Hiroshima J. Med. Sci.
Vol. 61, No. 3, 51~58, September, 2012
HIJM 61–10

Modelling Seasonal Variations in Presentations at a Paediatric Emergency Department

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ABSTRACT

Overcrowding is a phenomenon commonly observed at emergency departments (EDs) in many hospitals, and negatively impacts patients, healthcare professionals and organisations. Health care organisations are expected to act proactively to cope with a high patient volume by understanding and predicting the patterns of ED presentations. The aim of this study was, therefore, to identify the patterns of patient flow at a paediatric ED in order to assist the management of EDs. Data for ED presentations were collected from the Royal Children's Hospital in Melbourne, Australia, with the time-frame of July 2003 to June 2008. A linear regression analysis with trigonometric functions was used to identify the pattern of patient flow at the ED. The results showed that a logarithm of the daily average ED presentations was increasing exponentially (as explained by $0.004t + 0.00005t^2$ with t representing time, $p<0.001$). The model also indicated that there was a yearly oscillation in the frequency of ED presentations, in which lower frequencies were observed in summer and higher frequencies during winter (as explained by $-0.046 \sin(2\pi t/12)-0.083 \cos(2\pi t/12)$, $p<0.001$). In addition, the variation of the oscillations was increasing over time (as explained by $-0.002t*\sin(2\pi t/12)-0.001t*\cos(2\pi t/12)$, $p<0.05$). The identified regression model explained a total of 96% of the variance in the pattern of ED presentations. This model can be used to understand the trend of the current patient flow as well as to predict the future flow at the ED. Such an understanding will assist health care managers to prepare resources and environment more effectively to cope with overcrowding.

Key words: *Emergency department, Paediatric, Patient flow, Seasonal pattern*

Overcrowding is a phenomenon commonly observed at emergency departments (EDs) in many hospitals. ED overcrowding refers to patient needs exceeding the capacity of the department in terms of patient volume, patient severity, physical space and on-duty staff[5)]. The effect of overcrowding on patient welfare is of particular interest to hospital administrators and the community.

Several studies have investigated the causes, the mechanisms or processes, and the effects of ED overcrowding[1)]. ED overcrowding has been associated with delay in treatment administration[11)], delivery of sub-standard care for patients with severe pain[12,18)], and an increase in the mortality rate of patients treated at ED[7,13,19)]. The availability of ambulance services can also be impacted by ED overcrowding, as ambulances are occupied while waiting to transport their patients to an open ED[10)]. ED overcrowding also contributes to long patient waiting times in ED and patient dissatisfaction[7)].

ED overcrowding also impacts on the workforce and administration of hospitals. Staffs are exposed to high workloads and pressure to treat patients as quickly as possible in crowded EDs. It is likely that working in crowded EDs could result in staff 'burnout', a high staff turnover or difficulties in recruiting new staff. A study by Bayley et al[4)] demonstrated that ED crowding can result in financial loss to hospitals, specifically due to missed opportunities to treat patients. Bayley et al[4)] showed that if a patient with a chest pain occupied an ED bed for more than three hours before hospital admission, it could result in a loss of potential revenue of US$204 due to missed opportunities to treat other patients.

While there are several reported solutions for addressing ED overcrowding[13)], one solution involves understanding the patterns of ED demands, forecasting future ED presentations, and acting proactively to cope with the expected patient volume at ED. For example, mobilising health care professionals according to the forecast of ED flow could help the department to cope with a large volume of ED visits without compromising patient treatments.

There are several studies that have attempted to model and forecast patient flow at EDs or outpatient departments. However, they have largely focused on disease-specific presentations of adults or the elderly[15,16], and there are limited publications that examine the pattern of paediatric ED presentations. A recent study by D'Souza et al[9] investigated the seasonal variation of ED presentations for children in the Australian Capital Territory. Their study compared the rates of presentations with a limited range of disease/ symptoms across four seasons, and the pattern of presentations was not modelled. Hence, there are limited data available on the pattern of ED demands in paediatric settings. The aim of this study was, therefore, to identify the patterns of patient flow at a paediatric ED in order to assist the management of the department.

MATERIALS AND METHODS

Study design

The current study adopted a retrospective, observational study design. Data on patient presentations at ED were collected retrospectively to investigate patterns in the patient flow.

Data

Data were provided by the Royal Children's Hospital (RCH) in Melbourne, Australia. The RCH is the major specialist paediatric hospital in the state of Victoria, which has an estimated population of 5.6 million (in Year 2011)[2]. The RCH provides a full range of tertiary care for children living in Victoria as well as other states. The ED at the RCH serves as the only paediatric trauma centre in Victoria, and treats approximately 70,000 patients annually[20].

Data on patients, who presented at the ED in the RCH during July 2003 to June 2008 (i.e., five financial years), were collected from the Decision Support Unit, which compiles electronic patient information at the RCH. Data were available to the researchers only for this period. The following data were collected: the age, gender, the place of residency, the diagnostic classification (ICD-10) and triage category of patients, the date and the time of the ED presentation, waiting time at the ED, and whether or not a patient was admitted to the hospital. The frequency of ED presentations in each month was divided by the number of days in each month to produce daily averages for each month (i.e., the average presentations per day for each month).

Analysis

There is a wide range of analytical methods available to analyse time series data, for example, the methods presented by Bowerman et al[6]. A linear regression approach was adopted for this study because regression analysis allows for the identification of patterns of fluctuation in ED patient flow. In addition, based on the identified patterns (or a model), prediction of future patterns is possible.

There are two approaches in a linear regression framework that are used to model time series data that have patterns of variation. One is to use trigonometric functions and the other is to use dummy codes for months. To model the trends of ED presentations, a linear regression analysis with trigonometric functions was considered more appropriate for this study than regression with dummy codes. The reasons are two-fold. First, modelling with trigonometric functions allows us to represent smooth variation of the changes in data, whereas the dummy-code approach allows us to compare only the differences in the frequencies between months. Second, fewer parameters are required to model the patterns of frequencies in the trigonometric approach than the dummy-code approach, as the dummy-code approach requires at least 11 parameters (i.e., the dummy codes for February to December) to be fitted in a model. The parsimony and efficiency of the model was crucial, as there were only 60 time-points (July 2003 to June 2008) available for data analysis.

Trigonometric functions as well as linear and curvilinear functions are useful to illustrate various trends of time-series data. Combining them, thus, allows us to capture the complex patterns of ED flow. The functions used in the current analysis are presented in Table 1. Using these functions, a model was initially tested against the following full model with a variety of f and p values:

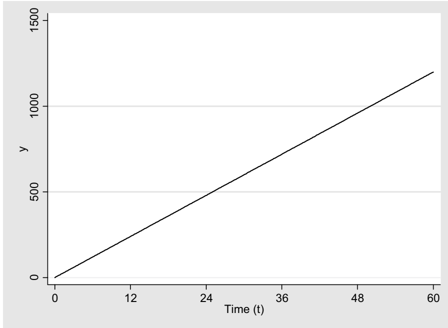
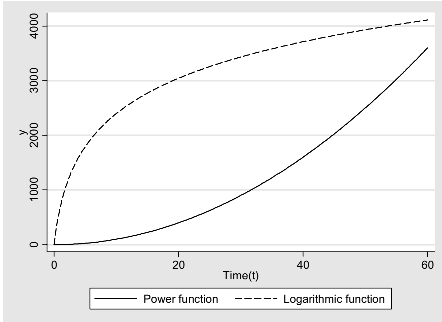
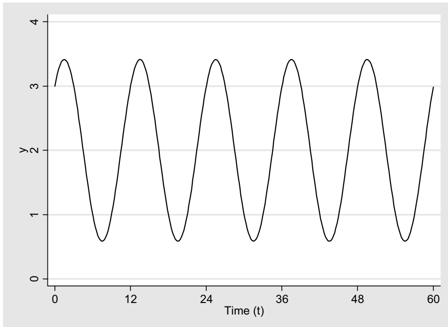
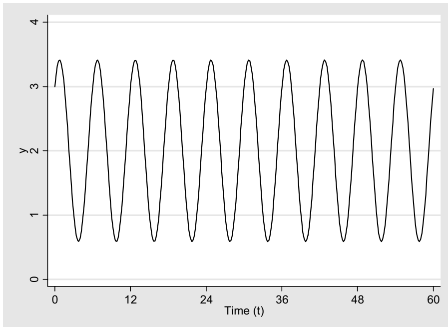
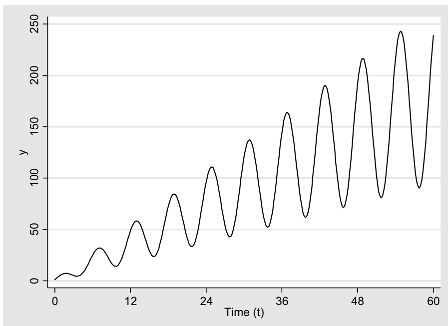
$$y(t) = \beta_0 + \beta_1 t + \beta_2 t^p + \beta_3 \cos(2\pi ft) + \beta_4 \sin(2\pi ft) + \beta_5 t * \cos(2\pi ft) + \beta_6 t * \sin(2\pi ft) + e_t$$

where e_t represents unexplained errors (Note. The analysis was also conducted by replacing $\beta_1 t + \beta_2 t^p$ with $\beta_1 \ln(t)$). The model development involved fitting and re-fitting all or a subset of the predictors above until a set of meaningful predictors was identified. In all the analyses, a significance level was set at <0.05 (two-tailed).

Ethical consideration

This study was reviewed and approved by the RCH Human Research Ethics Committee as a project that is compliant with the National Health and Medical Research Council (Australia) criteria for audit/quality assurance.

Table 1. Functions of time used in the current analysis, and their descriptions

Function of time#	Description	Exemplary figure
$y = \beta\ t$	This function illustrates an increasing or decreasing linear trend of y with respect to time, t. The direction of the slope depends on the sign (either positive or negative) of the coefficient, β. The figure on the right-hand side illustrates an increasing function, when β is positive.	
$y = \beta\ t^p$, or $y = \beta\ ln(t)$	Both a power and a logarithmic function describe either increasing or decreasing curvilinear trends of y with respect to time, t. The direction of the slope depends on the sign (either positive or negative) of the coefficient, β. The figure on the right-hand side (a solid line) illustrates an increasing function, when β is positive, and p=2 for the power function.	
$y = \beta\cos(2\pi ft) +$ $\beta\sin(2\pi ft)$	A pair of a cosine and a sine function of a time characterises a cyclic oscillation spanning a specific period of time. The f is the frequency of a cycle. When f=1/12, it exhibits cycles spanning over 12 months. When f=1/6, it illustrates half-a-yearly cycles.	 Example of yearly cycles  Example of half-yearly cycles
$y = \beta[t^*\cos(2\pi ft)]$ $+ \beta[t^*\sin(2\pi ft)]$	An interaction term between time (t) and a trigonometric functions ($\cos(2\pi ft)+\sin(2\pi ft)$) is also useful to characterise either an increasing or a decreasing oscillation of a cyclic waves. A figure on the right-hand side shows a linearly increasing trend with a greater oscillation in frequency over time.	

#Note. Time is represented by t, regression coefficients are represented by β, and the predicted ED patient volume is represented by y.

RESULTS

Summary characteristics of ED context

Table 2 summarises ED presentations, admissions, waiting time and patient characteristics for the financial years of 2003 to 2008 at the RCH. Within these five years, there was a total of 296,249 presentations at the ED, of whom 68,014 (22.96%) patients were admitted to the RCH. The number of ED presentations and admissions via the ED had increased over time. The proportion of patients who required immediate medical attention (Triage Category 1 and 2) also increased over time, while the number of patients who showed less acuity (Triage Category 5) decreased (Table 2). The average waiting time for patients to be seen by a doctor was approximately 70 mins between July 2003 and June 2005, approximately 60 mins between July 2005 and June 2007, and it increased to 66.9 mins in 2007-08.

Table 2 also presents the demographic characteristics of patients. The average age of patients presenting at the ED was relatively constant over time, and the gender proportion of patients also showed little change over time. The main diagnoses of these patients, based on ICD-10, were Respiratory diseases (i.e., Code J, comprising 18.87% of the patients), infectious and parasitic diseases (i.e., Codes A and B, comprising 17.49%), injuries (i.e., Code S, 17.36%), and unidentified causes (i.e., Code R, 15.79%). Overall, 1.46% of patients were recorded as residents outside the state of Victoria where Melbourne is located.

Figure 1 shows the pattern of ED presentations over 60 consecutive time points during July 2003 and June 2008. The figure shows that there were clear seasonal differences in the volume of ED presentations, as high frequencies were usually observed in winter (i.e., June to August in Australia) and low frequencies in summer (i.e., December to February). The figure also shows that the frequency of ED presentations was increasing with a greater variability in the later years. In particular, high frequencies of ED presentations were observed at three time points (listed in order of decreasing frequency): Time 50 (i.e., August 2007), Time 2 (i.e., August 2003), and Time 24 (i.e., June 2005) (see Fig. 1). A high frequency of patients who had a primary diagnosis of an infectious disease visited ED around these times.

Table 2. Summary characteristics of ED context by financial year[#1]

Financial year	2003-04	2004-05	2005-06	2006-07	2007-08
Average presentations per day	150.02	153.18	157.43	165.32	185.29
Presentations by Triage Category (%)					
Triage 1	0.30	0.33	0.32	0.35	0.45
Triage 2	3.28	3.38	3.67	3.54	4.05
Triage 3	26.46	27.19	28.50	26.70	27.03
Triage 4	54.44	53.09	55.21	57.87	57.87
Triage 5	15.50	15.99	12.28	11.53	10.59
Triage 6	0.02	0.02	0.02	0.02	0.02
Average admissions per day	32.69	36.59	37.82	40.55	38.60
Admission rate (%)	21.79	23.89	24.02	24.53	20.83
Average waiting time[#2] (min)	68.52	72.07	62.53	57.44	66.90
Average patient age (year)[#3]	4.58	4.72	4.74	4.72	4.54
Patient's sex (%)					
Male	56.50	55.51	55.87	55.87	56.32
Female	43.50	44.49	44.13	44.13	43.68

Note. [#1] Summary is based on data between July & December, 2003. [#2] The "time seen by a doctor" was missing for 30426 patients (see the reasons in Appendix B), thus they were excluded from the analysis. In addition, there was one patient who was recorded as seen by a doctor one month after the ED presentation. Thus, this patient was also excluded from the analysis. [#3] ED record showed that patient's age, calculated by the elapsed time between the date-of-birth and ED presentation date, ranged from 0 to 106 years old. The above figure excluded patients whose ages were calculated as being above 30 years old (n = 648, accounting for 0.22% of the total presentations) and whose records for the date-of-birth were missing (n = 9).

Model estimation

The distribution of the frequencies in ED presentations was positively skewed, thus a logarithmic transformation of the frequencies was made to normalise the distribution prior to data analysis. Several attempts for model-fitting tentatively identified the following model,

$$
\begin{aligned}
\ln y(t) = {} & 5.0593 + 0.0041t + 0.0001t^2 \\
& - 0.0608\sin\left(\frac{2\pi t}{12}\right) - 0.1170\cos\left(\frac{2\pi t}{12}\right) \\
& - 0.0017t * \sin\left(\frac{2\pi t}{12}\right) - 0.0006t * \cos\left(\frac{2\pi t}{12}\right) + e_t
\end{aligned}
$$

where t stands for scale-centred time-points.

This model meaningfully explained the frequencies in ED presentations while containing the minimum set of variables. This model accounted for 80% of the total variance of the frequencies in ED presentations (the adjusted R^2 = 77.3%). Diagnostic model-checking and the comparison of observed frequencies with the frequencies predicted by the above model (see Fig. 2) showed that the model constantly over-estimated the frequencies in January, where the lowest frequency in a year was observed. There was also under-estimation at several time-points, which appeared as outliers in the solution, and could significantly influence the model specification. These time-points were August 2003 (Time 2), June 2005 (Time 24), and August 2007 (Time 50), which represented the high peaks, and were mentioned previously.

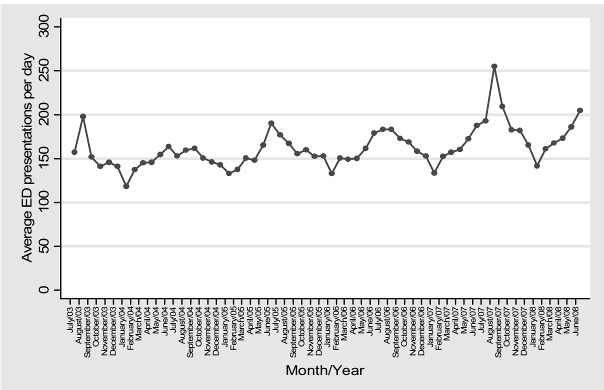


Fig. 1. ED presentations over time

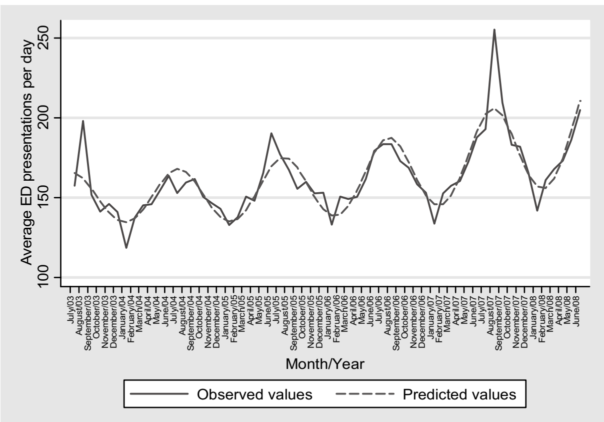


Fig. 2. The plots of the predicted ED presentations vs. the observed frequencies

Note. The predicted values were back-transformed to the original scale.

In order to remove undue influence of the outlying points on the model estimation, dummy variables were introduced into the model to account for the unusually high frequencies at Time 2, 24 and 50. In addition, a dummy variable for January was included in the model to better predict low frequencies in this month. The results of this revised model are presented in Table 3. This model explained 96% of the variance.

Table 3 shows that the coefficient on the linear term of time (i.e., t) is significant. Table 3 also shows that the coefficient on the quadratic term of time (i.e., t^2) is significant. This indicates that the daily average ED presentations were increasing, and the rates of increment had been accelerating with greater increment at the later time. The model also indicated that there was a yearly oscillation in the frequency of ED presentations, as indicated by significant coefficients on $\cos(2\pi ft)$ and $\sin(2\pi ft)$, where f=1/12. This oscillation demonstrated that the frequency of ED presentations was lower in summer and higher in winter. In addition, the significant coefficients on the interaction terms between time and the trigonometric functions (i.e., $t^*\cos(2\pi ft)$+ $t^*\sin(2\pi ft)$ where f=1/12) indicated that the oscillations of patient flow had been increasing over time, as consistent with the last figure in Table 1. When the patterns of the patient presentations by the ICD-10 were examined, yearly cyclic patterns were observed in the presentations of patients with the Codes B and J. Moreover, the increasing trend was observed in the Codes R and S.

The diagnostic tests in the revised model showed no violations of the model assumptions, as a constant variance and normal distribution of the residuals were satisfied, and there were no remarkable outlying time-points observed. Durbin-Watson d statistic also showed no serial correlations between the residuals (x^2 = 0.666, p = 0.414). Hence, this model was retained as the final model.

As stated previously, the model shown in Table 3 was based on a logarithmic transformation of the daily average ED presentations. By exponentiating the model, the predicted values on the original scale can be obtained. Figure 3 illustrates the prediction of the ED presentation during 2003 to 2008 on the original scale. Figure 3 also presents the predicted values for the next 12 months.

Table 3. The results of regression analysis for logarithmic transformed ED presentations with trigonometric functions

Predictors	Coefficient β	Std. Error	p	95% Confidence Interval	
Constant	5.066	0.006	0.000	5.054	5.077
t	0.004	0.0002	0.000	0.004	0.005
t^2	0.00005	0.00002	0.001	0.00002	0.00008
sine($2\pi t/12$)	-0.046	0.006	0.000	-0.057	-0.035
cosine($2\pi t/12$)	-0.083	0.006	0.000	-0.095	-0.071
t*sine($2\pi t/12$)	-0.002	0.0003	0.000	-0.002	-0.001
t*cosine($2\pi t/12$)	-0.001	0.0003	0.018	-0.0014	-0.00013
Time_2_50	0.253	0.022	0.000	0.209	0.298
Time_24	0.142	0.030	0.000	0.081	0.202
January	-0.110	0.015	0.000	-0.140	-0.080
R^2	0.958		Adjusted R^2	0.951	

Note. Dependent variable is the average ED presentations per day for a month on a logarithmic scale. The abbreviations for the predictors are as follows: t=Time with the mean adjusted to 0, Time_2_50=A dummy code for Times 2 & 50 where a value of 1 was assigned to Times 2 & 50 and 0 for elsewhere, Time_24=A dummy code for Time 24 where a value of 1 was assigned to Time 24 and 0 elsewhere, and January=A dummy code for January where a value of 1 was assigned to all time-points representing January and 0 elsewhere. The quadratic term of t was supported by fractional polynomial regression.

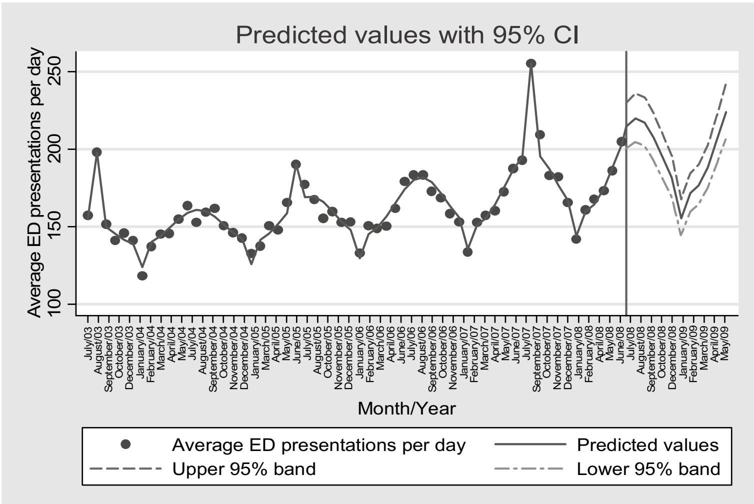


Fig. 3. The plots of the predicted ED presentations vs. the observed frequencies based on the revised model

Note. The predicted values were back-transformed to the original scale.

DISCUSSION

Although the data used in this study are dated, the present study demonstrated that patients' presentations at a paediatric ED have distinctive patterns, which can be reasonably modelled with a linear regression. The findings showed that there was a seasonality in ED presentations, which were characterised by a yearly cyclic pattern with an increasing trend in patient volume. A yearly cycle in the pattern of the ED presentations was more likely to be caused by the presentation of patients with respiratory and infectious diseases. These types of diseases tend to flourish in winter periods when temperatures are low, and subside in summer. Thus, they often create a seasonal variation in the presentation of patients[17]. On the other hand, the increase in the total number of ED presentations was found to reflect the increase in the numbers of children, who needed treatment for injuries or symptoms with unidentified causes. These groups of patients accounted for 17.36% (for the injuries) and 15.79% (for the unidentified causes) of the total ED presentations, respectively, and were identified as the second and the third largest patient groups, following that with disease of the respiratory system (18.87%), during 2003-2008. Although the causes of the injuries and the symptoms were unidentified, the increase in the number of these patients can be explained by a simple fact. According to the Australian Bureau of Statistics[2], Victoria has observed natural population growth as well as growth by overseas migration. Accordingly, the population of children under the age of 18 has also shown an upward curvilinear increase with growth rates of 0.3 to 1.2%. Since, the RCH is the only specialist paediatric hospital with a trauma centre in Victoria, growth in the young population could have resulted in more children suffering from injuries and symptoms with unidentified causes, and to their being transferred to the RCH ED.

The identified model can be used to improve paediatric emergency services. Providing timely services to children is important, as they cannot tolerate a long waiting-time until they are attended by a physician. Children may not also accurately monitor and express their conditions[21]. Thus, they are more likely to progress into severe health conditions, if appropriate medical intervention is not given. Understanding the pattern of ED presentations will assist in identifying future patient flow, which subsequently helps to manage human and material resources more effectively. Without fine ED management, quality care cannot be provided to the public. In this regard, the present study provided precious information for ED management. The potential managerial implications arising from the findings of this study are as follows:

- Mobilisation of health care professionals is necessary to cope with the increase and the greater variability in the number of future ED presentations. For instance, additional (casual) healthcare professionals should be called in to help cope during a period in which a large volume of patients is expected (i.e., in winter) at the ED.
- The physical environment of the ED may need to be improved to accommodate more patients, as ED overcrowding is not only a consequence of patient volume, patient acuity and staff allocation, but also of the physical space of the ED[4].
- The time in which the flow of ED presentations is at a minimum can be used for staff education to provide better services at the ED (especially for casual staff).
- Establishing a network with local General Practitioners (GPs) is necessary to divert less urgent patients to GPs.

A better management of EDs is essential to deal with a large volume of patients and to alleviate overcrowding. Equally important to resolving ED overcrowding is to take proactive measures, such as the introduction of disease prevention programs to reduce a number of sick children. For instance, our results as well as others[9] indicated that the large volume of patients who presented in winter was due to respiratory diseases and viral infection. Thus, educating children about hygiene-measures (e.g., hand-washing, gargling, and wearing a mask) might contribute to the prevention of infectious disease among children, thus reducing the number of presentations at EDs.

The above managerial implications are made based on the data from one paediatric hospital in Australia. However, the current study findings may also have some implications for a Japanese paediatric emergency context, since a seasonal variation in patient presentations at EDs has also been observed in other hospitals[9,14].

There are three limitations inherent in this study. First, the model development was made based on data available from only five years. Due to this short observation period, the estimated model captured only a basic trend in time (i.e., a linear or curvilinear increment) and some seasonal cycles observed within a year. A longer observation period might have allowed longer cyclic trends, such as 3-4 year-cycle of the patterns in ED presentations, to be explained.

Second, careful utilisation of the identified model is necessary. For instance, there may be an unexpected event that causes a high volume of patients to present at EDs. For instance, the pandemic of H1N1 influenza significantly increased the number of ED presentations in 2009[3]. Such an event, however, cannot be forecasted by the current model, which was developed based on a time factor alone. The identified models also cannot be used for a long-term prediction. For example, the model for ED presentations shown in Table 3 indicated an escalating number of ED visits in the later years. This does not mean, however, that the number of ED presentations will keep increasing exponentially forever. The patterns of ED presentations can be altered as a result of changes in hospital/public policies, population size, and environmental changes (e.g., meteorological changes and the changing level of air pollution[8]). Therefore, constant revisions and re-estimations of the models are required by including new observations at the ED as well as by taking other influential variables into consideration.

Third, the present project did not conduct a validation study, where the accuracy of the model predictions is examined by comparing them with future observed values. We could have modelled the pattern of ED presentations on four years of data, and reserved the fifth-year data for the model validation. Doing so, however, would reduce the number of time-points available for the model estimation, thus undermining the accuracy of the model. Further studies are needed to capture accurately the pattern of paediatric ED presentations.

CONCLUSION

The patient flow in paediatric ED showed seasonal variations, which can be reasonably modelled by regression analysis. Understanding the trend in patient flow and predicting the future by a regression model assist effective management of human and material resources, thus enhancing patient care.

ACKNOWLEDGEMENTS

The authors would also like to thank the Quality and Improvement Department at the Royal Children's Hospital for supporting this project.

(Received March 19, 2012)
(Accepted June 29, 2012)

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