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Quantile regression and an application: performance improvement of an emergency department in Eastern Europe*

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ED (emergency department) overcrowding is a problem faced by hospitals worldwide. Several studies have been performed to find solutions, but only few have proposed to decrease the length of stay by employing a radiologist in the ED. This study aims to improve emergency care in an Eastern European ED by measuring the parameters of crowding, introducing interventions based on the results, and evaluating their outcomes. As the length of stay is a typically skewed distribution variable, robust quantile regression is applied. The number of patients visiting the ED was measured from July 2014 to December 2015. The input, throughput and output parameters of ED crowding were evaluated throughout this period. The time intervals between the various stages of patient visits to the ED significantly decreased during the study period. The continuous measurement of ED process parameters is important to maintain time intervals within a specified range. Decreased process times between the pre- and post-intervention phases of the study were obtained by introducing several staff-centric changes. The presence of a dedicated radiologist in the ED has significantly decreased the turnaround times of imaging studies.

KEYWORDS: quantile regression, emergency medicine, crowding

EM (emergency medicine) was established in the second half of the 1960s and introduced simultaneously in the United States and the United Kingdom (*Zink* [2006]). However, it was only founded in Eastern Europe decades later; in Hungary, for example, the first emergency protocol was released in 1996. Therefore, most studies on ED (emergency department) structure, function and problems with overcrowding have been performed in the United States, with no data available on crowding difficulties in Eastern Europe.

The biggest problem within EDs is overcrowding, which occurs not only in the United States but also globally (*Derlet* [2002], *Moskop et al.* [2009]). In light of the lack of Eastern European EM data, this study addresses the current situation and level of crowding in a Hungarian ED. The staff in our ED have experienced long waiting times and patient dissatisfaction related to crowding (*Hansagi–Carlsson–Brismar* [1992]), and identified this as an area to be addressed. The main causes of crowding can differ by country and healthcare system (*Jayaprakash et al.* [2009], *Pines et al.* [2011]); some causes contribute to crowding at the regional level (*ACEP* [2016], *Derlet–Richards–Kravitz* [2001], *Forster et al.* [2003]).

This study analyses the characteristics of overcrowding (i.e. input, throughput, and output measures) in this ED to improve emergency care. In addition, we implement a system that allows for the continuous monitoring of the throughput parameters. Based on these data, several result-driven changes are implemented and the crowding measures are continuously assessed. As a component of the throughput measures, the turnaround times of imaging studies are also evaluated to assess delays. After the recognition of delays in this area, a part-time radiologist is hired.

The turnaround times for imaging studies are then compared between the days on which a radiologist is working and the days on which s/he is absent from the ED.

Detailed statistical analysis using QR (quantile regression) can provide insights into improvements in LOSs (lengths of stay). Because of the technical problems with OLS (ordinary least squares) estimation as well as to better understand the LOS structure, we apply QR.

The remainder of the paper is constructed as follows. Section 1 describes the data in our context, followed by the applied methods in Section 2. The results presented in Section 3 are discussed in Section 4. Finally, we conclude.

1. Materials

The study took place in Bács-Kiskun County Hospital and Teaching Hospital of University of Szeged, an 1185-bed teaching facility that services around one million local residents. The hospital contains a high-level trauma centre that provides healthcare services for emergency trauma patients, and our ED mostly serves internal medicine, neurology, and other emergency patients. The ED was established in 2010 after different internal medicine outpatient clinics were merged; therefore, this is the main profile of the department. On admission, patients are recorded in the electronic registration system before being moved directly to triage. From there, patients enter either the waiting room or the examination area if a bed is available. For life-threatening conditions that requires immediate care, patients are transferred to the resuscitation room immediately after triage. Following the initial examination and start of treatment, patients have to wait for their test results in the waiting room or observational area. The observational area contains 16 beds and includes a high-dependency care unit with four beds, and two isolation rooms containing a total of four beds. The Canadian Triage and Acuity Scale is used to classify patients on admission.

Based on *Asplin et al.* [2003], we identified the input, throughput and output parameters of our ED. Our measurements overlapped with the quantified crowding measures that *Beniuk–Boyle–Clarkson* [2012] found to be the most important in their Delphi study.

Measurements were recorded for every patient attending our ED between 1 July 2014 and 31 December 2015. July 2014 was designated the pre-intervention phase. During the following 17 months, the parameters were continuously measured, and several interventions were introduced to improve the quality of care. December 2015 served as the post-intervention phase.

The number of visits was recorded, and their daily and hourly distribution was analysed as the input parameters. The throughput measurements included the time of registration, triage, first physician contact, and admission or discharge. These data were used to determine the time interval from registration to triage, from triage to first physician contact, from first physician contact to discharge or admission, and the LOS. The time of request and receipt of radiology imaging (i.e. X-ray, ultrasound, and CT [computed tomography]) was also acquired from the hospital's registration system. The output parameters included patients who left without being seen and the mortality rate. In addition, the admission rate and departments that admitted patients were also recorded. A paper-based administration interface was used to record the throughput parameters.

2. Methods

The data retrieved from the hospital's registration system were cleaned (some entries had contradictory or missing timings) using the available information, and we had to delete about 0.3% of observations because of missing variables. Categories were merged for the inpatient care departments.

A descriptive statistical analysis of the time intervals was subsequently performed, with the results compared using Kruskal–Wallis and Mann–Whitney U tests to avoid distribution-related constraints. The time intervals of the pre- and post-intervention phases were compared using a Mann–Whitney U test. Several measures were introduced after analysing the results from the pre-intervention period. A part-time radiologist was hired in March 2015 to perform ultrasounds and analyse the X-ray and CT images for the ED. The turnaround times for the radiology examinations were measured between March 2015 and December 2015. The days on which the radiologist was working in the ED (always on the same days of the week) were compared with the days on which the imaging studies were performed in his/her absence. To avoid the problems caused by non-normal distributions, Mann–Whitney U tests were again used to assess the effect of employing an ED radiologist on the turnaround times for imaging studies.

To control for the factors that affect the impact of the presence of the radiologist, we applied linear multivariate regressions. To avoid the problems caused by the non-normality of the residuals, we used the robust QR method in addition to OLS. QR allows us to estimate not only the median instead of the mean but also the other quantiles such as the first quartile, third quartile, and 90th percentile. These estimations allow us to better understand the structure of the data and have deeper insights into the evolution of the service.

The original idea of QR is relatively old (*Koenker–Basset* [1978], *Koenker* [1982]), but its first applications 'arrived' around the millennium (*Gilchrist* [2000], *Garcia–Hernandez–Lopez-Nicolas* [2001], *Koenker–Hallock* [2001]), and *Koenker* [2005] 'opened the door' for the widespread use of this method (*Waldmann* [2018]). By that time, computing capacities had already allowed general users to apply QR to relatively large datasets. Compared with OLS regressions, QR is thousand times more computationally intensive (*Vidoni–Reininger–Lee* [2019]).

Conditional mean-based OLS regression has several limitations (*Hao–Naiman* [2007]). As it focuses on the central measure of the mean, information about the tails is limited, even though these regions of the distribution are more interesting in many cases (e.g. extreme losses in finance, extreme income groups of the population [inequalities], and extreme diagnostic values in medicine) (*Rodriguez-Caro–Vallejo-Torres–Lopez-Valcarel* [2016]). As a related problem, the mean–standard deviation pair does not describe the shape of the distribution. For heavy-tailed distributions, the mean is a misleading measure, and so is the conditional mean-based regression (*Lew–Ng* [2011], *Sauzet et al.* [2019]). As the median or quantiles tend not to be sensitive to outliers, conditional QR is more appropriate (*Hao–Naiman* [2007]).

Additionally, quantile-based standard errors and related tests do not suppose the normality of the residuals, so QR is distribution free. These features make QR suitable for our dataset where the response variable is a highly skewed distribution and a focus on high values is important to ameliorate the service.

The quantiles were defined through the cumulative distribution function. For a random variable *Y*, the cumulative distribution function is $F_Y(y) = P(Y \leq y)$. The τ-th quantile is defined as

$$q_\tau(Y) = inf\left\{y : F_Y(y) \geq \tau\right\}. \qquad /1/$$

QR evaluates the conditional quantiles, $q_\tau(Y|X)$ defined by

$$q_\tau(Y|X) = inf\left\{y : F_{Y|X}(y) \geq \tau\right\} \qquad /2/$$

without supposing that an explanatory variable has the same impact at different quantiles. In the standard from of QR, we suppose that the impact of the X variables is linear:

$$q_\tau\left(Y|X\right) = X'\boldsymbol{\beta}_{\boldsymbol{\tau}}\,, \qquad /3/$$

where $\boldsymbol{\beta}_{\boldsymbol{\tau}}$ is the vector of the coefficients of explanatory variables (including the constant). To estimate the parameters, we use optimization:

$$\hat{q}_\tau\left(Y\right) = \underset{b}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n}\rho_\tau\left(Y_i - b\right), \qquad /4/$$

where $\rho_\tau\left(.\right)$ is defined as $\rho_\tau\left(u\right) = u\left(\tau - I\left\{u < 0\right\}\right)$. In the case of the median, it is simply half the absolute value. In the case of standard QR with a linear combination of the explanatory variables, we obtain

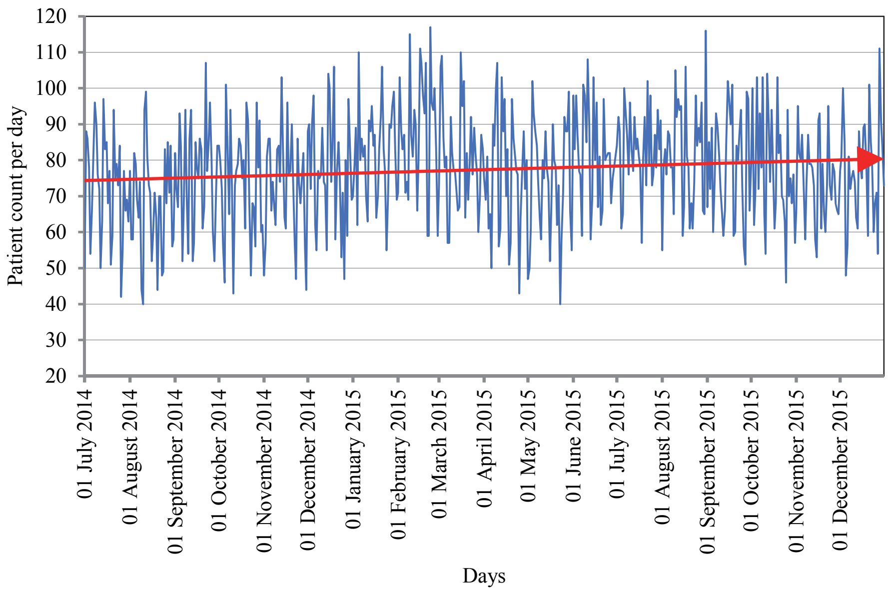
$$\boldsymbol{\beta}_{\boldsymbol{\tau}} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} E\left[\rho_\tau\left(Y_i - X'\boldsymbol{\beta}\right)\right]. \qquad /5/$$

The loss function is linear; in the case of the median, it is the least absolute deviation estimator (*Koenker* [2005]). The non-parametric tests were executed in SPSS24, while the regressions were run in gretl-2019c.

3. Results

The baseline values during the pre-intervention phase were initially determined before the observations continued over the 17-month period; however, several measures were introduced during this time to improve the quality of patient care. The total number of ED visits during the study period was 44,187. Their daily numbers varied throughout, with an average of 72.5 patients/day (SD [standard deviation] = 14.7) in July 2014 compared with 77 patients/day (SD = 14.3) in December 2015. (See Figure 1.) This increase may have occurred because of the reorganization of the administrative regions of the healthcare system, including the closure of several regional hospitals.

Figure 1. Daily visits to the emergency department



The busiest days of the week and the busiest hours of each day were also determined. The highest number of patients arrived on Mondays, with 91.7 visits on average, which was significantly different from all the other days (all Mann–Whitney test p values = 0.000). Patients arrived less frequently at weekends (also significantly different from all weekdays; all Mann–Whitney test p values = 0.000). The rest of the week was approximately equally attended on a daily basis (Kruskal–Wallis test p value = 0.323 for Tuesday–Friday). When determining which part of the day was the busiest, a peak was identified between 10:00 a.m. and 12:00 p.m. (See the Table.) These results led to a change in the work schedule of physicians to ensure that most were present at work during the peak hours on the busiest days. This reorganization of human resources was implemented to avoid a shortfall in healthcare providers. Therefore, fewer physicians worked at weekends, while more worked on Mondays and Fridays. Nurse numbers were also adjusted in the areas with the greatest need and as such more nurses were added to triage.

Different time intervals were calculated from the raw temporal data to determine the throughput parameters, which were used to characterize the functioning of the ED. However, the structure of our ED changed dynamically during the study period, which decreased the number of study parameters. Despite an increase in the number of patients between July 2014 and December 2015, the time between arrival and triage was found to have decreased by 36.2% during this period, from 7 minutes 35 seconds (SD = 12.80) to 4 minutes 50 seconds (SD = 8.63; Mann–Whitney p value = 0.000).

This decrease was mainly due to the redistribution of human resources. Although the need to add triage nurses to the system during peak times was identified, it was also deemed important to not waste human resources. Therefore, a flexible system was developed whereby work hours were shifted so that the more occupied the ED was, the more nurses worked in triage.

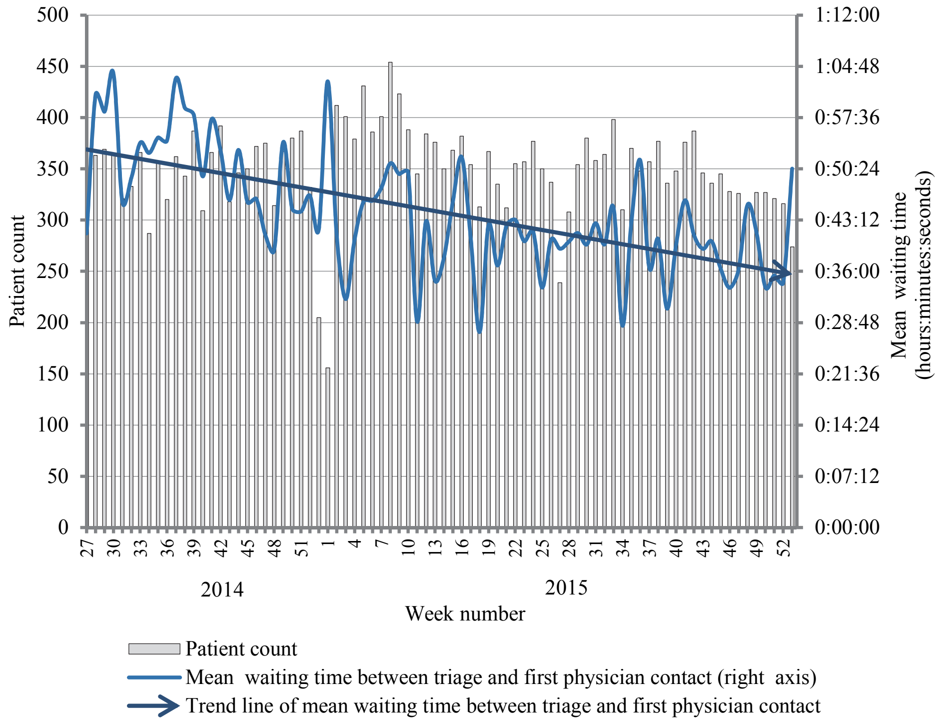
Busiest days and hours in the emergency department

Time of arrival	Average number of patients							
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	in the given hour
0–1	1.41	1.51	1.31	1.23	1.24	1.60	1.66	1.42
1–2	1.12	1.01	1.00	1.05	0.90	1.20	1.59	1.12
2–3	0.77	0.95	0.89	0.90	0.94	0.99	1.17	0.94
3–4	0.85	0.65	0.70	0.61	0.66	0.76	1.11	0.76
4–5	0.73	0.88	0.92	0.76	0.71	0.91	0.82	0.82
5–6	1.10	0.78	0.87	0.86	0.85	0.91	0.93	0.90
6–7	1.47	1.09	1.23	1.01	1.15	1.15	1.27	1.19
7–8	2.86	2.65	2.52	2.45	2.54	1.85	1.71	2.37
8–9	4.95	4.72	4.63	4.81	4.23	2.79	2.61	4.10
9–10	6.59	6.12	6.35	5.99	5.56	3.59	3.74	5.42
10–11	8.63	6.86	7.49	6.27	6.45	3.73	4.51	6.28
11–12	8.00	6.10	6.42	6.51	7.04	3.90	4.05	6.00
12–13	7.36	5.10	5.66	5.22	6.39	4.01	3.89	5.37
13–14	6.60	5.85	5.27	5.40	5.99	3.46	3.35	5.13
14–15	6.33	5.42	5.40	5.60	5.73	3.50	3.79	5.11
15–16	5.85	6.04	5.35	5.51	5.30	3.33	3.44	4.97
16–17	5.46	5.12	4.58	5.13	4.24	3.04	3.11	4.38
17–18	4.27	5.16	4.55	4.94	3.66	3.59	3.26	4.20
18–19	3.89	3.70	3.43	3.94	3.61	3.34	2.99	3.56
19–20	3.27	3.12	3.20	2.98	3.00	2.78	3.13	3.07
20–21	3.23	3.20	2.75	3.12	3.33	2.90	2.89	3.06
21–22	2.80	2.25	2.99	2.69	2.72	2.20	3.16	2.69
22–23	2.15	2.10	1.95	2.11	2.00	2.54	2.60	2.21
23–24	1.95	1.91	2.02	1.60	1.94	2.18	1.72	1.90
Average number of patients on the given day	91.65	82.30	81.48	80.66	80.18	60.24	62.49	76.98

Note. The colours indicate the average number of patients from the smallest (dark blue) to the greatest (dark red).

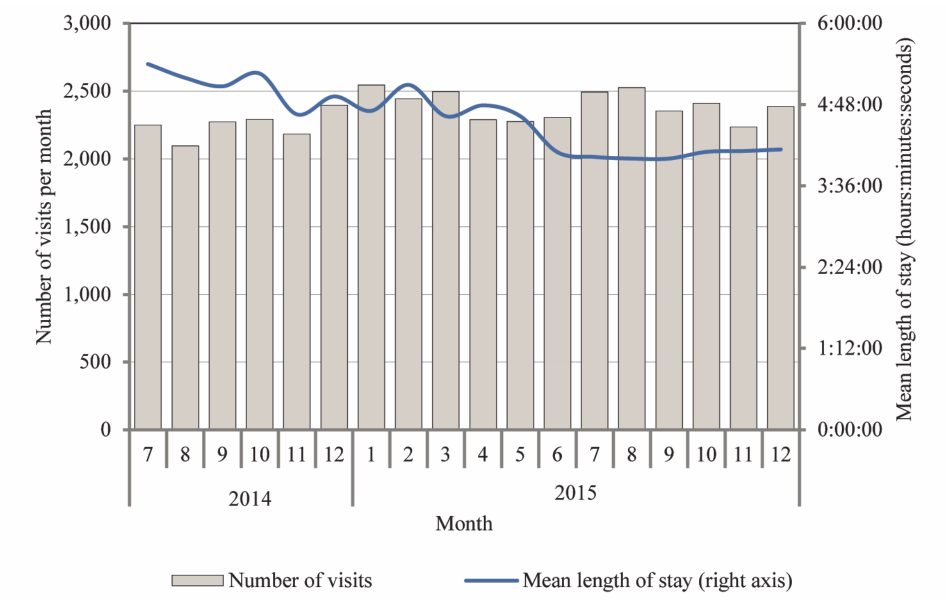
The time interval between triage and first physician contact also decreased significantly (Mann–Whitney *p* value = 0.000) during the study period. The average waiting time during the pre-intervention period was 56 minutes (SD = 43.39), which was considered to be too long. In July 2014, those that worked in the ED were mainly internal medicine specialists, as EM was still in its infancy in Hungary. As this specialty began to develop, more EM experts were employed and a higher level of emergency care could be provided. With these advances in specialist care, the average time from triage to first physician contact decreased to 39 minutes (SD = 31.65). (See Figure 2.)

Figure 2. Mean waiting time between triage and first physician contact in the emergency department



At the start of this study, there were long waiting times; however, no objective data were available. Therefore, our study aimed to both determine and decrease the LOS. In July 2014, the LOS was 5 hours 24 minutes (SD = 296); however, by the end of the study period, it had decreased significantly to 4 hours 8 minutes (SD = 221; Mann–Whitney *p* value = 0.000). (See Figure 3.)

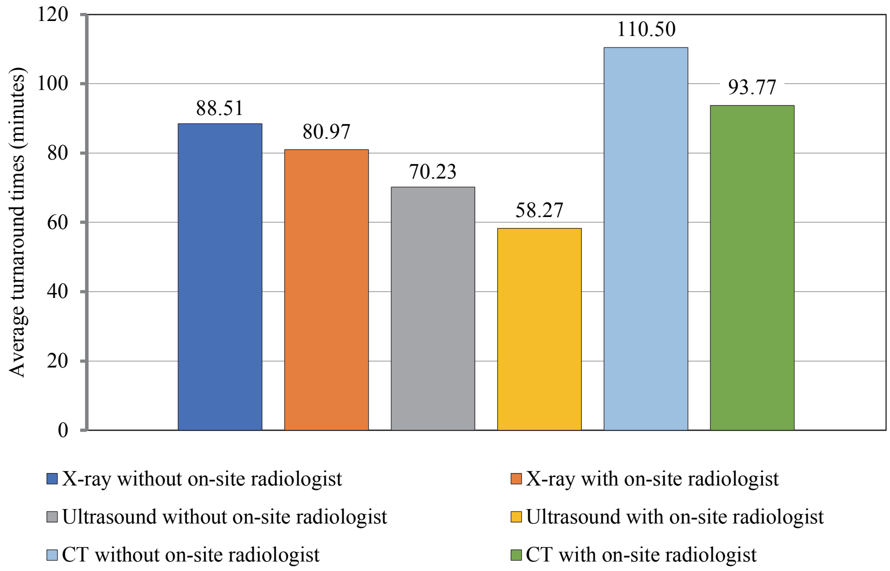
Figure 3. Number of emergency department visits and mean length of stay



After evaluating the LOS at pre-intervention, we decided to make modifications to decrease it based on previous research (*Cournane et al.* [2016]). As a result, an ED radiologist was hired to perform ultrasounds and interpret X-rays and CT images. Significant differences were observed in the turnaround times of all the imaging studies between the days on which the radiologist worked in the department and those on which s/he was absent. The mean turnaround time for X-ray studies was 80.97 minutes (SD = 69.98) with the on-site radiologist and 88.51 minutes (SD = 79.56) without (Mann–Whitney p value = 0.000). The average turnaround time for CT examinations was 93.77 minutes (SD = 83.57) on the days on which the radiologist was present and 110.50 minutes (SD = 86.26) in his/her absence (Mann–Whitney p value = 0.000). However, the largest difference was observed in the turnaround time for ultrasound examinations, which showed an improvement of 17%. The ultrasound turnaround time was 58.27 minutes (SD = 79.16) on the days on which the radiologist was working and 70.23 minutes (SD = 99.27) in his/her absence (Mann–Whitney p value = 0.000). (See Figure 4.)

In our models, we controlled for the average daily number of patients (which correlates with the LOS), weekend days (which result in a longer LOS), discharge/admission (compared with the reference discharge group which results in a longer LOS), the pre-intervention (July 2014) and post-intervention (December 2015) phases (with the intervention phase as the reference), and the presence of the radiologist (three days a week from March 2015). We used two dependent variables, namely, the LOS and the time from first physician contact to discharge or admission, with the latter more directly related to the activity of the radiologist.

Figure 4. Average turnaround times of ultrasound, X-ray and CT imaging studies in the presence and absence of the on-site radiologist



The LOS was positively affected by the average daily number of patients (23 s ± 0.11, p = 0.000 in OLS; 44 s ± 0.09, p = 0.000 in QR; 28 s ± 0.10, p = 0.000 for the 25th percentile; 38 sec ± 0.13, p = 0.000 for the 75th percentile; and –3 s ± 0.33, p = 0.891 for the 90th percentile) except for the longest time decile, where no significant impact was observed. This may have been caused by the specific needs of some patients rather than the number of patients. At weekends, the LOS was significantly longer (21 min 28 s ± 4.02, p = 0.000 in OLS and 18 min 5 s ± 3.39, p = 0.000 in QR), and this impact was proportional in the longer LOS time groups. This effect may have been caused by the lower number of physicians working weekends, including ED staff, radiologists, and laboratory specialists. Discharged patients, ceteris paribus, spent longer time in the ED (1 h 23 min 44 s ± 2 min 22 s, p = 0.000 in OLS and 1 h 13 min ± 2.00, p = 0.000 in QR) and the impact was significant at all LOS time percentiles. For an unambiguous clinical situation (e.g. stroke or myocardial infarction), the patient needs a fast intervention and therefore the LOS is short. If the problem needs more time to diagnose, then more examinations may be needed and the LOS is longer. This could explain these results. We also controlled for general improvements in the service to analyse the partial effect of the radiologist's presence. All the models confirmed the significant decrease in the LOS during the intervention phase compared with the pre-intervention phase (55 min 16 s ± 6.01, $p = 0.000$ in OLS and 39 min 44 s ± 4.73, $p = 0.000$ in QR); this decrease was almost 2 hours in the worst 10% of cases (1 h 53 min 58 s ± 25.56, $p = 0.000$). A further significant improvement was noted between the intervention and post-intervention phases (–22 min 17 s ± 4.67, $p = 0.000$ in OLS), but this was caused by the further decrease of long LOS times (–14 min 15 s ± 6.80, $p = 0.036$ for the 75th percentile and –1 h 5 min 33 s ± 13.67, $p = 0.000$ for the 90th percentile) and non-significant decrease below median times. Finally, the presence of the radiologist had no significant impact overall (–3 min 59 s ± 2.78, $p = 0.152$ in OLS), only in the upper percentiles (–7 min 22 s ± 3.59, $p = 0.040$ for the 75th percentile and –18 min 52 s ± 9.25, $p = 0.041$ for the 90th percentile).

As the presence of the radiologist had no real impact at the beginning (before first physician contact), we ran the same regressions for the time from first physician contact to discharge or admission. The daily average number of patients was not significant (at 5%) in either model, which means that peaks influence other phases (triage and before). Weekends also weakly affect the time from first physician contact to discharge or admission (+12 min 27 s ± 5.04, $p = 0.014$ in OLS and + 13 min 6 s ± 4.11, $p = 0.000$ in QR), but neither short nor long times are concerned ($p > 0.6$). Time from first physician contact to discharge is significantly longer in weekends than weekdays (1 h 54 min 34 s ± 3.01, $p = 0.000$ in OLS and 1 h 36 min 6 s ± 2.47, $p = 0.000$ in QR), and the impact of weekends is high for very long times from first physician contact to discharge (> 3 h 42 min in the 90th percentile). As previously described, admitted patients suffering from serious disease need to spend less time in the ED and, after stabilization, are transferred directly to the appropriate department. For discharged patients, the clinical situation is rarely as clear as with admitted patients suffering from a serious disease. The decision to discharge or admit someone is difficult and needs more examination time or the patient needs a few more hours of observation. Furthermore, some diseases can be cured in the ED but this needs more time. The decrease in time from first physician contact to discharge or admission between the pre-intervention and intervention phases was significant overall (–33 min 52 s ± 7.31, $p = 0.000$ in OLS and –22 min 29 s ± 6.28, $p = 0.000$ in QR) but not significant for short waiting times and highly significant for long times (–1 h 40 min 35 s ± 25.59, $p = 0.000$ for the 90th percentile). This means that the first interventional steps could affect the most serious medical problems, with extremely long waiting times being cut. An improvement between the intervention and post-intervention phases is less important (–19 min 54 s ± 6.21, $p = 0.001$ in OLS and –2 min 55 s ± 6.14, $p = 0.636$ in QR) but it is significant for short times (–11 min ± 3.22, $p = 0.000$ for the 25th percentile). This means that later reforms affected other elements and were successful in those fields that were not touched by the first steps of the reorganization. The radiologist's presence significantly decreased the overall time from first physician contact to discharge or admission as well as the different time categories (–11 min 6 s ± 6.21, p = 0.001 in OLS; –10 min 37 s ± 2.80, p = 0.000 in QR; –4 min 9 s ±1.96, p = 0.034 for the 25th percentile; –15 min ± 5.98, p = 0.012 for the 75th percentile; and –29 min 43 s ± 12.54, p = 0.018 for the 90th percentile).

In summary, the first reforms affected the longest waiting times from first physician contact to discharge or admission while the later reforms had an overall flatter impact. Owing to the radiologist's presence, general improvement in the service from first physician contact to discharge or admission was detected, especially in the case of long waiting times. To determine the output parameters, the percentage of patients admitted to the hospital was determined, as was their distribution by the respective departments. During the pre-intervention phase (July 2014), 50.5% of patients were admitted to the hospital; however, during the post-intervention phase (December 2015) only 43% were admitted, which amounted to a 7.5% decrease during the study period. In total, 20,388 patients were admitted, which accounted for 44.7% of all ED visits. Most patients were admitted to the internal medicine department (36.4%), followed by psychiatry (12.0%), pulmonology (11.2%), neurology (9.4%), gastroenterology (8.2%), general surgery (4.8%), invasive cardiology (3.3%), and urology (2.5%). The percentage of patients who left without being seen remained almost the same (0.9% in July 2014 and 1% in December 2015) and the number of patients who died in the ED during the study period was 72.

4. Discussion

While several studies examine overcrowding in EDs in the United States and Western Europe, there are no comparable studies for Eastern Europe (*Doupe et al.* [2018], *Hwang et al.* [2011], *Rathlev et al.* [2018]). *Pines et al.* [2011] summarized the crowding situation in several entities including Hong Kong, India, Iran, and Saudi Arabia, but none in Eastern Europe. Therefore, our study bridges a gap in the literature.

Efficiency, or lean thinking, is crucial to improving ED performance (*Holden* [2011]). Our study reported on an improvement project whose steps had been presented in the literature. First, we used a paper-based technique to record the timing of all the throughput steps and introduced the continuous monitoring of performance (likewise *Eller* [2009]). Only few studies had presented the detailed timing of patient flow as reported in our study, including the times of registration, triage, examination and admission (*Houston et al.* [2015]). Quality improvement measurements were also shared with staff on a monthly basis (*Dickson et al.* [2009b]). Before starting the project, they received brief orientation, as described by *Ben-Tovim et al.* [2007]. Healthcare staff were reorganized after determining the busiest periods in the week following *Eller* [2009]. In the event of high input, a fast-track system was operated in which a nurse/doctor could be quickly made available, following *Ieraci et al.* [2008]. In our project, the main modification was the reorganization of human resources; however, ED space was not extended or reorganized, as described in several studies (*Dickson et al.* [2009a], *Dickson et al.* [2009b], *Eller* [2009]). Nonetheless, the more efficient use of space, such as using all examination rooms, was instigated (*Dickson et al.* [2009b]).

We focused on radiology examinations because several studies have mentioned that reducing turnaround times for radiology imaging reduces the LOS. *Chiem et al.* [2014] showed that waiting times are much shorter for pelvic ultrasounds performed by ED residents compared with radiologists. *Cournane et al.* [2016] reported that delays in ultrasound, CT and MRI examinations can lead to longer LOSs in hospital. On-site imaging, especially ultrasound, has been shown to significantly decrease the LOS in an ED. Recent studies have suggested that dedicated ED radiologists shorten the turnaround times of imaging reports (*Lamb et al.* [2015]). As part of improving efficiency in our ED, the radiology examination system was changed following previous evidence that an on-site radiologist dedicated to working only for the ED significantly reduces the turnaround times of imaging studies (*Lamb et al.* [2015]). Furthermore, we controlled for several factors to examine the associations between the LOS and daily average patient number, weekend days, discharge/admission, the pre-intervention (July 2014) and post-intervention (December 2015) phases, and the presence of the radiologist. Using linear multivariate regression, we showed that the longest LOSs were shortened by the presence of a radiologist.

One limitation of our study was that patient satisfaction was not measured objectively; however, the number of complaints in the ED did decrease. Financial aspects, as they relate to our study, were not measured. Further, data collection is still ongoing, however, data analysis has not been performed yet.

5. Conclusions

A statistical analysis of the parameters of overcrowding in an Eastern European ED was presented. The rearrangement of human resources into a flexible system was shown to be important for managing the ED in a time-effective manner.

A paper-based monitoring system enabled the feedback of the measured parameters in real time. The continuous monitoring and constant feedback were also helpful for identifying problems and solving them in a timely manner. The applied robust methods allowed us to analyse and detect critical points in detail. An on-site radiologist contributed greatly to decreasing turnaround times, thereby lowering LOSs. The implementation of the measures described in this study could improve the performance of other EDs. To the best of our knowledge, this is the first report of patient flow data in an Eastern European ED.

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