DETECTING ASTHMA EXACERBATIONS IN A PEDIATRIC EMERGENCY DEPARTMENT

By

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Asthma is the most prevalent pediatric chronic disease and is characterized by airway obstruction caused by bronchospasm and airway inflammation. Exacerbations of asthma require prompt medical therapy and are a frequent reason for pediatric emergency department (ED) visits [1]. National guidelines for the treatment of acute asthma exist and have been shown to improve care when followed [2-4]. There are, however, barriers to adoption and compliance with guideline recommendations, and unnecessary variations in patient care remain [5-7]. One difficulty in using practice guidelines, when presented in either a computerized form or on paper, is the need to initiate their use [8]. If guideline enrollment requires deviation from the normal workflow, such as following extra steps in an order-entry system or remembering to pick up paper forms, guidelines often remain unused. Also, guidelines may offer recommendations that should be carried out before a physician evaluates a patient. Early electronic identification of patients presenting to the ED with asthma exacerbation could trigger automatic initiation of guidelines for all eligible patients and enable reminding providers, which may potentially lead to improved patient care.

Clinical diagnostic systems developed for conditions other than asthma have been developed and evaluated in the ED setting. Examples include systems for the detection of pneumonia [9], pulmonary embolism [10, 11], myocardial ischemia [12], and ankle fractures [13]. Only few studies intended to identify a patient's disease for guideline-enrollment, such as the detection of

pneumonia [14]. To my knowledge the real-time detection of asthma exacerbations in an ED setting has not been reported.

The purpose of my project was to develop and evaluate an electronic diagnostic system for the detection of asthma exacerbations in the ED. The hypothesis was that an electronic detection system can identify asthma exacerbation episodes in a pediatric ED population early during a patient's encounter. Goals included making a prediction in real-time immediately after a patient's completion of the triage process in the ED, using only electronic information, and not requiring providers to enter additional patient data.

The specific aims of the project were to:

1) Perform a systematic literature review of biomedical informatics applications for asthma care.
2) Develop an asthma identification algorithm using available patient-specific electronic data.
3) Implement the asthma identification system and integrate the system with the ED information system infrastructure to predict asthma exacerbations in real-time.
4) Prospectively evaluate the asthma prediction algorithm in Vanderbilt's pediatric ED.

Chapter II addresses aim one and describes prior relevant biomedical informatics studies through a systematic review of computerized applications for asthma care [15]. The chapter provides background describing prior research for asthma detection and diagnosis, monitoring and prevention, patient education, and implementation of guidelines or therapeutic recommendations.

Chapter III addresses aim two. The chapter describes the development of a rule-based asthma detection system [16]. The retrospective analysis examined the feasibility and performance of the algorithm in patients who presented to Vanderbilt's pediatric ED with chief complaints most common for asthma exacerbation. Predictions were based on a patient's presenting chief complaint and past history of asthma determined by examining the electronic problem list and billing records.

Chapter IV addresses aims three and four and describes the implementation and integration of the asthma detection system with the ED information system infrastructure to allow the prediction of the presence or absence of a patient's asthma status in real-time after completion of the ED triage process. The computerized asthma detection system was evaluated in a prospective observational study that included all patients aged 2-18 years old presenting to the pediatric ED during a two-month period.

Chapter V discusses implications of this research, possible methods to overcome the discovered limitations, and directions for future study.

CHAPTER II

SYSTEMATIC LITERATURE REVIEW

Introduction

Asthma is one of the most common chronic medical conditions and affects an estimated 300 million people worldwide [17]. In the United States, more than 20 million children and adults have asthma. It is responsible for significant patient morbidity and mortality, including an estimated 11.8 million lost work days for adults and 14.7 million lost school days for children in 2002, as well as 4,261 deaths per year [18]. Medical care for asthmatic patients places a considerable burden on health care systems in the outpatient, emergency department, and inpatient settings. In 2002, there were 13.9 million outpatient physician office visits related to asthma, 1.9 million emergency department visits, and 484,000 hospitalizations. The National Heart, Lung, and Blood Institute estimated the total cost of asthma care in 2002 to be $14 billion [18].

Although asthma is a common disease, there remains great variation in the care of asthmatic patients. Discrepancies between current therapeutic standards and clinical practice have been observed. Published examples of suboptimal asthma management include under-estimation of disease severity by patients and high rates of persistent symptoms [19], under-treatment of symptoms by providers [20], low rates of outpatient follow-up after emergency room visitation and hospitalization for asthma [21, 22], and low rates of preventive care measures such as influenza immunization [23]. As a result of practice variability, different organizations have

developed practice guidelines for asthma care [24-26], including the widely accepted guideline created by the National Heart, Lung, and Blood Institute through its National Asthma Education and Prevention Program [27]. These guidelines were published as the first Expert Panel Report in 1991 [28] with a second Report in 1997 [29] and with revisions in 2002 [24].

The common goal of asthma guidelines is to provide an evidence-based and standardized approach to patient care. The National Asthma Education and Prevention Program guidelines outline a multifactorial care plan that includes the use of objective measures for diagnosis and monitoring of therapy, the need for symptom prevention through environmental control measures, a comprehensive approach to medical therapy for the treatment and reversal of airway inflammation, and the need for patient involvement and education in asthma management. Studies of asthma management have validated these recommendations and shown improved outcomes when care is consistent with guidelines [30].

Despite the publication of these comprehensive guidelines, practitioner and patient compliance with guidelines has been low [22, 31-33]. Many barriers to guideline use and optimal care for asthmatic patients have been identified. Barriers include provider factors such as time pressure, limited knowledge of or belief in current best practice recommendations, administrative factors such as the inability to identify and track patient populations, and patient factors such as poor medication compliance and limited knowledge of effective disease self-management [34, 35].

Computer applications for patient care are becoming increasingly common methods for addressing barriers to optimal medical care. They have been applied in a variety of clinical

settings for the improvement of the process, delivery, and evaluation of medical care [36, 37]. Computer systems have been used to improve the use and adherence to practice guidelines, provide clinical care alerts and reminders, and generate patient-specific treatment recommendations and educational material. Specific applications include electronic patient records and registries, computerized provider order entry systems, computer-assisted diagnostic systems, and computer-assisted education programs. Clinical computer systems also have been applied in a wide range of clinical settings, including outpatient, inpatient, acute care, and patient homes. Computer-based interventions have successfully targeted the full spectrum of personnel involved in heath care, including physicians, patients, nurses, and administrators.

Because of the multifaceted nature of asthma care and the development of comprehensive clinical care guidelines, asthma is a disease where computer-based applications may help to overcome the barriers to improving patient care. We performed a systematic literature review of medical computing applications for asthma and examined the clinical domains and various aspects of patient care for which computer applications have been developed. We characterized computerized asthma applications according to their level of development, implementation and evaluation, and examined the study designs applied for evaluating the applications' impact on asthma care.

Methods

Selection Criteria

We targeted publications that described or evaluated a computer-based intervention or application to support clinical asthma care. Asthma care was defined broadly and included

diagnosis or detection systems, applications for the prevention or monitoring of symptoms and outcomes, decision support tools for asthma treatment including electronic implementation of practice guidelines, and patient-centered education tools. We considered articles published in peer-reviewed journals or conference proceedings including review articles and surveys that described or evaluated such applications. Only articles in English with available online abstracts at the time of searching were included. Abstracts, poster presentations, and editorial publications were excluded, as were studies which did not involve patient care. Examples of excluded reports were studies that compared the efficacy of drug therapies, described the creation of a database, measured epidemiological statistics, or created a patient registry without applying the registry content for clinical care.

Search Strategy

We queried the following electronic publication databases from their start date through February 1, 2005:

- PubMed (MEDLINE) [38].
- OVID CINAHL [39].
- OVID All EBM Reviews. (Cochrane DSR, ACP Journal Club, and DARE) [39].
- ISI Web of Knowledge - Web of Science [40].

Searches in PubMed were performed using medical subject headings (MeSH) and keywords, while the other databases were only searched using keywords. Each search required the presence of the concept "asthma" in combination with any of the following terms: "medical informatics," "decision support," "informatics," or "computer-assisted instruction." Included MeSH terms

were *asthma*, *medical informatics*, *decision support techniques*, *informatics*, and *computer-assisted instruction*.

Review Criteria

For each reference, we obtained the title, abstract, authors, source, and date of publication. The two authors independently evaluated and classified the information of each reference as either relevant or not. Disagreements between the two reviewers were resolved by discussion until a consensus was reached. If the abstract did not include enough information to judge inclusion or exclusion, the full text of the publication, if available, was reviewed. If not available, the paper was excluded. The rates of positive and negative agreement were calculated and corrected for agreement by chance using Cohen's kappa (κ) [41].

Paper Evaluations

The full texts of all included publications were obtained and evaluated by one author (DLS). We developed a framework for categorizing and evaluating papers based on three primary criteria: 1) the clinical domain 2) the development stage of the computer application; and 3) the study design.

Each paper was classified and assigned to one of the following four clinical domains, describing the area of patient care where the research was applied:

a) Asthma Detection or Diagnosis;

b) Disease Monitoring or Prevention;

c) Patient Education; or

d) Therapy (including guideline implementation) of acute or chronic asthma.

If a paper described multiple domains, the most emphasized aspect was chosen.

The development stage of a project is an evaluation of the level of maturity that the research has obtained. In contrast to other clinical research, biomedical informatics applications are often described while still in earlier developmental stages, and before clinical endpoints such as patient outcomes are evaluated. We used the "tower of achievement" model proposed by Friedman et al., which describes the various development phases of biomedical informatics applications [42]. Each study was classified as being at one of the following, successive stages:

a) model formulation;

b) system development;

c) system installation, and

d) study of effects.

Model formulation refers to the creation of an idea for acquiring, representing, processing, displaying, or transmitting biomedical information or knowledge. System development is the actual creation of a computer-based system for clinical care, and is often a prototype or stand-alone system. System installation refers to the integration of a system into a clinical care environment and the study of how the system affects the surrounding workflow. Study of effects is the evaluation of the impact of a clinical computer system, both on patients and patient outcomes, as well as effects on the users and the overall impact on the organization and the delivery of health care. Each study was assigned a single level based on the highest level of development described.

We characterized the study design of each publication as one of the following types:

a) Survey;

b) Descriptive study (no intervention tested);

c) Retrospective analysis of an intervention; or

d) Prospective analysis of an intervention.

Additionally, each paper reporting a prospective study of a clinical intervention was analyzed for its study design strength. The strength was evaluated using a study design evaluation instrument, published by Hunt et al., that applies a 5-criteria scale to determine potential sources of biases [37]. For each of the following criterion, a score of 0 to 2 was assigned based on the likelihood of avoiding study biases: 1) Method of subject allocation between the control and intervention groups (random, quasi-random, or selected controls); 2) Unit of allocation and analysis (by clinic, physician / provider, or patient); 3). Baseline differences between study groups (no baseline differences or appropriate statistical adjustments made for differences, baseline differences present and no statistical adjustments made, or unable to assess differences); 4) Type of outcome measure (objective outcome or subjective outcome with blinded assessment, subjective outcome without blinding but clearly defines and explicit criteria for each outcome, or subjective outcome without blinding of assessors and no explicit criteria for each outcome); and 5) Completeness of follow-up (> 90%, 80-90%, or < 80%). These scores were summed to give an overall evaluation score ranging from 0 (most potential study bias) to 10 (least potential study bias).

Study characteristics for prospective trials were further examined by the clinic setting, the primary users, the target patient population, and the type of primary outcome measure. Clinical

settings included: outpatient, inpatient, emergency department, patient home, multiple clinical settings, or no specified setting. The primary users of the systems included: clinicians, patients, administrators, or no users specified. The targeted asthmatic patient populations were: any patient age, only adults, only children, or unspecified. Finally, the primary outcome measure was a clinical, health-related measure (e.g., hospitalization or vaccination rates, asthma symptom reduction, or patient quality of life) or a non-clinical measure (e.g.,. patient knowledge or behavior, patient education, guideline adherence, or asthma trigger avoidance).

Results

We identified a total of 555 references from citation database queries, composed of 529 from PubMed [38], 10 from CINAHL [39], 14 references from OVID EBM Reviews [39], and 2 references from ISI Web of Knowledge [40]. These results represented 549 unique citations once duplicates were removed. From this set the two reviewers identified 64 relevant articles. The raw rate of reviewer agreement was 94.9% overall, and was 78.8% for included articles and 97.1% for excluded articles. The chance corrected agreement [41] between the two reviewers was substantial ($\kappa = 0.76$; 95% confidence interval = 0.67-0.85). Table 1 displays a summary of included articles.

Table 1. Included publications. Ordered by clinical domain and year of publication.

Reference	Author	Year	Dev. Stage[a]	Domain[b]	Study Design
43	VanMeerten	1971	1	DD	Retrospective
44	VanMeerten	1971	2	DD	Retrospective
45	Bennett	1988	2	DD	Prospective
46	Toop	1989	1	DD	Descriptive
47	Sager	1994	2	DD	Retrospective
48	Aronow	1995	2	DD	Retrospective
49	Aronow	1995	2	DD	Retrospective
50	Ertle	1996	2	DD	Retrospective
51	Donahue	1997	2	DD	Retrospective
52	Premaratne	1997	2	DD	Retrospective
53	Burge	1999	2	DD	Retrospective
54	Rietveld	1999	1	DD	Descriptive
55	Grassi	2001	1	DD	Retrospective
56	Hirsch	2001	1	DD	Descriptive
57	Kable	2001	2	DD	Descriptive
58	Sefion	2003	1	DD	Descriptive
59	Daley	2004	4	DD	Retrospective
60	Vollmer	2004	2	DD	Retrospective
61	Ayers	1972	3	MP	Descriptive
62	Osman	1994	4	MP	Prospective
63	Curtin	1998	4	MP	Descriptive
64	Finkelstein	1998	2	MP	Descriptive
65	Finkelstein	1998	2	MP	Survey
66	Finkelstein	2001	2	MP	Descriptive
67	Gaglani	2001	4	MP	Prospective
68	Porter	2001	1	MP	Descriptive
69	Adams	2003	3	MP	Descriptive
70	Chan	2003	4	MP	Prospective
71	Crabbe	2004	2	MP	Retrospective
72	Glykas	2004	2	MP	Descriptive
73	Porter	2004	2	MP	Descriptive
74	Huss	1992	4	PE	Prospective
75	Huss	1992	4	PE	Prospective
76	Takabayashi	1999	4	PE	Prospective
77	Bartholomew	2000	4	PE	Prospective
78	Bartholomew	2000	1	PE	Descriptive
79	Homer	2000	4	PE	Prospective
80	Jaing	2001	2	PE	Descriptive
81	McPherson	2001	1	PE	Descriptive
82	Shegog	2001	4	PE	Prospective
83	McPherson	2002	4	PE	Prospective
84	Huss	2003	4	PE	Prospective
85	Krishna	2003	4	PE	Prospective
86	Oermann	2003	1	PE	Survey
87	Gonzalez	1989	4	TG	Prospective
88	Kino	1991	4	TG	Prospective
89	Szilagyi	1992	4	TG	Prospective
90	Shiffman	1994	1	TG	Descriptive
91	Modell	1995	1	TG	Descriptive
92	Austin	1996	2	TG	Descriptive
93	Adams	1998	2	TG	Descriptive
94	Kuilboer	1998	1	TG	Descriptive
95	Shiffman	1999	2	TG	Survey
96	Tai	1999	3	TG	Prospective
97	Thomas	1999	4	TG	Prospective
98	Johnson	2000	1	TG	Descriptive
99	Shiffman	2000	4	TG	Prospective
100	McCowan	2001	4	TG	Prospective
101	Dobre	2002	1	TG	Descriptive
102	Eccles	2002	4	TG	Prospective
103	Kuilboer	2002	2	TG	Retrospective
104	Kuilboer	2003	2	TG	Descriptive
105	Shegog	2004	1	TG	Descriptive
106	Shiffman	2004	1	TG	Descriptive

[a] Development Stage from ref. [42]. 1: Model Formulation; 2: System Development; 3: System Installation; 4: Study of Effects.
[b] DD: Detection or Diagnosis; MP: Monitoring or Prevention; PE: Patient Education; TG: Therapy or Guidelines

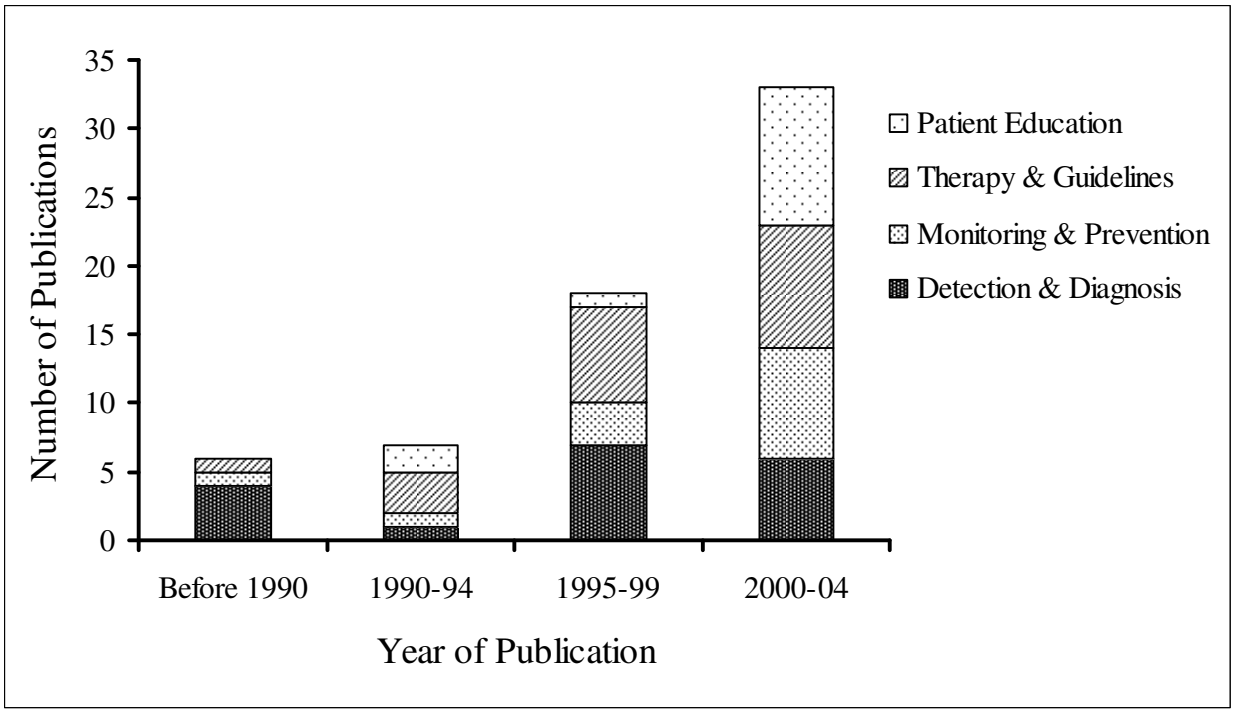

Figure 1. Distribution of publications by time intervals, subdivided by clinical domains.

Figure 1 shows the number of publications by time intervals. Publications increased in each successive time interval, with the majority of studies (54%) published in the last period (2000-2004). There were 28 studies (44%) published in clinical journals, 27 (42%) in biomedical informatics journals, five (8%) in epidemiological or medical quality journals, three (5%) in patient education journals, and one study appeared in a basic science environmental journal. The 64 included publications represented 51 unique projects. There were 1.25 mean publications per project with a range of 1 to 3 publications.

Clinical Domains

The distribution of clinical domains demonstrates the breadth of asthma informatics research pursued by the individual projects. Eighteen papers (28%) describing 17 projects involved asthma detection and diagnosis [43-60]. These studies had three main areas of concentration: 1)

Studies analyzing clinical data such as breath sounds, pulmonary function test results, or peak flow values to determine the presence or severity of asthma; 2) Studies using existing clinical and administrative data such as clinic notes, discharge summaries, billing codes, or chief complaints to identify or classify asthmatic patients; and 3) Studies applying methods such as computer-based surveys or questionnaires to obtain information from patients in order to diagnose asthma or determine asthma severity.

The domain of asthma monitoring or prevention contained 13 papers (20%) describing 10 unique studies [61-73]. These primarily described applications that allow patients to record their degree of symptom control, remind patients to use prescribed medications, or track the use of rescue medications. The type of implementation varied, including home-based tools such as web pages and patient-centered data collection tools that were designed for the ambulatory care setting such as the emergency department.

The domain of patient education contained 13 papers (20%) reporting on 9 unique studies [74-86]. These studies all described computer based programs used by asthmatic patients. Examples of these applications include a computer game for children, a presentation of instructional multimedia clinical scenarios designed to improve recognition of asthma symptoms, a system to teach the avoidance of triggers such as dust mites, and a program to assess patients' knowledge of proper therapy for asthma exacerbations.

The most common domain was the implementation or evaluation of a system to guide therapy or support clinical guidelines, accounting for 20 publications (31%), and 16 unique projects [87-

106]. Studies covered a wide variety of topics including computerized systems for determining optimal drug dosing regimens, implementation of computerized decision support systems for use in outpatient clinics, systems to critique care plans for asthmatics, and reminder systems to prompt clinicians to give vaccinations to eligible asthmatic patients.

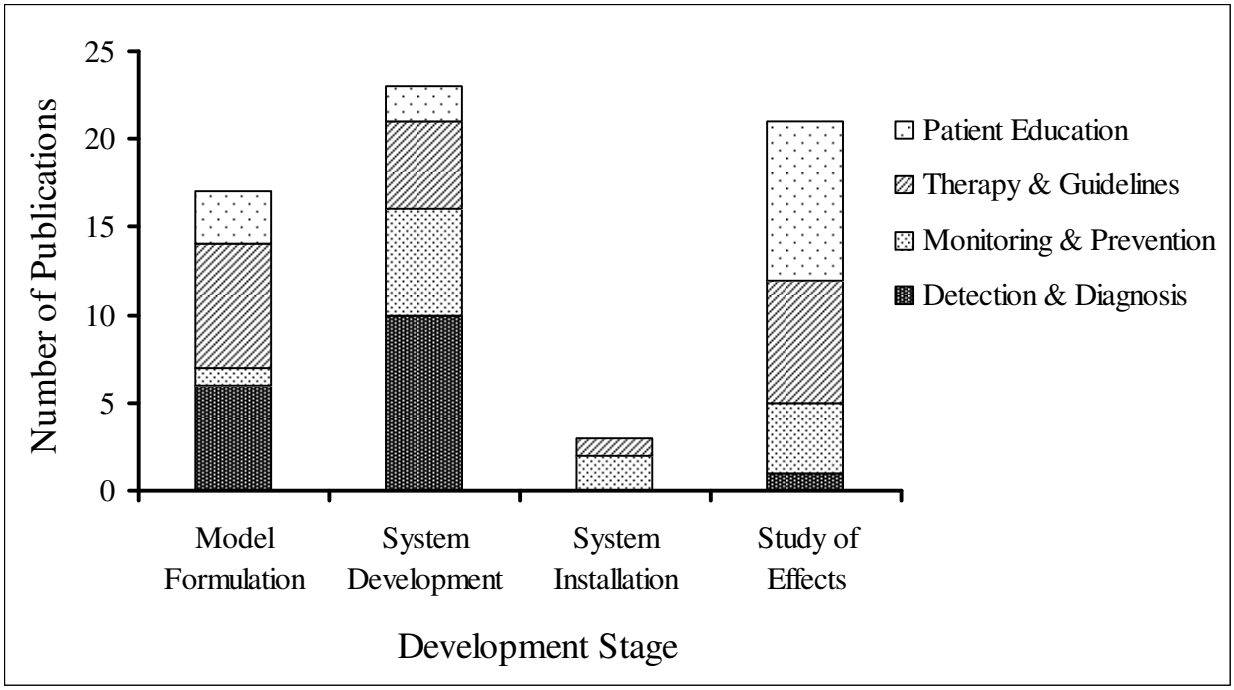

Figure 2. Distribution of publications by successive development stages, subdivided by clinical domains.

Development Stages

Figure 2 shows the number of studies at each of the varying developmental stages, as described by Friedman et al. [42]. The majority of studies (63%) described an early stage of application development. The most basic stage, model formulation, accounted for 17 publications. These focused on the description of conceptual models and plans for future system implementation. Examples include a report detailing the design of a computer decision support tool for asthma management [98], an evaluation of the possible difficulties in translating published clinical

guidelines into a computer-readable format [90], and a proposed design of a computer game to increase patient knowledge of asthma care [78]. The next stage, system development, comprised the largest number of studies with 23 publications. These were primarily the reporting of results of small pilot, prototype, or feasibility studies. Examples include the remote monitoring of patients' asthma symptoms [64], a system for collecting patient data in the emergency department waiting room [73], and a system to diagnose asthma from pulmonary function study results [43]. Only 3 studies were at the system installation stage. All 3 studies described the implementation of patient record systems for use in outpatient settings [61, 93, 96]. The remaining 21 studies achieved the most advanced stage, the study of system effects. These studies evaluated the effects of computer applications on their users and on patient outcomes. Outcomes measured included the increase in patient knowledge [76, 77, 83, 85], rate of provider compliance with asthma care guidelines [100, 102], the change in patient symptoms or hospitalizations, and the impact on clinic visit length and costs [99].

Study Design

Figure 3 shows the number of reports for each study design category, and is subdivided by clinical domain. Of 29 studies that did not apply an experimental design, 26 studies were descriptive and 3 reported results from surveys. The remaining 35 studies evaluated a hypothesis through an intervention. These were composed of 14 retrospective studies and 21 prospective studies, composed of randomized and non-randomized controlled trials. Consideration of clinical domains revealed that for detection and diagnosis projects, the majority (67%) were retrospective studies. Most studies involving asthma prevention or monitoring were descriptive in nature (8 of 13, 62%). Descriptive studies were also the most common study design for the

therapy or guidelines domain, although 7 papers (35%) were prospective trials. For publications in the patient education domain, the most common study design was a prospective trial, accounting for 6 of 13 publications (46%).

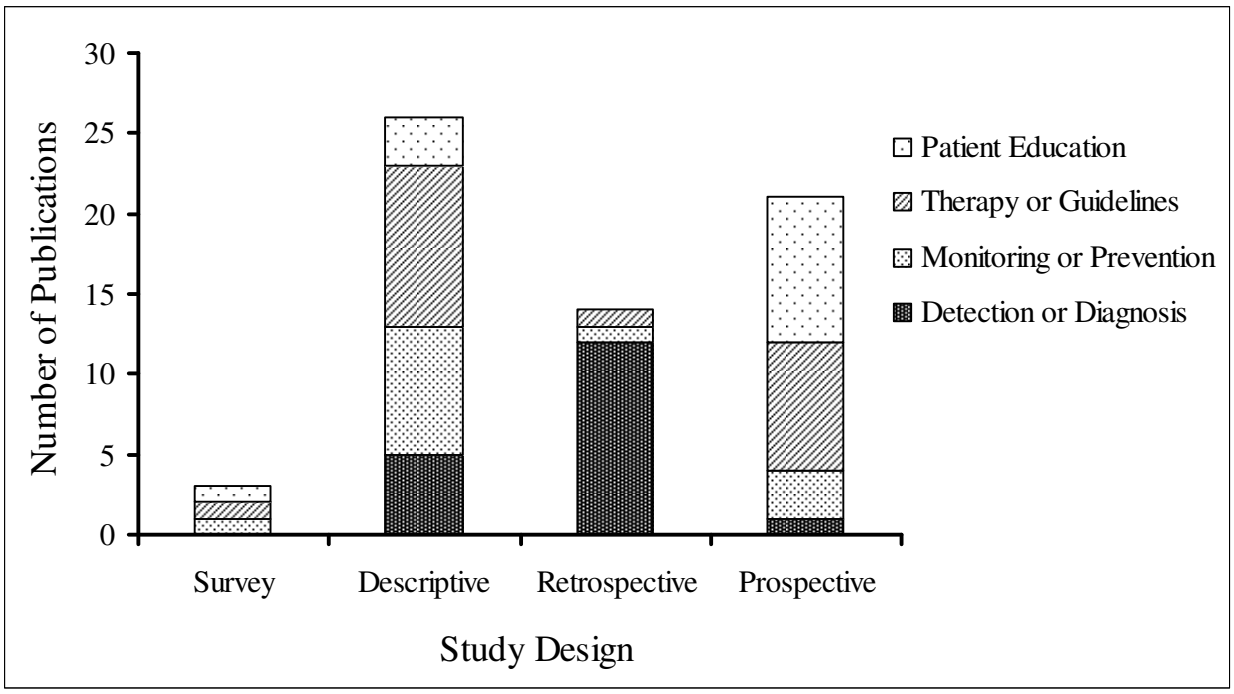

Figure 3. Distribution of publications by study design, subdivided by clinical domains.

Prospective Trials

Among the 64 studies we identified 21 prospective trials, summarized in Table 2. Of these, eight were in the clinical domain of therapy or guidelines, three were in the monitoring or prevention domain, one trial involved asthma detection or diagnosis, and the remaining 9 studies were in the patient education domain. Results from the evaluation of the studies, following Hunt et al. [37], revealed a wide range of study strengths. The mean score was 6.5 (std. dev = 1.8) with scores ranging from 3 (lowest study strength) to 10 (highest study strength). Thirteen studies (62%) used randomization, the least biased method to allocate subjects to control or intervention group,

while five studies (24%) used selected or historic controls. Three studies (14%) used the clinics as the unit of randomization, which is considered the most effective means for reducing bias because possible crossover effects, when a provider cares for patients in both groups, are avoided. Two studies (10%) randomized by providers, while the remaining 16 studies (76%) randomized by patient. For baseline characteristics, fourteen studies (67%) made comparisons between study groups and corrected for any observed differences. Six studies (29%) did not report baseline comparisons between control and intervention populations, while the remaining study reported differences between study groups but did not make corrections. Another technique for minimizing bias is to use an objective outcome measure or to assess a subjective outcome in a blinded manner. This was done in 16 studies (77%), with the remaining 5 studies (23%) measuring subjective results without blinding. The final criterion was the completeness of study follow-up. The participant follow-up rate was >90% in most studies (17 of 21, 81%), 80-90% in one study, and less than 80% in three studies.

The first aspect of study information analyzed was the clinical setting. Eighteen studies (86%) were performed in an outpatient setting. There were 2 studies set in the emergency department, both of which evaluated a computerized recommendation for aminophylline dosing [87, 88]. A single study was set in patients' homes and studied the impact of a video-enabled internet application for improving asthma care [70]. No studies examined in-hospital care of asthmatic patients. Consideration of the primary user group revealed that 14 (67%) applications were designed to be used by patients and the remaining 7 by clinicians. The targeted asthma population included adult patients in 6 studies, pediatric patients in 10 studies, any age group in 3 studies, and was unspecified in the remaining 2 studies.

Table 2. Results from 21 prospective trials, ordered by clinical domain and year of publication.

Reference Number	Description	Clinical Domain[a]	Outcome[b]	Evaluation Score[c]	Study Effect[d]	Sample Size	Clinical Setting	System Users	Patient Population
45	Assessment of a patient survey to detect asthma	DD	N	5	+	36	Outpatient	Patients	Adult
62	Impact of an asthma education program	MP	C	6	+	801	Outpatient	Patients	Adult
67	Reminder system for vaccination of asthmatics	MP	C	4	+	925	Outpatient	Patients	Pediatric
70	Internet-based video system for asthma care	MP	C	8	-	10	Home	Patients	Pediatric
74	CAI for trigger avoidance (dust mites)	PE	N	8	+	52	Outpatient	Patients	Adult
75	CAI for trigger avoidance (dust mites)	PE	N	8	+	52	Outpatient	Patients	Adult
76	CAI for asthma education	PE	C	3	+	33	Outpatient	Patients	Adult
77	Multimedia game for asthma education	PE	C	6	+	171	Outpatient	Patients	Pediatric
79	Interactive educational computer program	PE	C	6	-	137	Outpatient	Patients	Pediatric
82	CAI program for asthma education	PE	N	7	+	76	Outpatient	Patients	Pediatric
83	Multimedia program for asthma education	PE	N	4	+	31	Outpatient	Patients	Pediatric
84	CAI game for improving asthma symptoms	PE	C	6	-	101	Outpatient	Patients	Pediatric
85	Multimedia program for asthma education	PE	C	8	+	228	Outpatient	Patients	Pediatric
87	Computerized guidelines for aminophylline dosing	TG	C	8	-	67	ED	Providers	Adult
88	Computer-assisted aminophylline dosing	TG	C	6	+	89	ED	Providers	Any
89	Reminder system for vaccination of asthmatics	TG	C	8	+	124	Outpatient	Patients	Pediatric
96	Evaluation of an internet CDSS systems	TG	N	7	+	27	Outpatient	Providers	Any
97	Computerized templates for asthmatic care	TG	N	6	-	279	Outpatient	Providers	Any
99	Asthma care CDSS on handheld computers	TG	C	7	-	11	Outpatient	Providers	Pediatric
100	Evaluation of a CDSS for asthma care	TG	N	8	+	477	Outpatient	Providers	Unspecified
102	Computerized guidelines for outpatient asthma care	TG	C	10	-	2230	Outpatient	Providers	Unspecified

CAI: Computer assisted instruction; CDSS: Computerized decision support system.

[a] DD: Detection or Diagnosis; MP: Monitoring or Prevention; PE: Patient Education; TG: Therapy or Guidelines.

[b] C: Clinical health related patient outcome; N: Non-health related outcome.

[c] Range = 0 – 10. From ref. [37].

[d] Presence or absence of a statistically significant improvement in the intervention group for the measured primary outcome.

Among the 21 prospective trials, 13 measured a clinical and 8 a non-clinical outcome. Seven (54%) of the 13 studies with a clinical outcome reported a positive effect, while the remaining 6 found no statistically significant improvement. Improved clinical outcomes included decreased hospitalization rates [62, 76, 77], increased vaccination rates for asthmatic patients [67, 89], and decreased need for rescue medication by patients [85]. Among the eight studies assessing a non-clinical outcome, seven (88%) showed a statistically significant positive effect of the computerized intervention. The improvements included increased dust mite prevention measures [74], increased patient knowledge about asthma self-management [82, 83], and improved adherence to guideline recommendations by clinicians [97].

Discussion

This systematic literature review explored the diversity of computer applications for asthma. Published studies in the field span four decades of research and the number of projects has been increasing over time. This increase reflects the rapid advance of computer technology and the application of biomedical informatics to patient care medicine. The many facets of care for asthmatic patients are well represented in the literature, including diagnostic, patient care, and educational applications. Overall, there is a fairly even distribution of covered topics, although applications to assist with therapy and guideline implementation have been the most common. Early studies commonly reported diagnostic and detection systems, often focusing on automated signal analysis techniques to diagnose asthma. More recently, other types of applications have been emphasized, especially systems designed to be used by patients themselves. In the patient education domain, 10 studies, including 5 randomized controlled trials, were published since the year 2000, while only 3 were published prior to that time.

In this review we applied two measures to characterize the maturity of the published research. The first included an analysis of the research study design, which is an indicator of the rigor used in evaluating a new model or intervention. Two-thirds of the publications used a descriptive or retrospective study design, demonstrating the need for additional research prospectively assessing informatics applications for asthma patients. Randomized controlled trials are considered the gold standard for minimizing bias, but only 16 published studies applied this design. Prospective study designs were particularly uncommon for the detection/diagnosis and monitoring/prevention domains. The second measure of maturity included an application's development stage, evaluating progression through the "tower of achievement," i.e., moving from a laboratory or testing environment to being routinely used for patient care. Only a minority of studies occurred in a practical clinical environment, while two-thirds reported on research in a pilot or other early stage. This may demonstrate that research appearing promising in early stages may not necessarily be beneficial or practical in widespread use. Taken together, these two evaluations reveal that few studies reported a sufficient level of maturity to determine large benefits to clinical practice, and highlight areas which are amenable to further feasibility testing and clinical application. As asthma remains a common disease with a considerable burden to patients, providers, and the payor community, more and stronger evaluations of new asthma applications are desirable.

The outpatient clinic was the study setting for most of the prospectively evaluated informatics applications. While this may be the most common location for caring for asthmatic patients, those with acute exacerbations are more frequently cared for in the emergency department and

hospital environments. There were no studies that examined asthma care in the hospital, and only two that considered emergency room care. Because of the profound differences in workflow and time constraints between different patient care settings, applications developed for one setting, even if successful, may not be practical or beneficial in other areas. This fact highlights the current need for studies to assess the evaluation of applications in the various clinical environments.

Evidence-based care guidelines, such as those developed by the National Heart, Lung, and Blood Institute, are widely accepted; however, their adoption level among providers remains suboptimal. Published standards of care present practical targets for measuring the quality of health care delivery and the success of systems designed to improve care can be evaluated against these goals. The development and dissemination of care guidelines alone is inadequate for solving the problem of unexplained variation in care [107]. Barriers to guideline adoption and compliance include poor accessibility to the most recent recommendations, a perceived lack of time to follow recommendations, and a low perceived need to follow guidelines for common disorders [7]. The application of biomedical informatics applications may represent a promising method for overcoming implementation barriers for asthma care; we found, however, few studies that evaluated the impact of using computerized systems to implement asthma care guidelines. While great opportunity exists for future development, many challenges await. Comprehensive care for asthmatic patients is multidisciplinary and requires coordination and communication between patients and providers in the home, outpatient, and acute care settings. This will require a high degree of integration between computer systems such as electronic patient records across many locations. Additionally, there is a need to individualize asthma treatment plans and to

revise therapy based on patient response. Simply replicating static care guidelines into a computer system will be an inadequate solution to provide the individualized and dynamic care needed by patients. Effective systems will need to track patient outcomes over time and be able to generate personalized care plans for both acute and chronic asthma care.

Conclusion

There is an increasing amount of research studying the application of biomedical informatics applications for the care of asthmatic patients; however, more research is needed. As electronic tools for patient care such as computerized decision support systems and electronic medical records become increasingly mature and more widely adopted, we expect that additional opportunities to improve the care of asthmatic patients through informatics solutions will arise, be implemented, and evaluated in clinical settings.

CHAPTER III

SYSTEM DEVELOPMENT AND PILOT STUDY

Introduction

Asthma is the most common pediatric chronic disease, with an estimated prevalence of 6 million cases in 2002 [108]. Although a number of effective preventive treatments are available, asthma exacerbations are common and cause significant patient morbidity. In the United States, asthma is estimated to account for more than 2 million emergency department (ED) visits annually [1] . Studies have demonstrated unnecessary variability in the care of asthmatic patients, including those who present to an ED [5, 6, 109]. In response to this problem, the National Heart, Lung, and Blood Institute developed and published national guidelines for asthma care in 1991 and updated the recommendations in 1997 [2]. The guidelines include recommendations for the treatment of acute asthma exacerbations in an ED or urgent care setting.

For many acute and chronic diseases, including asthma exacerbations, the implementation of clinical guidelines has been shown to improve compliance with recommendations and to improve patient outcomes in a variety of settings [3]. In the ED, increased adherence to practice standards and improved measures of clinical care occur when clinical asthma guidelines are followed [110]. Despite the availability of guidelines their use for routine patient care remains low, especially in the acute care setting [107, 110]. Traditionally, guideline recommendations are printed on paper and are not well integrated into the clinical workflow. Other barriers to physician guideline adherence include poor guideline accessibility, a lack of time, and a low

perceived need to follow guidelines to treat common diseases [7].

One approach to increasing guideline use is to implement them in computerized provider order entry (CPOE) systems. This has the advantage of integrating guidelines with the clinical workflow and allowing for decision support at the time of order writing. Although computerizing guidelines is a step towards improved adoption, the initiation of their use for a patient remains the responsibility of the care provider. Automatic identification of suspected asthmatics and electronic initiation of guideline use for a patient is challenging, but would allow for asthmatic patients presenting to an ED to more quickly receive appropriate therapy, such as oxygen delivery or beta-agonist administration.

Computerized methods to identify asthmatic patients have traditionally been used to detect prevalent asthma in a population. Such efforts have included the administration and analysis of computerized questionnaires [45, 56, 57], searching and classifying patient medical or billing records [51, 59], analyzing epidemiological records [55], and the use of classification techniques such as artificial neural networks to analyze breath sounds and pulmonary function test measurements [43, 44, 53, 54]. Few studies have attempted to detect acute asthma exacerbations. Text classification methods have been applied to retrospectively identify asthma exacerbations from electronic encounter notes [48, 49] and from free-text, ED presenting complaints [52]. Additionally, one study investigated cough sound analysis as a means for diagnosing acute asthma [46]. However, computerized methods to identify asthma exacerbations in real-time, such as at the time of initial patient registration or triage, have not been described.

The purpose of the study was to determine the feasibility and accuracy of identifying patients with an asthma exacerbation using only information that is available in electronic format at the time of initial patient triage in the ED and does not require providers to enter additional information. Correct identification of patients with asthma exacerbations would permit automatic triggering of computerized asthma-management guidelines early during a patient's ED encounter.

Methods

Setting

The Vanderbilt Children's Hospital ED is a 29-bed facility in an academic medical center, which provides care for more than 40,000 patients annually. The ED uses an electronic information system that includes an advanced computerized whiteboard [111], a computerized ED triage application, a longitudinal patient record [112], a computerized provider order entry system (CPOE) [113], and an electronic order tracking system. The computerized whiteboard tracks clinical and operational patient data and is displayed on all clinical workstations within the ED. A nurse captures triage information in the computerized ED triage system. Patient information is stored on the locally developed longitudinal computerized patient record system (StarPanel). ED patients' orders are entered using WizOrder, a locally developed CPOE system. The different ED information system components are integrated and allow providers access through the computerized whiteboard system.

Study Population

We identified a list of chief complaints that accounted for the most common presenting complaints in asthma exacerbations. The list of chief complaints was derived from an analysis of billing records for a 9-month period (January 2004 to September 2004) prior to the study period and included 17,230 ED visits of patients aged 2-18 years. We identified all patients with a primary ICD-9 (International Classification of Diseases, Ninth Revision-Clinical Modification) discharge diagnosis of asthma (493.*). We abstracted the patients' chief complaints from the ED information system and selected the chief complaints that accounted for at least 95% of all asthma related ED visits. Five chief complaints were identified: "wheezing," "fever," "dyspnea," "shortness of breath," and "cough." We then performed a 1-month (November 2004) retrospective, cross-sectional study that included all patients aged 2-18 years who presented to the ED with one of the five targeted chief complaints. The local Institutional Review Board approved the study.

Construction of Asthma Management Cohort

For all patients with one of the five chief complaints who presented to the ED during the 1-month study period, we established for the presence or absence of asthma guideline eligibility for the ED visit. We examined the attending physician's dictated note and a summary of all orders (e.g., medications, lab tests) placed during the visit and available in the computerized patient record. We adapted published criteria for diagnosing asthma exacerbation from ED records [52] and included cases as positive for asthma exacerbation if any of the following diagnoses were given: "asthma," "status asthmaticus," "reactive airway disease," or "wheezing." Visits also were classified as eligible for guidelines if the ED attending documentation included a suspected

diagnosis of asthma exacerbation that was later ruled out by a therapeutic trial of brochodilators. For patients with more than one ED visit during the study period, each visit was considered separately. Patient visits were excluded if the dictated attending physician note was missing from the computerized patient record.

Asthma Identification Algorithm

For every patient presenting with one of the five targeted chief complaints, the presence or absence of an acute asthma exacerbation was predicted. We created a rule-based asthma identification algorithm that combined patient information from three different electronic data sources as shown in Table 3. The patient information included a) the presenting chief complaint from the ED information system; b) the past medical diagnoses and medications from the patient's problem list on the computerized patient record; and c) the past ICD-9 discharge diagnoses from the billing database.

a) Presenting chief complaint: As part of the ED triage process, the nurse selects a chief complaint from a list of common presenting complaints. The chief complaints are mapped to ICD-9 codes and recorded in the ED's computerized whiteboard application.

b) Past medical diagnoses and medications: The patient's problem list includes various free text sections that list the medical history, current medications, allergies, social history, and health maintenance history. The problem list is maintained in the computerized patient record and can be updated at any time by treating physicians or clinic staff. To query the patient's past medical history and current medication section, we created a list of diagnosis and medication concepts

(Table 3). Asthma concepts for the past medical history included "asthma," "reactive airway," and "RAD" (i.e., reactive airway disease). Asthma related medication concepts included inhaled and nebulized beta-agonists, inhaled and oral steroids, and other asthma-related medications such as theophylline and leukotriene inhibitors. The list of text search strings for medications included drug generic and trade names. A patient was classified as having a past history of asthma if the listed medications included two or more beta-agonists or any two classes of a beta-agonist, steroid or other medication.

Table 3. Concepts for the Identification of an Asthma Encounter

Source			Detection Criteria
Presenting chief complaint			Cough (786.2), Dyspnea (786.09), Fever (780.6), Wheezing (786.07), Shortness of breath (786.05)
Past Medical History			Asthma, reactive airway, RAD, 493
Medications	Beta-agonists	Nebulized	levalbuterol, xopenex, accuneb, duoneb
		Short-acting	alb, albuterol, alupent, metaproterenol, brethine, terbutaline, ventolin, proventil, volmax, salbutamol, combivent, vospire, maxair, pirbuterol
		Long-acting	formoterol, foradil, salmeterol, serevent, advair, vospire
	Steroids	Inhaled	advair, aerobid, flunisolide, azmacort, traimcinolone, flovent, fluticasone, pulmocort, pulmicort, budesonide, qvar, beclomethasone
		Oral	prednisolone, orapred, prelone, pediapred, prednisone, sterapred, deltasone
	Other		atrovent, ipratropium, combivent, duoneb, ipatropium, singulair, singlular, montelukast, uniphyl, theophylline, tilade, nedocromil, xolair, omalizumab, accolate, zafirlukast, aminophylline, cromolyn, intal
Billing Data (ICD-9 codes)			493, 493.*

c) Past ICD-9 discharge diagnoses: For the search of ICD-9 billing codes, all inpatient and outpatient encounters were searched for one year prior to the study period. We recorded the number of encounters billed for each patient with an ICD-9 code related to asthma as either a primary or secondary diagnosis. The presence of one or more billing codes for asthma was considered positive for a past history of asthma.

To indicate the presence of a past history of asthma, we adapted criteria from published computerized algorithms for identifying asthmatic patients from medical record data [60, 114, 115]. A patient was considered to have a past medical history positive for asthma if the queries from the past medical diagnosis and medications or the past ICD-9 discharge diagnosis were positive. Computerized patient records were examined only if they existed prior to the ED visit date during the study period. For example, a problem list that was updated during the visit in question would not be included in the query. If the identification algorithm detected a past history of asthma, an acute exacerbation episode was predicted. If no evidence of a prior history of asthma was found, the patient was predicted not to have an acute exacerbation.

Outcome Measures

We calculated the operational characteristics for the detection of asthma exacerbations, including sensitivity, specificity, positive and negative predictive values, and positive and negative likelihood ratios. The test characteristics were determined for the combination of all considered chief complaints, and each chief complaint individually. In order to quantify the contribution of adding previous encounter information to current encounter information (patient's presenting chief complaint), we calculated test characteristics for each chief complaint and for the

combination of all chief complaints with and without information from previous encounters. For each test characteristic, the 95% confidence intervals were determined.

Results

During the study period (11/1/2004 – 11/30/2004), there were 1,835 ED visits by patients aged 2-18 years. The patients' mean age was 7.9 years, 45.3% were female, the mean Emergency Severity Index [116, 117] was 3.5, and the hospital admission rate was 12.1%. Among the 477 (26.0%) patient encounters that were coded with one of the five target chief complaints, 449 patients had one, 24 had two, and 2 patients had three visits to the ED. We excluded 109 (22.9% of total) encounters that had no electronic documentation of the attending physician's note, leaving 368 patient encounters in the study population. Lack of electronic documentation may have occurred if the patient was seen in a lower-acuity, "fast track" area. In the fast track area attending physicians used paper to document patient care (regular ED form or clinical pathway document) and did not dictate a note that would enter the computerized patient record. Among the 368 included patients, 154 (41.8%) patients received an ED discharge diagnosis or treatment consistent with asthma exacerbation. For the 368 patients, the average age was 6.2 years, 41.3% were female, the mean Emergency Severity Index was 3.4, the mean ED length of stay was 252 minutes, and the hospital admission rate was 17.9%.

The frequency of asthma for the five individual chief complaints is displayed in Table 4. For the 154 patients with a reference diagnosis of asthma exacerbation, wheezing was the most common chief complaint and accounted for 87 (56.5%) cases. The least common chief complaints were fever (6%) and shortness of breath (5%).

A problem list that noted the patient's past medical diagnoses and medications in the computerized patient record was available for only 203 (55.2%) of the 368 ED encounters (Table 4). Patients without a problem list were retained in the study, but considered to have no past history of asthma. A problem list existed for 61.0% of patients with asthma and for 50.9% of patients without asthma. For patients with a problem list, the average time since last updating the list was 261 days prior to the date of the ED visit and ranged between 1 and 2651 days. Of the 203 patients with a problem list, 54 (26.6%) had an asthma concept in the past medical history field. From the medication field, 64 patients (32%) had one or more beta agonists medications, 48 (24%) had at least one steroid, and 15 (7%) had one or more other asthma medications.

Table 4. Frequency of chief complaints, availability of problem list, and ICD-9 billing codes.

	Asthma Exacerbation		
	Present (n = 154)	Absent (n = 214)	Total (n = 368)
Chief Complaint			
Wheezing	87	6	93
Dyspnea	25	10	35
Cough	24	38	62
Fever	10	151	161
Shortness of Breath	8	9	17
Electronic Problem List			
Present	94	109	203
Absent	60	105	165
Number of asthma ICD-9 codes			
One or more	56	12	68
None	98	202	300

A prior billing record for an asthma encounter existed in 68 (18.5%) of the 368 study patients. Among the 154 patients with asthma exacerbation, 56 (36.4%) patients had one or more asthma billing codes, while only 12 (5.6%) patients with another ED diagnosis had at least one asthma billing code. If one or more asthma-related billing codes were present, the final ED encounter diagnosis was asthma exacerbation in 82% of the patients.

The test characteristics for the five chief complaints with and without information from previous encounters are displayed in Table 5. All included study patients had one of the five chief complaints. Consequently, the combination of all chief complaints without considering past medical history information resulted in a sensitivity of 100%, a specificity of 0%, and a positive predictive value of 41.8%, which was the prevalence of an asthma exacerbation in the study group. Addition of the past medical history data increased the positive predictive value increased from 42% to 79%. The sensitivity was 45%, specificity was 92%, and the negative predictive value was 70%. The positive likelihood ratio was 5.3 (95% CI: 3.3 to 8.6) while the negative likelihood ratio was 0.6 (95% CI: 0.5 to 0.7).

Considering the presenting chief complaints individually without including past asthma history, the positive predictive value for asthma exacerbation was highest for wheezing (93.5%) and lowest for fever (6.2%). When information from the past medical history of asthma was added to a chief complaint of wheezing, the positive predictive value increased to 95.5%, but at the expense of the negative predictive value, which decreased from 75.6% to 65.4%. The increase in positive predictive value indicates that having a past history of asthma makes a current visit with a chief complaint of wheezing more likely to be due to asthma exacerbation. The decrease in

negative predictive value highlights the situation of patients who present with wheezing and an asthma exacerbation, but do not have evidence of a prior asthma diagnosis in the electronic patient record. The sensitivity of the prediction decreased when past history data were included. This was due to the requirement that a patient have both a chief complaint of wheezing and a positive past history of asthma for a positive prediction of asthma exacerbation to be made. In this case, any patient with asthma exacerbation presenting with wheezing but without a prior problem list and past billing data would be incorrectly predicted to not have active asthma.

Patients presenting with the common pediatric chief complaint of fever rarely (10 of 161 patients, 6.2%) were diagnosed with asthma exacerbation. However, adding the past medical history information increased the positive predictive value to 33.3% and increased the negative predictive value from 30.4% to 57.8%. Similar to the complaint of wheezing, the sensitivity decreased (from 6.5% to 3.2%) but the specificity increased (from 29.4% to 95.3%). Adding previous encounter information to dyspnea, cough, and shortness of breath likewise increased the specificity and predictive values (Table 5) at the expense of sensitivity. Thus for each of the five chief complaints, evidence of a prior history of asthma in the computerized patient record increased the positive predictive value, and thus the likelihood of correctly classifying patients presenting with asthma.

Table 5. Test characteristics for the five chief complaints

	Sensitivity (95% CI)	Specificity (95% CI)	Positive PV (95% CI)	Negative PV (95% CI)
Wheezing (n = 93)				
Chief complaint alone	56% (48%-65%)	97% (94%-99%)	94% (87%-98%)	76% (70%-81%)
CC + Asthma history	27% (20%-35%)	99% (97%-100%)	96% (85%-99%)	65% (60%-71%)
Dyspnea (n = 35)				
Chief complaint alone	16% (11%-23%)	95% (92%-98%)	71% (54%-85%)	61% (56%-67%)
CC + Asthma history	8% (4%-13%)	99% (97%-100%)	86% (57%-98 %)	60% (55%-65%)
Cough (n = 62)				
Chief complaint alone	16% (10%-22%)	82% (77%-87%)	39% (27%-52%)	58% (52%-63%)
CC + Asthma history	4% (1%-8%)	99% (96%-100%)	67% (30%-93%)	60% (54%-64%)
Fever (n = 161)				
Chief complaint alone	6% (3%-12%)	29% (23%-36%)	6% (3%-11%)	30% (24%-37%)
CC + Asthma history	3% (1%-7%)	95% (92%-98%)	33% (12%-62%)	58% (52%-63%)
Shortness of Breath (n = 17)				
Chief complaint alone	5% (2%-10%)	96% (92%-98%)	47% (23%-72%)	58% (53%-64%)
CCt + Asthma history	3% (1%-7%)	99% (97%-100%)	80% (29%-100%)	59% (53%-64%)
All complaints combined (n = 368)				
Chief complaint alone	n/a	n/a	41.8% (36.8%-47.1%)	n/a
CC + Asthma history	44.8% (36.8%-53.0%)	91.6% (87.0%-94.9%)	79.3% (69.3%-87.3%)	69.8% (64.0%-75.1%)

* PV: predictive value; CI: Confidence interval; CC: Chief Complaint

Discussion

Early detection of patients presenting to an urgent care setting with asthma exacerbations is critical to the prompt initiation of treatment for their disease. It is desirable to use informatics tools in identifying asthma patients in order to enroll them into guideline-based care. Although wheezing is the classic presenting symptom of asthma, in our study population 43.5% of patients presenting to the ED with asthma exacerbation had less typical chief complaints. This demonstrates the inadequacy of using just a single chief complaint for the detection of asthma exacerbations. Adding asthma related information from previous encounters increased predictive ability in patients presenting to the ED with chief complaints that are less suggestive of asthma exacerbation. This can be a desirable feature for a computerized decision support system, as health care providers may value computerized support more in uncommon situations.

The improvement in predictive information was greatest when the previous encounter information was positive for a past history of asthma. The positive predictive value for the combination of all five chief complaints with prior asthma information was high (79%), meaning that if the algorithm identified an asthma patient, it was correct in four out of five patients. However, the negative predictive value was lower (70%), meaning that the identification algorithm would miss some asthma exacerbations. Missing patients may occur in several situations, such as if the ED encounter was the patient's first presentation of asthma. Also, a patient may have an established asthma diagnosis, but previously had received care from a provider outside the institution, in which case computerized patient record information would not be available. This is commonly the case in a dedicated pediatric hospital serving a large geographic area, and in our study, 45% of patients did not have a prior problem list in the

computerized patient record. Even established patients may have an outdated or absent problem list. Although documentation to the electronic problem list is routinely used at our institution for both inpatient and outpatient encounters, its use is optional. The problem list fields are maintained manually and are not automatically verified against other data sources such as prescription records or billing diagnosis codes. With further implementation, integration, and adoption of clinical information systems, it can be expected that additional reliable electronic data sources will become available, and as a result, the performance of the asthma identification algorithm will likely improve. For example, since the completion of the study our ED has implemented a computerized triage application that includes the availability of vital signs and the coded documentation of a patient's past medical history. Integrating this relevant information in real-time may improve the algorithm's overall accuracy.

The goal of our study was to create an asthma identification algorithm that integrates computerized patient information available early during a patient's ED encounter, does not require health care providers to enter additional data, can be implemented for real-time detection, is relatively simple, and can be implemented by other institutions that use a clinical information system infrastructure for patient care. Early detection is challenging because little information about a patient may be available in electronic format prior to initiating treatment. Requiring busy health care providers to enter additional information needed for an asthma identification algorithm may be tolerated for one disease; however, scalability to many disease-specific identification algorithms in an active clinical setting would challenge feasibility and user acceptance. The simplicity of our algorithm may facilitate portability to other institutions that have access to billing information and maintain a problem list in their clinical information

system. A coded chief complaint is the only site-specific variable used in our algorithm, as few EDs assign a coded chief complaint in real time. However, national efforts towards a coded list of ED chief complaints exist [118] and there are several algorithms available that group free text chief complaints into syndromic categories [119-121]. From this perspective, we believe that the asthma identification algorithm demonstrates an interesting and promising step towards automatic, real-time identification mechanisms that can be applied as reminders for initiating guideline-based treatments.

Our study has several limitations. To initially identify cases of asthma in developing the list of targeted chief complaints, we used ICD-9 billing codes, which have known inaccuracies for defining a clinical condition [59, 122, 123]. However, during the 1-month study period, the final ED diagnosis was verified through chart review and not by examining ICD-9 codes. We also limited the chart review to the most frequent coded chief complaints that historically included 95% of asthma episodes. We did not consider asthma exacerbation in patients who presented with rare chief complaints, which would have challenged the feasibility due to the increase in the number of patients requiring chart review for disease verification. These limitations are a result of the retrospective study design. We are planning to validate the asthma identification algorithm in a prospective study that will include all patients presenting to the ED and may decrease the potential impact of these limitations.

Detection algorithms such as the one described have several possible application areas, including prompting clinicians to initiate guideline-driven treatments for eligible patients. Computerized asthma guideline reminders may be integrated with computerized provider order entry systems or

could be delivered through other information technology applications to remind clinicians to use existing paper-based treatment guidelines. Other applications may include the recruitment of patients for research studies or the identification of poorly controlled asthmatic patients. Although our study attempted to detect only asthma exacerbations, it is conceivable to apply similar techniques to other diseases for which practice guidelines have been developed.

In summary, the study demonstrated that a simple, real-time algorithm using readily available electronic data from a clinical information system infrastructure can detect asthma episodes in real-time and early during a patient's encounter in an ED setting.

CHAPTER IV

SYSTEM IMPLEMENTATION AND PROSPECTIVE EVALUATION

Introduction

Asthma is a common pediatric chronic disease with an estimated prevalence of 6 million cases in 2002 [108]. Asthma exacerbations are a significant cause of patient morbidity in the United States and account for more than 2 million emergency department (ED) visits annually [1]. National guidelines for asthma care were developed by the National Heart, Lung, and Blood Institute and published in 1991 with updates in 1997 [2]. The guidelines include recommendations for the treatment of acute asthma exacerbations in an ED or ambulatory care setting. Despite guideline availability unnecessary variability in the care of patients remains and studies have demonstrated significant deviations from best care practices for patients presenting to an ED with acute symptoms [5, 6].

Compliance with guideline recommendations has been shown to improve patient outcomes and measures of clinical care, such as costs and length of stay [3, 4, 110]. Still, adoption for use in patient care remains low, especially in the acute care setting [107, 124-126]. Barriers to physician adherence include poor guideline accessibility, a lack of time, and a low perceived need to follow recommendations to treat common diseases [7]. Furthermore, guidelines are traditionally printed on paper, infrequently incorporate patient-specific recommendations, and are not well integrated into the clinical workflow.

One method to increase guideline use is to implement them in computerized clinical systems [37, 127]. However requiring busy clinicians to search for and actively initiate guidelines can limit their use [128, 129]. Reported features of decision support systems that improve clinical care include the automatic provision of recommendations as part of normal workflow [130]. Automatic identification of suspected asthmatics in the ED is challenging but would permit electronic initiation of guidelines and minimize the need for clinicians to remember to initiate their use. This could improve guideline acceptance, increase compliance with care recommendations, and minimize delays in administration of appropriate therapies.

Computerized methods have been developed to identify asthmatic patients but remain limited to the screening of prevalent cases. Efforts have included the administration of computerized questionnaires [45, 56, 57], searching patient medical or billing records [51, 59], and analyzing epidemiological records [55]. Few studies have attempted to detect acute asthma exacerbations. These include identifying asthma exacerbations from electronic encounter notes [49] and from free-text ED presenting complaints [52]. All studies were performed retrospectively and were not evaluated for application in a clinical environment.

We have previously reported the development of a computerized system to identify patients in the ED with asthma exacerbations [16]. The goal of this study is to prospectively evaluate the system which only uses information that is available in electronic format at the time of initial patient triage. Identification is performed in real-time and no additional data entry is required from providers. Automated identification of patients with asthma exacerbation in the ED would enable initiation of asthma management guidelines early during a patient's encounter.

Methods

Setting

This study was performed at the Vanderbilt University Children's Hospital ED, a 29-bed facility in an urban, academic medical center with more than 40,000 visits annually. Computerized patient care applications used for patient care include an electronic white board [111], a system for patient triage, a longitudinal electronic medical record system [112], a computerized provider order entry (CPOE) system [113], and an electronic order tracking application. The computer applications are integrated to allow for centralized access through desktop computers located in examination rooms and in physician work areas.

Study population

We performed a prospective cohort study of all patients presenting to the ED during a 2-month period (11/1/2005 through 1/1/2006). Patients were included in the study if they were between the ages of 2 and 18 years at the time of ED presentation and had a coded chief complaint assigned in the computerized triage application. Chief complaints are assigned during the triage process using a standardized list of ICD-9 CM (International Classification of Diseases, Ninth Revision – Clinical Modification) encoded chief complaints [118, 131, 132]. Patients were excluded if a) they were not assigned an ICD-9 encoded chief complaint; b) they left before being seen by a physician; c) they were transferred to another clinical area without physician evaluation; or d) documentation of the patient's final diagnosis was unavailable through paper or electronic chart review. For patients with multiple ED visits during the study period, only the

first encounter was included and subsequent encounters were excluded. The study was approved by the local Institutional Review Board.

Data Sources

We developed a computerized, real-time system to predict the presence of asthma exacerbation using only electronic information available at the time of triage without requiring providers to enter additional data elements. The computerized system included patient data from three electronic information systems: the ED triage application, the computerized patient record system, and a billing database that contained all inpatient and outpatient ICD-9 diagnosis codes recorded at our institution since 1/1/2000. During triage, a nurse selects a chief complaint from a computerized list of the most common presenting complaints. At the conclusion of the triage process, the application was queried for the patient's coded chief complaint. The computerized record contains a structured problem list that is composed of a free text list of a patient's active and past medical problems, current medications, allergies, social history, and health maintenance history. Clinicians can maintain and update the problem list at any time. The computerized system queried the most recent problem list, the past medical history and the current medication section for concepts representing asthma and medications commonly used to treat asthma (Table 6). Concepts for asthma included "asthma," "reactive airway," and "RAD." Asthma medication terms included trade and generic names for inhaled and nebulized beta-agonists, oral and inhaled steroids, and other medications used to treat asthma, such as theophylline and leukotriene inhibitors [133]. For each patient the billing database was queried for a diagnosis of asthma (493.*).

Table 6. Concepts for the Identification of Asthma Encounters

Source			Detection Criteria
Chief complaint			Cough (786.2), Dyspnea (786.09), Fever (780.6), Wheezing (786.07), Shortness of breath (786.05)
Past Medical History			asthma, reactive airway, RAD, 493, ashtma (common misspelling)
Medications	Beta-agonists	Nebulized	levalbuterol, xopenex, accuneb, duoneb
		Short acting	alb, albuterol, alupent, metaproterenol, brethine, terbutaline, ventolin, proventil, volmax, salbutamol, combivent, vospire, maxair, pirbuterol
		Long acting	formoterol, foradil, salmeterol, serevent, advair, vospire
	Steroids	Inhaled	advair, aerobid, flunisolide, azmacort, traimcinolone, flovent, fluticasone, pulmocort, pulmicort, budesonide, qvar, beclomethasone
		Oral	prednisolone, orapred, prelone, pediapred, prednisone, sterapred, deltasone
	Other		atrovent, ipratropium, combivent, duoneb, ipatropium, singulair, singlular, montelukast, uniphyl, theophylline, tilade, nedocromil, xolair, omalizumab, accolate, zafirlukast, aminophylline, cromolyn, intal
Billing Data (ICD-9 codes)			493, 493.*

Asthma Prediction Algorithm

Prediction rules were adapted from published criteria for building an asthma registry to detect a prior asthma diagnosis [60, 114, 115]. A past history of asthma was defined as present if one of the following criteria was met: a) one or more terms representing asthma present in the past medical history field of the problem list; b) two different beta-agonist medications in the current medication section; c) any two of the three drug classes: beta-agonists, steroids, or other asthma medications; or d) one or more past billing codes for asthma. The rules were evaluated in real-

time immediately after conclusion of the ED triage process. In a retrospective study more than 95% of ED patients with asthma exacerbation presented with one of five chief complaints: "wheezing," "cough," "dyspnea," "shortness of breath," or "fever." For every patient encounter, the presence or absence of asthma exacerbation was predicted according to the following rules: If the presenting chief complaint was "wheezing", then an exacerbation was predicted, independent of the presence or absence of a past history of asthma. Approximately 93% of patients with a chief complaint of "wheezing" are diagnosed with an acute exacerbation of asthma [16]. If the presenting complaint was one of the other four targeted symptoms and the patient had evidence for a past history of asthma, then acute exacerbation was predicted. For all other chief complaints, the absence of asthma exacerbation was predicted.

Reference Standard Diagnosis

For each patient we used a published standard [52] to determine the final diagnosis for the ED visit through review of written and dictated physician notes and a summary of all orders performed during the ED visit. We included cases as positive for asthma exacerbation if any of the following diagnoses were given: "asthma," "status asthmaticus," "reactive airway disease," or "wheezing." Additionally, visits were classified as asthma if the ED attending documentation indicated a suspicion of asthma exacerbation that was later ruled out by a therapeutic trial of beta agonists with an alternative final diagnosis assigned.

Outcome Measures

For each patient encounter, the system's predicted presence or absence of asthma exacerbation was compared to the reference diagnosis. Each case was classified as a true positive if the

system correctly predicted the presence of asthma exacerbation, or false negative otherwise. Likewise, the system's predicted absence of asthma exacerbation was classified as true negative if the system correctly predicted the absence of asthma, or false positive otherwise. We calculated the system's operational characteristics including sensitivity, specificity, positive and negative predictive values, and positive and negative likelihood ratios, with 95% confidence intervals (CI). Test characteristics were determined for the population as a whole and for each of the five targeted chief complaints individually. To better understand the system's characteristics we analyzed false positive and false negative cases.

Results

During the study period, we included 3,629 (88.2%) of 4,115 ED visits by patients aged 2 – 18 years. Of the 486 excluded visits, 64 patients were transferred to another clinic before the physician examination, one patient was immediately admitted to an inpatient bed after triage, 21 patients left without being seen by a physician, and six patients did not have a written or dictated attending physician note. The remaining 394 exclusions were for patient repeat visit. A reference standard diagnosis of asthma exacerbation was established for 342 (9.4%) patient visits. The ED cared for an average of 6.2 asthma episodes per day (standard deviation: 2.6; range: 0 – 15). Table 7 displays patient demographics. Patients with asthma exacerbations were on average younger than those without, were more likely to be male, presented with a higher acuity level (Emergency Severity Index [116, 117]), had a longer ED length of stay, and a higher hospital admission rate. An electronic problem list was present at the time of triage for 47.5% of study patients. Problem list availability was higher for patients with asthma exacerbation (52.6%) as compared to those without asthma exacerbation (47.0%).

Table 7. Patient Demographics

	All Patients	Asthma Exacerbation	
	(n = 3,629)	Present (n = 342)	Absent (n = 3,287)
Age (mean) in years	7.8	6.5	7.9
Sex (% Female)	47.1%	42.4%	47.6%
ESI (mean)	3.1	2.7	3.2
ED Length of Stay (minutes)	246	369	233
Admission Rate	14.3%	17.0%	14.0%
Problem List Availability	47.5%	52.6%	47.0%

Operational characteristics for the asthma detection algorithm are shown in Table 8. The sensitivity for predicting acute asthma exacerbation was 71.6% (95% CI = 66.5% – 76.4%) and the specificity was 97.8% (95% CI = 97.2% – 98.3%). The positive predictive value (PPV) was 77.0% (95% CI = 72.0% – 81.6%) while the negative predictive value was 97.1% (95% CI = 96.4% – 97.6%). The likelihood ratio for a positive prediction was 32.3 (95% CI: 25.5 to 40.1) and 0.29 (95% CI: 0.25 to 0.34) for a negative prediction.

Table 8. Test characteristics.

	Sensitivity (95% CI)	Specificity (95% CI)	Positive PV (95% CI)	Negative PV (95% CI)
All patients (n = 3629)	71.6% (66.5–76.4)	97.8% (97.2–98.3)	77.0% (72.0–81.6)	97.1% (96.4–97.6)
Wheezing (n = 192)	100% n/a	n/a	91.7% (87–95)	n/a
Dyspnea (n = 68)	57% (40–73)	81% (63–93)	78% (58–91)	61% (45–76)
Cough (n = 164)	41% (29–55)	88% (80–93)	65% (48–80)	73% (65–81)
Fever (n = 327)	82% (48–98)	89% (85–92)	21% (10–36)	99% (98–100)
Shortness of Breath (n = 61)	46% (28–64)	86% (67–96)	79% (54–94)	57% (41–72)

* PV: predictive value; CI: Confidence interval

A total of 148 different chief complaints were coded electronically by triage nurses for the 3,629 patient visits. Fever was the most common presenting complaint, followed by abdominal pain, nausea/vomiting, wheezing, and cough. Wheezing was the chief complaint most predictive of asthma (91.7%), then by dyspnea (54.4%), shortness of breath (54.1%), and cough (35.4%). Patients with asthma exacerbations presented with 16 different chief complaints (Table 9).

The five targeted chief complaints were those most common of patients with asthma attacks accounting for 315 (92.1%) of all cases. Ten cases (2.9%) presented with other chest or upper respiratory chief complaints, including “chest pain,” “sore throat,” and “croup.” Eight patients (2.3%) presented with gastrointestinal complaints, while four patients (1.2%) had complaints involving other organ systems, such as “ear pain” and “rash”. The remaining five cases (1.5%) presented with vague or non-specific complaints such as “general illness” or “flu-like symptoms”.

Table 9. Presenting complaints of all patients with asthma exacerbation.

Chief Complaint	Asthma Exacerbations (n = 342)	Percentage of Total	Cumulative Percentage
Wheezing	176	51.5	51.5
Cough	58	17.0	68.4
Dyspnea	37	10.8	79.2
Shortness of breath	33	9.6	88.9
Fever	11	3.2	92.1
Chest pain	5	1.5	93.6
Nausea / vomiting	5	1.5	95.0
Flu like symptoms	4	1.2	96.2
Sore throat	4	1.2	97.4
Abdominal pain	3	0.9	98.2
Congestion	1	0.3	98.5
Croup	1	0.3	98.8
Ear ache, ear pain	1	0.3	99.1
Eyelid problem	1	0.3	99.4
Rash	1	0.3	99.7
Skin infection	1	0.3	100.0

All patients with a chief complaint of wheezing were predicted to have an asthma exacerbation. Thus wheezing was 100% sensitive for predicting asthma. The positive predictive value for wheezing was 91.7%. Sixteen of the 192 patients who presented with wheezing (8.3%) had a false positive prediction. The second highest positive predictive value among the five chief complaints was dyspnea at 77.8%. Dyspnea had 56.8% sensitivity and 80.6% specificity for detecting acute asthma. A presenting complaint of cough had 64.98% positive predictive value, 41.4% sensitivity, and 87.7% specificity. Shortness of breath was associated with a positive predictive value of 78.96%, 45.5% sensitivity, and 85.7% specificity. A prediction of asthma exacerbation with a chief complaint of fever had the lowest positive predictive value, 20.9%, with a sensitivity of 81.8% and specificity of 89.2%.

The prediction system missed 97 of 342 asthma exacerbations. Since classification of an encounter as acute asthma required both the presence of one of the five targeted chief complaints and a past history of asthma, the absence of either criterion resulted in a negative prediction. Twenty-seven of the 97 false negative cases did not present with one of the five targeted complaints. In the remaining 70 false negative predictions the algorithm did not detect a past history of asthma. In 25 of the 70 cases, subsequent manual chart review also did not reveal a past history. These represented new presentations of asthma. In the other 45 false negative cases a past history of asthma was present and documented in the patient's paper-based portion of the chart, but inaccessible to the computerized evaluation. Thirty-four of the 45 false negative records had no prior electronic problem list and 11 patients had a problem list, but without an asthma concept listed.

The detection system incorrectly predicted an asthma exacerbation for 73 patient visits who did not have asthma as defined by the reference standard. Table 10 shows the frequency of false positive results for each targeted chief complaint and assigned final diagnoses.

Chief complaints of fever accounted for 34 false positive cases, followed by 16 cases with wheezing, 13 with cough, 6 with dyspnea, and 4 with shortness of breath. The most common ED diagnoses assigned to false positive cases were upper respiratory infections and febrile illness, with 16 cases each. Acute febrile illness was the most common misclassified diagnosis in patients presenting with a chief complaint of fever, croup in a chief complaint of wheezing, upper respiratory infection in cough, pneumonia with the complaint of dyspnea.

Table 10. Diagnoses for false positive results.

Diagnosis	Chief Complaint					
	Wheezing	Cough	Shortness of Breath	Dyspnea	Fever	Total
Upper respiratory infection	2	8		1	5	16
Febrile illness		1		2	13	16
Pneumonia	2	1	1	3	6	13
Viral syndrome	2	2			4	8
Croup	6		1			7
Strep throat					3	3
Pharyngitis	1				1	2
Otitis media	1	1				2
Gastroenteritis					1	1
Meningitis					1	1
Laryngitis	1					1
Pleurisy			1			1
Cough				1		1
Respiratory distress	1					1
Total	16	13	4	6	34	73

Discussion

This prospective evaluation of a simple, real-time, computerized system demonstrated high accuracy in identifying acute asthma exacerbations. To our knowledge this study presents the first prospective evaluation of an electronic prediction system for asthma exacerbations. Similar clinical decision rules have been used in other domains for disease detection or to assist clinicians in medical decision making. Examples include identification of low-risk patients with pulmonary embolism [134], detection of pneumonia [14], and classification of patients with chest pain to predict myocardial infarction [135].

The diagnostic tool is automated, requires no additional provider prompting or documentation,

produces a result immediately after patient triage, and could be integrated into routine clinical care. Early detection of asthma exacerbations would facilitate the triggering of asthma treatment guidelines and could reduce delays in initiating appropriate care. While intended for use with guidelines integrated into a computerized provider order entry system, implementing the asthma detection algorithm as a clinical reminder could also prompt providers to use paper-based care pathways. Other applications could include early notification of respiratory therapy staff or the automated screening of patients for asthma-related research studies or patient registries.

From a clinical perspective, approximately one in every 11 patients aged 2-18 years presenting to the ED was predicted by the detection system to have an asthma exacerbation. At our institution this equates to six triggers per day on average. A false positive identification would be expected for about every 4 positive predictions. Additionally, one missed case would be expected for every 34 patients who were not suspected to have an asthma attack, or 1-2 per day. We feel that current performance levels are sufficient to be considered for clinical use. Automated identification of patients eligible for guidelines has been shown to be a factor in achieving compliance [136, 137], and requiring clinicians to actively initiate treatment protocols has been associated with low adoption rates [128, 129]. False positive identifications by the system would be infrequent and could be easily rejected by clinicians.

Performance of the detection system was limited by electronic availability of patient record data. Our setting was an academic medical center with a large geographic referral base, and patients frequently receive their primary care outside of the medical center. Consequently, many patients do not have any past records at our institution at the time of their ED visit. Electronic problem

lists were available in less than half (47.5%) of patients who presented to the ED. Increased electronic data availability could improve system performance and improve overall patient care in the ED [138]. One way to augment data capture would be to increase the detail of computerized documentation during triage. If reliable past medical and medication histories are obtained in triage in electronic form, these could be used complementary to an electronic problem list. As regional health information organizations are developed, data sharing may help overcome this limitation by increasing the availability of electronic patient record information [139]. At our institution, presenting chief complaints were available in coded form. This could limit the generalizability of our detection system to departments without coded chief complaint capture. There are, however, national efforts to adopt a coded list of ED chief complaints [118] and natural language processing tools for mapping free text to a coded format are available, including specialized applications for mapping free-text chief complaints. [140-143].

Even if a more accurate past history of asthma could be determined, new cases of asthma and patients presenting with less common chief complaints would not be detected, limiting the sensitivity of our system. We identified the five most common presenting complaints accounting for asthma exacerbations. However, these complaints were present in more than 92% of all asthma exacerbations. Also, the incorporation of additional clinical information, such as vital signs, and modification of the detection algorithm could result in improved performance.

In summary, we have demonstrated that a simple rule-based algorithm can be used to accurately predict the presence of asthma exacerbation in pediatric patients presenting to an ED. This technique relies on existing clinical data available in electronic form at the time of patient triage

and requires no additional documentation or data entry. This tool could be used to improve the care of asthmatic patients by facilitating early diagnosis and through automatic guideline enrollment.

CHAPTER V

CONCLUSION

This thesis described the development and prospective evaluation of a system for automated detection of asthma exacerbations. The system's operational characteristics were favorable with acceptable sensitivity, high specificity, and high positive predictive value for detecting acute asthma in the targeted population. The system is designed to be compatible with current clinical workflow. Prediction of asthma status early in the ED visit could support early initiation of guideline-based care for eligible patients. Detection was completely automated, requiring no user intervention or increased data capture burden. Technical strengths include the integration of patient-specific information from multiple clinical databases, toleration of missing data elements, and making real-time predictions of a patient's asthma status. The prospective evaluation included all patients who were potentially eligible for an asthma guideline, not only those with a high probability of having asthma exacerbation. Patients with all presenting coded chief complaints were included and those without electronic problem lists were retained in the study. Also, the final ED diagnosis of every patient in the study was verified through chart review, eliminating the potential bias of random case verification or of using billing data to determine positive and negative cases.

The detection system operated solely on electronic information that was available early during a patient's encounter in the ED. This requirement revealed interesting aspects of an identification system whose accuracy is influenced by the quality of information represented in a computerized

patient record infrastructure. Determining a past history of asthma depended on availability of electronic patient records such as a problem list and billing codes. Billing codes are known to be a limited proxy for true clinical diagnoses and it is possible that the use of administrative data contributed to incorrect predictions [59, 122, 123]. Nearly half of patients presenting to the ED did not have an electronic problem list. Reasons for this absence included patients being new to our facility, inconsistent maintenance of problem list records by clinics at our institution, and infrequent updating of problem lists after visits in the ED. Due to the lack of electronic documentation the system frequently was unable to detect a patient's past history of asthma. Increasing use of electronic medical records in primary care and data sharing between institutions would help overcome this limitation; however, widespread adoption of these practices nationwide is in its infancy.

Inclusion of only the most common chief complaints for predicting asthma cases was a potential limitation in our study. In the prospective evaluation, 8% of patients with acute asthma presented with other chief complaints, limiting the maximum sensitivity of the system to 92%. Also, the association between each of the five targeted chief complaints and asthma exacerbation varied greatly. Wheezing was highly associated with asthma (91%), while fever was much less predictive (4%). As a consequence, patients predicted to have acute asthma with a chief complaint of fever had less than a 20% chance of truly having the reference standard diagnosis, and accounted for nearly half of all false positive cases. A more complex rule-based or scoring system could assign differing weights to chief complaints and past history data where the weights would be based on the association with true asthma exacerbation. This might improve system performance but would be more difficult to develop. An alternate approach would be to

use artificial intelligence classifiers such as a Bayesian network, artificial neural network, or support vector machine, as these techniques have demonstrated to perform well in other clinical diagnostic systems [9, 14, 144]. Such methods could account for the prior probability of each chief complaint and better model missing data when a problem list is unavailable. In addition, they are not limited to the fixed operational characteristics of a rule-based implementation, and allow an investigator to choose an optimal detection threshold that balances desired sensitivity and specificity.

Improvements in electronic documentation during the ED triage process are another method to increase electronic data availability. Recording medications and past medical histories in an electronically coded format during triage could increase information available to a detection system, such as the asthma system, and improve predictive accuracy. Almost all patients are triaged when presenting to our ED, which provides an opportunity to obtain patient information in electronic format for the large majority of patients.

The storage of data in the electronic problem list in non-coded free text represented a challenge. There are known syntactic and semantic drawbacks to simple text searches, such as negation (e.g. “no history of asthma”), misspellings, expressions of uncertainty (e.g. “possible asthma”), and the use of alternate terms or abbreviations for a single concept [145]. Use of coded concepts would minimize this limitation, but would require additional efforts from all providers involved in a patient’s care when creating or updating problem lists. Alternative approaches include the application of available tools to map free text to clinical concept vocabularies such as the United Medical Language System or the implementation of natural language understanding systems

[141, 142, 146, 147]. These advanced approaches require specialized biomedical informatics knowledge and tools that have not yet reached widespread adoption. The keyword search techniques used in the asthma system are relatively simple and are amenable to implementation in institutions with basic clinical information system capabilities.

Many applications exist for a clinical detection system, such as the asthma system. These include the screening of patients for research protocol eligibility or the enrollment in disease registries. Emphasized most in this research was the potential to automatically trigger electronic guidelines for patient care. At our institution, ED orders are entered in a computerized provider order entry system and guideline use is limited by the ability of the system to suggest guidelines for an individual patient. Initiating guideline-based care relies on the provider actively searching for a guideline, selecting one from a menu, or placing of a specific triggering order. Available guidelines are often not used, initiated too late, or not followed in a timely fashion. For example, management of asthma exacerbation requires clinical asthma scoring, which should be performed during the initial patient examination and before the order entry session. Automatic identification of eligible patients after triage would permit early alerting of clinicians that a guideline-specific evaluation should be performed. This could be executed through an electronic whiteboard application or through more classic methods of clinician prompting such as a flag on the paper chart. Once a patient has been enrolled in a guideline-based treatment pathway, the system can continue to remind the provider at times specified by the guideline. For example, rescoring of asthma patients is recommended every 1-2 hours, allowing providers to adjust treatment and evaluate the need for hospital admission.

This prediction system for asthma could serve as a model for detecting other conditions which are managed by standardized guidelines in the ED. Disorders requiring time-sensitive diagnosis or therapy could also benefit from a real-time detection system. Examples include evaluation for thrombolytic therapy in acute stroke and the treatment of suspected sepsis, meningitis, or pneumonia. The advantages of not requiring providers to enter additional data and providing real-time predictions may support the scalability of this approach to other conditions.

In summary, the simple rule-based detection system demonstrated high accuracy in identifying patients with acute asthma exacerbations in a pediatric ED and could be a useful tool for the automated detection of patients eligible for guideline-based care.

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