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Evaluating the impact of human resource management on the patient flow at an outpatient orthopedic clinic

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ABSTRACT

This paper treats the problem of patient flow in an outpatient orthopedic clinic. A detailed description of the system and the main pathways followed by patients during their care process are provided. In fact, analyzing the patient flow has served to improve healthcare delivery in this clinic by identifying the sources of delay which are mainly related to inefficient human resources management. Therefore, a list of improvement scenarios is proposed and evaluated using discrete event simulation model. The proposed changes have resulted in a great improvement in terms of minimizing the patient waiting time (WT) and total length of stay (LOS). Furthermore, we proposed a multiple linear regression model that helped us to analyze the relationship between the performance-related factors (WT and LOS) and the influencing variables related to patient flows. Indeed, these models enable managers to plan reorganization of this outpatient clinical and adopt the suitable strategies for each type of pathway.

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Patient flow; pathway; waiting time; length of stay; discrete event simulation; multiple linear regression

Introduction

Hospitals today strive to meet the growing demand subject to limited resources. In other words, there are different and limited resources (human and material) in hospitals that need a good planning and utilization [1] in order to set a balance between the supply and the demand for services. The outpatient clinics are among the services that suffer from congestion and, therefore, require good resources and patients management. In fact, these hospital divisions face an increasing pressure to improve the quality of their services [2]. In this paper, we selected a case study from a Tunisian hospital. In fact, the Tunisian healthcare system is divided into two sectors: the public sector that acquires the 40% of the health infrastructure and the private one that receives the rest. The majority of the Tunisian people prefer to seek medical care in government/public hospitals over private ones on seeing the free treatment they offer. This circumstance has put pressure on these facilities and has prompted the government to ameliorate this sector. Indeed, the health expenditure in Tunisia contributes to only 5% of the gross domestic product (GDP). This is considered as very poor contribution compared to the USA (17%) and the large European countries (about 10%) [3]. In fact, there have been many continuous efforts from the Tunisian government to maintain and to improve the healthcare system such as developing the social security fund as well as improving the accessibility of hospital in-patient and outpatient care. Tunisia has also focused on improving the management process to become more efficient by training staff on better communication skills. But, nonetheless these efforts, another reality that could not be hidden is that the Tunisian public hospitals are actually becoming inadequate in providing the proper treatments that are needed. Hospitals have become under staffed due to lack of funds, which has caused highly trained doctors and nurses to leave the publicly run facilities. This has caused overcrowded and long waits in the public sector.

Our case study is an outpatient orthopedic clinic in one of the most recognized public hospitals in Tunisia (Habib Bourguiba hospital). Indeed, outpatient clinics in Tunisian public hospitals, in particular, Habib Bourguiba hospital, are using a block scheduling appointment system that consists of bringing all the patients in the morning and keeping them waiting until their turn comes. As an example in our case study, the outpatient orthopedic clinic, all patients are required to come at the beginning of the session. This brings about a tremendous waste of their time, creates congestion, and puts further pressure on the medical staff. Therefore, according to several staff members, patients are not satisfied with their long waiting time (WT). Moreover, the lack of hospitals and healthcare facilities outside of the major cities requires the ill to make an extensive journey for treatment. All these causes and others motivated us to study the patient flow problem

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in this clinic in order to establish a relationship between their length of stay (LOS) and the number of human resources. Accordingly, the patient WT and LOS are maintained under control.

The main contributions of this paper can be summarized as follows:

- Detecting the mains pathways followed by patients during their care process.
- Using the simulation modeling to detect the sources of patient delay in each pathway.
- Using the linear regression model to establish a relationship between the human resources number and patient LOS.
- Propose a list of improvement scenarios that help the manager to adopt suitable decisions to minimize patient WT and LOS in each pathway.

Literature review

Patient flow is still one of the most important issues of the hospitals [4,5]. It can be defined as the movement of patients through stages of care. It covers everything (such as medical care, support, etc.) from the point of admission to the point of discharge. According to Sheahan [6], patient flow evaluates the length of time required for patients to be admitted, fill out their paperwork, submit their vitals, and see a doctor. It reflects how quick and efficient hospitals are in providing healthcare services.

In fact, improvements in healthcare quality ensure the improvement of health status and enable the attainment of desirable health outcomes [7]. This improvement may be associated with a continuous quality improvement process that starts with identifying problems and ends with providing corrective action. The study of the patients' flow may help to find different factors that affect the effectiveness of hospital or its departments [8]. The continuous increase in the number of patients arriving to services is one of the factors that make the patient flow management problematic. Actually, this task reveals some problems that are related to the space and resources (human and material) management [9]. According to Bhattacharjee and Ray [10], the complexities in patient flows are mainly due to the existence of various care pathways (that may depend on many factors such as the severity of illness, the decisions taken by physicians, the progression of patient's health status). The very large number of stages in the service and the various priority rules for patients to be seen by a physician or to be investigated at a radiology department. Therefore, modeling of patient flows plays a key role in improving healthcare delivery. In fact, it helps to find the most influential factors affecting the performance of the system and exploring the interrelationships between parameters.

Actually, the patient flows are considered to be very complex because of the different pathways patients may take and the inherent uncertainty and variability of healthcare processes [11]. In fact, the patient pathway is the list of stages the patient passes through from its arrival to care facility under leaving. It does not necessarily contain all the stages of the care process. In addition, the pathway can be different from patient to another according to the health status of each one.

Indeed, managing patient pathway could help in determining the best configuration and number of resources. It also allows managers fixing the source of dysfunction and source of long WT. In this context, in a British Columbia center, Santos et al. [12] focused on the problem of modeling, the pathway of patients with acute spinal cord injury. By studying three typical scenarios, they found that modeling the system highlights the indirect impact of several medical and administrative interventions. The practical results reduced the LOS, the WT and decreased the use of rehabilitation beds.

The WT is one of the problems related to the patient flow treated in the literature. In fact, the service bottlenecks arising from the ill-managed patient flow could result in excessively long WT for patients for various hospital departments such as the radiology departments [13]. In Canada precisely Calgary, Alberta, Rohleder et al. [14] treated the problem of patient's WT in an orthopedic outpatient department. They proposed scenarios for improvements that are based on adding new resources and reviewing appointments. The results showed a substantial reduction in time. In fact, about 200 h of patient time is saved every month on average with an average monthly volume of 1000 appointments. In the same context, Ahmed and Alkhamis [15] proposed an aid decision tool for an emergency service in a governmental hospital in Kuwait. The main contribution of the research is the increase of the patient's flow by 28% and the reduction of the average patient's WT by 40%. To shorten the imaging center WT in Chile, Ramis et al. [16] used a Flexsim GP simulator. The researchers identified all the flows, resources, schedules and exams. After comparing seven configurations, they arrive to reduce the total patient WT by 35% without changing the staff, but the assignment of common functions. Therefore, the productivity of the center can be increased by 54%, assuming infinite demand. According to the literature review and to the best of our knowledge, models that have been used for the handling of the patient flow problem are empirical.

Indeed empirical models are very suitable for this kind of problems. They are based on observations of the system characteristics and experimentations on the system in order to analyze the relationship between the performance-related factors and the influencing variables and parameters related to patient flows [10].

In addition, there are a very few studies, in the literature, which apply statistical techniques for modeling patient flows and determining WT measures [17–21]. Indeed, this paper can be considered as one of these few papers. In fact, in addition to the simulation modeling which is used to model the patient's pathway, we used the statistical modeling (precisely the linear regression model) to analyze the relationship between the average LOS and the different proposed scenarios.

One of the patient flow-related problems is the human and material resources management. In fact, in hospital,

> employees have all kinds of qualifications, and many can (or must) be assigned to various tasks. For instance a nurse can register patients, do night surveillance or assist a surgery. The available human resources have to be scheduled to meet various requirements such as to insure service enforce the rules, assign unpopular shifts in a fair manner and last but not least get the best service at the least cost. [22]

Thus, a poor human resource management or a lack of human resources can affect the overall care process and causes many problems such as long patient's WTs and overtimes for personals and medical stuff. In addition, there are some factors that affect the health professionals performance such as work engagement and work alienation. Consequently, they affect the whole performance of the hospital performance [23]. In fact, the hospital's performance, effectiveness, and image could be also be greatly influenced by the health professionals' tendencies in exerting organizational citizenship behavior [24].

One alternative for improving the performance of a healthcare delivery process is through making changes in the process of care. Such changes may include eliminating unnecessary activities, eliminating duplicate activities, performing some of the activities in parallel, and identifying alternative process flows [10].

In fact, the major contribution of this work is to show how to explore the linear regression model to handle with the patient flow problem by detecting the variables influencing the patient average LOS. In fact, this time contains the WT and the time of service at each stage of the care process. The use of the time service is justified by the fact this later is not constant. In reality, this time is defined by probability distributions. Thus, by determining the influential variables that affect the patient LOS, we help managers to adopt the suitable decisions to improve clinical performance and improve the patient satisfaction.

Methodology

Process description and data collection

In this paper, we used as case study the outpatient orthopedic clinic of Habib Bourguiba hospital of Sfax, Tunisia. It is considered as one of the most congested department. In order to understand the functioning of the actual system and collect necessary data to model the patient pathways, we conducted an on-filled survey from one month for an average of 100 patients per day. This survey allowed us to collect statistics on patient's arrivals and service times that helped us to determine the patient arrival rates during different days of the week and the distribution of service times at each stage of the service.

Indeed, from a structural point of view, the outpatient orthopedic surgery department has seven functional sub-assemblies: admission, consultation of surgery (resident), consultation of medicine (assistant), plaster room, radiology, and treatment room. Usually, this public healthcare department receives a daily variable demand ranging from 150 to 200 patients per day that should be treated. But, given that some appointments are made outside this outpatient clinic, the number of patients cannot be known in advance, which causes a variable workload for the orthopedists. This clinic is open from 6:30 am, but registration generally starts at 7 am. A total of one radiologist, five orthopedists (divided into two residents and three assistants), four receiving agents (for registration and payment tasks) and three nurses (assigned to the following tasks: bandage, plaster removal, and making appointments) are working 5 days a week from Monday to Friday. In fact, the current outpatient department brings all the patients in the morning and keeps them waiting until their turn comes.

At the admission, patients are divided into two groups: patients who undergo a surgery will be assigned to the two residents and the rest will equally be divided between the three assistants. Depending on the case, after the registration and payment process there is two main patient pathways: the first which contains the medical consultation (with an assistant) is the shortest one while the second is the longest pathway during which the patient should meet a resident (the surgical consultation). In fact, the tasks through which patients pass in each pathway are respectively:

(1) Patient directly meets the orthopedist (assistant) then fixes an appointment (if necessary) or
(2) Patient meets the orthopedist (resident), goes to the radiology after removing the plaster, then meets his orthopedist for the second time, and finally fixes an appointment (if necessary).

Two types of pathways can be disengaged from this and schematized as follows (Figure 1):

Discrete event simulation modeling

The DES is used to model the patients' flow into the outpatient orthopedic clinic in order to detect the

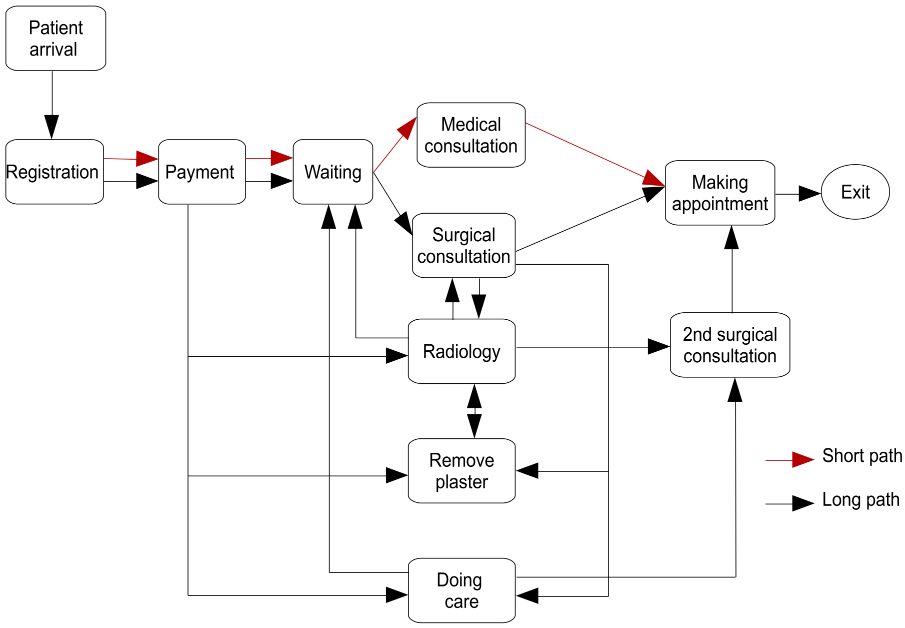

Figure 1. Patients flow in the outpatient orthopedic clinic.

sources of the process dysfunction. In fact, the main advantage of simulation over other modeling techniques is its ability to perform the 'what-if' scenarios by changing the model rules and assumptions. This model not only provides information to managers but also engages them in the development process so as to enable them to use the model independently as a decision support tool [25]. The simulation modeling helped to identify improvement alternatives including better patient scheduling and optimized staffing level [26]. The DES model is used to better understand the actual process and detect the sources of dysfunction. Such capability makes it better than mathematical models and more practical and less expensive than physical experimentation [27]. In addition, the DES model help us to implement the proposed scenarios and then evaluate the system performance to determine if the implemented change resulted in real improvement. In fact, we modeled the system using Arena 14 software. Patients were generally seen in First Come First serve manner in the real system and therefore were always processed this way in the DES model.

Collected data about the patient arrivals and patient service times are used as input to the Input Analyzer tool of evaluating statistical fit. The latter is an Arena tool, which is specifically designed to adjust the theoretical distributions with the observed data by estimating their parameters. Therefore, we establish the appropriate probability distributions to use in the DES model.

In addition to the best reproduction of the studied system, the advantage of the DES is its capability of integrating probability distributions and statistical parameters that describe the real system behaviors. This capability enables us to integrate the different statistical distributions of the system parameters (presented in Table 1).

After building the DES model, we proceeded with the validation step which consists of proving that this model effectively reflects the observed real system. For this reason, the model was run for 100 replications of 24 h and then the generated results are compared to the real collected data. A comparison was conducted between the observed LOS (real) and simulated one at each stage of the care process. This included computing 95% confidence intervals for patient LOS at each stage for both simulation output and historical data. The result of the comparison is shown in the following figure (Figure 2).

The differences between the observed and the simulated LOS are less than 4 min. These results confirm the validity of the simulation model. Therefore, the proposed model is useful to generate the proposed scenarios, to test and to evaluate them according to the key performance measures (LOS).

In fact, the collected data show a great disparity in the elapsed time to go through the different stages of the care process. This disparity can essentially be explained by:

Table 1. List of statistical distributions used in the DES model.

Task	Statistical distribution (minutes)
Patient's arrival	EXPO (5)
Registration	TRIA (1, 2, 3)
Payment	TRIA (1, 2, 3)
Meeting the orthopedist (consultation)	TRIA (5, 10, 15)
Fixing appointment	TRIA (0.5, 1, 1.5)
Plaster removal	TRIA (5, 10, 15)
Radiology	TRIA (5, 7, 10)
Doing care	TRIA (5, 7, 10)

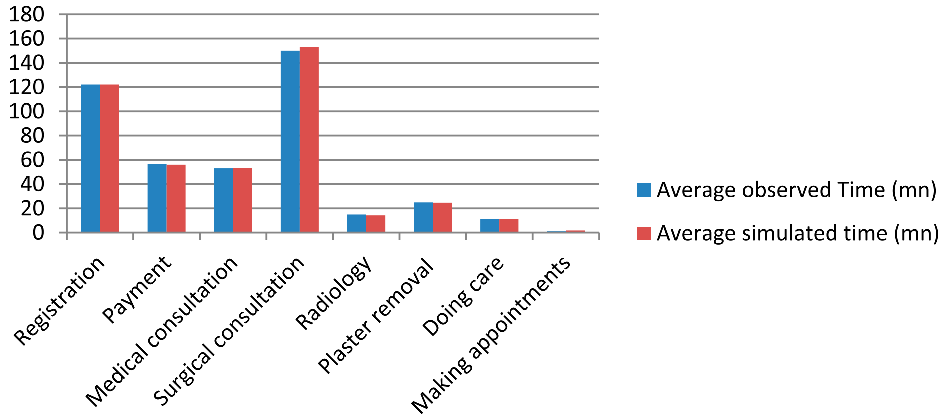

Figure 2. Comparison results between real and simulated average LOS.

Table 2. Summary statistics.

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Average TUS (Short trajectory)	400	0	400	25,000	103,000	62,056	10,824
Average TUS (Long trajectory)	400	0	400	42,000	102,000	70,315	10,189

- A long average time until finishing the registration and payment tasks compared to the real-time needed for the procedures which do not exceed 2 min in each of them. For example, the average time spent in waiting until the payment process is equal to 120 min. This can be justified by a bad resources management or insufficient number of registration agents.
- Average time spent in waiting and meeting the assistant is 43 min, whereas the consultation time is less than 10 min on average: insufficient number of assistants.
- Average time spent in waiting and meeting the resident is 140 min, whereas the consultation time is less than 10 min on average: insufficient number residents.

The simulation model confirms our expectations about the source of the long LOS. The model indicates that patients spent the majority of time at registration payment and consultation (medical surgical). In addition the model showed that the late arrival of surgeon is another problem that causes significant delays for patients.

In this work, we detect a list of area in which we could potentially produce a significant improvement without disrupting the outpatient clinic practice. Actually, since that the sources of dysfunction are fixed and after discussions with the administration, three scenarios can be proposed: (1) increase the number of registration (or payment) agents; (2) increase the number of assistants; or (3) increase the number of residents.

Linear regression

The linear model is a forecasting technique that helps to make a simple modeling of the relationship between the dependent variable and one or more explanatory variables. Therefore, in our case, managers could predict the deviation of the WT if one of the proposed changes (scenarios) is chosen. Thus, they will be able to adopt the suitable strategies for each of the two pathways (short and long) followed by patients inside the outpatient clinic.

Modeling the average patient's *LOS* into a linear model aims to highlight the potential effect of each of the three proposed scenarios. The average length of stay LOS_k of patients following pathway k can be written as follows:

$$LOS_k = \beta_0 + \beta_i X_i + \varepsilon_i$$

where X_i represents the scenario of index i, i=1, 2 or 3; k = 1or 2, with 1 represents the short pathway and 2 represents the longest one; ε_i is a correction.

Data analysis was made using XLSTAT tool of Microsoft Excel. Before applying this analysis, we should prepare our database. For this reason, we simulate each of the three proposed scenarios with 100 replications for each type of pathway (short and long). As a result, we obtained 600 values of average LOS (3 scenarios * 2 pathways * 100 replications). In additions, we had 200 values of average observed LOS of the real system (with the short and long pathway). The summary statistics is given in Table 2.

In order to study the potential effect of the three proposed scenarios on the average LOS, two regression models are separately made for each type of pathway. The results of goodness of fit tests are summarized in Table 3.

As mentioned in the table above, both models are significant. In fact, the explanatory variables (R^2) explain 71% and 69% of the LOS variability of respectively the short and the long patient pathways. Thus we can use these models to predict the effect of the increasing

Table 3. Goodness of fit statistics.

Goodness of fit statistics (TUBS (Short path))		Goodness of fit statistics (average TUBS (Long path))	
Observations	400,000	Observations	400,000
Sum of weights	400,000	Sum of weights	400,000
DF	396,000	DF	396,000
R^2	0.710	R^2	0.690
Adjusted R^2	0.708	Adjusted R^2	0.688
MSE	34,239	MSE	32,394
RMSE	5851	RMSE	5692
MAPE	7481	MAPE	6442
DW	2228	DW	1872
Cp	4000	Cp	4000
AIC	1417,329	AIC	1395,165
SBC	1433,295	SBC	1411,131
PC	0.296	PC	0.316

number of the registration agents, the assistants or the residents on the average LOS generated by each pathway. Therefore, managers will be able to compare the three proposed scenarios and adopt the suitable strategies, for each pathway, in order to improve the overall outpatient's clinic performance and patient satisfaction.

Results and discussion

After analysis, the models parameters are determined and therefore the effect of each scenario on the average LOS is now determined.

Statistical analysis of data taken before and after the implementation indicates that the average WT is significantly improved and the average LOS in the outpatient clinic is reduced.

Short patients pathway

For the short patient pathway, the linear model could be formulated based on Table 4 that gives the main LOS in the short patient pathway and respectively the estimated individual effect of each scenario.

The linear model is given as follows:

$$LOS_1 = 77.72 - 20.22X_1 - 22.65X_2 - 19.78X_3$$

As indicated in this model, the average LOS in the short pathway is 77.72 min. This value can be reduced, respectively, by 20.22, 22.5, or 19.78 min when, scenario1, scenario2, or scenario 3, respectively, are adopted. Therefore, adding one new registration (or payment) agent improves the average LOS by 20.22 min, while adding respectively a new assistant or a new resident can reduce the average LOS by 22.5 and 19.78 min, respectively.

Figure 3 shows the standardized coefficients or beta coefficients of the first regression model. These coefficients show the effect of the three scenarios on the average LOS of the short pathway. In fact, scenario 2, which consists of adding a new assistant, shows the best result which has a greater effect on the average LOS, compared to the two other scenarios (Figure 4).

Long patients pathway

Similarly to the short pathway, the linear model for the long patient pathway could be formulated based on the parameters generated by XLSTAT and presented in Table 5. These parameters give the main LOS in the patient's pathway and respectively the estimated individual effect of each scenario.

Thus, the model could be formulated as follow:

$$LOS_2 = 84.43 - 16.92X_1 - 17.10X_2 - 22.48X_3$$

The estimated average LOS in the long patient pathway is 84.43 min. According to the linear regression model, this value can be, respectively, reduced by 16.92, 17.10, or 22.74 min, if scenario 1, scenario 2, or scenario 3,

Table 4. Model parameters (average LOS (short path)).

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	77,720	0.585	132,822	<0.0001	76,570	78,870
Basic scenario	0.000	0.000				
Scenario-S1	−20,225	0.828	−24,441	<0.0001	−21,852	−18,599
Scenario-S2	−22,650	0.828	−27,371	<0.0001	−24,277	−21,023
Scenario-S3	−19,780	0.828	−23,903	<0.0001	−21,407	−18,153

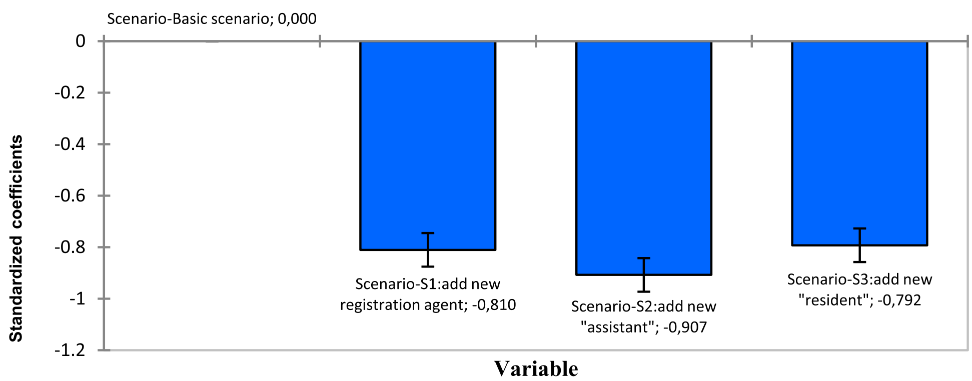

Figure 3. Average LOS (short path)/ Standardized coefficients (95% conf.interval).

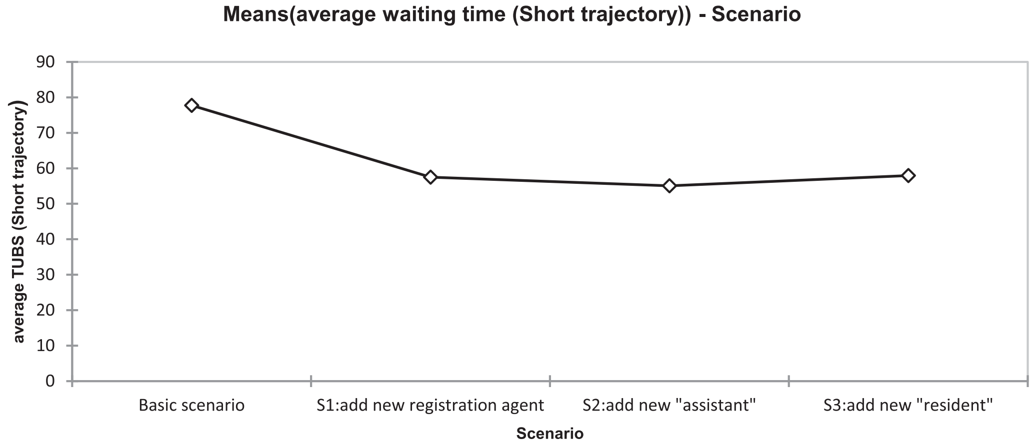

Figure 4. Average estimated LOS for the short patient paths.

Table 5. Model parameters (average LOS (Long path)).

Source	Value	Standard error	*t*	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	84,440	0.569	148,361	<0.0001	83,321	85,559
Basic scenario	0,000	0.000				
Scenario-S1	−16,920	0.805	−21,021	<0.0001	−18,502	−15,338
Scenario-S2	−17,100	0.805	−21,245	<0.0001	−18,682	−15,518
Scenario-S3	−22,480	0.805	−27,929	<0.0001	−24,062	−20,898

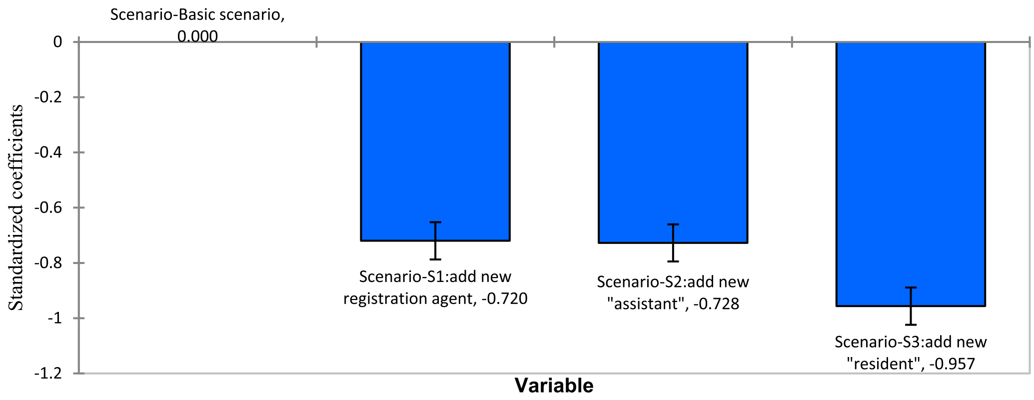

Figure 5. Average LOS (Long paths) / Standardized coefficients (95% conf. interval).

respectively, are adopted. For example, one additional resident can reduce the average LOS by 22.48 min, which represents the best possible improvement of the average LOS. This strong effect of adding a new resident (as an independent variable) on the dependent variable is also justified by its standardized coefficient which is equal to 0.957 (see Figure 5).

Figure 6 shows the potential improvement of the average LOS achieved by the three proposed scenarios.

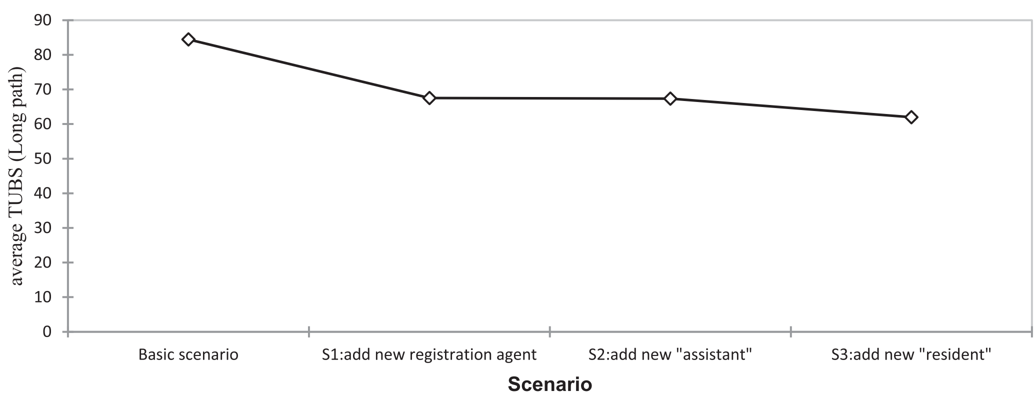

Figure 6. Average estimated LOS for the long patient's path.

Conclusion and future research

In this paper, we aim to control patient LOS in the outpatient orthopedic clinic of Habib Bourguiba Hospital by identifying factors influencing WT. This control could help us in maintaining the suitable strategies for improving the outpatient clinic performance and decreasing the patient dissatisfaction.

By using the DES model, we detected two main pathways followed by patients during their care process. These pathways differ in terms of the number of stages through which the patient passes until leaving the process. Consequently, they differ in terms of average LOS. In addition, simulation analysis results allowed us to detect the sources of the long WT which are mainly related to resources management. Based on these results, a list of improvement scenarios are proposed and evaluated using the simulation model. The proposed changes have resulted in a great improvement in terms of minimizing the patient WT and show that there is a strong relationship between varying the number of human resources and the improvement of patient LOS. To clearly study this relationship we used the linear regression model which showed its effectiveness and good results for this kind of problem. This relationship enables hospital managers to evidently understand how the number of human resources could affect the selected performance criteria (LOS and WT). Thus, they are able to define the actions of improvement that can be made and to predict the strategic decisions to adapt in the long term.

In this work, we separately treat each type of patient pathway and propose a suitable improvement scenario for each one. Actually, given that both pathways are strongly related and many resources are shared, authors plan to extend this work by using methods of compromise that take into account the different pathways in a single solution. Furthermore, the authors believe that the actual outpatient appointment system should be revised in order to avoid the random arrival of the patient. Consequently, a huge waste of time could be avoided so the patient WT and the total LOS could be significantly be minimized.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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