on the impacts of e-health services on the efficiency of emergency department and they can have also implications for care delivery, optimizing resources, planning, and improving the quality of care.

INDEX TERMS Emergency department, length of stay, telemedicine and e-health, agent-based modeling and simulation, clinical data collection and analysis, non-urgent visits.

I. INTRODUCTION

An Emergency Department (ED) is a major part of a healthcare system that has to constantly provide arrival patients with medical services. The performance of an ED directly affects the quality of the healthcare system. Due to the globally increasing number of visits to EDs, the quality of the healthcare system has become a concern for healthcare providers. Spain is one of the countries experiencing population aging, and it is predicted that the elderly will be dominant demographic group by 2050. A direct consequence of population aging would be overcrowding of EDs and the subsequent demand and pressure on the system, leading to a longer ED Length of Stay (LoS) for patients [1]. ED LoS is an objective quantitative criteria extensively used in related literature for evaluation the quality and performance of EDs, and refers to

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the total time from when a patient arrives at the ED to their departure.

As soon as an arrival patient is admitted to ED process of triage begins. According to the Spanish triage system, ED visits are divided into five acuity levels (based on patients' clinical condition) in order to determine the priority of treatments and/or optimize the use of physical resources in an ED [2]. Our statistical analysis of real data set (Collect from Parc Tauli Hospital) consistent with another study [3], however, has reported that $\sim 70\%$ of patients visiting ED are not in an urgent clinical condition and can be considered as outpatients. Use of ED services for non-urgent medical care leads to hospital overcrowding, high medical expenses, delays in clinical service delivery, and a low service efficiency for urgent patients who truly need emergency care. Non- communicable diseases (NCDs), also known as chronic diseases, are one of such clinical conditions leading to frequent non-urgent visits to EDs. It has been reported that in Spain, the incidence of NCDs has increased by \sim 90% (mainly due to aging population) resulting in more frequent readmission of the elderly to EDs and [4].

Telemedicine and e-health are considered as solutions for the remote delivery of health services to care seekers in order to decrease hospital visits for patients in less of an emergency condition. Incorporating smart devices and health monitoring platforms allows us to create electronic follow-up care and medication adherence such that non-urgent care seekers could receive medical services without the need to visit an ED. In recent years, several studies have been conducted to investigate the impacts of a telemedicine framework [5], implementation models [6], and the difference between online and regular medical service quality [7] on patient safety and satisfaction for specific diseases such as dementia and chronic conditions [8]. However, the impact of telemedicine on time and efficiency of EDs and hospital utilization is not clear.

Simulation is a powerful tool that allows us to model and predict the behavior of an ED as a complex system for a given set of desired inputs. There are several modeling approaches in literature including Discrete Event Simulation (DES), Analytic Queuing Models (AQM), System Dynamics (SD), and Agent-based Modeling (ABM) to simulate complex systems such as EDs. Almost 75% of earlier ED simulation studies have been using DES that is a traditional established method. DES is more powerful for modeling complex and non-linear systems compared to AQM and SD methods, but there are some limitations on the modeling of individual entities and their behavior. These limitations cause the unrealistic representation of ED [4]. Accordingly, in recent years, agent based modeling and simulation (ABMS) systems have successfully been used to overcome such limitations and study the behavior of an ED by taking detailed modeling parameters into account. ABMS systems use a set of independent decisionmaking entities, called agents [9] which can interact with each other and with their own environment based on a set of rules. Our research group has recently simulated an ED using ABMS systems wherein patient, ED staff, and physical

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hospital resources were considered as agents whose actions and interactions were characterized by the ED simulator [3] and [4]. The simulation allowed us to analyze and predict behavior and performance of Spain's EDs for different scenarios of future projections of population and NCDs [4]. One limitation of earlier studies is that they did not investigate the impacts of non-urgent ED visits on behavior and ED performance. Furthermore, to the best of our knowledge, there is scant quantitative information in the related literature on the role of telemedicine in ED performance.

The first objective of this study was to improve an existing agent-based ED simulator [10] by taking into account a varying non-urgent arrivals, as inputs into the model. Inputs are the result of using telemedicine and e-health, which were provided through statistical analysis of clinical data (collected from Parc Tauli Hospital) [10]. It enabled us to predict how telemedicine changes the ED visits. The second objective of this study was to use the ED simulator to investigate and predict impacts of potential changes in the number of visits (from first objective) on ED performance through estimations of LoS. It was hypothesized that telemedicine would reduce the number of ED visits which in turn would result in a decrease in saturation of the ED and an improvement in hospital LoS.

II. MODELING OF EMERGENCY DEPARTMENT

A. AGENT-BASED ED SIMULATOR

Agent-based models are a class of microscale computational models that simulate operations, actions, and interactions of multiple independent entities (i.e., agents) in an attempt to reproduce and predict the behavior of a complex phenomenon/system as a whole. Our research group has developed and validated a simulator using an agent-based design of systems to predict ED behavior and performance. The model was built with collaboration of healthcare staff in Parc Tauli Hospital, Sabadell (Spain). This hospital is one of the most important in Spain, attending over 160,000 patients per year. The full model has been implemented in NetLogo simulation environment, which is an agent-based programming language and integrated modeling environment. Our research team has designed an execution engine to launch and execute the agentbased model on cluster with NetLogo. The simulation was carried out on an 8-node cluster and 2TB RAM. The simulator can receive different types of variables as inputs, some of which require clinical data collection and analyses, statistical modeling, etc. In this simulator, a spatial ABMS approach has been used to simulate actions and interactions between healthcare staff, patients and physical resources of the ED as the three types of agents in the model. Each agent has a set of attributes, behaviors, and rules through which they controls their own situation and make decisions (Fig. 1). The triage phase in ED specifies the treatment area (i.e., area A and B in Fig. 1) where patients with ALs 1, 2 and 3 are assigned to area A and stay in care-boxes during all hospitalization time and processes and patients with ALs 4 and 5 are assigned



FIGURE 1. ED workflow and actions and interactions between different elements of the system. Patients, healthcare staff, and physical resources of ED were modeled as agents in the simulator. Areas A and B were designed for urgent and non-urgent patients respectively and have their own allocated staff [11] and [4].

to area B to receive treatment. All patients in admission and triage phases have the same nurses and healthcare staff. After triage, in diagnoses and treatment stages, separate doctors and assistant nurses serve at each area while sharing same test service resources such as laboratory test, X-Rays, etc [11]. The non-linear behavior and actions/interactions of agents in our ABM have been characterized by if-then rules according to signals the agents receive: If [signal vector x is present], Then [execute act y. If an agent is busy with an interaction while a signal is received, the signal will be pushed into its task queue, [4] and [12]. In addition to the existing inputs in our simulator, a set of Environment Configuration Parameters, which are particular inputs of non-urgent arrival patients to the service, were generated (Fig. 2 and Fig. 3). These inputs included the non-urgent arrival patients and their ALs (Fig. 3) (see also the next section where we have elaborated on methods used to obtain information on non-urgent arrival patients and their ALs, and have investigated the potential impacts of telemedicine and e-health on such inputs). As soon as a patient visits the ED in our model, the simulator starts running and different steps including admission, triage, diagnoses, treatment, and discharge are executed (Fig. 2).

Outputs of the agent-based simulator are: 1) interaction information of all agents in the form of four Ws (who, when, where, why) and one H (How long does it take i.e. LoS) 2) performance information of ED environment, including number of waiting patients, utilization of physical resources, and occupation of healthcare staff. Therefore, the simulator does not provide explicit information about the behavior of the simulated ED, and such information should be derived through the cross-analyzing of different simulation scenarios [13]. Specifically, the focus of this study has been on ED LoS, as this index is an objective measure of ED quality and performance. In the following section we have integrated **TABLE 1.** An example of an if-then rule for patient's agent. Patients in the ED are guided by the information system (IS), which is a system for communicating and coordinating among staff, patients and test rooms. Patients go to a relevant place to receive treatment/service when they are notified, and stay in their current place otherwise. 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.

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

clinical data and computational approaches to define nonurgent (i.e. AL 4 and 5) ED visits and frequency of visits per patient for different scenarios. The scenarios were designed to take the impacts of telemedicine into account by assuming that e-health system can remotely connect non-urgent patients to the ED and reduce the number of ED visits for these patients. These scenarios were then implemented into our simulator (to specify the number of ED visits and acuity levels for the patient's agent, as indicated in Fig. 3), and ED LoS was calculated for each scenario as the outcome of ED simulation.

B. NON-URGENT ARRIVAL PATIENTS: CLINICAL DATA COLLECTION AND ANALYSES

To define the relationship between number of non-urgent arrival patients and ED saturation, we have followed these patients when visiting the ED. In the triage stage, patients are classified into 5 acuity levels (ALs), [2] and [14] where patients with ALs 1, 2 and 3 are considered as urgent patients and prioritized to receive treatment and/or physical resources according to the Spanish triage system [14]. Patients with



Output

LoS: obtained directly,(How long does is take) **Ws**: can be derived through cross-analyzing (who, when, where, why)

FIGURE 2. General workflow of ABM simulator wherein patients, ED staff, and physical hospital resources were considered as agents. Number of arrival patients and their ALs were attributed to the patient agent, and actions and interactions between the agents were modeled in the ED simulator. LoS of ED, as an index of healthcare quality, was directly obtained from the simulator.



FIGURE 3. Inputs of patient's agent into the model including age distribution, body condition, location, acuity level, and number of visits. Acuity level and number of visits were introduced as new variables into the patient's agent and were defined through clinical data collection and analyses.

ALs 4 and 5 are classified as non-urgent patient who have a lower priority to receive treatment and/or physical resources. Statistical analyses of clinical data collected (from Parc Tauli hospital) indicate that arrival patients with ALs 4 and 5 are responsible for $\sim 70\%$ of total ED visits (Table 2). Information on ED visits and frequency of visits for patients with AL 4 and 5 relative to all patients visiting the ED demonstrate that the average number of visits per non-urgent patient is ~ 1.48 visits (Table 3). This means that on average $\sim 50\%$ of non-urgent patients are readmitted to the hospital. Furthermore, patients who visited the ED at least twice (i.e., $Frq \geq 2$)

TABLE 2. Classification of patients visiting the ED based on their level of urgency (Spanish triage system). The data represent 1 year of ED visits (collected from Parc Tauli Hospital in Sabadell/Spain).

| 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 |

TABLE 3. ED visits and their frequencies for patients with non-urgent AL (AL 4 and 5) relative to all patients visiting ED. (Urgent: U, Non-urgent: NU). The last column was obtained through the division of the column 3 by the column 4(Avg: Average).

| | | ED NU Visits | | | | |
|-------------|--------|--------------|--------------------|-----------------|--|--|
| | U & NU | NU | Unique NU patients | Avg per patient | | |
| All | 135.6 | 94.5 | 64.1 | 1.48 | | |
| $Frq \ge 2$ | 86.4 | 48.0 | 17.6 | 2.73 | | |
| $Frq \ge 3$ | 54.8 | 25.9 | 6.5 | 3.99 | | |

and three times (i.e., $Frq \ge 3$) made averages of ~ 2.7 and ~ 4.0 visits per patient, respectively (Table 3).

We assume there is an e-health system that can connect non-urgent patients to the ED and reduce the number of visits for AL4 and 5. These patients can remotely be monitored and receive remote medical services. Because of scant information on e-health users and their potential impact on frequency of ED visits per patient, we considered a range for the frequency in order to be able to study different scenarios (Table 4). The existing frequency was replaced by the proposed frequencies to estimate the new annual ED visits as follows (Table 4):

$$NNV(i) = NP(i)NFrq$$
 (1)

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

NNV = Number of urgent visits + NNV(4) + NNV(5)(2)

where NNV is New Number of Visit in ED.

$$PNV = \frac{NNV * 100}{135.6 \times 10^3}$$
(3)

where *PNV* is the percentage of new visits relative to current visits and 135.6×10^3 is the existing total number of ED visits per year (the sum of all values in the last column of Table 2. In addition, a second more conservative scenario was defined wherein only the least urgent group (AI 5) was assumed to receive e-health services. Patients with AL 5 comprises $\sim 19.55\%$ of non-urgent visits (Table 2) so that by solely reducing their ED visits may significantly contribute to a reduction of ED demand and the corresponding ED LoS. As such, in this scenario we assumed ED visits for AL 1, 2, 3 and 4 are constant but for AL5 they are replaced with new number of visits corresponding to different frequencies (the

TABLE 4. New annual visits of ED for different frequencies of visits per patient. (Frq: frequency of visits per patient, P: unique number of patients, V: number of visits). The last two columns are relative to the existing total number of ED visits (i.e. 135.6×10^3).

| | new valu | e of variab | ED visit (%) | | | | |
|-----|----------|-------------|--------------|-------|-----------|-----------|-------|
| Frq | P-AL4 | V-AL4 | P-AL5 | V-AL5 | ED visits | AL4 + AL5 | AL5 |
| 0 | 51.12 | 0.0 | 21.11 | 0.0 | 40.83 | 30.11 | 80.45 |
| 1 | 51120 | 51208 | 21115 | 21118 | 113.15 | 83.44 | 96,02 |
| 2 | 11169 | 62377 | 3619 | 24736 | 127.94 | 94.35 | 98.69 |
| 3 | 3369 | 65746 | 1004 | 25740 | 132.32 | 97.58 | 99.43 |

TABLE 5. Number of ED visits for different days and hours. Each row represents a day of the week and each column represents an hour of the day.

| 24 hours of a day, (00:00 am to 23:59 pm) | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 7 | 6 | 5 | 4 | 3 | 3 | 4 | 4 | 6 | 10 | 16 | 24 | 22 | 20 | 17 | 15 | 20 | 20 | 17 | 17 | 15 | 17 | 13 | 10 | 9 |
| day | 6 | 4 | 3 | 3 | 3 | 3 | 3 | 5 | 9 | 16 | 18 | 19 | 17 | 15 | 13 | 16 | 17 | 15 | 15 | 15 | 15 | 15 | 13 | 10 |
| a | 6 | 5 | 4 | 3 | 3 | 3 | 3 | 5 | 9 | 15 | 19 | 18 | 17 | 16 | 14 | 16 | 17 | 15 | 15 | 15 | 14 | 12 | 10 | 8 |
| week | 6 | 4 | 4 | 3 | 3 | 3 | 4 | 5 | 9 | 14 | 20 | 19 | 17 | 15 | 13 | 16 | 17 | 14 | 15 | 15 | 15 | 13 | 11 | 8 |
| (Monday | 6 | 4 | 3 | 3 | 3 | 3 | 4 | 4 | 8 | 15 | 19 | 18 | 16 | 15 | 13 | 16 | 17 | 16 | 14 | 15 | 14 | 13 | 10 | 8 |
| to | 6 | 5 | 5 | 4 | 4 | 4 | 4 | 5 | 7 | 11 | 16 | 18 | 16 | 13 | 12 | 13 | 15 | 14 | 13 | 13 | 12 | 11 | 9 | 8 |
| Sunday) | 7 | 5 | 5 | 5 | 4 | 4 | 4 | 5 | 7 | 11 | 16 | 20 | 18 | 14 | 13 | 14 | 14 | 14 | 14 | 13 | 13 | 11 | 10 | 7 |

results are presented in the last column of Table 4). The new number of visits for this scenario is calculated as:

NNV = (Number of visits for AL 1 to AL 4) + NNV(5)(4)

It should also be noted that the number of arrival patients changes based on time of the day and day of the week. For instance, the ED gets the maximum number of arrival patients on Mondays and the minimum on Saturdays. The 'ED provides patients with 24-hour services seven days a week. An arrival rate model carries a table of normalized hourly and daily patient arrival for all days of a week [15], as it is shown in Table 5.

Accordingly, we applied our new estimations of ED visits for each frequency (Table 4) to the values in Table 5 so as to be able to update daily/hourly ED visits as well:

New dailyhourly metrics

= New percentage of visit * dailyhourly metrics

We have a constant number of visits for AL 1, 2 and 3 and new number of visits for AL 4 and 5. Since AL values in our ED simulator are entered in the form of a percentage, the new percentage of visits for each AL (for different frequencies) was calculated (Table 6):

Percentage of new visits in
$$AL(i) = \frac{NNV(i) * 100}{NNV}$$
 (5)

where *i* is the index for AL (i = 1 to 5). The *NNV*(*i*) values for AL 1, 2, and 3 can directly be taken from the last column of Table 2, as these numbers are not affected by new values of frequencies.

Similarly, for the second scenario, where only the least urgent group (AL 5) was assumed to receive e-health, the new percentage of visit for each AL (for different frequencies) was calculated (Table 7).

New daily/hourly metrics and results obtained in Table 7 were used in our ED simulator as input to estimate ED LOS.

| TABLE 6. | Percentag | e of each | AL for | different | frequencies. | The second |
|-----------|------------|-----------|----------|-----------|--------------|------------|
| column re | presenting | the curr | ent situ | ation wa | s taken from | Table 2. |

| | Percentage of each AL for different frequencies | | | | | | | | | |
|----|---|-------|-------|-------|--------|--|--|--|--|--|
| AL | Current situation | 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 | | | | | |

TABLE 7. Percentage of each AL for different frequencies when only AL 5 group receives e-health services. The second column representing the current situation was taken from Table 2.

| Percentage of each AL for different frequencies | | | | | | | | | |
|---|---|-------|-------|-------|-------|--|--|--|--|
| AL | Current situation FRQ=0 Frq=1 Frq=2 Frq=3 | | | | | | | | |
| 1 | 0.39 | 0.48 | 0.42 | 0.41 | 0.40 | | | | |
| 2 | 4.36 | 5.42 | 4.73 | 4.60 | 4.57 | | | | |
| 3 | 25.37 | 31.5 | 27.57 | 27.20 | 26.61 | | | | |
| 4 | 50.33 | 62.56 | 54.70 | 53.20 | 52.8 | | | | |
| 5 | 19.55 | 0 | 12.57 | 14.9 | 15.61 | | | | |

III. RESULT

An ED simulator can have various outcomes, including interaction information of patients, healthcare staff, and physical resources. One such piece of interaction information is patient LoS in ED, which is an objective indicator of the quality of care. We have evaluated and predicted ED LoS for different scenarios with regards to frequency of non-urgent arrivals. We assumed there is an e-health system that can connect non-urgent patients to the ED and reduce the frequency of visits for non-urgent patients (ALs 4 and 5, or only AL 5). We considered a range for the frequency and replaced the existing frequency by the proposed frequencies to estimate the new annual ED visits.

Our results indicated that ED would experience a decrease in total LoS through reducing frequency of non-urgent visits as a result of telemedicine, provided that the same human and physical resources, as well as same ED configuration,



Percentage of improvement in ED LoS as a result of tele-medicine service
Percentage of ED LoS relative to current situation

FIGURE 4. Annual ED LoS for different assumed frequencies of visits for non-urgent patients (AL 4 and 5).



FIGURE 5. Annual ED LoS for different assumed frequencies of visits for patients with AL 5.

are used. Removing non-urgent visits (i.e., Frq = 0) resulted in a significant reduction (41.14% equivalent to 1.69 million hours/year) in ED LoS (Fig. 2). However, a frequency of zero for non-urgent visits may not represent a real situation. By restricting the maximum allowed non-urgent visits to 1, 2, and 3 (i.e., Frq = 1, Frq = 2, and Frq = 3), we observed 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. 4).

Eliminating only patients with Al 5 (i.e., Frq = 0) resulted in a reduction of 11.54% (equivalent to 0.476 million hours/year) in ED LoS (Fig. 3). Furthermore, restricting the maximum allowed non-urgent annual visits to 1, 2, and 3 (i.e., Frq = 1, Frq = 2, and Frq = 3) led to reductions in ED LoS equal to 2.92% (0.12 million hours/year), 0.72% (0.029 million hours/year), and 0.31% (0.012 million hours/year), respectively (Fig.5).

Applying telemedicine to patients with ALs 4 and 5 versus patients with AL 5 resulted in larger differences between the two conditions (i.e., 41.14% versus 11.54% improvements in ED LoS) for the scenario of removing the visits (i.e., Frq = 0) as compared to other three scenarios (i.e., Frq = 1, Frq = 2, and Frq = 3). The maximum difference between the two



FIGURE 6. Comparison between percentage of ED LoS relative to current situation for two different conditions: 1) telemedicine applied to all non-urgent patients (i.e., ALs 4 and 5), 2) telemedicine applied only to patients with AL 5.



FIGURE 7. Comparison between percentage of improvements in ED LoS as a result of telemedicine service for two different conditions: 1) telemedicine applied to all non-urgent patients (i.e., ALs 4 and 5), 2) telemedicine applied only to patients with AL 5.

conditions for these three scenarios was found to be 9.12% versus 0.72% improvements in ED LoS (Fig. 6 and Fig. 7).

IV. DISCUSSIONS AND CONCLUSION

Traditionally, several solutions have been proposed to reduce overcrowding, ED LoS and improve its performance. These solutions include increasing resources (e.g., physicians, nurses, and physical resources), managing patients through redirecting them to different wards, and applying operational research methods to increase the efficiency of the resources [16]. While literature is well-established on studying the traditional solutions, less research has been conducted to objectively investigate the impacts of advanced technologies such as telecommunications on the performance of ED. Telemedicine and e-health allows health care professionals to evaluate, diagnose and treat patients using telecommunications technologies such as smart devices and health monitoring platforms. Telemedicine is time-saving for both patients and physicians, less costly and, in many cases, more effective than other health care options. Specifically, telemedicine can subrationally be important when it comes to patients with less

of an emergency condition who impose a significant burden to EDs, diminishing their performance and quality of service.

Integration of computational methods and simulations with clinical data, as conducted in this study, provided us with a powerful tool to predict the results of changes in an ED system or designing different scenarios without actually altering the ED. The main objective of this study was to use the ED simulator to investigate and predict impacts of potential changes in the number of visits, as a result of telemedicine and e-health, on ED performance through estimations of LoS. Our hypothesis on the decreases in saturation of ED and improvements of ED LoS through limiting non-urgent visits of ED was confirmed. Specifically, we observed improvements from $\sim 2\%$ to $\sim 41\%$ in ED LoS for a partial (i.e., up to 3 annual visits) to a full elimination of less urgent (i.e., AL 4 and 5) visits of ED, respectively. Furthermore, for non-urgent (i.e., AL 5) visits of ED we observed improvements from $\sim 0.3\%$ to $\sim 12\%$ in ED LoS for a partial to a full elimination of ED visits. The developed computational tool in this study and the corresponding results obtained will provide decision makers and health care providers with objective information on the impacts of e-health services on ED efficiency and it will have implications for care delivery, economic impacts, optimizing resources, planning, and improving the quality of care. As most EDs in Spain have the same structure and configuration, and follow guidelines from the Spanish triage system (Sistema Español de Triage) [17], the results from this study can be generalized and used nationally to predict the future of all EDs in Spain with regards to the impacts of telemedicine and e-health on ED performance. Similarly, the method developed here can be used to asses and forecast performance and quality of service of EDs in other countries, provided that required data and information are available.

The findings from this work should be interpreted with consideration of our study limitations. Firstly, because of the scant information on e-health users and their potential impact on the frequency of ED visits, we considered a range, rather than a certain value, for the frequency of ED visits. Such an assumption, however, allowed us to study different scenarios, including marginal cases (e.g. Frq = 0 and Frq = 3), to have conservative estimates from the upper and lower ends of the reduction in ED LoS. Secondly, the clinical data used in this study were collected from only a few resources (i.e., from Parc Tauli Hospital in Sabadell (Spain) and from GDB, WHO). Therefore, collecting data from more hospitals and using these data as inputs into the model can further improve predictions of ED behavior. Thirdly, for ED simulation we used same environment configuration such as number of care boxes and staff in areas A and B for different scenarios of frequency of visits, while the number of patients with AL 4 and 5 dropped in area B. Designing a system that can take a flexible environment configuration of ED into account will further improve the reliability of the results, though such a design needs data collection and analysis from the real ED environment. As future work, we plan to continue with the investigation of the impacts of telemedicine on ED performance through narrower information/data on configuration of staff and physical resources as well as information/data on the patient input such as type of disease, level of education, ability to use smart devices, etc.

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