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## **TRIAGE OF THE CHILD WITH ABDOMINAL PAIN: A CLINICAL ALGORITHM FOR EMERGENCY PATIENT MANAGEMENT**

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Running title: Abdominal Pain: Clinical Algorithm for Emergency Management

### **Abstract**

**Objective:** To create a simplified *clinical algorithm* for the triage of children with abdominal pain.

**Design:** Data mining methodology (Rough sets analysis) was applied to a randomized data set obtained from patients' emergency admission charts.

**Setting:** Emergency Room at the Children's Hospital of Eastern Ontario in Ottawa.

**Population Studied:** Retrospective analysis of 175 emergency records. Patients were grouped into 2 categories - those having appendicitis (confirmed by a pathology report), and those discharged from the emergency room and not returning for the same or a related problem.

**Results:** A set of 9 clinical symptoms and signs was identified as being important for patient management. A clinically-based algorithm for the triage of these children is suggested.

**Conclusions:** It is possible to develop a *clinical algorithm* for triage of abdominal pain that can be used even by non-medical professionals. A template for such an algorithm can be further extended into other pediatric emergencies, such as chest pain, headache, joint pains, *etc.*

**Keywords:** Appendicitis, Children, Emergency Care, Rough Sets analysis.

## **1. Introduction**

Despite the advent of ultrasonography, computer assisted tomography and magnetic resonance technology, clinical assessment remains the major diagnostic tool in pediatric emergencies. In the management of pediatric abdominal pain (where most of these patients are referred to the emergency room (ER)), rapid diagnosis depends on the clinical acumen and experience of the caregiver. The presence of other more acute problems and the number of patients in the ER delay individual patient assessment. In a teaching hospital, the initial evaluation is a physician in training. Unable to make a diagnosis, he may order investigations that may further defer definitive management. Complex radiological investigations such as abdominal ultrasound are “operator dependent” i.e. require the presence of an experienced radiologist. The frustration of the parents and the anxiety of the patient may further complicate management.

Fiscal responsibilities are forcing medical institutions and physicians to curtail the cost of the diagnostic process. There is a prevailing view that the costs of medical care can be partially controlled through innovative approaches to health care management (1). Research in health care management shows that the usefulness of information provided by tests and procedures diminishes as the diagnostic process approach certainty (2). This observation has prompted the development of different measures for the evaluation and rationalization of tests and diagnostic procedures (3). These measures either deal with proposals for organizational changes in the care-providing organization (4), or focus on new, usually information - based approaches to patient management (5). This study falls into this second category.

Evidence from both clinical and psychological studies (6) points to an obvious advantage to the rapid triage<sup>1</sup> of patients with abdominal pain. Such children constitute a significant proportion of pediatric emergencies. The central difficulty of their triage is the choice of clinical symptoms and signs (attributes) that in combination contribute the most to the diagnosis and management. A pertinent reduced set of attributes should assist the triage nurse and help the ER physician.

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<sup>1</sup> The term *triage* used throughout the paper refers to the initial assessment of the patient.

In this paper we discuss the identification of such a set of attributes, and the development from it of a *clinical algorithm* to facilitate the triage of the child with abdominal pain. The attendant goals of parental satisfaction, improved patient compliance and a reduction in overall cost of medical services may also be achieved.

## **2. Patients and Methods**

A retrospective analysis of the ER records of 175 children with abdominal pain admitted to the Children's Hospital of Eastern Ontario in 1997 was completed. Based on the final diagnosis, the patients were classified into two distinct groups (decision classes):

1. *appendicitis* confirmed by pathology and
2. *resolution* - this implied resolution of all clinical complaints and physical findings with no pathological diagnosis and no operative procedure.

In order to maintain a homogenous data set, patients were excluded from analysis if the final diagnosis was neither *appendicitis* nor *resolution*. The distribution of data between these two groups is given in Table 1.

Insert TABLE 1 here

For each patient we tried to collect information on all 12 clinical symptoms and signs, but this wasn't always possible. These are described in Table 2, which also includes the record of information missing from the patient's chart.

Insert TABLE 2 here

The data set contains both qualitative and quantitative information. Comprehensive treatment of such data can be accomplished with the help of new methodologies developed for so-called knowledge discovery applications. The discipline of knowledge discovery encompasses several fields, such as artificial intelligence, intelligent information systems, operations research, and knowledge acquisition in expert systems. Numerous powerful knowledge discovery theories were developed to extract patterns from imprecise data. The rough sets (RS) theory is one of them (7). The RS theory, its mathematical foundations, basic concepts, and the applications are described, amongst others, in (7), (8), (9). RS has been successfully used to analyze Canadian medical data

(10), in addition to several other data mining problems (9). It was used to analyze data described in this paper.

The RS theory is based on the observation that it is very difficult to properly describe the characteristics of a problem while relying on imprecise information about the values of the problem's attributes (here they are clinical symptoms and signs). In other words, imprecise information causes indiscernibility of patients' groupings into *appendicitis* and *resolution* classes in terms of information available from the charts (while the final diagnosis is excluded). The RS theory provides a powerful tool to identify a minimal subset of attributes (a *reduct*) which gives a satisfactory description of a decision problem. In this paper we describe an application of the RS theory to identify a *reduct* enabling the classification of a patient (with an unknown final diagnosis) as either *appendicitis* or *resolution*. Prior to the analysis, each patient chart was evaluated for the clinical attributes and a pathology report or final ER diagnosis was recorded. This information was tabulated, with an example of such a table given in Table 3. Rows of the table represent individual charts, while columns correspond to the attributes being extracted from the charts.

Insert TABLE 3 here

Using the RS terminology, in a complete table used in the study, a set of diagnostic decisions consists of  $\{appendicitis, resolution\}$ , a set of the clinical attributes consists of  $\{Age; Sex; AbdPainDur; AbdPainSite; AbdPainType; Vomiting; Vombile; PrevVis; Tempr; AbdTend; AbdMass; WBC\}$ , and value domains for them are expressed as, for example  $Age = \{\_2y; 2\_7y; 7\_16y\}$ . It is important to stress that values of all attributes were discretized and coded according to their clinically judged significance.

One of the common problems associated with analysis of medical data is the issue of missing values in patients' charts. We dealt with this problem by considering each piece of missing information as a separate value, thus assigning it a unique artificial value (*cf* Table 2).

Application of RS allowed us to identify a *reduct* used to develop a *clinical algorithm*. The purpose of the algorithm was to describe in easily acceptable form causal

dependencies leading towards the classification of a patient as either *appendicitis* or *resolution*. In the development of a *clinical algorithm*, we relied on the information provided by the *interesting rules*<sup>2</sup> that were generated using the RS methodology. All calculations were conducted on an IBM-compatible computer using the *ProFit* software (11).

### 3. Results

Reduction of the original set of 12 clinical symptoms and signs resulted in the generation of four *reducts*. Three of these *reducts* consist of 9 attributes, and one consists of 10 attributes. The longer *reduct* was discarded and three shorter *reducts* are presented in Table 4. The last row of Table 4 gives the result of the *classification tests* when patients were classified into one of the decision classes with the help of the attributes comprising a *reduct*. The classification accuracy is given as the average value obtained after a series of *10-fold-cross-validation*<sup>3</sup> tests, and the decision rules used for classification were generated using a *minimal covering*<sup>4</sup> algorithm (8). The highest accuracy was achieved for the third *reduct* (#3), and it was selected as a basis for further investigation.

Insert TABLE 4 here

The causal relationship between the patient's final diagnosis and *reduct #3* is expressed in terms of *interesting rules* from which we derived a *clinical algorithm*. *Reduct #3* is comprised of the following clinical attributes: number of years (Age); gender (Sex); duration of pain (AbdPainDur); location of pain (AbdPainSite); type of pain (AbdPainType); number of times vomiting occurred (Vomiting); previous visit to ER in last 48 hours (PrevVis); fever (Temp); white blood cell count (WBC). The purpose of this algorithm is to rapidly and reliably triage a patient as either *appendicitis* or *resolution*. Table 5 presents the average values of

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<sup>2</sup> The *interesting rules* are the rules possessing certain properties, such as for example the rule's strength (minimal number of historical cases being correctly classified by a rule). Here we assumed that a rule is considered to be an *interesting rule* only if it correctly classifies at least 14% of the patients when applied to the historical data.

<sup>3</sup> This is one of possible measures of accuracy of an classification. The initial data set is divided into 10 disjoint sets, called *folds*. The learning and classifying phases are then conducted 10 times, with each of the *folds* acting successively as the testing sample and all the remaining *folds* as the learning sample. This type of test is normally used with medium-sized data sets.

<sup>4</sup> This algorithm is designed to generate a minimal numbers of rules that classify all objects (patients) on a basis of the analyzed data set (ER charts).

classification accuracy of the *interesting rules* obtained after fifty passes of the *10-fold-cross-validation* tests.

Insert TABLE 5 here

It can be seen that the total classification accuracy of the *interesting rules* is slightly lower than that given in Table 4 for a *minimal covering* method. This is so because the *interesting rules* are more general, thus representing broader classification patterns that might not be applicable to some very specific cases. However, it is important to note that there is no significant difference in the classification accuracy of the *interesting rules* within the *resolution* and the *appendicitis* classes.

The *interesting rules* are not diagnostic (i.e. do not give the patient's final diagnosis), but capture general patterns of medical information associated with the assessment of the child with abdominal pain. These patterns are written in the form of a *clinical algorithm*. Following a format accepted by the medical profession, such an algorithm can be expressed as a system of conditional statements:

The diagnosis may be *appendicitis* and the management maybe *appendectomy* when one of the following occurs:

- A male patient experiences right lower quadrant abdominal pain and his white blood cell count is above 20000/mm<sup>3</sup>;
- A male patient experiences right lower quadrant abdominal pain lasting between 4h and 24h, combined with frequent (more than 3 times) vomiting;
- A male patient who already visited the ER in last 24 hours experiences right lower quadrant abdominal pain, combined with frequent (more than 3 times) vomiting;
- A patient experiences right lower quadrant abdominal pain combined with frequent (more than 3 times) vomiting and his/her white blood cell count is above 20000/mm<sup>3</sup>;
- A patient experiences right lower quadrant abdominal pain combined with a fever of 37C - 39C and his/her white blood cell count is above 20000/mm<sup>3</sup>.

The diagnosis maybe *resolution* and the management maybe *discharge* when one of the following occurs:

- A patient experiences abdominal pain (neither right lower quadrant nor suprapubic) lasting between 4h and 24h;
- A patient experiences abdominal pain (neither right lower quadrant nor suprapubic) of intermittent character;

- A patient experiences abdominal pain (neither right lower quadrant nor suprapubic) not accompanied by vomiting;
- A patient experiences abdominal pain (neither right lower quadrant nor suprapubic) combined with a normal temperature and his/her white blood cell count is between  $10000/\text{mm}^3$  and  $20000/\text{mm}^3$ ;
- A patient experiences non-localized pain of intermittent character, combined with a normal temperature and his/her white blood cell count is between  $10000/\text{mm}^3$  and  $20000/\text{mm}^3$ .

The relative importance of the attributes in the statements comprising the *clinical algorithm* is further supported by an analysis of their relative frequencies calculated for the *interesting rules* during the validation tests (where frequency of 100% denotes the most frequent attribute). It is illustrated on Figure 1 below.

Insert FIGURE 1 here

A label “correct” refers to those rules that classified patients correctly while “all rules” refers to all *interesting rules* regardless of the correctness of their classification. Analysis of the graph in Figure 1 confirms that an effective *clinical algorithm* must include the following medical information: location of abdominal pain (AbdPainSite), type of abdominal pain (AbdPainType), and a white blood cell count (WBC). The other diagnostic items may provide useful supplementary diagnostic information for management of appendicitis.

#### **4. Discussion**

The purpose of this study was to develop a *clinical algorithm* for the triage of a child with abdominal pain. We have reduced a set of clinical symptoms and signs (attributes), considered routinely in the diagnosis of appendicitis. Nine attributes were identified for the development of a *clinical algorithm*.

The *clinical algorithm* discussed in the paper reflects the physician’s inductive reasoning while diagnosing a patient with an abdominal pain. It asks primarily for the evaluation of the abdominal pain site and type, together with the white blood cell count, further supported by the information on pain duration, fever, vomiting, patient’s gender, a history of previous visits to the ER, and patient’s age. The sensitivity of a *clinical algorithm* in the diagnosis of abdominal pain may be less than that of ultrasonography or

computer tomography, but on the other hand it is very easy to implement. Thus, our study suggests that with appropriate methodology, clinical data might be efficiently used in at least the triage, if not the final diagnosis of the patients, without resorting to expensive diagnostic procedures. The *clinical algorithm* requires field-testing and validation prior to its use in a clinical setting. Therefore, a prospective assessment of the algorithm is at present being planned at two teaching hospitals in Canada.

There have been attempts to develop diagnostic scoring systems that support the management of the abdominal pain patient (see (12), (13)). However, the usefulness of these systems relies on the assumption that a sophisticated trained user is operating it. This is not required for the *clinical algorithm* presented in this paper, as it is comprehensible even for a non-medical user and thus, can be easily introduced into any health care environment.

It is important to stress that a similar approach may be applied to study data related to other specific complaints that at present are referred to the pediatric ER. The selection of appropriate clinical symptoms and signs and the development of a structured *clinical algorithm* for conditions such as chest pain, headache, joint pains, breathing difficulties and so on, may allow rapid management and streamlined triage of such patients. As a result, it is not unreasonable to envisage satisfied parents, less stressed staff and ultimately improvement in the management of pediatric emergencies.

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**TABLES and FIGURES**

**Table 1**

Diagnostic classes		
Class	# patients	%
<i>Resolution</i>	139	79.4
<i>Appendicitis</i>	36	20.6
<b>Total</b>	<b>175</b>	<b>100.0</b>

**Table 2**

Clinical symptoms and signs and missing values			
Attribute	Class		Description
	<i>Resolution</i>	<i>Appendicitis</i>	
1. Age	0	0	Number of years
2. Sex	0	0	Gender
3. AbdPainDur	0	0	Duration of pain
4. AbdPainSite	1	0	Location of pain
5. AbdPainType	31	14	Type of pain
6. Vomiting	0	0	Number of times vomiting occurred
7. Vombile	4	0	Bilious vomit
8. PrevVis	12	0	Previous visit to ER in last 48 hours
9. Temp	0	0	Fever
10. AbdTend	1	1	Site tenderness
11. AbdMass	2	2	RLQ mass
12. WBC	3	1	White blood cell count

**Table 3** Example of a table

Age	Sex	AbdPainDur	AbdPainSite	AbdPainType	Vomiting	Vombile	PrevVis	Temp	AbdTend	AbdMass	WBC	Class
_2y	F	_4h	else	interm	1	no	no	37-39	abs	no	10_20	resolution
2_7	M	4_24h	RLQ	cont	_3	yes	no	_39	pres	yes	_20	appendicitis

**Table 4**

		REDUCTS		
<b>Clinical symptoms and signs</b>		#1	#2	#3
1	Age	√	√	√
2	Sex	√	√	√
3	AbdPainDur	√	√	√
4	AbdPainSite			√
5	AbdPainType	√	√	√
6	Vomiting	√	√	√
7	Vomible			
8	PrevVis	√	√	√
9	Temp	√	√	√
10	AbdTend		√	
11	AbdMass	√		
12	WBC	√	√	√
Accuracy		73.5 ± 2.0	73.5 ± 1.9	77.3 ± 1.0

**Table 5**

Results of classification tests ( <i>interesting rules</i> )			
	Correct	Incorrect	No decision
<b>Total</b>	<b>65.9 ± 2.3</b>	<b>33.3 ± 2.3</b>	<b>0.8 ± 0.9</b>
<i>Resolution</i>	64.6 ± 3.2	33.6 ± 3.2	0.8 ± 1.0
<i>Appendicitis</i>	67.0 ± 4.7	32.2 ± 4.5	0.7 ± 1.4

**Figure 1**

