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A cross-sectional content analysis of Android applications for asthma

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Abstract

Providing patients opportunities for self-management and education about their disease, asthma applications designed for use on an Android operating system can have positive health outcomes across the range of demographics who use mHealth applications. This study provides a content analysis of freely available Google Android Platform Mobile Applications for Asthma. A list of applications was collected on 26 October 2014, using the search feature of the Google Play Android platform and using the words and phrases "Asthma," "Lung Function" and "Peak Flow." Each application was coded for its approach to asthma self-management, based on categories adapted by Huckvale et al., which are based on the Global Initiative for Asthma and the National Asthma Education and Prevention Program. The characteristics of the 15 asthma applications are described. Most of the asthma applications' primary function focused on patient self-monitoring and self-assessment. Using the HON Code, we found low health information quality across all asthma applications. Android asthma applications can have positive outcomes in helping patients as they provide opportunities for self-management and education about their disease. Future research should

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continue to monitor and evaluate the development and use of mHealth Asthma Applications. Based on these findings, and their indication of a gap in existing research, subsequent studies can continue to evaluate the development and use of mHealth Asthma Applications with increasing methodological consistency to improve the quality of in-app health information.

Keywords
Android, asthma, content analysis, mHealth

Background

As of the beginning of 2014, there were over 100,000 mHealth applications available on the Apple and Android platforms.[1] It is estimated that by 2015, there will be 500 million people around the globe using mHealth applications.[2] Fitness applications constitute over 30 percent of the mHealth market followed by medical references at 16.5 percent. Wellness applications represent 15.5 percent of the market and medical condition management represents 6.6 percent of the mHealth market.[1] Medical condition management applications help patients by displaying health parameters, medication intake for specific chronic diseases such as asthma, diabetes, and congestive heart failure.[1]

In 2013, a study was conducted on mHealth applications using the World Health Organization (WHO) Global Burden of Disease to categorize mHealth applications.[3] The authors found that most studies for mHealth focused on chronic diseases such as diabetes, asthma, and depression. Although some work has been conducted around these three main chronic diseases, there remains a need for the development of more scholarly work about the quality of mHealth applications and their provided health information.[4] To address the dearth of scholarly analysis and evaluation of mHealth applications, and to examine mHealth practices with one of the aforementioned prevalent chronic diseases, this research will focus specifically on asthma mHealth apps available on Android operating systems.

Asthma is a condition characterized by an airflow obstruction for short periods of time that restrains airflow in the intrapulmonary airways.[5] Reports indicate that over 300 million people globally and of all ages suffer from asthma.[6] The type of asthma has a direct relation to the management, diagnosis, and potential prevention of the disease. A major factor in classifying types of asthma is the presence of underlying airway inflammation, which is variable and has distinct but overlapping patterns reflecting different aspects of the disease, such as intermittent versus persistent or acute versus chronic manifestations. Acute asthma usually arises from bronchospasm and requires and responds to bronchodilator therapy in a few hours, while the chronic inflammatory type usually responds to anti-inflammatory drugs over longer periods of treatment.[7]

The principles of asthma pathogenesis are evolving and have been modified over the last three decades as many phenotypes for asthma are being defined and larger insight linkages are being found between clinical presentations of asthma and genetic patterns.[8] It is beyond the scope of our study to predict or correlate future changes in classifying asthma with mHealth apps. It is still important to note that as research deepens our understanding of the disease, it is integral that the management of diseases such as asthma through technology platforms continually must be re-evaluated and updated. This would ensure better patient autonomy and self-care practices in disease management with the assistance of easy to access platforms provided on mHealth apps.

It has also been observed that diseases such as asthma are considered to be a vastly variable.[7] This feature of variability is more commonly referred to as the "Natural History of Asthma." One such example includes the progressive exacerbation of airway inflammation leading to airway change and remodeling. This may eventually lead to irreversible airway obstruction.[7] The onset, presentation and development of asthma are heavily dependent on the age of the patient. Studies revealed that the course of asthma is vastly different between children of a young age, children of an

older age, adolescents, and adults.[9,10] This is relevant when considering mHealth applications used in self-management with regard to disclaimers that should make users aware of age-appropriate measures in the apps. Access to care is an added issue, especially in developing countries, where people living with asthma do not have access to medical care and basic asthma medication.[6] Over 80 percent of deaths relating to asthma occur in lower-middle income countries.[11–13]

The understanding of the pathophysiology and pathogenesis of asthma tells us that airway inflammation in patients fluctuates based on the intensity, cellular/mediator pattern, and response to therapy. Analysis of these determinates helps in making treatment more specific and effective.[7] Advancement in the appreciation and effectiveness of treatment would help application developers around the world include these advancements.

Over the past few years, there have been research studies on asthma mHealth applications. Huckvale et al.[14] conducted a review of applications for asthma self-assessment. The authors identified 103 applications for asthma in English, of which, 47 were for asthma self-management. The authors conclude there are no applications that provide reliable and comprehensive conditions for self-management. Other studies have examined the impacts of mHealth asthma apps. Hyekyun et al.[15] developed a mHealth application for asthma monitoring of adolescents. The authors found that the application can help in the daily symptom monitoring and it was found easy to use by the participants of the study.[15]

Another study was conducted by Ryan et al. on the use of mHealth applications for the management of asthma. The authors conducted an observational study using electronic peak flow monitoring and mobile technology over a 9-month period in a UK general practice population. The authors found that 74 percent of the participants determined mobile technology helped improve their symptoms and most were pleased with the technology's ease of use. The mHealth applications helped patients to monitor and receive instantaneous feedback on their asthma control which would help patients to integrate management into everyday life, engage them more fully in their care and thus potentially improve their asthma control.[16]

The National Asthma Council Australia (NACA) released an asthma application which became the most popular asthma management application for Australians in 2013. Over 2 million Australians suffer from asthma, making it one of the highest global prevalence rates. Australian figures, recorded in 2011, indicate that 386 people died from asthma. [17]

Research has indicated that when asthma patients follow an action plan and are intimately engaged in their care process this results into fewer asthma attacks, reduced absence from work/school days, and decreased the use of relief medicine. Moreover, self-management plans help in reducing or avoiding emergency trips to healthcare centers and hospitals, leading to an increase in the quality of life for patients, their families and the community in general.[17]

Asthma Buddy, the Android application developed by NACA, helps record patient medication plans, provides a what-to-do list in cases of emergency, facilitates communication with your doctor on the progress of your management plan, and records details of all emergency contacts and medical providers relevant to the patient in question. As more mHealth asthma applications are created, there is a need to evaluate their purpose and the quality of the health information they provide. The purpose of this work is to conduct a content analysis of asthma mHealth applications to assess the health information provided and their role in asthma treatment and self-management. In doing so, this article is a contribution in bridging the gap between innovative medical research for asthma management and the accessible platforms of technology used by diverse patient demographics around the world.

Methods

A list of mHealth applications was collected on 26 October 2014, using the search feature on the Google Play Android platform available at https://play.google.com/store/apps. The search was

restricted to applications that are compatible with the Android platform. The phrases "Asthma," "Lung Function" and "Peak Flow" were the search terms used in the query. The initial search identified 175 applications for the word "Asthma." An additional 10 applications were found for the term "Peak Flow" and another 2 for "Lung Function." Of the 175 mHealth applications, 165 were excluded for the following reasons: 61 applications were not in the English language (e.g. applications in Chinese, Arabic, Spanish and French), 34 applications were irrelevant to asthma (e.g. an application on coronary heart disease), 22 applications were physician focused and 41 were paid applications. In all, 22 applications made it to the next stage of the review.

After careful evaluation, another seven mHealth applications were excluded because they were not closely related to asthma. This final evaluation included checking whether the application includes at least three of the main eight approaches to asthma self-management, based on categories adapted by Huckvale et al., which are based on the Global Initiative for Asthma (GINA) and the National Asthma Education and Prevention Program (See Table 1). These eight information categories are: the inclusion of basic facts about the nature of the condition, information about the nature of treatment, information about allergens and trigger avoidance, instructions on how to use treatment, information about self-monitoring and assessment, suggestions on an action plan, recognizing and responding to acute exacerbations, and personalizing the definition of good asthma control. The analyzed sample consisted of a total of 15 applications.

Each application was coded for its approach to asthma self-management, using the eight categories mentioned above. Each Application was coded into one of the following categories: (1) Basic facts about the nature of the condition; (2) The nature of treatment: relievers and preventers; (3) Allergen and trigger avoidance; (4) How to use treatment; (5) Self-monitoring and assessment skills; (6) The role of a written, personalized action plan; (7) Recognizing and responding appropriately to acute exacerbations; or (8) Personalizing the definition of good asthma control. Each application was coded by the researcher and cross-checked with another researcher. There were no disagreements between the coders.[6,7,14]

Asthma applications were also coded for their level of adherence to the Health On the Net (HON) Foundation principles for health information on the Internet as adapted by Huckvale et al.[14] The authors selected the HON Foundation principles since the Foundation is a leading not-for-profit organization founded under the Ministry of Health, Geneva, Switzerland, and aims at guiding both users and medical professionals to reliable sources of electronic health information.[14] Each asthma app included in the study, was coded into eight possible HON codes (See Table 2): (1) information must be authoritative; (2) purpose of the app; (3) confidentiality; (4) information must be documented, referenced and dated; (5) justification of claims; (6) application contact details; (7) funding and (8) editorial and advertising policy.[14]

Each application was coded by the researcher and cross-checked with another researcher. Each application received a "0" or "1," a "0" for not meeting the HON code requirement, and 1 for meeting the HON code requirement. For example, if the purpose of the application was not mentioned the application would receive a "0" code. If the purpose of the application was mentioned, it would receive a "1" code. Each application had to be explicit in mentioning, for example, the purpose of the application. If it was not clear, it would receive a "0." Any disagreements were resolved between the two coders. The maximum score that each application could receive for meeting the HON code requirements was 8.

Other metrics were collected for each of the apps. Date of creation, number of times downloaded, rating, and the number of times it was rated by users of the application and their written feedback and reviews about the applications (See Table 3). The information was obtained for

Table 1. Huckvale et al., GINA table.

Topic	Criteria
Basic facts about the nature of the condition	States that asthma is a lung disease characterized by inflammation and narrowing of the airways
	States that the four main symptoms of asthma are cough, wheeze, shortness of breath and chest tightness
	States that asthma cannot be cured (although childhood symptoms may remit) but can be effectively controlled
	States that the cause of asthma is not known
The nature of treatment: relievers and preventers	States that there are two classes of medication: relievers and preventers
	Explains possible side effects of medication (tachycardia/tremor in B2 agonists; thrush/cataracts/dysphonia for inhaled steroids; possible additional effects for high-dose steroids)
	States that early treatment can prevent symptoms from worsening
Allergen and trigger avoidance	States that recognizing and avoiding personal triggers is an important part of asthma control
	Provides guidance consistent with the primary and secondary prevention components of the BTS/SIGN guidelines in relation to specific triggers
How to use treatment	States that preventer medication must be used regularly to be effective
	States the importance of good inhaler technique and appropriate use of a spacer device
	States the importance of ensuring inhalers are in date and are not empty
Self-monitoring and assessment skills	States that learning to recognize signs of change in asthma symptoms is an important personal skill
	States that all patients with asthma should have a peak flow meter
	Explains the purpose of a peak flow meter and how to use it
	States the importance of regular physician review
The role of a written, personalized action plan	States that patients with asthma should have an up-to-date written action plan. Explains the purpose of an action plan (to step up and step down treatment, and to seek appropriate help in response to changing symptoms and/or peak flow)
Recognizing and responding appropriately to acute exacerbations	Describes signs/symptoms of worsening asthma (increasing wheeze; cough; night time disturbance breathlessness limiting activity; reliever inhalers not working)
	States the importance of changing treatment and/or seeking help promptly
	Lay management of acute asthma
Personalizing the definition of good asthma control	States that it is reasonable for most people to achieve minimal symptoms and limitation of activities
	Asks patients to reflect on what they would consider as good asthma control
	Advocates discussion with personal health provider to set treatment goals in partnership

GINA: Global Initiative for Asthma; BTS: British Thoracic Society; SIGN: Scottish Intercollegiate Guidelines Network; EPR-3: expert panel report 3.
Topics were based on UK BTS/SIGN, US EPR-3 and GINA guidelines.

each application as of 26 October 2014. The information on each application was updated daily. The measure of number of times downloaded is indicative of the popularity of the application.

Table 2. Health information quality criteria.

N	Health information quality criteria
1	Information must be authoritative: all medical information presented by [and/or calculations performed by an app] must be attributed to an author and his/her training in the field must be mentioned.
2	Purpose [of the app]: A statement clearly declaring that the [app] is not meant to replace the advice of a health professional has to be provided. A brief description of the [app]'s mission, purpose and intended audience is necessary. Another brief description of the organization behind the [app], its mission and its purpose is also necessary.
3	Confidentiality: The [app publisher] must describe its privacy policy regarding how you treat confidential, private or semi-private information such as email addresses and the content of emails received from or sent to [its users]
4	Information must be documented, referenced and dated: All medical content [including calculations and formulae] has to have a specific date of creation and a last modification date.
5	Justification of claims: All information about the benefits or performance of any treatment (medical and/or surgical), commercial product or service are considered as claims. All claims have to be backed up with scientific evidence (medical journals, reports or others).
6	[App] contact details: The [app] must be operational and the information must be accessible and clearly presented. There must be a way to contact the [app publisher], such as a working email address or contact form, for visitors who would like to have more details or support.
7	Funding: [The app publisher] must include a statement declaring its sources of funding.
8	Editorial and advertising policy: Conflicts of interest and external influences which could affect the objectivity of the editorial content must be clearly stated in the disclaimer. All [apps] displaying paying banners have to have an advertising policy. This policy must explain how the [publisher] distinguishes between editorial and advertising content and which advertisements are accepted. Any conflict of interest has to be explained.

Adapted from the Health On the Net Foundation principles for health information on the Internet.[14]

Data analysis and results

Descriptive statistics were used to summarize the results of the content analysis. The characteristics of the 15 asthma applications included in the content analysis are presented in Table 3. The dates of when the applications were created ranged between June 2011 and October 2014. One of the asthma applications had between 10,000 and 50,000 downloads. Two of the applications had between 1000 and 5000 downloads and another two applications had between 500 and 1000 downloads. In all, 47 percent (n = 7) of the applications had between 100 and 500 downloads.

The mean user ratings for the asthma applications were 4.6; the median was 4.8; and the mode was 5. The range of 1 and 293 was for the number of user rating responses for each asthma application with a mean of 32 user rating responses per asthma application.

Each of the applications was categorized according to the GINA and the National Asthma Education and Prevention Program (See Table 4). Six of the applications' primary function focused on "self-monitoring and self-assessment" of asthma patients. Two of the applications focused on providing asthma patients with "basic facts about the nature of the condition"; two of the applications focused on providing patients with "the nature of treatment: relievers and preventers"; two of the applications also focused on "recognizing and responding appropriately to acute exacerbations"; and two of the applications focused on "personalizing the definition of good asthma control." Only one application focused on "how to use the treatment."[6,7] Detailed functions of examined applications are listed in Table 5.

Table 3. Characteristics of the asthma mHealth apps.

Name of mHealth App	Update	Installs	Rating	User feedback
Asthma Check	13 June	10,000–50,000	4.1	293
Peak flow	14 January	5000–10,000	4	90
Allergy Monitor	14 July	1000–5000	4.7	57
Kids Beating Asthma	13 February	1000–5000	4.2	14
Asthma Info	11 June	5000–10,000	4.1	7
Huff & Puff Free	13 May	500–1000	4	6
Breathing improvement games	14 April	100–500	4.8	4
Peak flow meter calculator	14 October	100–500	5	3
Asthma Relief (Acupressure)	12 October	100–500	5	2
Dealing with Asthma	12 November	100–500	5	2
Connolly Asthma App	14 September	100–500	5	2
Allergy Pollen Mulberry Asthma	14 May	100–500	5	2
Asthma (Plug)	14 January	500–1000	4.5	2
Yoga Poses for Curing Asthma	14 July	100–500	5	1
Scripps Health Asthma Coach	14 September	10–50	5	1

Table 4. Categorizing asthma applications.

Application	Asthma mHealth materials
Asthma Info	Basic facts about the nature of the condition
Kids Beating Asthma	Basic facts about the nature of the condition
Allergy Pollen Mulberry Asthma	The nature of treatment: relievers and preventers
Huff & Puff Free	The nature of treatment: relievers and preventers
Dealing with Asthma	How to use treatment
Asthma Check	Self-monitoring and self-assessment
Connolly Asthma App	Self-monitoring and self-assessment
Scripps Health Asthma Coach	Self-monitoring and self-assessment
Peak flow	Self-monitoring and self-assessment
Allergy Monitor	Self-monitoring and self-assessment
Peak flow meter calculator	Self-monitoring and self-assessment
Asthma Relief (Acupressure)	Recognizing and responding appropriately to acute exacerbations
Breathing improvement games	Recognizing and responding appropriately to acute exacerbations
Asthma (Plug)	Personalizing the definition of good asthma control
Yoga Poses for Curing Asthma	Personalizing the definition of good asthma control

In addition to categorizing the type of asthma mHealth application, the study also measured the quality of health information provided by each application (See Table 6) based upon the HON Foundation principles (mentioned in Table 2). The sum of each of the eight categories coded for health information quality could have a minimum of 0 and a maximum of 8. The range of health information quality for all the asthma applications was between 0 and 5. The mean was 2.5 for information quality across all categories for all of the asthma apps. The median was 2 and the mode was 2. The highest rating was received for each of the applications stating their function and aim. In all, 14 out of the 15 asthma applications indicated the purpose of the application, and 14 of the

Table 5. Asthma applications detailed functions.

Application	Detailed functions
1 Asthma Info	• Test of asthma • Statistics on the peak flow, the ACT and the quality of life • Journal for transmission to your doctor • Fourteen measuring stations with information on pollen load • Weather 5-day forecast • Information on air pollutants such as ozone and fine dust • Info tips on living with asthma
2 Kids Beating Asthma	• Learning contents adapted to kids and teenagers • Up to five modules of information • English and Spanish voices • Up to eight different games to help understanding the medical contents (puzzle, alphabet soup, find the differences, make pairs, etc.) • The educational path, medical content and artwork are made by the Pediatrics Service at the Hospital Universitario San Carlos de Madrid (Spain) and supervised by the Instituto de Investigación Sanitaria at HCSC
3 Allergy Pollen Mulberry Asthma	• Classifying of pollen, mulberry, asthma of environmental allergies, peanut gluten, lactose food allergies, weather allergies • Find symptoms • Allergy testing • Allergies • Allergy cause • Pathophysiology • Allergy testing • Food allergy (like peanut gluten, lactose, etc.) • Environmental allergies like pollen, mulberry, asthma
4 Huff & Puff Free	• Two fully animated videos (~7 min) • Two quizzes (10 questions each) • Electronic score card for quizzes • One game (Tic Tac Blo)
5 Dealing with Asthma	• Dealing with Asthma is a free e-book designed to help people understand some of the natural ways to possibly treat asthma • This e-book is not intended to replace seeing a medical doctor or qualified professional • This free e-book about asthma is offered for informational purposes and entertainment purposes only
6 Asthma Check	• Electronic peak flow record • Individual medication planer • Notifications of peak flow readings, checks and medication • Clear overview of your asthma record: as list, chart or diary • Functional and intuitive user interface • Symptom control with a simple 5-point check (GINA) • Smoking and sport tracking • Comprehensive statistical evaluation • Export data as PDF, CSV or as plain text in an email

Table 5. (Continued)

Application	Detailed functions
7 Connolly Asthma App	• User's experience is personalized • Easy for users to improve their knowledge and complete tasks in seconds • Intelligent and proactive alerts • Decreases excessive visits to doctor • Decreases visits to the ER • This app is developed in conjunction with the Connolly Hospital Blanchardstown Respiratory Department
8 Scripps Health Asthma Coach	• The same as "Connolly Asthma App"
9 Peak flow	• Access peak flow readings on phone or tablet • Provides history graph for peak flow values • Send last month' history graph by email • Export the entire history to a text file on SD card
10 Allergy Monitor	• Access via login • Accurate and easy user interface • Daily recording of symptoms by the symbolism of the smile • Registration of the symptoms (eye, nose, respiratory, sleep, ER visits, limitation of daily activities and problems at work/school) • Graphical display of symptoms • The background of the graph is colored with three bands of different colors (green, yellow, red) corresponding to the symptoms' severity • Shortcuts through button to display the time of registration
11 Peak flow meter calculator	• Measure the amount of air exhaled out in liter per minute • Calculate your peak flow
12 Asthma Relief (Acupressure)	• Relieve asthma instantly without medications (Chinese Massage Points) • Easily find the right Massage Points with simple Full HD Videoclips and Photos in the App • Never forget a Massage with a built-in reminder • Save costs of doctor visits and medications • Spare medications side effects • No danger of being hurt, infected or experiencing pain
13 Breathing improvement games	• Falling asleep faster • Higher athletic endurance • Help managing asthma and COPD • Decreased blood pressure • Relief from headaches and migraines • Less stress and better mood
14 Asthma (Plug)	• Long and deep breathing (pranayama) helps users to become more aware of their breathing • Increasing the duration of expiration without contraction • Make users more aware of their body and reduce stress
15 Yoga Poses for Curing Asthma	• Following the eight yoga poses shown in this app, slowly can improve the lung functioning and reduce the symptoms of asthma with no medicines • Learn more about each yoga pose, the inward and outward breathing is very important

ER: emergency room; COPD: chronic obstructive pulmonary disease.

Table 6. Quality of health information for asthma applications.

Application	Information quality								
	1	2	3	4	5	6	7	8	Sum
Asthma Check	0	1	0	0	0	1	0	1	3
Asthma Info	0	0	0	0	0	0	0	0	0
Kids Beating Asthma	1	1	0	0	0	1	0	0	3
Asthma (Plug)	0	1	0	1	0	1	0	0	3
Asthma Relief (Acupressure)	0	1	0	0	1	1	0	0	3
Dealing with Asthma	0	1	0	0	0	1	0	0	2
Connolly Asthma App	1	1	0	1	0	1	0	0	4
Allergy Pollen Mulberry Asthma	0	1	0	0	0	1	0	0	2
Scripps Health Asthma Coach	1	1	0	1	1	1	0	0	5
Yoga Poses for Curing Asthma	0	1	0	0	0	1	0	0	2
Breathing improvement games	0	1	0	0	0	1	0	0	2
Allergy Monitor	0	1	0	0	0	1	0	0	2
Huff & Puff Free	0	1	0	0	1	1	0	0	3
Peak flow meter calculator	0	1	0	0	0	1	0	0	2
Peak flow	0	1	0	0	0	1	0	0	2
Sum	3	14	0	3	3	14	0	1	38

15 applications listed contact details. None of the applications clearly indicated how the application was funded. None of the applications discussed confidentiality or any of their privacy policies. Only 3 out of 15 applications attributed their work to an author. Only three of the applications documented and dated the medical information content. Only three of the asthma applications noted that the information presented in the asthma application was based on scientific evidence.

Discussion

Free Android applications for asthma have only recently been developed and made available online over the past 3 years. Some of the applications have not been updated for 3 years but are available on the Android market. Applications which are not being updated periodically, such as "Asthma Info," "Asthma Relief" and "Dealing with Asthma" could be harmful due to outdated information provided in the asthma application. Only one of the apps, Asthma Check, had a high number of installs, while most of the asthma applications had a low install rate of about 100 to 500 downloads. The Asthma Check application also had a high number of user rating responses at 293 in comparison with other asthma applications that had user feedback of 1. These results show that the free Android market applications for asthma are still in their infancy when compared to the number of free applications for diabetes for example; over 1800 applications for diabetes compared to less than 200 for asthma.[3]

Most of the free Android applications were determined to be for self-monitoring and self-assessment. Self-monitoring and self-assessment have positive outcomes for asthmatic patients and tools for self-management and self-assessment help in educating patients.[18] This may explain the higher number of self-monitoring and self-assessment applications for asthma patients. Of the sample, only one application was focused on how to use treatment, which indicates that there is little interest in applications that focus on teaching treatment methods.

The strength of this study is in the focus of systematically studying the content and types of free Android applications available to help asthma patients. Where there is a proliferation in the number

of mHealth applications on the market, there is a need to systematically evaluate the content of such applications. Recent work is being developed to guide developers of mHealth applications to produce safer applications for the public.[19]

Overall, the quality of health information for the asthma applications was low. Of the sampled applications, none provided indication of about protecting the confidentiality of the patients, no applications noted funding sources in detail, and only one of the applications attributed information to an author with noted credentials in the field. These findings are consistent with those of Huckvale et al.[14] These omissions present serious shortcomings of the free asthma mHealth applications. Therefore, more work is needed in the development of mHealth asthma applications that use high-quality evidence. It might be useful and maybe necessary that academic and professional healthcare bodies supervise or authorize the release of medical applications; this should also be supported by more strict regulations and legislations that govern the release of such applications to public.

There are several limitations presented in the research study. First, the content analysis included free mHealth asthma applications and not paid ones. The paid applications may mention funding sources, provide more evidence of the work and provide overall better quality. However, paid applications were not included in the review. It is also possible that new applications were created subsequent to the completion of the data collection process of this study. There may have been are other applications that were missed by not including other search terms. Furthermore, there was no clear evidence to the exact number of downloads for each asthma application; there was only an approximate range for each application. In addition, the user ratings for the asthma applications had to be at least four to be included in the review. It is not possible to know the source of rating such applications, which may bias the results relating to the inclusion of the application. Finally, only Android applications were included in the review, while other platforms such as Apple or BlackBerry were excluded.

Implications for practice

With their recent rapid development, mobile and electronic health have become beneficial tools that have not only reduced the financial costs, but have eased modes of screening and treatment. Applications for Android asthma can complement the existing systems of screening by engaging large numbers of diverse groups of users at one point in time. They can be used for educating patients about preventive and treatment remedies which can reduce the burden on hospitals and doctors. Android asthma applications do not only encourage the patients to remain particular about their health, they also keep patients updated about day-to-day advancement in the management of asthma. The main contribution to the literature is analyzing the content of one type of medical smartphone application, showing the existing gap between the medical research and available evidence gathered from a sample of currently available mHealth asthma applications. With these findings as a starting point, the benefit of the Health on the Net Foundation and the Global Initiative for Asthma's principles are demonstrated to be a functional framework for evaluating specific aspects of mHealth applications. Further research can define the specifics of best practices in collaborative projects with application developers, medical professionals, and standardization organizations.

Conclusion

Android asthma applications show a promising future in helping patients suffering from asthma. The asthma applications provide an opportunity to reach a large number of asthma patients, which

aids in educating them about their disease and in preventing possible hospitalization. Although there is potential for mHealth Asthma Apps in impacting the health of asthma patients, comprehensive work is needed to develop more evidence-based asthma applications that respect the privacy and confidentiality of patients. mHealth applications and research will continue to develop as described by a number of authors;[20–23] however, this initial study recommends the quality of the content accords with to the International HON Code Standards.

Author's Note

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Article

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Health information seeking and scanning among US adults aged 50–75 years: Testing a key postulate of the information overload model

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Abstract

Past research has found that older US adults (aged 50–75 years) exhibit high levels of cancer information overload and cancer worry; however, no study to date has examined whether these perceptions are related to information seeking/scanning. To explore this relationship, older adults ($N = 209$, $M_{age} = 55.56$, $SD = 4.24$) were recruited to complete a survey measuring seeking, scanning, cancer information overload, and cancer worry. Most participants were high-scan/seekers (40.2%) followed by low-scan/seekers (21.1%), high-scan/no seekers (19.6%), and low-scan/no seekers (19.1%). Low-scan/no seekers had significantly higher cancer information overload compared to all other groups, consistent with the postulate that overload and seeking/scanning are negatively related. Low-scan/no seekers and high-scan/seekers both exhibited higher cancer worry severity, consistent with past research suggesting that cancer worry explains high levels of activity/inactivity.

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Keywords
cancer information overload, cancer worry, scanning, seeking

Health information seeking and scanning has become increasingly important over the last several decades.[1–6] Individuals can access an abundance of health information by actively using various search tools (information seeking) or by passively taking in desired information as they encounter it (information scanning).[7] Health information seeking and scanning are directly and indirectly related to individuals' performance of health behaviors.[7]

Modern communication technologies rapidly create, duplicate, and disseminate health information. However, the quality and quantity of health information could prove problematic,[8,9] especially for traditionally underserved groups.[10–12] For instance, the ever-increasing volume of accessible health information and proliferation of information channels—accompanied by a lack of cancer-relevant knowledge and cognitive ability to comprehend cancer information—could cultivate cancer information overload (CIO). Information overload is not a new concept in information science generally;[13,14] yet CIO specifically has recently drawn the attention of health communication scholars.[15,16] CIO is of interest to health communication researchers because surveys of the US public have suggested that approximately three-fourths of adults show signs of overload.[8] Secondary data analysis has suggested that CIO is related to lower socioeconomic status, poor health, low media attentiveness, and high affective components of information seeking.[17]

CIO is a perception of the information environment that is likely shaped by past information seeking/scanning experiences.[15] The information overload model (IOM) postulates that individuals with dispositional overload for a particular type of content will attack, disregard, and/or avoid that content over time;[18] yet no study to date has tested this postulate with a validated measure of information overload. The recent validation of a multi-item measure of CIO[15] allows researchers to test postulates of the IOM, including whether individuals with higher overload avoid particular content.

Past research has mostly focused on the antecedents and consequences of health information seeking, such as how it influences subsequent decision-making[19] rather than factors that trigger or motivate seeking/scanning behavior.[20] The purpose of the current study is to investigate how cancer information seeking and scanning behaviors (SSBs) are influenced by CIO and cancer worry. The latter advances our understanding of dispositional cancer worry[21] and provides an alternative cancer-specific affective disposition to compare/contrast with CIO. Although researchers have found that CIO is distinct from other similar constructs—such as cancer fatalism[15]—the utility of measuring different cancer-specific dispositions is still an unresolved question. Thus, investigating whether CIO and cancer worry relate to health seeking/scanning will help researchers to decide whether one or more of these constructs is essential to future information acquisition models. It is especially important to address these questions with older populations, as the United States has an unusually large older demographic at the moment (i.e. the Baby Boomers) who are increasingly utilizing modern communication technology to seek/scan for health information.[22–25]

Cancer information seeking and scanning

In 2008, 45 percent of individuals in the United States had searched for cancer-related information at least once in their lives; among them, three of four had searched in the past 12 months.[8] As individuals typically engage in different levels of information seeking and scanning activities based on their individual interests and characteristics, Shim et al.[7] developed an instrument to measure health information SSB. SSB is important to measure because it has the potential to influence an

individual's decision-making, and consequently, it can impact health outcomes. For instance, Shim et al.[7] found that health information seeking and scanning were both associated with healthy food consumption and cancer knowledge.

Previous research has primarily studied health information seeking by focusing on two main aspects: antecedents and outcomes. Lambert and Loiselle[26] suggested that personal and situational factors can influence the type of information an individual seeks, how much information he or she seeks, what sources he or she uses, and how he or she ultimately obtains this information. The literature notes that information seeking behavior could be influenced by a number of personal factors, including self-efficacy, health status, affect, the type of communication(e.g. face-to-face communication, mediated communication), preexisting anxiety about a particular communication channel, and demographic variables such as age, gender, and income.[31–33] With regard to situational factors that can influence information seeking, the literature identifies news coverage[34] and the accessibility and quality of online health information[35] as the main factors to consider. Health information seeking is a behavior that can lead to specific positive health outcomes, including facilitating individual involvement in personal health care,[8] increased quality of life,[36] and decreased negative emotions.[37]

Individuals are not always active health information seekers, and there is growing recognition that less effortful information exposure also has the potential to influence an individual's health behavior. Previous research has focused primarily on active health information seeking, while less attention has been devoted to studying passive health information exposure. In this study, we follow the definition of information scanning provided by Niederdeppe et al.[34] as "… information acquisition that occurs within routine patterns of exposure to mediated and interpersonal sources" (p. 154). Although information seeking and scanning share some common aspects, we suggest health information scanning is distinct from health information seeking behaviors based on previous research.

Most research on cancer information seeking has focused on cancer patients;[38,39] consequently, the frequency of cancer information seeking and scanning within the general population is currently unclear.[40] Therefore, to fill this gape in the knowledge, the current study focuses on cancer information seeking and scanning patterns present among the general population, as opposed to cancer patients.

Wilson[41,42] indicated that information behavior is a broad term that encompasses both active information seeking and passive information reception. Even though the importance of passive information gathering has been recognized by researchers,[7,43] Longo et al.[44] suggested that there is insufficient research that explicitly examines "passive receipt" of information, which also refers to scanning, incidental, or mere exposure to information. While many passive information gathering terms are used exchangeably, there are still some differences between these terms. For example, information scanning and passive information seeking differ from incidental or mere exposure to information as individuals pay more attention or are motivated to process the information when they scan or seek information passively. While acknowledging some conceptual overlap with other terms, cancer information scanning is the focus of this research as the goal is to study individuals attending to a particular piece of idea or fact in the normal flow of information that goes beyond incidental exposure.[7] Kelly et al.[40] also argued that the term "information scanning" does "a careful balancing act between seeking and completely passive exposure" (p. 737).

CIO and the IOM

Although "the potential for overload has existed since information became an important input to any human activity" (p. 33),[45] information overload is an increasingly concerning byproduct of the overwhelming amount of information produced today. Bawden and Robinson[46] indicated that

information overload is caused by too much information at hand and worsened by multiple competing formats and channels.

The IOM was developed to theorize causes and effects of overload.[18] The IOM is based on decades of research devoted to social cognition and information processing. Research in those areas has consistently demonstrated that human beings have deep information storage capacity tempered by limited immediate processing ability.[47–49] To survive, humans only devote time and energy to select information.[47] For example, Lang[48] argued that receivers are cognitive misers who selectively focus on information that is consistent with their goals and/or indicative of change.

In a larger sense, the IOM is consistent with fear control as articulated by the extended parallel processing model (EPPM; for a review, see Witte and Allen[50]). Fear control occurs when people perceive limited efficacy—but significant threat—and thus engage in an emotion controlling behavior (e.g. avoiding information so it does not trigger fear). Moreover, the IOM is also akin to research that suggests messages can produce unintended effects (such as obfuscation, see Cho and Salmon[51]), unintended construct activation,[52] or avoidance, blunting, and coping.[53] That is, information overload is an unintended byproduct of the saturated information environments.

Information overload also occurs in health settings. CIO is a concept that addresses cancer specifically. CIO is defined as "… feeling overwhelmed by the amount of cancer-related material in the information environment."[15] According to data from 2013 Health Information National Trend Survey, 69.94 percent of respondents ($N = 3630$) agreed with the statement, "There are so many different recommendations about preventing cancer, it's hard to know which ones to follow." Even though a large portion of participants reported high levels of CIO, few studies have investigated how health information seekers actually cope with this overload.[17]

Previous research has suggested that online health information seeking/scanning is not significantly associated with information overload.[17] However, this particular study may not be generalizable, as it used an unvalidated measure of CIO and focused on online information seeking specifically, rather than general health information SSBs. Moreover, the IOM postulates that overload is context specific.[18] For example, highly arousing content, like cancer information, may require additional resources to process, a situation that facilitates cognitive or information overload.[18,54] Thus, we hypothesize that individuals who perceive higher levels of CIO are less likely to engage in cancer information seeking activities.

H1: CIO is negatively related to health information seeking.

H2: CIO is negatively related to health information scanning.

Cancer worry

Previous research has shown that emotional status is a good predictor of one's health and health behavior.[55,56] Different types of negative emotions, such as anxiety, fear, and worry, are closely related but distinct constructs that can have very different impacts on an individual's health behaviors.[29] For example, research suggests that health anxiety may moderate the relationship between online health information seeking and health care utilization decisions.[57] A number of previous studies focused on the negative health outcomes caused by negative emotions.[58,59] For instance, Sirois and Burg[60] indicated that negative emotions could cause cardiac risk factors. A separate line of research from Davey[61] has demonstrated that negative emotions such as worry could also lead to positive health behaviors, in cases where day-to-day worry motivates individuals to cope with the threats that are causing them to worry.

Cancer worry is a concept that is empirically distinct from worry in general.[21] Cancer worry is defined as "an emotional reaction to the threat of cancer" (p. 571).[62] Jensen et al.[21] suggested that dispositional cancer worry has two underlying factors: severity and frequency. Previous research has examined the effects of dispositional worry on various health preventive behaviors, including screening behavior,[63,64] breast self-examination,[65] and skin cancer preventive behaviors.[66] Cameron and Diefenback[67] demonstrated that cancer worry can lead to greater interest in, and more favorable beliefs toward, genetic testing for breast cancer. Additionally, Renahy et al.[68] found that worry about one's health is positively associated with online health information seeking.

Most cancer worry research to date has focused on how cancer worry relates to risk perceptions and cancer-screening behavior, while little research has been conducted to examine the relationship between cancer worry and cancer information seeking specifically. Beckjord et al.[29] indicated that high levels of cancer worry are associated with more attention to health information and worse information-seeking experiences. However, their findings are limited by their use of a one-item scale to measure cancer worry.

The current study adheres to the conceptual framework of dispositional cancer worry established by Jensen et al.[21] and utilizes a newly validated multi-item scale as a more comprehensive measure of this construct. We intend to examine the relationship between dispositional cancer worry and cancer information SSBs. Based on past research, we propose the following research questions:

RQ1: What is the relationship between health information seeking and dispositional cancer worry?

RQ2: What is the relationship between health information scanning and dispositional cancer worry?

Method

Study design

Adults aged 50–75 years completed a survey assessing their information SSBs. Participants received US$25 for completing the study. The study protocol was approved and monitored by a university institutional research board.

Participants

Adults ($N = 209$) were recruited from one of eight worksites (six hospitals and two manufacturing plants) via their human resource (HR) representatives. HR representatives at each respective site sent out recruitment e-mails to employees who were 50–75 years of age. The mean age of participants in the current sample was 55.56 ($SD = 4.24$) with a range of 50–71. Most participants were female (71.8%) and Caucasian (97.1%). Education was distributed as follows: high school degree (27.3%), some college (8.6%), associate degree (19.1%), and bachelor degree or higher (45.0%). In terms of household income, approximately 18.7 percent of the sample earned below the US average ($51,000 per year).

Measures

CIO. Overload was measured using the 8-item CIO scale.[15] The CIO scale measures feelings about the overwhelming quantity of cancer information. Sample items include, "there are so many

different recommendations about preventing cancer, it's hard to know which ones follow," "Information about cancer all starts to sound the same after a while," and "It has gotten to the point where I don't even care to hear new information about cancer." Participants indicated their feelings using four response options (*strongly disagree* to *strongly agree*) where higher scores indicate greater overload ($M = 2.37$, $SD = .77$, $\alpha = .87$).

Cancer worry. Dispositional cancer worry was measured using an 8-item scale from Jensen et al.[21] Participants responded using a 7-point Likert scale ranging from *not at all* to *very much*. Dispositional cancer worry has two underlying dimensions: severity and frequency. Sample severity items include, "I feel anxiety when I think of the possible consequences of getting cancer" and "I brood about the physical consequences of getting cancer." Sample frequency items include, "I have dreams about cancer" and "Pictures about cancer have popped into my mind." Accordingly, four of the items measured cancer worry severity ($M = 3.26$, $SD = 1.53$, $\alpha = .86$) and four measured cancer worry frequency ($M = 1.39$, $SD = .85$, $\alpha = .82$).

Seeking and scanning. Seeking and scanning were measured in line with Shim et al.[7] For cancer information seeking, participants were asked "Have you looked for information about cancer from any source?" and "About how long ago was that?" The two items were combined into a single score that reflected whether they had looked for cancer information in the last year (coded as a 1) or not (coded as a 0), referred to as high and low scanners, respectively ($M = .60$, $SD = .49$). Scanning was measured using five items that asked, "How much attention do you pay to information about health or medical topics on/in [source]?" Participants reported information scanning for radio, television, newspapers, magazines, and the Internet using a 4-point scale (*not at all*, *a little*, *some*, and *a lot*). The last source (Internet) was not included in Shim et al.[7] but was added here due to increased use of the Internet as a source of health information ($M = 2.64$, $SD = .62$, $\alpha = .75$). Scanning was transformed into a dichotomous measure by splitting the variable at 2.5 (in line with Shim et al.[7]). Those above and below 2.5 were referred to as seekers and no seekers, respectively ($M = .61$, $SD = .49$). Information scanning focuses on health information in general (rather than cancer) per Shim et al.[7]

Results

Seeking and scanning measures can be used to form a 2×2 information seeking/scanning table. The information seeking/scanning table categorizes participants as low-scan/no seekers, low-scan/seekers, high-scan/no seekers, and high-scan/seekers (see Table 1). In the current study, the largest category was the high-scan/seekers (40.2%).

H1 and H2 postulated that health information seeking and scanning would be negatively related to CIO. A two-way analysis of covariance (ANCOVA) was conducted with CIO as the outcome, seeking and scanning as fixed factors, and gender, age, and education as covariates. There was a significant main effect for seeking, $F(1, 200) = 5.91$, $p = .016$, $r = .18$, and a marginally significant main effect for scanning, $F(1, 200) = 3.21$, $p = .075$, $r = .15$. Consistent with H1, information seekers had lower CIO scores ($M = 2.25$, $SD = .79$) than those who did not seek cancer information ($M = 2.52$, $SD = .71$). Consistent with H1, information scanners had lower CIO scores ($M = 2.27$, $SD = .72$) than those who did not scan for cancer information ($M = 2.50$, $SD = .82$). There was also a marginally significant interaction between seeking and scanning, $F(1, 200) = 3.04$, $p = .083$. Post-hoc tests revealed that low-scan/no seekers had significantly higher CIO scores than participants in all other categories (see Figure 1).

Table 1. 2 × 2 categorization of participants as seekers/scanners.

	Not a seeker	Seeker
Low-scan	19.1% ($n = 40$)	21.1% ($n = 44$)
High-scan	19.6% ($n = 41$)	40.2% ($n = 84$)

Responses to seeking and scanning measures were dichotomized so that all participants could be categorized per Shim et al.[7]

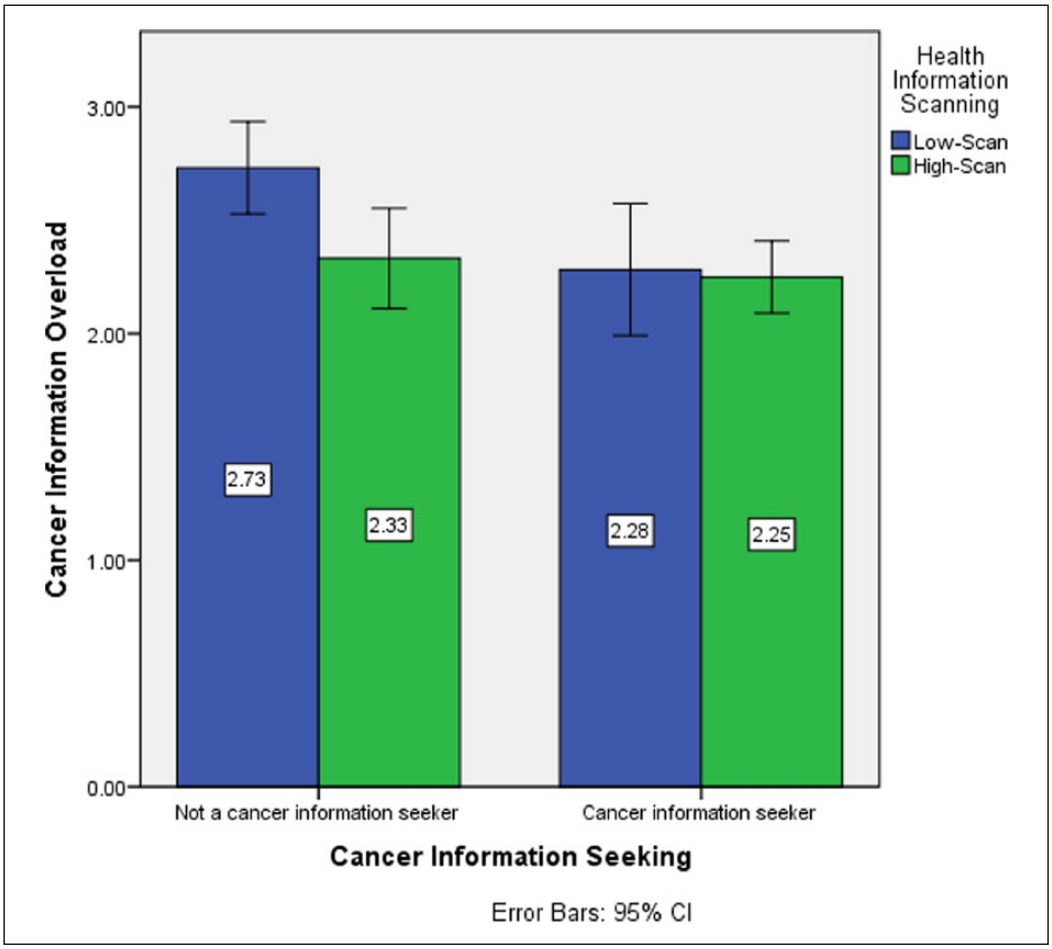

Figure 1. Cancer information overload (CIO) by seeking/scanning behavior. Bars present mean (in boxes) and 95 percent confidence intervals (brackets). Post-hoc tests revealed that low-scan/no seekers had the highest CIO scores.

RQ1 and RQ2 questioned the relationship between health information seeking and scanning and dispositional cancer worry. Two-way ANCOVAs were conducted with cancer worry severity/frequency as the outcome and all other variables identical to the CIO analysis. For cancer worry severity, there were no significant main effects for seeking, $F(1, 193) = .10$, $p = .758$, or scanning,

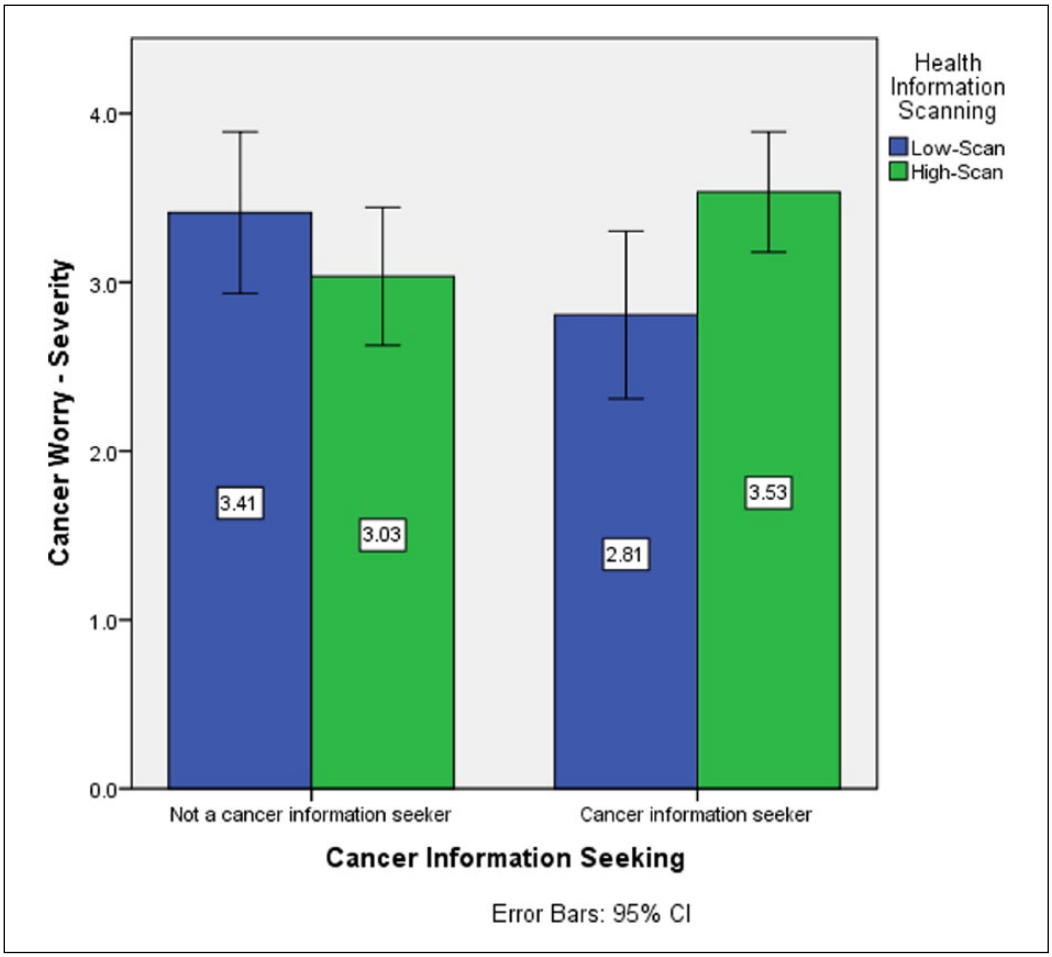

Figure 2. Cancer worry—severity (CWS) by seeking/scanning behavior. Bars present mean (in boxes) and 95 percent confidence intervals (brackets). Post-hoc tests revealed that low-scan/no seekers and high-scan/seekers had higher cancer worry severity scores than those in the other conditions.

$F(1, 193) = .44$, $p = .508$. There was a significant seeking × scanning interaction effect, $F(1, 193) = 5.63$, $p = 019$. Post-hoc tests revealed that low-scan/no seekers and high-scan/seekers had higher cancer worry severity scores than those in the other conditions (see Figure 2). For cancer worry frequency, there were no significant effects for seeking, $F(1, 193) = 2.09$, $p = .150$, scanning, $F(1, 193) = .95$, $p = .331$, or the seeking × scanning interaction, $F(1, 193) = .75$, $p = .387$.

Discussion

We tested the relationship between cancer information seeking/scanning and CIO. As expected, cancer information seeking and scanning was negatively related to CIO. Even though a significant effect was not found between information seeking and scanning and cancer worry, interestingly, the results did indicate a significant effect for the seeking × scanning interaction, with low-scan/no seekers and high-scan/seekers having higher cancer worry severity. The results of our study are

consistent with the findings of Kim et al.[17] that information seeking is far from being a linear process or a single event. Overall, our study offers a preliminary analysis of the relationship between cancer information seeking and scanning and CIO.

This study also highlights the role of dispositional cancer worry as a two-dimensional concept. We used eight items to measure dispositional cancer worry, in an effort to address the limitations of previous studies that have either utilized single item measures or failed to specify the total number of items dedicated to worry.[69] Most research tends to assume that the relationship between negative affect and health prevention behavior is linear;[69] however, the relationship appears to be more complex than a linear relationship allows. This study reveals that the interaction between information seeking and scanning is significant for cancer worry severity. The fact that only low-scan/no seekers and high-scan/seekers have high cancer worry severity could be explained by several possibilities. Ramanadhan and Viswanath[70] indicated that non-seekers are those who have lower education and income, who typically score lower on attention to health in the media, and who are less trusting of health information from mass media. Since individuals with lower education and income have less resources and skills to seek health information, either from health professionals or from media channels, it is reasonable to assume that these people may have higher levels of cancer worry. For the high-scan/seeker group, previous research suggests that worry about one's health is positively associated with online health information seeking.[68] Individuals who frequently experience cancer worry are more likely to actively seek and scan cancer-related information.

These results also shed light on cancer information seeking and scanning patterns of older populations. According to statistics revealed by the Administration on Aging (AoA),[71] the number of older US adults (persons who are 65 years or older) will be 72.1 million by 2030, more than twice the number in 2000. Older populations generally have more health problems than younger populations. There is evidence that the vast majority of cancer occurs in people aged over 50 years,[72] and this is also the group of people who are most likely to suffer from CIO—as information processing ability decreases with age. Future studies should more closely examine how older individuals cope with CIO and cancer worry.

The results of this study also point toward several actionable steps health practitioners can take to enhance cancer-related health behaviors. First, both highly active (high-scan/seekers) and inactive (low-scan/no seekers) exhibit high levels of cancer worry severity. The former are showing signs of active avoidance[50] which often stems from low efficacy. Moreover, low-scan/no seekers also exhibit high levels of CIO. Taken together, practitioners looking to reach highly inactive individuals/groups should avoid passive informational sources (e.g. pamphlets, brochures) in favor of interactive, efficacy promoting alternatives (e.g. personal stories about individuals successfully navigating challenges, games that teach basic skills). Second, approximately 60 percent of participants were passive in information seeking, scanning, or both. In a larger sense, this suggests practitioners should devote resources to promoting more active information seeking and scanning activities.

Limitations

This study has several limitations. The causal relationship between cancer information seeking/scanning and CIO still remains unclear. Even though we treat CIO as the outcome in the analysis, there remains the possibility that the level of overload also influences information seeking/scanning behaviors. Indeed, it seems more plausible to conceptualize the relationship between CIO and dispositional cancer worry as mutually causal, perhaps influencing one another slowly over time. A rigorous examination of this possibility will require a longitudinal design measuring CIO and

dispositional cancer worry at multiple points in time. This is more than a semantic query as a mutually causal relationship would suggest that some of our theoretical frameworks might be a suboptimal fit. For example, the EPPM posits that worry triggers fear control which can take the form of backlash.[50] The current study conceptualized CIO as a form of backlash; yet this idea would appear flawed if the hypothesized one-directional relationship was instead mutually causal.

There are also other limitations that are worth noting. The measure we used for cancer information seeking and scanning is adopted from Shim et al.'s[7] study, which was originally created for the Health Information National Trends Survey (HINTS). The problem with the current measure of information scanning, as pointed out by Shim et al.,[7] is that the wording of the measure may not represent the actual construct because it may confound attention to one medium with exposure to this medium. For the cancer information seeking measure, the two-item measure does not account for the frequency of information seeking/scanning behavior and the number of sources used.[40]

Conclusion

In summary, the results of our study suggest that cancer information seeking and scanning is negatively related to CIO. Our data also show that the interaction between information seeking and scanning is associated with one underlying dimension of dispositional cancer worry: severity. This study sheds light on the importance of cancer information seeking and scanning patterns of older populations as well as offers support for a key postulate of the IOM: CIO is related to information avoidance. Future work should continue to explore the relationship between overload, information avoidance, and other cancer-related dispositions with the goal of explicating a single comprehensive theoretical framework to guide cancer control research.

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Development of a web-based epidemiological surveillance system with health system response for improving maternal and newborn health: Field-testing in Thailand

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Abstract
Surveillance systems are yet to be integrated with health information systems for improving the health of pregnant mothers and their newborns, particularly in developing countries. This study aimed to develop a web-based epidemiological surveillance system for maternal and newborn health with integration of action-oriented responses and automatic data analysis with results presentations and to assess the system acceptance by nurses and doctors involved in various hospitals in southern Thailand. Freeware software and scripting languages were used. The system can be run on different platforms, and it is accessible via various electronic devices. Automatic data analysis with results presentations in the forms of graphs, tables and maps was part of the system. A multi-level security system was incorporated into the program. Most doctors and nurses involved in the study felt the system was easy to use and useful. This system can be integrated into country routine reporting system for monitoring maternal and newborn health and survival.

Keywords
electronic and mobile health, electronic health records, maternal and newborn health, surveillance system, web-based information service

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Introduction

According to the World Health Organization, 15 percent of all pregnant women are at risk of developing major obstetric complications.[1] Common major obstetric complications attributed to maternal and newborn death are pregnancy-induced hypertension, particularly preeclampsia/eclampsia, antepartum/postpartum hemorrhage, obstructed labor/uterine rupture, septic abortion, preterm birth and newborn with low birth weight.[2] The incidence of these complications is highest during the first two days after birth when the majority of women are still in hospital.[3] There are many studies highlighting the limitations of evidence-based practices and substandard care in hospital, especially in developing countries.[4–6] Moreover, major obstetric complications and their managements are often improperly and inadequately recorded. This may result in providing national health services with incorrect data, and thus less than ideal health policy planning.[6] A well-designed surveillance system for monitoring these complications would reduce these problems.

Various considerations must be addressed in the establishment of a good surveillance system, of which we believed the following the most important: (a) integration of the surveillance system with existing health information systems, (b) establishment of high standards for data recording, (c) health-related data recorded in electronic form and (d) relevant information in the system that facilitates accurate and timely public health decision-making.[7] The main problems of existing surveillance systems are irrelevant or inadequate quality of data collected, delayed reporting, low data utilization and a lack of feedback to health providers.[8] A system that can be used to gather information of maternal and newborn events on a daily basis and provide evidence for immediate corrective actions may be helpful for monitoring and improving maternal and newborn health and survival. One way to address these problems would be a web-based epidemiological surveillance system with integration of action-oriented responses using evidence-based policies and decision-making processes.[9,10]

Whenever health information technology is designed and implemented, the acceptance of its use and the intention to use it, which predicts actual use, should also be assessed.[11,12] Therefore, the objectives of this study were to develop a web-based epidemiological surveillance system for maternal and newborn health with integration of action-oriented responses and automatic data analysis with results presentations and to assess the system acceptance by the nurses and doctors involved. To our knowledge, this is the first time that an epidemiological surveillance system with immediate action responses has been developed for maternal and newborn health using web-based technology.

Materials and methods

The proposal for this study was approved by the Institutional Ethics Committee of the Faculty of Medicine, Prince of Songkla University. Permission to conduct the study was obtained from the directors of all study hospitals.

System design and development

Development tool

A web-based application was designed for this development tool due to ease of access and flexibility of operating systems. The system can be accessed through all web browsers that support the hypertext markup language version 5 (HTML5), including Internet Explorer,

Chrome, Firefox and Safari. HTML5 allows generation of cross-platform applications. Information in the central database can be added, deleted or updated using jQuery and Hypertext Preprocessor (PHP).

Database design

Three levels of database access were executed. Level 1 is for use by the "data entry operator," a nurse or clerk who enters the individual baseline data of pregnant women and newborns in a participating hospital. Level 2 is for the "actor," a responsible doctor or nurse who enters important clinical details and patient management for action responses and reviews the individual data in a participating hospital. Level 3 is for the "administrator," an upper-managerial staff or policy maker who has access to all individual data, action responses and aggregated summaries of the data from all hospitals including result presentations in terms of tables, graphs and maps.

During the trial period, the individual data of women during their pregnancy, labor and delivery, and the immediate postpartum period, as well as that of the newborn were recorded in the database on a daily basis. Data were stored into various database tables which were linked using the women's unique identification number and hospital number. As soon as the data of individual women were entered and confirmed in a particular hospital by a nurse or clerk, all the data from that hospital were saved and the maternal and newborn complications which were assigned to be monitored as the indicators would be summarized and updated on the server for the actor to view and perform the action-oriented responses. All data were recorded in a web server at the data center, located at the Epidemiology Unit, Faculty of Medicine, Prince of Songkla University. Administrators at policy levels could view the complications and individual data of women presenting the complications with their managements in the forms of summary tables, graphs and maps by selecting various options from the menu. Remarkable incidence of complications and improper managements in any hospitals can be timely observed and discussed. The system allowed data entry from multiple users as shown in Figure 1.

Functional design

Nurses and doctors—both general practitioners from the district hospitals or obstetricians in the tertiary hospitals—were trained on how to use the system, which consisted of data entry techniques and following up cases to check the accuracy and the functionality of the system. Data entry for individual women and newborns was the responsibility of trained nurses or health personnel in the labor and delivery rooms or emergency room in each hospital. Trained nurses acted as the data entry operator and trained doctors as the actors. During the development and testing period, T.L. and M.I. acted as the administrators to check the database and design the presentation of results.

All data were entered into the system using a smartphone, pocket PC or desktop computer. The confidentiality and security of data were protected by the use of username and password for determining the scope of functions and access to the data. Daily analysis and aggregation of data were performed using automatic data analysis techniques. To check the accuracy of data entered, the data were first reviewed before being confirmed in the system. If the data were not confirmed, a notification appeared in the database and remained until the data were confirmed. Once a record was confirmed, no further changes to the data were allowed. Complications occurring within 24 h after delivery were allowed to be added to a confirmed record.

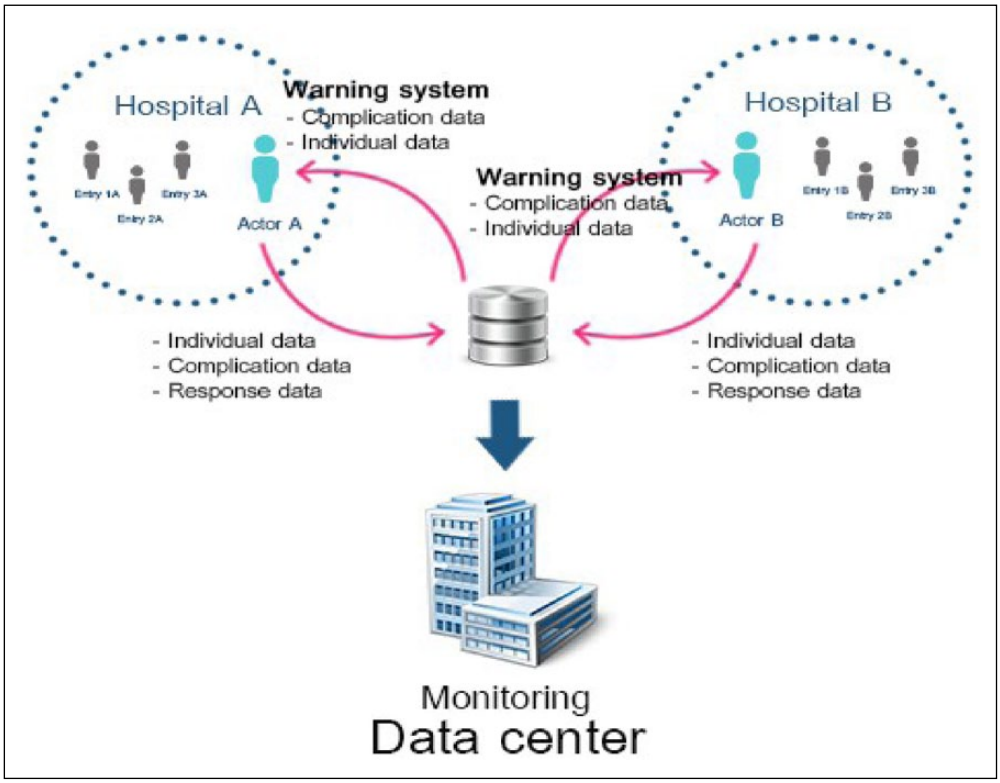

Figure 1. Multi-user system design for linking data between hospitals, the web server and the data center.

Figure 2 shows the main screen after a successful login to the system for data entry. Five options are available, namely aggregate indicators, statistics, entry individual data, confirmed data and sign out. The aggregate indicators list 10 complications which were monitored in this testing database. The 10 indicators were severe preeclampsia/eclampsia, postpartum hemorrhage, sepsis, obstructed labor, cesarean section, maternal death, preterm birth, low birth weight, stillbirth and neonatal death. After data related to these indicators were confirmed, the system would automatically update the summary page of aggregated indicators and totals for viewing by the actor as shown in Figure 3. Cases with complications that had not been acted upon by the actor would be highlighted in red, indicating that these cases should be reviewed, evaluated, and confirmed. This process involved evidence-based healthcare and review of attributed factors and actions done.

At the administrative level, the summary of data from each individual hospital could be reviewed in the form of a table, graph or map (Figure 4). The administrator could evaluate the percentage of action-oriented responses and individual data of women through the system (Figure 5). In addition, the data entered could be extracted for further analysis or printed.

Data security techniques

Three levels of data security were implemented, namely client level, data transmission level and server level. Client level applied the user authentication credentials with session timeout every 10 min to protect attacks from session hijacking and escaping questionable characters in queries

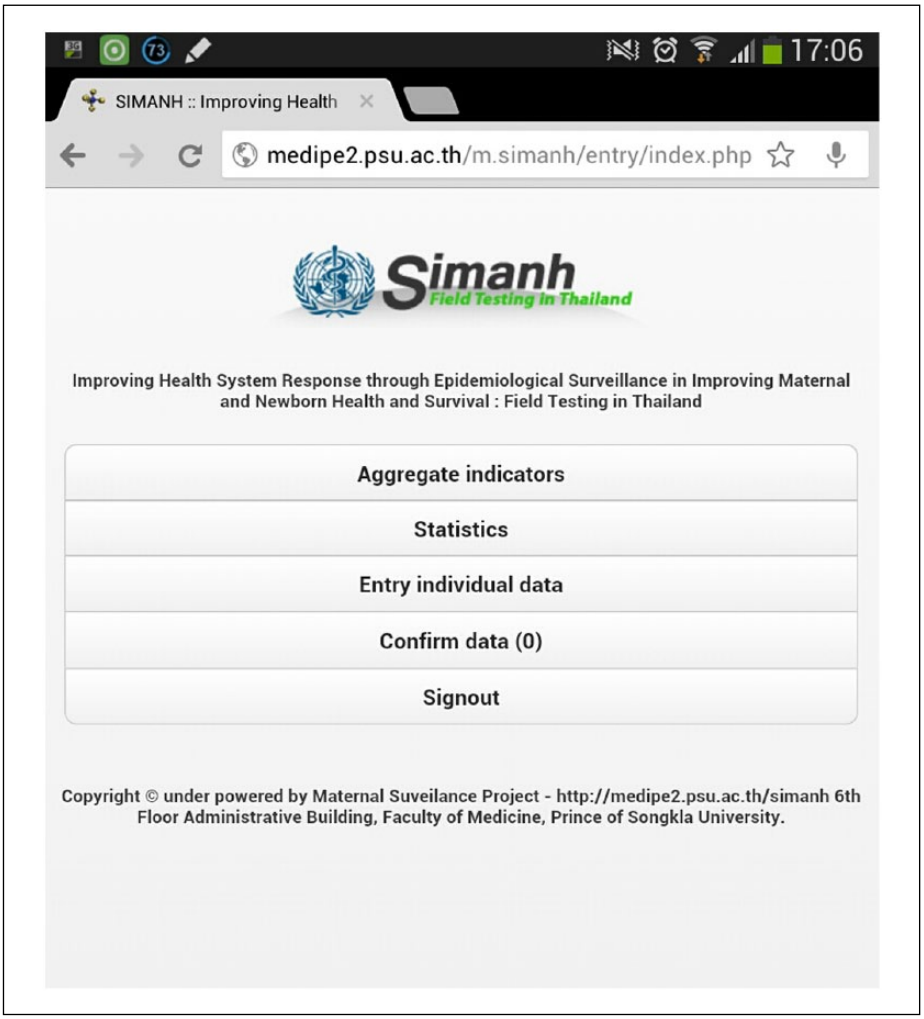

Figure 2. Sections in the level of data entry after login page.

were used to prevent SQL injection.[13–15] Moreover, encoding HTML entities and input validation with sanitization to prevent cross-site scripting were also used.[16] Data transmission level used encryption of the data between client and server through open-source software (NoSSL).[17] A multi-level firewall protection system was used for server security.[18]

Testing system

Study design and setting

The system was tested by health personnel from eight hospitals in Songkhla province, southern Thailand. Songkhla province was selected because it contains district, general and regional hospitals and a university hospital, all providing maternity services. District hospitals are the lowest-level facilities which provide delivery services for pregnant women. In order to have sufficient

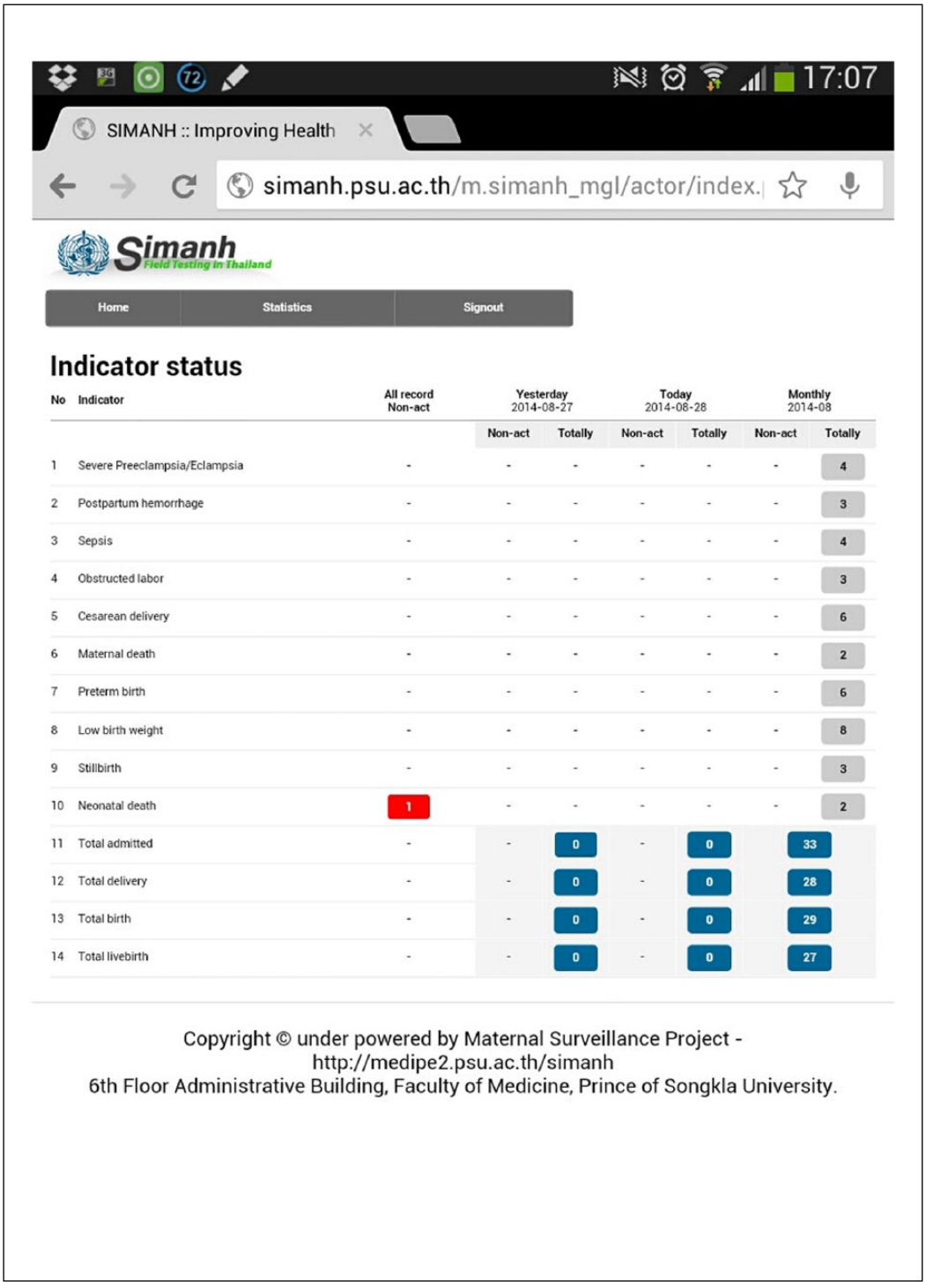

Figure 3. Sections in the level of actor after login page.

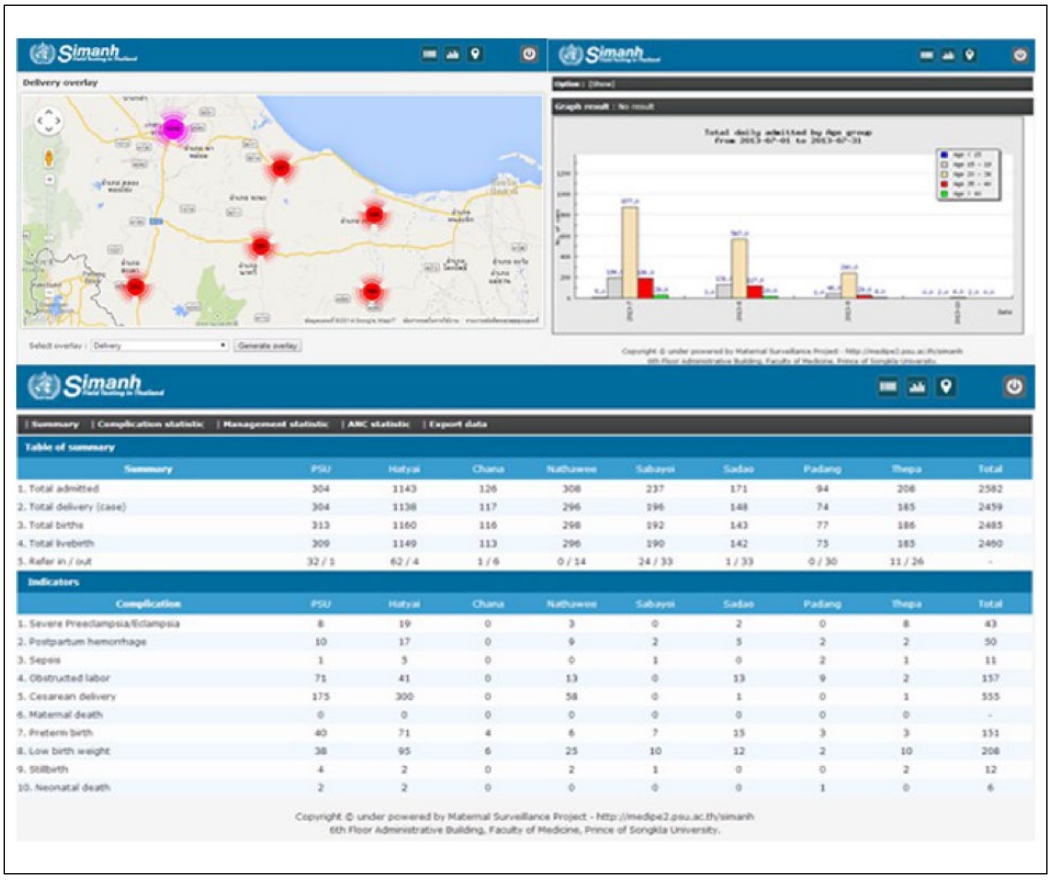

Figure 4. Summary of data at administrative level.

cases for field-testing of the surveillance system and to facilitate timely actions, the criteria for selecting the hospitals were as follows: at least 600 deliveries per year on average for district hospitals and at least 2500 deliveries per year on average for tertiary hospitals. From the 19 public hospitals in the province, six district and two tertiary hospitals met this criteria and all were included in the study.

Study samples

One or two labor and delivery nurses and one obstetrician from each of the selected hospitals were invited to attend a one-day training workshop on 16 June 2013 aiming to orientate them on the objectives of the study and train them on how to use the system. They were informed about the study and asked to sign a consent form to participate in the study. During the workshop, the principles of the system were explained and they were given an opportunity to practice data entry with module instruction and an interactive demonstration. An evaluation of the online web-based system, including mobile device application, important variables related to pregnancy, delivery and complications, the system for checking the accuracy of the data, real-time data presentation and daily and monthly demonstration of results, was performed at the end of the workshop. More than

Figure 5. Percentage of action-oriented responses and individual data assessment.

80 percent of the participants were satisfied with the system and provided feedback for improvements.

Data collection

One smartphone (Samsung Tab2, 7.0), including 3G for web-based functions with the instruction of system use was made available in the delivery rooms of all participating hospitals for the express purpose of entering data into the trial system. Data of all pregnant women who were admitted to the study hospitals for delivery during the study period were entered within 2 h after delivery. If any of the 10 complications monitored occurred within 24 h after delivery, then they were recorded as well.

Another smartphone of the same model was given to the trained doctors who worked as the actors of the study hospitals for entering action-oriented responses. The actors were responsible for reviewing the indicator events and recording the essential information of the indicator cases, and important treatments and actions performed. Continuous monitoring of data entry for the surveillance system and action responses was performed by the administrator at the data center. After the period of field-testing the system ended, an anonymous evaluation form was sent to all doctors and nurses who participated in the study to get their opinions on how well the system performed, and if it would be a useful thing to implement in their hospitals.

Outcome measures and data analysis

The main outcome measures in this study were the completeness of data entry in terms of the number of women who were admitted and delivered with or without complications, those who had

complications which were entered into the system and acted on, and the acceptance of the system as evaluated by the health personnel at the end of study. The percentages of number of data entered completely were analyzed. The results in the system were updated automatically and presented in the form of tables, graphs and maps. The tabular results were created automatically using a PHP script. The graphs were displayed using JpGraph, a freeware PHP library.[19] The map showed the location of events using a geographic information system via the Google Maps application. Different options, such as daily or monthly frequency, by hospital or by indicator were made available for data analysis and data visualizations including individual data. Number of deliveries and complications by age and other variables were summarized and shown in the tables.

The acceptance of the system was measured by evaluating the perceived ease of use and perceived usefulness of the system from the users' perspective. Perceived ease of use was measured through three items, overall functionality of the system, the data entry process and time consumed for data entry. Overall functionality and data entry process were rated using a 5-point Likert scale ranging from 1 (very difficult) to 5 (very easy) while time consumed was rated using a 5-point Likert scale ranging from 1 (too long) to 5 (very reasonable). Perceived usefulness of the system was measured on three items in terms of the benefit of variables recorded in the system, improvement of services provided and a perceivable effect on improving women health using a 5-point Likert scale range from 1 (not beneficial at all) to 5 (strongly beneficial). The percentage of each rating scale for the items was descriptively presented. The internal consistency of the three items for measuring the perceived ease of use and usefulness of the system was tested by Cronbach's alpha before summing into scores of perceived ease of use and usefulness of the system. The Cronbach's alphas of perceived ease of use and usefulness were 0.78 and 0.80, respectively.

Intention to use the system for data entry operators and actors was measured by asking the following question: "How likely would it be for you to use the system in the future if implemented into your hospital in terms of individual data entry and action-oriented responses?." The responses were rated using a 5-point Likert scale ranging from 1 (very difficult) to 5 (very easy). Responses of 1, 2 and 3 were categorized into "no intention" and responses of 4 and 5 into "intention." Scores of perceived ease of use and perceived usefulness of the system were tested for their association with the intention to use by univariate and multivariate analysis. A p-value of less than 0.05 was considered as significant.

Results

During the field-testing period, 2459 deliveries were recorded. Of these, 920 women had at least 1 of the 10 complications monitored in the surveillance system. Table 1 presents a summary of deliveries and complications. The individual data of all admitted and delivered women in the hospitals during the study periods were entered in the system as planned. The proportion of women with monitored complications which required a response from the actor varied by complication and by hospital.

A total of 2 obstetricians, 3 general practitioners and 40 nurses who were involved in the data entry process assessed the system. Their mean age and working experience were 34 and 11 years, respectively. The assessments of perceived ease of use and perceived usefulness of the system are shown in Tables 2 and 3, respectively. Approximately half of them assessed the system as easy or very easy. Two-thirds said that the system was beneficial or strongly beneficial. Less than 10 percent thought that the system was not beneficial.

Table 4 presents the responses of the study personnel regarding their intention to use the system in future routine use. Approximately 40 percent thought that the data entry was somewhat easy and

Table 1. Number of deliveries and complications recorded by hospitals in the surveillance system.

	Hospital								Total
	A	B	C	D	E	F	G	H	
Deliveries	304	1138	117	296	196	148	74	185	2459
Total births	313	1160	116	298	192	143	77	186	2485
Live births	309	1149	113	296	190	142	75	185	2460
Complications, n (%)									
Severe preeclampsia/eclampsia[a]	8 (2.6)	19 (1.7)	0	3 (1.0)	0	2 (1.4)	0	8 (4.3)	43
Postpartum hemorrhage[a]	10 (3.3)	17 (1.5)	0	9 (3.0)	2 (1.0)	5 (3.4)	2 (2.7)	2 (1.1)	50
Sepsis[a]	1 (0.3)	5 (0.4)	0	0	1 (0.5)	0	2 (2.7)	1 (0.5)	11
Obstructed labor[a]	71 (23.4)	41 (3.6)	0	13 (4.4)	0	13 (8.8)	9 (12.2)	2 (1.1)	157
Cesarean section[a]	175 (57.6)	300 (26.4)	0	58 (19.6)	0	1 (0.7)	0	1 (0.5)	555
Maternal death	0	0	0	0	0	0	0	0	0
Preterm[c]	40 (12.9)	71 (6.2)	4 (3.5)	6 (2.0)	7 (3.7)	15 (10.6)	3 (4.0)	3 (1.6)	151
Low birth weight[c]	38 (12.3)	95 (8.3)	6 (5.3)	25 (8.4)	10 (5.3)	12 (8.4)	2 (2.7)	10 (5.4)	208
Stillbirths[b]	4 (13)	2 (2)	0	2 (7)	1 (5)	0	0	2 (11)	12
Neonatal deaths[c]	2 (6)	2 (2)	0	0	0	0	1 (13)	0	6

[a]Per deliveries.
[b]Per 1000 births.
[c]Per 1000 live births.

Table 2. Perceived ease of use.

Items	Assessment scale, N = 45				
	Very difficult, n (%)	Difficult, n (%)	Somewhat easy, n (%)	Easy, n (%)	Very easy, n (%)
	Too long, n (%)	Long, n (%)	Fair, n (%)	Reasonable, n (%)	Very reasonable, n (%)
Overall functionality of system	0	2 (4.4)	18 (40)	22 (48.9)	3 (6.7)
Data entry process	0	3 (6.7)	17 (37.8)	20 (44.4)	5 (11.1)
Time consuming for data entry	0	4 (8.7)	20 (43.5)	18 (39.1)	4 (8.7)

Table 3. Perceived usefulness of the system.

Items	Assessment scale, N = 45				
	Not beneficial at all, n (%)	Not beneficial, n (%)	Undetermined, n (%)	Beneficial, n (%)	Strongly beneficial, n (%)
Variables in the system	0	4 (8.9)	10 (22.2)	24 (53.3)	7 (15.6)
Improvement of services provided	0	3 (6.7)	14 (31.1)	23 (51.1)	5 (11.1)
Effect on improving women health	1 (2.2)	1 (2.2)	14 (13.1)	22 (48.9)	7 (15.6)

Table 4. Intention to use the system in routine use.

Items	Assessment Scale, N = 45				
	Very difficult, n (%)	Difficult, n (%)	Somewhat easy, n (%)	Easy, n (%)	Very easy, n (%)
Entering data for data entry	0	8 (17.8)	19 (42.2)	14 (31.1)	4 (8.9)
Entering data for actor response	0	10 (22.2)	16 (35.6)	17 (37.8)	2 (4.4)

the actor response was easy. The overall rate of intention to use the system for individual data entry was 39.1 percent and for action-oriented responses 41.3 percent. The main reasons given by those who were reluctant to commit to the system was they were too busy to enter the data on a daily basis within 2 h of delivery and monitoring complications and 24 h after delivery. Both perceived ease of use and usefulness of the system were significantly associated with the intention to use for data entry and actor response in univariate analysis. Only perceived ease of use was shown to be significant for data entry (adjusted OR = 4.15, 95% confidence interval 1.08–15.98) and actor response (adjusted OR = 8.17, 95% confidence interval 1.50–44.58), when adjusting for the perceived usefulness of system.

In addition, the system was informally presented to two policy makers in the Ministry of Public Health, Thailand. Both of them showed interest in the timely reports of aggregated data for complication indicators, automatic updates and ability to view the results instantly.

Discussion

The consensus by all stakeholders was that this electronic web-based database system, including both surveillance and action-oriented responses for common complications, was acceptable and useful. Epidemiological surveillance systems are mostly used for monitoring diseases or disease outbreaks to provide important information for future actions.[7] However, low accuracy or poor functionality of surveillance and health information systems in most developing countries is common. Maternal and newborn health was chosen for this trial study because it is a global public concern, and there is currently no surveillance system to monitor common morbidities with the individual data of pregnant women. Timely analysis and use of information for program monitoring and taking corrective actions are virtually absent.[8] A warning system was found to be useful in surveillance systems.[20,21] In addition, the dissemination of results and actions should be provided in a timely manner.[9] According to these concepts of lessons learned, a facility-based electronic epidemiological surveillance system for maternal and newborn health with timely action-oriented responses for important obstetric complications was successfully developed and tested.

Recently, surveillance systems of maternal and perinatal/neonatal morbidity have been used in Canada, Brazil and China.[22–30] However, the maternal morbidities were measured variously in terms of obstetric or maternal complications, severe obstetric complications or life threatening complications.[31] Within the system of our study, both common maternal and newborn morbidities and mortality were recorded, and automatically measured with the linkage of all important holistic information to represent representativeness and quality of data and the flexibility, timeliness and stability of the system.[10]

However, the goals of developing a surveillance system will not be achieved if the system is not used properly or if the data are not entered completely and in a timely fashion. Nurses and doctors in the field-testing period accepted the system, stating it to have high perceived ease of use and usefulness which was partially consistent with the concept of the technology acceptance model.[11] Perceived ease of use and usefulness of the technology system were commonly applied in previous studies to measure users' reactions to health information technology.[11,12,32] A literature review by Holden and Karsh[11] showed various theories to measure the technology acceptance. Attitude as the determinant component as in the original Technology Acceptance Model (TAM), a "subjective norm" component as in the extended Technology Acceptance Model (TAM2) and social influence as in the Unified Theory of Acceptance and Use of Technology (UTAUT) were not measured in our study.[33–35]

The prediction of actual use by acceptance and intention to use was also emphasized in the model of technology acceptance; however, the determinants of intention to use were explained differently in related theories.[11] The perceived ease of use and usefulness of the system as determinants of attitude measurement were used to predict the intention to use directly. A previous study found that "subjective norm" or social influence showed no direct effect on adoption of healthcare information technology among Thai healthcare personnel.[36] Our web-based system and use of mobile devices were accepted in our settings which have also been noted in previous studies.[12,32] Attitudes of medical doctors have been shown to influence the intention to use a smartphone at the hospital more than social influences. Cost of the smartphone, quality of information, ease of use and support were associated with doctors' attitudes.[37] In our study, perceived ease of use, not usefulness, was significantly associated with intention to use the system, which was opposite to a previous study that showed a direct effect of usefulness.[32] This may be explained by the positive agreement of health personnel on the requirement of a surveillance database system via electronic health records. Apart from evaluating the perceived ease of use and usefulness of the system, the acceptance of the system based on its image, job relevance, output quality and result demonstration as in the TAM2 were also assessed in our study.[11,38]

When a web-based system is developed, the field-testing is crucial in both non-functional and functional requirements, aiming to check both the process of data input and any failures to link with the various tables in the database.[39] This system would provide two main added values which can improve existing systems: real-time, online electronic health records with a surveillance system for major obstetric complications and a warning system for timely action response for case review to prevent avoidable maternal and newborn morbidities and deaths. In addition, stakeholders at higher levels, such as policy makers or program managers, can monitor the aggregate workloads, fluctuations and performances of the system on a daily basis. Having a good infrastructure for entering the data in a database system is important to ensure that the correct number of complications is recorded. Information from women who visit more than one health facility, due to referral or otherwise, can be linked by their unique identification number.

There were some limitations in our study. First, the main purpose of the field-testing was to test the user-friendliness of the system in terms of data entry, data analysis and visualizations, thus the outcome of action responses on health and survival could not be assessed. Second, only complications that occurred within 24 h after delivery were recorded. Third, stratification of deliveries and complications was possible only for a limited number of variables such as age group, gravidity and some antenatal care parameters. However, more variable options can easily be added in future versions if required. Fourth, quick and uninterrupted internet access is essential for data entry and processing. Finally, the social influences or subjective norms and perceived control were not tested.

In conclusion, our study found that a web-based surveillance system with action-oriented responses accessible from various electronic devices for monitoring and evaluating maternal and newborn health and survival at hospital and policy levels is feasible. Appropriate functional designs and administration of this system should be considered for its implementation in different health systems. This system can be modified appropriately and tested in other settings. Active participation of all healthcare workers and administrative officials is important, therefore introduction of the system must be done with appropriate orientation and training of the various levels of providers.

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Article

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A discrete event simulation tool to support and predict hospital and clinic staffing

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Abstract

We demonstrate how to develop a simulation tool to help healthcare managers and administrators predict and plan for staffing needs in a hospital neonatal intensive care unit using administrative data. We developed a discrete event simulation model of nursing staff needed in a neonatal intensive care unit and then validated the model against historical data. The process flow was translated into a discrete event simulation model. Results demonstrated that the model can be used to give a respectable estimate of annual admissions, transfers, and deaths based upon two different staffing levels. The discrete event simulation tool model can provide healthcare managers and administrators with (1) a valid method of modeling patient mix, patient acuity, staffing needs, and costs in the present state and (2) a forecast of how changes in a unit's staffing, referral patterns, or patient mix would affect a unit in a future state.

Keywords

decision-support systems, forecasting, management, simulation tool

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Introduction

Adequate staffing levels in hospitals are critical to daily operations and for ensuring optimal care delivery, patient safety, and patient and staff satisfaction. Inadequate staffing increases adverse patient outcomes, including pneumonia, shock, cardiac arrest, and urinary tract infections;[1] it also increases the likelihood of staff turnover. Hospitals spend US$22,000–US$64,000 per registered nurse who leaves the workforce and is replaced, leading to US$12 billion in excess costs each year.[2,3]

To predict staffing needs, managers use (1) the number of patients admitted and discharged per day and per year to a unit or service, (2) the acuity of the patient population and an inventory of needed resources, and (3) the estimated growth or decline in these factors over time. But managers must often base planning on insufficient data and are further affected by uncertainty regarding the effects of local and national policy changes, such as the US Affordable Care Act[4] which has increased access to care. Moreover, some localities mandate particular staffing levels, and it would be helpful for managers to have tools that would allow better prediction of staff needs based upon patient population. Discrete event simulation incorporates probability distributions estimated from existing data as well as previous experiences to model complex, dynamic systems. Discrete event simulation can help nurse managers better predict staffing needs, thereby potentially improving patient safety, health outcomes, and predictability of nursing assignments.[5–7] It may also reduce stress associated with understaffing and ultimately reduce costs and improve the efficiency of care. Although it is impossible to account for all variables affecting daily fluctuations in census and acuity at hospitals or clinics, staffing needs in 1 unit can be simulated based upon historical data of patient admissions, discharges, transfers, and acuity over days, months, and years. Furthermore, a simulation model can be adjusted to predict needs related to growth by addressing strategic questions such as the following:

- If two hospitals partner, can current staffing levels tolerate 100 additional transfers each year?
- If population growth continues for 10 years, how many new beds will be needed?
- If new nursing assistants free each registered nurse to take one additional patient and the maximum nurse:patient ratio drops from 1:3 to 1:4, how will the cost structure change?

This study demonstrates how we developed and piloted a discrete event simulation model of nursing staff needed using data from a neonatal intensive care unit (NICU) to help managers better meet patients' needs. We developed the simulation by combining historical data elements from our hospital and US national-level outcomes data.[8] We then assessed model validity and accuracy using two different staffing levels (26 and 28 nurses) and comparing the model's output with historical data.

Methods

Model development: data elements

To develop our model, we used various data elements, including the hospital bed size, number of staff, patient flow structure, nursing practices, and de-identified, retrospective patient outcomes from the Duke University Hospital NICU from January 2008 to June 2013. An existing database maintained by the unit's administrative staff included patients' demographic information, diagnoses (date of specific disease states or therapies), billing and coding details by each day of patients' stay,

and discharge status (sent home, transferred to another unit or facility, or deceased). Following approval by the Duke University Institutional Review Board, data were de-identified, analyzed, and combined with published US national-level outcomes data[8] to estimate admission and morbidity inputs. The final probability distributions were anonymized. No simulated patients were based directly on any actual patient.

Discrete event simulation: process flow

A discrete event simulation model requires a defined "process flow," which we refer to here as a simulated NICU (Figure 1). The objects or entities that flow through the simulated NICU represent babies ("simulated patients").

The number of simulated patients admitted to the simulated NICU each day was sampled from a probability distribution based on the hospital's historical data. We distributed the arrival times of the simulated patients uniformly across a 24-h interval. Each arriving simulated patient was randomly assigned one of the three admission types: inborn (same NICU; 66%), outborn-in-network (different in-network birthplace, transferred into the NICU; 9%), or outborn-out-network (different out-of-network birthplace, transferred into the NICU; 25%). We created different admission types for inborn and outborn babies because their admission frequencies differ in this setting and could influence strategic staffing decisions.

Based on admission type, simulated patients were assigned a gestational age (number of weeks (range: 22–42 weeks) of gestation completed before birth), which was randomly sampled from an empirical distribution. Gestational age is a critical determinant of length of stay (LOS) in the NICU. Babies born close to term (40 weeks) with mild illnesses may be discharged home within days; however, babies born at 24 weeks have a mandatory stay of many weeks in any NICU, even in the absence of significant long-term medical problems of prematurity. Figure 2 shows the historical distribution of gestational age of inborn admissions.

Using gestational age, an estimated baseline length of stay (bLOS) in days for each simulated patient was calculated as follows: if gestational age $\leq$29 weeks, then bLOS = (37 − gestational age) × 7 days; if 29 $\leq$ gestational age $\leq$ 33 weeks, then bLOS = (35 − gestational age) × 7 days; if gestational age >33 weeks, then bLOS = 14 days.

Gestational age also determined the simulated patient's initial acuity level, defined as nurse:patient ratios of 1:1, 1:2, and 1:3. A 1:1 simulated patient was the only patient a nurse cared for during that shift; a 1:3 simulated patient could be assigned to a nurse who had two other 1:3 patients or one additional 1:2 patient, and so on. If gestational age was <28 weeks, then the simulated patient's initial acuity level = 1:1; if gestational age was 28–38 weeks, acuity = 1:2; if gestational age was $\geq$ 39 weeks, there was a 50% chance that acuity = 1:1; otherwise, acuity = 1:2.

Based on acuity level, each simulated patient was assigned either a "critical-care" or "step-down" bed. As in our NICU, the simulated NICU included 47 critical-care and 21 intermediate-level beds. Critical-care beds allowed patients assigned 1:1, 1:2, or 1:3 ratios; step-down beds allowed only patients assigned a 1:3 ratio.

Within the simulated NICU, shift changes occurred every 12 h to simulate our actual NICU shift changes at 07:00 and 19:00. Because admission, crash (acute decompensation in clinical status), and death could occur at any point during a nursing shift, each simulated patient's acuity was recalculated at the end of each shift. At that time, patients could remain in their current status, transfer out of the unit, or move between critical-care and step-down beds in either direction, as appropriate. Based on recalculated acuity, nurses were likewise reassigned every 12 h to only as many patients as appropriate for the acuity level of his or her most acute simulated patient.

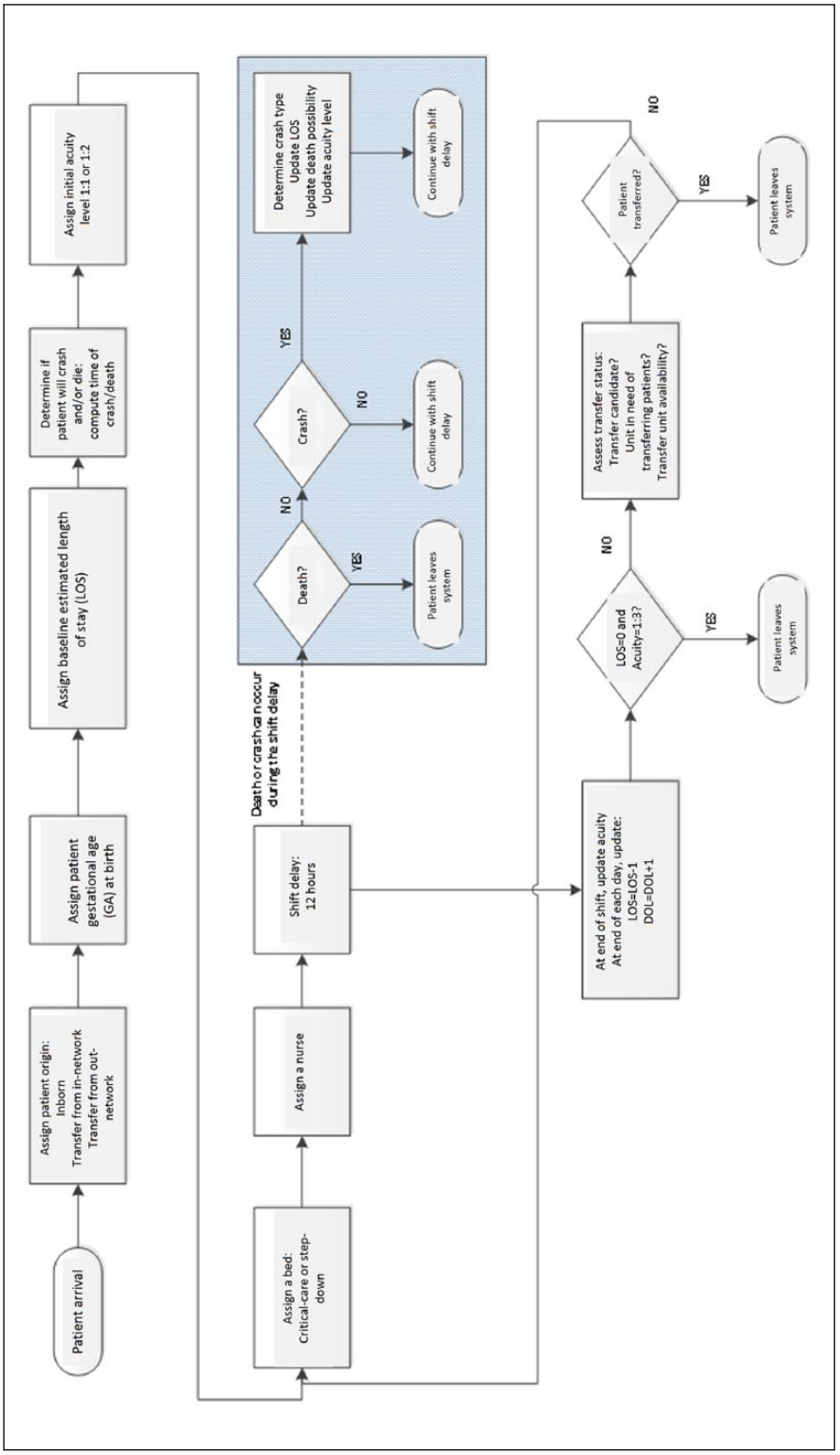

Figure 1. Final process map: simulated patients in the NICU.

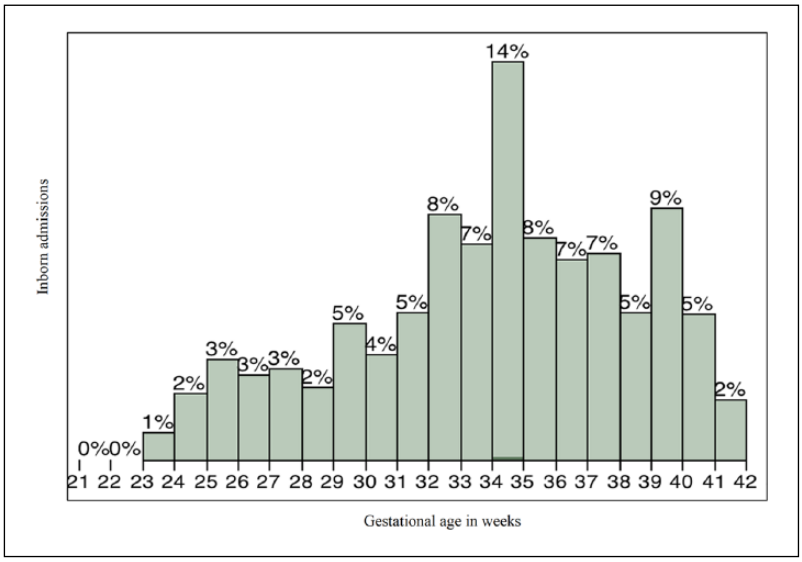

Figure 2. Gestational age (weeks) for inborn admissions (N = 3307).

bLOS was updated according to five major morbidities that influence NICU LOS: (1) sepsis (infection in the bloodstream), (2) necrotizing enterocolitis (a deadly neonatal intestinal condition), (3) patent ductus arteriosus (a neonatal cardiovascular anomaly requiring medical or surgical intervention), (4) retinopathy of prematurity (a condition affecting blood vessels in the eye that leads to blindness if not promptly treated), and (5) intraventricular hemorrhage (bleeding into the internal structures of the brain). Because the probability of each condition varies by gestational age,[8] separate empirical distributions were estimated and sampled to determine which simulated patients would experience one or more of these conditions, and how LOS, acuity, and potential for mortality would be affected. For example, necrotizing enterocolitis is several times more likely in infants born at 24 versus 28 weeks and effectively absent in infants born close to term. Table 1 describes the effects of each morbidity on outcomes. The LOS effect data in Table 1 are based on a multivariate regression model using internal data incorporating each morbidity into the model in addition to gestational age, while temporal effect on acuity was based on subject-matter experts from neonatologists at the authors' institution.

The anonymized admission and morbidity distributions predefined each simulated patient's entire course of admission to departure from the simulated NICU. This included whether and at what hour a crash would occur, shift-to-shift variations in acuity, and ultimate LOS, which was reduced by 1 day at the end of each simulated day. A simulated patient exited the simulated NICU by (1) succumbing to a morbidity identified on admission, (2) dying from another aspect of prematurity not crash-related, or (3) surviving to discharge or transfer.

Criteria for discharge were acuity = 1:3 and LOS = 0; indicating that the infant needs less care and is getting healthier. Discharge could occur at any shift change when a simulated patient met these criteria. Criteria for transfers included benchmarks for gestational age, days of life (days since birth), and postmenstrual age (gestational age × 7 + days of life). Postmenstrual age is the time elapsed between the first day of the last normal menstrual period and the day of delivery. A transfer was calculated as follows: if gestational age <9 weeks, then postmenstrual age ⩾238 days, acuity = 1:3, and no retinopathy of prematurity; if 29 ⩽ gestational age ⩽ 31 weeks, then postmenstrual

Table 1. Defining morbidities for individual patients in the discrete event simulation model.

Morbidity	Time window	Effect on LOS	Effect of acuity
Sepsis	Exponentially distributed with a mean of 14.5 days	Type I (fungi): increase LOS by 21 days Type II: increase LOS by 28 days Type III: increase LOS by 14 days	Type I: 1:2 for 10 days Types II and III: no effect
Necrotizing enterocolitis	Centered around DOL = 30 with min = 14 and max = 42 days	50% mortality within 24 h for surgical NEC; 20% mortality within 3 days for medical NEC. If no death, increase LOS by 7 days for surgical NEC and by 21 days for medical NEC	For surgical NEC: 1:1 for 3 days 1:2 for 7 days For medical NEC: 1:2 for 7 days
Patent ductus arteriosus	Uniform (3, 14) days	If surgical management, then increase LOS by 21 days; otherwise, increase LOS by 7 days	If surgical management: 1:1 for 3 days 1:2 for 7 days Otherwise, no effect
Retinopathy of prematurity	(32 − GA) × 7 days (occurs at 32 weeks)	Stage I: no effect Stage II: increase LOS by 21 days Stages III and IV: increase LOS by 42 days	Stages I and II: no effect Stages III and IV: 1:2 for 3 days when patient reaches 32 weeks old
Intraventricular hemorrhage	Uniform (7, 14) days	Increase LOS by 10 days	None

LOS: length of stay; GA: gestational age; NEC: necrotizing enterocolitis DOL: day of life.

age ⩾224 days, acuity = 1:3, and no retinopathy of prematurity; if gestational age ⩾32 weeks, then days of life ⩾7, acuity = 1:3, and no retinopathy of prematurity. Transfers required simulated patients to meet individual criteria, the simulated NICU to meet census-based requirements for transfers, and a transfer bed to be available based on a probability distribution at the start of each day. At the end of a shift, if a simulated patient had not crashed and his or her postmenstrual age ⩾210 days, the acuity level was set to 1:3.

Data analysis

The process flow was translated into a discrete event simulation model using SAS Simulation Studio (SAS Institute Inc., Cary, NC, 2013). Figure 3 shows a high-level view of the simulation model. The model collected the following information from de-identified, retrospective data from <<blinded>> Hospital, using a simulation run-length of 1 year: (1) number of admissions, (2) number of admissions with gestational age <28 weeks, (3) number of transferred patients, and (4) number of patients who died. Additional information included average daily census, average LOS of all patients, and average LOS for those whose gestational age was <28 weeks. This information was estimated using steady-state analysis methods along with statistically valid confidence intervals.

System "warm-up"

It is typically difficult to start a simulation in steady-state operation in which there is no change in the data. This would require knowing exactly what steady-state behavior looks like ahead of time

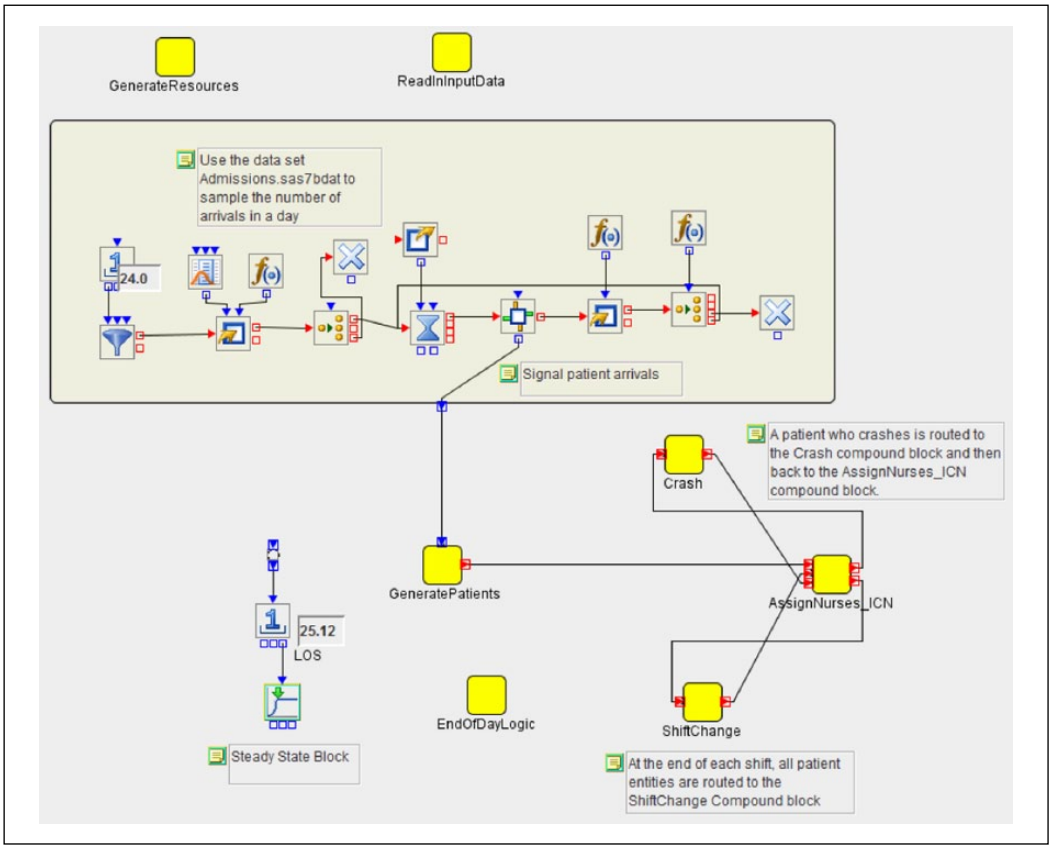

Figure 3. SAS Simulation Studio model.[9]
*Each yellow square in the model was a compound block that could be opened to display the Simulation Studio logic contained within.

so that the model could be prepopulated with an appropriate number of patients in various states. Thus, the model was started empty and idle with no patients in the system. Patients were then added to the system over time until, as determined by a statistical test for randomness in the output data, we could verify whether it had reached steady-state operation in the simulation. When the end of this warm-up period was reached, only observations collected after the end of the warm-up period were included in the analysis to avoid biasing response point estimates. For nurses (n = 30), 64 simulation days were required to reach steady-state; however, we used a conservative warm-up length of 120 days and ran the simulation for 485 days.

Results

Model results

Results averaged from 50 independent replications of the simulated NICU model were compared with averaged actual hospital NICU data from 2008 to 2013. During this period, our actual NICU was generally staffed with 26–28 nurses per shift. Consequently, we staffed our simulated NICU with 26, 27, and 28 nurses per shift; the results for 26 and 28 nurses are shown in Table 2. The

Table 2. Discrete event simulation model predictions versus actual data from <<blinded>> NICU, 2008–2013.

Response	Model with nurses = 26 Mean (95% CI)	Model with nurses = 28 Mean (95% CI)	Actual Mean (95% CI)
Admissions in 1 year	824.0 (814.4, 833.6)	870.0 (862.8, 877.3)	792.2 (732.4, 851.0)
Admissions for GA <28 weeks in 1 year	126.7 (124.1, 129.4)	132.6 (130.3, 134.8)	119 (108.9, 129.1)
Total transfers in 1 year	307.6 (300.0, 315.2)	277.6 (268.0, 286.4)	255.2 (168.6, 341.7)
Total deaths in 1 year	36.2 (34.0, 38.4)	36.2 (34.2, 38.1)	38.4 (33.7, 43.1)
Average daily census	56.5 (56.3, 56.8)	60.3 (60.1, 60.6)	57.1 (53.5, 60.7)
Length of stay (days)	25.4 (25.2, 25.8)	26.0 (25.3, 25.9)	26.3 (25.1, 27.7)
Length of stay (days) with GA <28 weeks	76.7 (75.5, 77.9)	76.6 (75.5, 77.7)	86.0 (81.1, 90.8)

GA: gestational age; CI: confidence interval; NICU: neonatal intensive care unit.

28-nurse model demonstrates how the addition of two nurses per shift would allow for an increased daily census of approximately 4 patients (56.5–60.3) and an increased yearly census of approximately 45 patients (824–870). Adding two nurses per shift would allow for an additional five to six patients with a gestational age <28 weeks per year (126.7–132.6). Although one might expect that more infants with a gestational age <28 weeks might increase LOS due to their acuity, the model showed that this would have no effect on average LOS (25.4–26.0 weeks, overlapping confidence intervals).

Discussion

These results demonstrate that it is possible to develop a simulation that managers and administrators might use when staffing a hospital unit. The model demonstrates an accurate method of simulating patient mix, patient acuity, staffing needs, and costs in the present state, and it also forecasts how changes in a unit's staffing, referral patterns, or patient mix would affect a unit in a future state. Our results demonstrated the validity of the present-state and future-state modeling as reflected in the actual data from the unit's real patients over a 66-month period.

Although present-state models alone have significant value for hospital administrators to estimate staffing needs, accurately modeling future states is even more valuable. This value, in addition to a unit's proprietary cost information, becomes clear as management contemplates the return on investment for additional hiring per added patient and staffing the unit for growth. For example, managers could calculate how many nurses to hire for each bed added during a growth phase, or how variations in bed allocation (step-down versus critical-care) would affect the flow of patients over a week, month, year, or decade. Furthermore, this tool could be valuable in situations of uncertain staffing needs (e.g. disaster responsiveness, mass casualty, flu outbreak).

Others have demonstrated the validity of analytical models for predicting hospital needs, including physician residents in surgical units,[5] LOS in geriatric adult patients with schizophrenia[6] and acute psychiatric hospitals,[7] hospital-associated mortality for Medicare patients,[10] bed unit utilization in obstetric hospitals,[11] and understanding patient characteristics in NICUs.[12] Our model expands these by including additional elements for predicting staffing needs such as patient acuity, referral patterns, and LOS. Furthermore, using probability distributions based on real data to simulate individual patients creates a more accurate and useful tool.

Like others,[13] we have demonstrated that predictive modeling can be refined and made more accurate by using factors tailored to a unit's patient population, such as later-occurring morbidities. With modifications to input variables specific to the unit (e.g. patient age or morbidities), our model is easily transferable to other NICUs. More broadly, the discrete event simulation structure underlying this model could be used in any clinical setting that can access appropriate data: patient acuity; LOS; demographics; and historical admission, transfer, and discharge frequencies. Although the major drivers of admission, discharge, staffing, and LOS will differ by unit, data on these factors are likely immediately available to clinical managers.

Our next steps are to test this model in real time by comparing its forecasting with prospective hospital data. This will allow us to further validate our model and then translate it into practice for managers and administrators as a decision-making tool.

Limitations

This model is predicated on 66 unique past months of data. Policy changes may produce effects not captured in these findings. Furthermore, we have not yet implemented the model to obtain an understanding of its utility in a real-world planning environment. Nevertheless, this model may provide managers with better data with which to make staffing judgments.

Implications and conclusions

As medical technologies have advanced over time, patients of lower acuity who previously would have received inpatient medical care have been moved to outpatient settings. From 1980 to 2000, the average length of an inpatient hospital stay fell from 7.5 to 4.9 days.[14] Thus, patients who would have spent the early stages of their recovery in the hospital are now discharged to skilled nursing facilities or home. By implication, hospitals have a higher overall concentration of sick people who need more care and thus more overall staff and resources. To maintain standards of quality care and to prevent adverse events, adequate numbers of staff are critical.[15] This model could be used to investigate the effects of different treatment protocols for morbidities on patient outcomes in the NICU. While we presented an example from nurse staffing, this model can be easily altered to plan for other staff, including physicians, pharmacists, and social workers and to estimate physical needs and facilities support. Predicting and preparing for staffing levels and physical space needs are challenging and may impact patient outcomes, hiring, and capital expenses. Discrete event simulation modeling is a tool that can be applied to any hospital unit, empowering leadership to make more informed, data-driven staffing judgments and can give managers better operational awareness as the healthcare landscape changes.

Declaration of Conflicting Interests

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An analysis of electronic health record–related patient safety incidents

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Abstract

The aim of this study was to analyse electronic health record–related patient safety incidents in the patient safety incident reporting database in fully digital hospitals in Finland. We compare Finnish data to similar international data and discuss their content with regard to the literature. We analysed the types of electronic health record–related patient safety incidents that occurred at 23 hospitals during a 2-year period. A procedure of taxonomy mapping served to allow comparisons. This study represents a rare examination of patient safety risks in a fully digital environment. The proportion of electronic health record–related incidents was markedly higher in our study than in previous studies with similar data. Human–computer interaction problems were the most frequently reported. The results show the possibility of error arising from the complex interaction between clinicians and computers.

Keywords

electronic health records, health information technology, hospital incident reporting, patient safety, sociotechnical

Background

Electronic health records (EHRs) are promoted due to their capacity to reduce clinicians' workloads, costs and errors.[1–4] Health information technology (HIT) is also expected to improve the co-ordination of care, thereby allowing for improved follow-up.[5] However, new technology may

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also pose novel risks to patient safety by disrupting established, traditional working norms and creating new risks in practices related to HIT design, implementation and use.[6–10] Despite this, current evidence concerning HIT safety is relatively limited,[11,12] and the few studies on the subject suggest that HIT contributes to less than 1 per cent of total errors in healthcare systems.[2,13]

The establishment of a voluntary patient safety incident reporting system is a core method for receiving and processing patient safety-related information and creating a more accurate understanding of patient safety risks. The data on patient safety incident reporting presented in this study provide a sample of hazards well-suited for identifying risks.[14] Characteristic profiles may be identified when collecting and analysing large numbers of incidents.[15] Magrabi et al.[16] searched and analysed computer-related patient safety incidents in a state-wide Australian Advanced Incident Management System (AIMS) database. Only 0.2 per cent of all reports in the AIMS database were HIT related. Machine-related problems were more common than human–computer interaction issues. The framework described by Magrabi et al.[16] has been used in more recent studies related to incident reporting data in the United Kingdom,[17,18] and the results stress the significance of machine-related errors. Controversial evidence about HIT safety shows that HIT-related errors have complex sociotechnical origins.[19–22]

More information regarding EHR-related patient safety concerns is needed. Different patient safety data sources that complement each other are useful in identifying hazards and providing a more comprehensive view of the risks in a particular system.[23,24] Adverse events occurring in one institution are known to recur in other institutions, often with the same causes and contributing factors.[25] By identifying the nature of patient safety incidents, initiatives for improvement can be developed and prioritised.[26] The lessons learned from incident reporting data can also be used to prevent the same incidents from occurring in other organisations on an international level. Currently, these systems do not include specific interventions to reduce risk, which requires consideration.[14,26]

Methods

Objective

The first aim of this study was to analyse EHR-related patient safety incidents in a patient safety incident reporting database in a fully paperless, digital hospital environment and, consequently, to contribute evidence about HIT safety. Our second aim was to compare these data to a similar international database in public hospitals and discuss the data content. In particular, we aimed to answer the following research questions:

What is the proportion of EHR-related patient safety incidents in a patient safety incident reporting database in a fully paperless, digital hospital environment? Which are the most common types of computer-related patient safety incidents in a patient safety database in a fully digital hospital environment and have actions been taken to prevent such incidents from recurring? And finally, what are the main differences between the two similar databases?

Setting

According to the Finnish Act on Health Care from 2011,[27] all healthcare organisations must maintain a patient safety incident system as a part of their patient safety system. The Finnish patient safety incident reporting model and instrument, HaiPro, was developed mainly during 2006 and is anonymous.[28]

The incident reports in HaiPro consist of structured and free-text fields and describe the background details of the incident (e.g. incident unit, time of the incident, reporter's profession, incident, contributing factors, consequences for the patient and the organisation, quantification of harm on a

5-point scale/risk matrix and corrective measures). Events are classified into 13 incident types using HaiPro's national classification. The most frequently used incident categories are 'Medication and Transfusions', 'Information Flow' and 'Information Management' categories as well as 'Laboratory', 'Imaging' and 'Other Patient Treatment Procedures' categories. All the HaiPro main categories include more detailed subcategories. An incident report can contain multiple event descriptions.

The hospital district of Helsinki and Uusimaa with over 21,000 employees and some 500,000 patients annually is the largest hospital district in Finland and includes tertiary university hospital functions. By 2011, its reporting system had included all clinical units in its 23 hospitals. The hospital district devotes resources to reporting and analysing the events. The hospital district offers on-going classroom training as well as an e-learning programme to train its staff to report and other responsible persons to handle the reports. Every unit has two medical and nursing managers to classify the incident reports according to uniform national guidelines, which include classification rules. Duplicate reports must be deleted from the database. The quality managers, the hospital district's chief patient safety officer and a group of the hospital's HaiPro classification development experts ensure the consistency and compliance with the classification principles. The hospital's patient safety committee monitors the incident data on a regular basis. Managers are obligated to share reports with staff, and the person reporting an event receives feedback on the investigation through the system.

Since 2007, the entire hospital district has been using a fully paperless, comprehensive EHR system. The hospitals in this study used the same EHR system. HaiPro is not an integrated component of the EHR system, but an Internet-based user-friendly interface.

Data collection

Our analysis included all safety incidents reported through the HaiPro system between December 2011 and November 2013. The study involved searching the HaiPro incident reporting system and identifying incidents according to the current HaiPro classification of incidents. The following search conditions were 'reports by the category "Information Flow" or "Information Management,"' 'reports by the subcategory "Patient Information Management (Documentation)"' and 'reports by the category "Devices and Use of Devices."' Free-text searches used the keywords 'EHR', 'HIT', 'computer', 'documentation', 'incorrect information', 'referral', 'missing test result', 'identification', 'contact details', 'EHR downtime', 'hardware devices', 'device dysfunction', 'screen', 'mouse', 'output', 'print', 'printout', 'interface' and the most common EHR proprietary names to avoid misclassification of the intended reports into categories other than those used in this study.

The query of structured data generated a total of 2379 incident reports, while the total number of incident reports in the entire database was 23,023. Of HaiPro's 13 event types, the analysis included the 'Information Flow' and 'Information Management' subcategory 'Patient Information Management (Documentation)', with its detailed subcategories, as well as the category 'Devices and Use of Devices'. The free-text search using keywords and analysis of this sample reflected the use of appropriate classifications, and the reports included the subcategory 'Patient Information', 'Device and Use of Devices' or 'Unknown'. The frequencies of HaiPro incident reports, according to the HaiPro classification, appear in Figure 1.

Taxonomy mapping

Mapping, or the process of linking terms that share the same meaning, is a research method for testing the reliability and validity of standardised taxonomies.[29–33] We performed taxonomy mapping between the HaiPro classification and the HIT-specific taxonomy developed by Magrabi

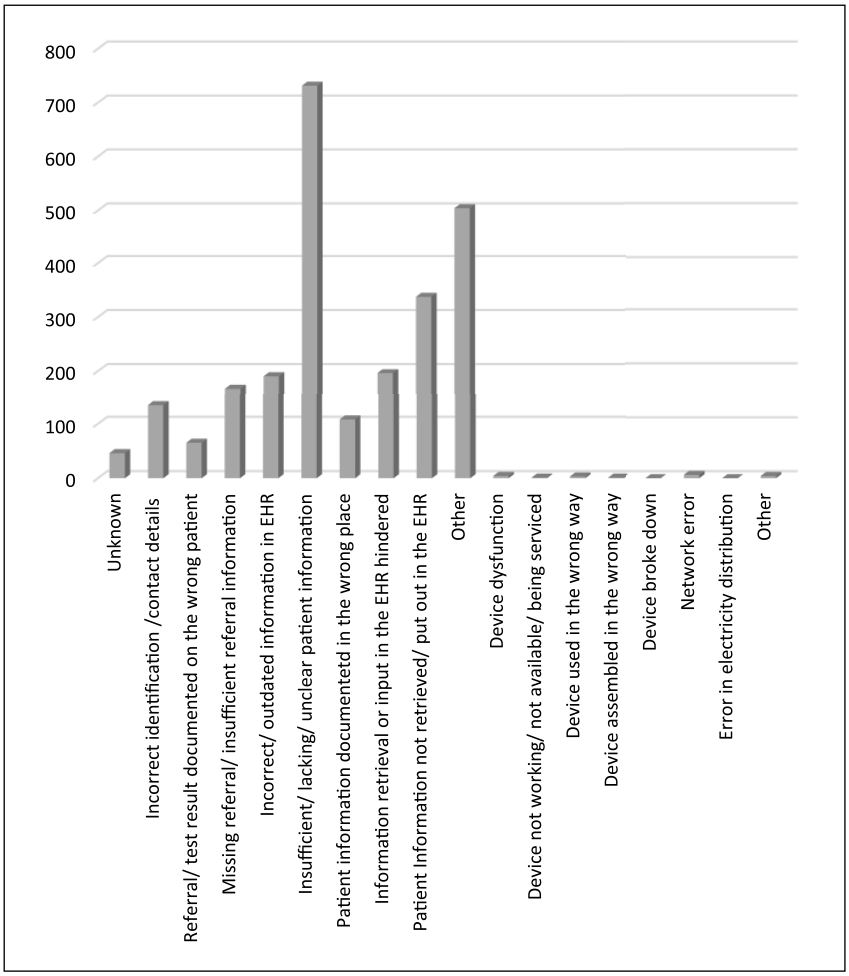

Figure 1. Frequencies of HaiPro incident reports.

et al.[16] because Magrabi's taxonomy is more widely used and was developed specifically to classify HIT-related incidents.[16,34,35] This enables comparisons to international research results.

We first categorised problems into those principally involving human factors or technical problems, and then assigned them to one or more subclasses. Problems involving human factors are related to human interaction with information technology.

We cross-mapped the HaiPro classification subcategory 'Patient Information Management (Documentation)' as well as the category for incidents related to a 'Device or Use of Devices' with Magrabi's taxonomy because these categories include HIT-related content. The main categories of the two classifications appear in Figure 2.

To measure intercoder reliability, two researchers performed the taxonomy mapping independently in September 2014 on the basis of available definitions and examples according to HaiPro national guidance and the literature.[16,28,34–36] The researchers placed appropriate HaiPro classifications into the categories created by Magrabi et al. and performed an inter-rater reliability analysis to ensure consistency between the researchers. One of the researchers is a chief patient safety officer and the other is a senior medical officer; both are experienced in informatics.

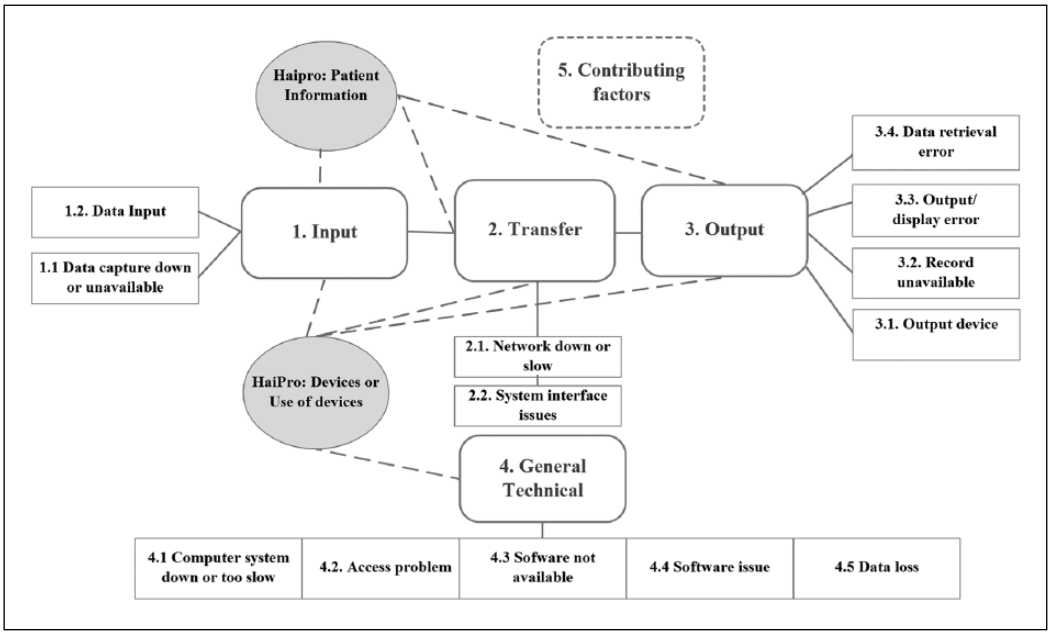

Figure 2. Classification of problems reported in computer-related patient safety incidents modified according to Magrabi et al.[16] and HaiPro.

After the first coding, the researchers discussed the rules and coherence of the mapping, which neither yielded nor compared any results. The researchers then recoded and compared the chosen categories before compiling the data. Selecting the same category created a match. Choosing a different alternative or failing to recognise the category at all was considered a non-match. In one situation, one researcher understood the definition of the category differently than the other. In another case, the researcher interpreted the content of the class according to his previous understanding rather than the research context. In these cases, discussion made choosing the certain match obvious, and no complex situations developed.

The researchers used percent agreement and Cohen's kappa coefficient to perform the intercoder reliability measurements. Small corrections and a brief discussion yielded 100 per cent (i.e. perfect) agreement (Table 1).[37–39]

The analysis indicated that most of the HaiPro Documentation classes were related to Magrabi's 'Input' category, and the HaiPro 'Device or Use of Devices' category was related to all Magrabi's main categories. If the mapping procedure for the two classifications showed that one HaiPro class was equivalent to several of Magrabi's categories, the HaiPro classification recognised all Magrabi's classes and identified the primary class.[16] Responsible persons at the organisations did not classify some of the HaiPro reports (18.5%) or the class was unknown. Cases containing too little descriptive information to classify them in detail fell into the HaiPro main category, with no indication of the exact class (e.g. 'Missing Referral' or 'Wrong/Outdated Information'). Consequently, the tested framework could not classify these incidents exactly.

HaiPro features a separate category 'Circumstances and Contributing Factors', which represents an important part of the data on incident reporting. These HaiPro category classes are not interpreted unambiguously as a direct cause of an incident, as is the case in Magrabi's framework. In HaiPro, 'Circumstances and Contributing Factors' may play an important role in the origin of an incident, but the class is still incomparable to Magrabi's Contributing Factor. Thus, although the

Table 1. Intercoder reliability measurements.

	Original measurement	Measurement after discussion and correction
Kappa	0.97	1
Percent agreement	99.3	100

researchers in this study decided not to cross-map contributing factors in order to avoid research validity issues, they did identify similarities.

Results

Machine- and human-related problems

In the Finnish HaiPro system, only 8.45 per cent (n = 211) of the reports involved machine-related problems. The category 'Devices or Use of Devices' contained only 12 (0.5%) machine-related reports, whereas the category 'Patient Information Management (Documentation)' included 199 reports (8.4%). A total of 73 per cent (n = 1755) of the reports involved problems related to human–computer interaction and were classified originally in the HaiPro system category 'Patient Information Management (Documentation)'. Only three reports (0.13%) in the category 'Devices or Use of Devices' were human-related. These cases were related to Magrabi's categories 'Data Input' and 'Data Retrieval Error'; the remaining HaiPro cases were either not classified or the category was unknown, so the framework could not serve to classify the incidents.

Both machine- and human-related problems in the HaiPro system led to rework (e.g. additional tests or treatments) in 49.5 per cent of cases.

Risk assessment

Of the 2379 HaiPro reports, 2119 (89.1%) contained a completed risk assessment. A majority (89.2%) of the incidents involved low-risk cases, and only a minority (0.8%) involved high-risk incidents.

Information input problems

The information input problems, clearly the largest category in the HaiPro data, accounted for 59.5 per cent (n = 1415) of the incidents, and incorrect identification or contact details accounted for 5.8 per cent (n = 139) of the computer-related incidents. In total, 2.8 per cent (n = 67) of the incidents were related to a case involving assignment of a referral or test result to the wrong patient, and 7.1 per cent (n = 170) of the cases were missing the referral or contained insufficient or wrong referral information. In 30.7 per cent (n = 731) of the incidents, insufficient, lacking or unclear patient information triggered incident reporting. In 4.6 per cent (n = 109) of incidents, patient information had been documented in the wrong place in EHR. Wrong or outdated patient information accounted for 8.2 per cent (n = 196) of the reports. Three reports (0.13%) in the HaiPro 'Devices or Use of Devices' category were related to data input.

Information transfer problems

In the HaiPro, data 8.8 per cent (n = 210) of the reports involved information transfer problems and were classified in the category 'Information Retrieval or Input in the EHR Hindered' (n = 199, 8.4%), the category's only machine-related condition. Six reports (0.25%) involved network errors

Table 2. Classification of the problems.

(Type) problem	Frequency n = 117 (%) in AIMS database	Frequency n = 1971 (%) in HaiPro database
1. Information input problems	36 (31)	1415 (59.5)
2. (Machine) information transfer problems	23 (20)	210 (8.8)
3. Information output problems	23 (20)	342 (14.4)
4. (Machine) general technical	28 (24)	4 (0.17)

in the HaiPro 'Devices or Use of Devices' category, and a total of five reports (0.2%) in the HaiPro 'Devices or Use of Devices' category were classified as information transfer problems. The HaiPro categories used in this problem were 'Device Dysfunction' and 'Device not Working, Unavailable, being Serviced (in Repair)'.

Information output problems

In HaiPro, 14.4 per cent (342) of the reports involved human–computer interaction problems coded in the category 'Patient Information Not Retrieved or Put Out in the EHR'. Moreover, the previously mentioned HaiPro category 'Insufficient, Lacking or Unclear Patient Information' is equivalent to this category and accounted for 30.7 per cent (731) of the incidents, although these incidents are primarily regarded as information input problems.

Machine-related problems partly overlapped with Magrabi's category 'Information Transfer Problems'. The HaiPro categories used for this problem were 'Device Dysfunction' and 'Device not Working, Unavailable, being Serviced (in Repair)', which accounted for the same five reports (0.2%) as did the category 'Information Transfer Problems'.

General technical

In HaiPro, the class 'Other' in the 'Devices or Use of Devices' category was equivalent to Magrabi's 'General Technical' category, which accounted for four reports (0.17%). In addition, the HaiPro category 'Unknown' was mapped as 'General Technical', despite having no cases.

The classification of problems in the HaiPro and AIMS databases appears in Table 2.

Contributing factors

The HaiPro category 'Circumstances and Contributing Factors' fails to indicate the specific reason for an incident even if these factors play a major role in the origin of the incident. The researchers decided not to perform a full cross-mapping procedure with regard to contributing factors in order to avoid problems with research validity. We analysed HaiPro's contributing factors and recognised similarities. Of all HaiPro incidents, 69.3 per cent identified the contributing factor. One of the most common contributing factors in this dataset is communication in general. Reports show that the available information is used only partially and that both oral and written communication contribute to the event.

Some of the HaiPro subcategories were equivalent to Magrabi's categories. Magrabi's 'Staffing and Training' category corresponded to the HaiPro category 'Education and Training', which includes the categories 'Knowledge and Skills', 'Competence and Qualification' and 'Availability and Sufficiency of Education and Guidance'. These categories accounted for 8 per cent of the HaiPro incidents.

Table 3. Development interventions in the HaiPro system.

Development intervention type	Frequency n = 124 (%) in HaiPro database
Processes, procedures and methods	50 (40.3)
Health information systems and devices	27 (21.8)
Information flow and communication procedures	32 (25.8)
Training	8 (6.5)
Leadership	4 (3.2)
Other development work	3 (2.4)

The HaiPro category 'Procedures' included methods, instructions and the availability or use of written material, whereas 'Clarity of the Task' is equivalent to Magrabi's 'Staffing and Training' and 'Interruption and Multitasking'. The HaiPro category 'Circumstances, Tools and Resources', which includes the category 'Problems in the EHR or Other HIT Systems and Problems Using Them', was considered to be linked to all Magrabi's categories. Of the HaiPro incident reports, 8.7 per cent identified this as the contributing factor.

Learning from incidents

HaiPro contains information on ways to prevent incidents recurring. A team comprising a responsible physician and a head nurse in the unit suggest the measures; 8 per cent of the cases led to no actions. The most common (82.6%) way to prevent incidents recurring was to inform the staff of the incident and share the data with other parties; 4.9 per cent of the incidents were transferred to the leaders of the hospital due to the seriousness and recurrence of the case or because support of the need for support to manage the incident. A concrete development intervention took place in 4.3 per cent of the incidents. The action taken was related to EHR downtime, which caused serious problems in a surgery department. The administrators decided to develop structured communication procedures with the information and technology (IT) department and to provide paper copies of patients' records available depending on the likelihood of EHR downtime. The types of development interventions appear in Table 3.

Discussion

The data with respect to the literature

Our study shows that computer-related safety incidents are far more common than previous studies suggest.[2,13,16] Our data are primarily discussed with regard to Magrabi et al.'s[16] study findings, which are based on similar data. In Magrabi's study, a search of 42,616 patient safety incidents during a 2-year period yielded only 123 computer-related incidents. The Australian data describe 99 computer-related patient safety incidents, which had been analysed by examining free-text descriptions.[16] Our research data contain over 20,000 reports classified by a trained physician and head nurse. Our finding is based on a large, structured dataset of quality reports.

The following facts may account for the number of computer-related incidents in the Finnish data compared to Magrabi et al.'s[16] data. First, the coverage of EHR in Finland is 100 per cent, and Finnish hospitals are fully digital. Previous research shows that new technology increases the number of technology-related errors.[6–10,40] Second, hospital districts in Finland devote institutional resources to incident reporting procedures, obtain feedback and share reports. Consequently, the staff are also encouraged to report HIT incidents, because managers consider them as important as

clinical bedside events. Our results show that HIT-related problems pose a noteworthy safety risk in fully digital hospitals.

The risk profiles of the two databases clearly differed. In the AIMS data,[16] 69 per cent of the cases received a medium-risk score, whereas in HaiPro the corresponding figure was only 10 per cent. This disparity may partly stem from the wide coverage of HaiPro incident reporting, which especially stresses the importance of reporting both minor incidents and near misses. The Finnish Act on Health Care and the National Patient Safety Program[27,28] have emphasised the importance of anticipating potential problems.[41]

A key finding of our study is that human–computer interaction problems were reported far more often in our study than in Magrabi's studies,[16,18] whereas machine-related problems were reported more rarely. A total of only 8.5 per cent of the incidents were machine-related problems, and 73 per cent were problems of human–computer interaction. Of all Australian AIMS reports, 55 per cent (n = 64) included machine-related problems, and 45 per cent (n = 53) problems of human–computer interaction.[16] In Magrabi's more recent study,[18] the majority of IT events consisted of notifications about hazardous circumstances related to technical problems.

In the AIMS database, 'Information Input Problems' was the largest category, accounting for 31 per cent (n = 36) of the incidents. Most incidents, such as incorrect entry of patient name, diagnosis, discharge hospital or typographical errors, were associated with 'Incorrect Human Data Entry' (17%, n = 20). This category was also the largest in the Finnish data, accounting for 60 per cent of incidents. 'Problems in the Transfer of Information' accounted for 20 per cent of all AIMS incidents and for 9 per cent of Finnish incidents. 'Information Output Problems' did not differ markedly between databases.

Our results support a growing body of research which shows that adverse events result from the complex interaction between Health Information System (HIS) and clinicians.[22,42–44] The Finnish data clearly show that the interaction of technology with non-technological factors requires more in-depth research from different perspectives. Users' interactions with EHR are linked to complex processes which should be better understood. According to a recent study, problems involving human factors were four times more likely to result in harm to patients than technical problems, further stressing the importance of sociotechnical aspects.[18] Moreover, research confirms the importance of a sociotechnical perspective in system design.[45]

Incident reporting systems provide a mechanism for identifying safety risks. Although the data suggest that interventions can reduce risks, these systems have not led to expected improvements and interventions to reduce risk.[14,46] This raises a question about the appropriate implementation and use of such systems. Measuring the successful use of an incident system is challenging, but can be accomplished by counting the number of system changes made as a result of the system.[14] In the Finnish data, only 8 per cent of the IT-related incidents were left without measures, which can be considered reasonable progress in the optimal use of an incident reporting system, if still below the target level. The aspect of learning from previous incidents must inevitably be the future focus of incident reporting systems and research. Furthermore, studies show that technology-based solutions alone will only partially mitigate concerns. Interventions for EHR-related safety improvement must concentrate on how end-users actually use EHR.[19]

The use of standard classifications, including clear category descriptions, makes data more valid and data use across countries possible. At the moment, single organisations are the main users of this valuable data source. Mapping the on-site reporting taxonomy with international standards is feasible,[47,48] and Magrabi et al.'s[16] taxonomy constitutes a basis for patient safety incident reporting recommended for use as a starting point for international incident reporting classifications of machine-related incidents. Research shows that pre-defined reporting categories are well-suited to voluntary reporting needs and could also provide solutions for international quality reports.[47]

Limitations

In this Finnish dataset, structured responsibilities, manifold surveillance of the quality of data and an on-going training programme all ensure the appropriate use of classifications. However, without content analysis of the incident reports, one cannot be 100 per cent sure of the correct use of classifications. The risk of invalid data, however, is presumably relatively low.

Voluntary incident reporting is an important tool for recognising patient safety issues in healthcare settings. However, these systems have their limitations;[49,50] reports do not provide exact frequencies of incidents. Consequently, our data provide not exact error rates but rather a descriptive analysis of typical EHR-related safety problem types in fully digital, paperless hospitals. Large collections of incidents may serve to identify characteristic profiles, thereby enabling the aggregation and analysis of incidents.[15]

The cross-mapping procedure clearly showed that the strength of Magrabi's classification is its ability to identify technical problems. The human–computer perspective in the classification is weaker than it could be, given the complexity of a healthcare organisation. The sociotechnical perspective could be combined into this classification, because it contains multiple dimensions of HIT use.[9,20,44,51]

Conclusion

The Finnish safety data analysed in this study show that human–computer interaction associated with most HIT-related incidents. Detecting these safety concerns is challenging because they result from complex interactions among heterogeneous triggering factors. Consequently, healthcare information systems require an infrastructure for proactive risk assessment, specifically for EHR-related patient safety concerns. Developing techniques to support user awareness of EHR-related risks and their monitoring and management is therefore necessary.

Declaration of conflicting interests

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Abstract

Clinical practice guidelines are valuable sources of clinical knowledge for healthcare professionals. However, the passive dissemination of clinical practice guidelines like publishing in medical journals is ineffective in changing clinical practice behaviour. In this work, we proposed a framework to help adopting an active clinical practice guideline dissemination approach by automatically extracting clinical knowledge from clinical practice guidelines into a clinical decision support system–friendly format. The proposed framework is intended to help human modellers by automating some of the manual formalization activities in order to minimize their manual effort. We evaluated our framework using all recommendations from two clinical practice guidelines produced by the Scottish Intercollegiate Guidelines Network: the 'Management of lung cancer' clinical practice guideline and the 'Management of chronic pain' clinical practice guideline. We conclude that the proposed framework can be effectively used to formalize drug and procedure recommendation in clinical contexts.

Keywords

clinical decision support system, clinical practice guideline, health information systems, Unified Medical Language System

Introduction

Clinical practice guidelines (CPGs) as defined by the Institute of Medicine are 'systematically developed statements to assist practitioner and patient decisions about appropriate health care for specific clinical circumstances'.[1] CPGs offer concise instruction on the optimal care for the patient

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based on the latest clinical findings. The main benefit of CPG is to improve the quality of care and the consistency of care. For a healthcare professional, a CPG can help offer explicit recommendations when a healthcare professional is uncertain about how to proceed.[2]

It is been shown that passive dissemination of CPGs like publishing in a medical journal is ineffective in changing clinical practice behaviour.[3] Many healthcare practitioners are not aware of the existence of the CPG, and even when they are directed to the relevant CPG, they experience difficulties using it in their daily practice.[4] Nevertheless, integrating CPG knowledge into clinical systems, such as decision support systems, has shown to be more effective.[5] In order to best benefit from the CPGs' knowledge by following an active CPG dissemination approach, an interest in formalizing medical knowledge contained in CPGs has grown. The heritage of the narrative text CPGs will remain a source of medical knowledge that awaits its formalized counterpart to be developed and integrated into clinical systems. This integration could be manifested in different technical facades like clinical decision support system (CDSS) or extension to the electronic health record (EHR) system used by healthcare facilities.

There are several formal languages developed to help modelling clinical guidelines into computer-interpretable guidelines (CIGs); the review study[6] presents some of the CIG modelling languages. Assuredly, the development of the guideline modelling languages is an important step towards facilitating the CPG formalization process, yet the formalization task remains laborious and complex, mainly because it requires human modellers with two different areas of expertise: a medical expertise to correctly interpret the medical knowledge of CPGs and a knowledge engineer expertise to correctly represent the medical knowledge using the syntax of the modelling language.

Nonetheless, CPG formalization approaches have been published.[7–14] These approaches are either based on a set of manual steps to gradually convert narrative text CPGs into CIGs,[7,8] or based on automated information extraction mechanisms frequently using linguistic patterns.[9–14] While the accuracy of the manual approaches is straightforwardly controlled, as the resulted accuracy is as good as the input provided by the human modellers, these approaches are impractical to use in formalizing large numbers of CPGs. On the other hand, the automated and semi-automated information extraction–based approaches are more suited to formalize a relative large number of CPGs, but these approaches have not shown how expandable they are in handling a large number of heterogeneous CPGs, CPGs with different styles, granularity, and so on – a common challenge with all large-scale information extraction systems.[15] Therefore, the motivation of our work in building a CPG formalization framework is to enable the human modeller to control the expressiveness of the extraction rules in the formalization system without rebuilding the system.

The purpose of this work is to minimize the effort required by human modellers to bridge the gap between CPG and CIG by extending the automation of the formalization process of the drug recommendation and procedure recommendation clinical contexts. We followed a two-level clinical context extraction mechanism to assist the human modeller to better control the balance between accuracy and scalability with heterogeneous CPGs.

Methods

The proposed framework follows a multi-step approach, which has been shown to be a good strategy for CPG formalization.[16] We architected the framework to set boundaries around the aspects of the drug recommendation in the CPG formalization, where each aspect is implemented as a separate autonomous component in a CPG formalization pipeline. The framework is based on the Unstructured Information Management Architecture (UIMA).[17] In the following sections, we provide a description of each component in our CPG formalization pipeline as illustrated in Figure 1.

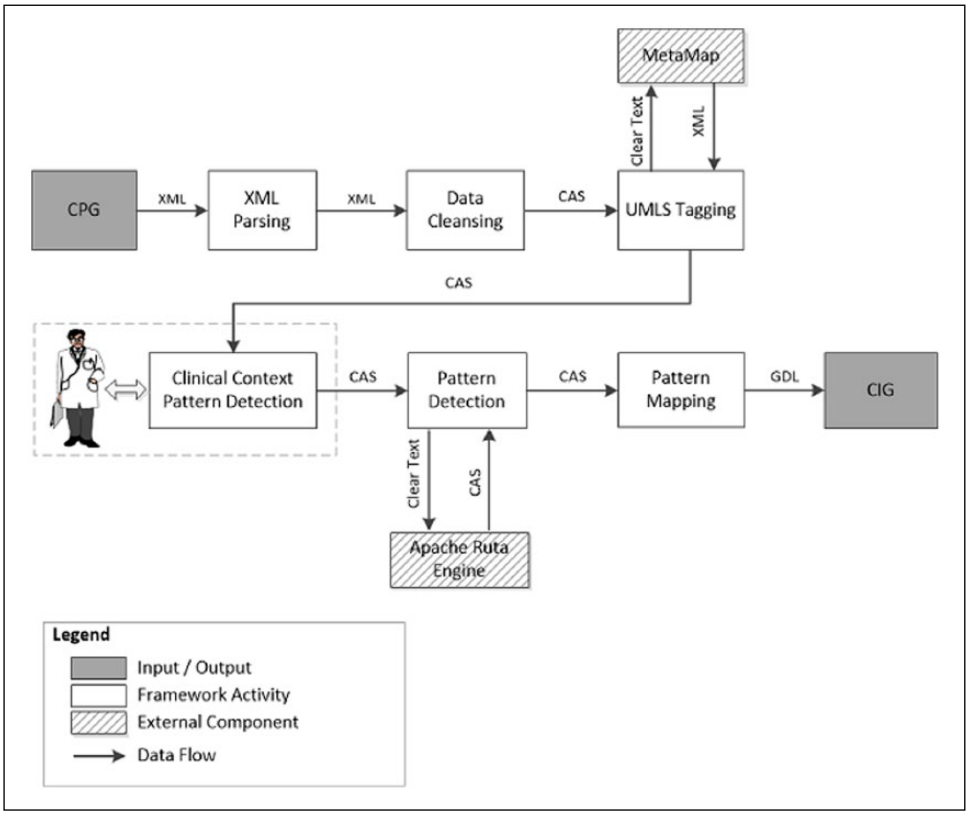

Figure 1. CPG formalization pipeline.

XML parsing

We used CPGs extracted from the National Guideline Clearinghouse (NGC)[18] in XML format. The XML parsing component extracts the content of the XML CPG documents into a structured object.

Text cleansing

Most of the sections extracted by the XML parsing component contain narrative text mixed with HTML tags. HTML tags are used by Web browsers to render text for visual display, but as we are not interested in composing the text for web browsers, we removed all HTML tags from the text.

Medical concept tagging

This is a component to map CPG text to a medical vocabulary; we used the Unified Medical Language System (UMLS) Metathesaurus as our biomedical vocabulary database. The UMLS Metathesaurus contains more than 2.6 million concepts each assigned to at least one semantic type from the set of 133 semantic types of the UMLS semantic network. We used MetaMap,[19,20] to map CPG text to the UMLS Metathesaurus concepts. For integrating MetaMap with the UIMA

Table 1. MetaMap UMLS concept mapping for the word *lens*.

Concept		Semantic type
Unique Id	Name	
C0023308	Lens diseases	Disease or syndrome
C0023318	Lens (device)	Medical device
C0023317	Lens, crystalline	Body part, organ, or organ component

UMLS: Unified Medical Language System.

framework, we leveraged the MetaMap UIMA Annotator[21] which is a wrapper that makes the MetaMap tool usable as an UIMA analysis engine.

Medical tags disambiguation

This is the process of finding the correct UMLS concepts, when multiple concepts are assigned by MetaMap with the same score. For example, the word *lens* could get annotated by MetaMap with three different UMLS concepts that have different meanings as shown in Table 1.

To solve this type of ambiguity, we used a graph-based disambiguation algorithm[22] to rank the generated MetaMap UMLS concepts based on their relatedness to the context of co-located text.

Clinical context pattern detection

This is a rule-based extraction component. This component is the first level of our clinical context extraction mechanism; its function is to extract text fragments that contain the minimum necessary features of the clinical context in question. Extracting clinical context based on the minimum necessary features follows the top-down approach[15] where only general rules that cover as many possible instances of clinical context need to be defined, which means rules that have high coverage and poor precision. Because general extraction rules tend to be in small numbers and are simple to define, the rule authoring task is a good fit for the medical experts who usually lack extensive knowledge in rule authoring. To further simplify the rule authoring task for the medical expert, we used UIMA Ruta[23] as it has a defined rule-based language with the ability to build rules against the text as well as against the semantic annotations of the text. We also defined a guideline of four steps to structure the effort required. In the following sections, we describe each of the four steps to author drug recommendation extraction rules with sample Ruta syntax highlighted in Figure 2:

Step 1. Set text analysis boundaries: since analysing the CPG as one big unit is too complex and impractical, we need to break down the CPG document into text chunks small enough for easiness of analysis. The modeller can choose the boundary at the section, paragraph, sentence, or even token level.

Step 2. Cluster UMLS semantic types: each UMLS tag is assigned to one UMLS semantic type. This gives us a wide spectrum of semantic types that is too granular for our analysis. Clustering the UMLS semantic network into smaller set of semantic types will help eliminate duplicate rules across UMLS semantic types. To achieve this goal, we followed the approach presented in Bodenreider and McCray[24] and aggregated semantic types. In Table 2, we show two groups of semantic types, the Chemical & Drugs (CHEM) and the Disorder (DISO) used for the drug recommendation clinical context.

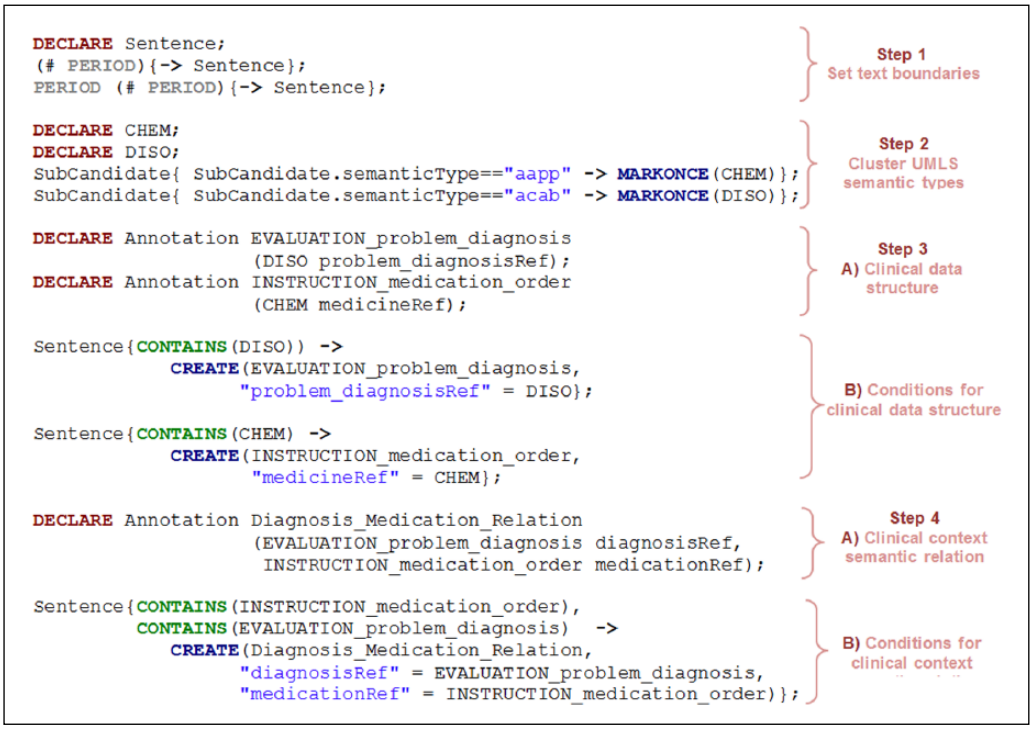

Figure 2. UIMA Ruta patterns for drug recommendation.

Step 3. Structuring clinical data: in this step, the human modeller (1) defines the clinical data structures and (2) provides conditions to assign the newly defined clinical data structure to tokens in the CPG text. Defining clinical data structures could be coarse, for example, the drug prescription data structure composed of the medicine name and the dose, or more granular to include the dose timing and the duration of the treatment. The expressivity of the clinical context extraction rules heavily depends on the granularity of data structures used; the more granular the clinical data structures, the more expressive rules can be authored but also the more complex the rule authoring task becomes. To follow pre-reviewed clinical data structures, we defined our clinical data structures based on the openEHR archetypes.[25]

Detecting an instance of the defined clinical data structure in the CPG text is achieved by annotating the CPG text with the clinical data structure types based on predefined conditions. The conditions could be based on specific lexicon, syntax, or previously annotated semantics; Step 3 in Figure 2 shows the Ruta code of our version of the 'problem diagnosis' *evaluation* archetype and the 'medication order' *instructions* archetype. The defined clinical data structures contain one element for simplicity, but each of these data structures can contain multiple elements; we also defined relaxed conditions that capture tokens annotated with the DISO and CHEM semantic groups and tagged the former as an element of the 'problem diagnosis' *evaluation* archetype and the latter as the medicine element of the 'medication order' *instructions* archetype.

Step 4. Clinical context semantic relations: each clinical context could be modelled as an instance of semantic relation between clinical data, for example, drug recommendation could be

Table 2. UMLS semantic type grouping.

Chemical & Drugs (CHEM)		Disorder (DISO)	
Semantic type	Abbreviation	Semantic type	Abbreviation
Amino acid, peptide, or protein	aapp	Acquired abnormality	acab
Antibiotic	antb	Anatomical abnormality	anab
Biologically active substance	bacs	Cell or molecular dysfunction	comd
Biomedical or dental material	bodm	Congenital abnormality	cgab
Carbohydrate	carb	Disease or syndrome	dsyn
Chemical	chem	Experimental model of disease	emod
Chemical viewed functionally	chvf	Finding	fndg
Chemical viewed structurally	chvs	Injury or poisoning	inpo
Clinical drug	clnd	Mental or behavioural dysfunction	mobd
Eicosanoid	eico	Neoplastic process	neop
Element, ion, or isotope	elii	Pathologic function	patf
Enzyme	enzy	Sign or symptom	sosy
Hazardous or poisonous substance	hops		
Hormone	horm		
Immunologic factor	imft		
Indicator, reagent, or diagnostic aid	irda		
Inorganic chemical	inch		
Lipid	lipd		
Neuroreactive substance or biogenic amine	nsba		
Nucleic acid, nucleoside, or nucleotide	nnon		
Organic chemical	orch		
Organophosphorus compound	opco		
Pharmacologic substance	phsu		
Receptor	rcpt		
Steroid	strd		
Vitamin	vita		

modelled as a *disease-to-drug* semantic relation or *symptoms-to-drug* semantic relation. Annotating CPG text with clinical context semantic relation requires the human modeller to (1) define a semantic relation and (2) define conditions for mapping instances of clinical data structures to a semantic relation.

In Figure 3, we show the 'Fluoxetine (20–80 mg/day) should be considered for the treatment of patients with fibromyalgia' sentence from the 'Management of chronic pain: a national clinical guideline'.[26] CPG and the annotations are assigned based on the four clinical context pattern detection steps.

Clinical context filtering

This component is responsible for removing the clinical context instances wrongly labelled by the clinical context pattern detection component. We used a logistic regression[27] classification algorithm to decide on the correctness of the drug recommendation labels. Because this classification algorithm is supervised, which means it requires to be trained using a correctly annotated data set, we generated a training data set composed of 117 recommendation sentences extracted

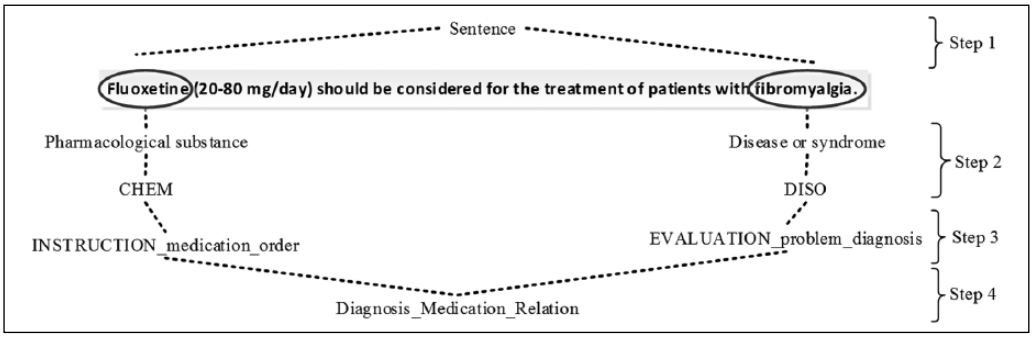

Figure 3. Annotations for the drug recommendation clinical context.

from the Yale Guideline Recommendation Corpus (YGRC).[28] The YGRC is composed of 1275 recommendations which cover a broad range of diseases and mental disorders extracted from the NGC. We annotated all YGRC sentences with MetaMap and then selected 117 sentences that have tokens in the DISO semantic group in addition to other tokens in the procedure or CHEM semantic group. We manually tagged each sentence as either drug/procedure recommendation or non-drug/procedure recommendation.

Clinical context mapping

This is a component to map instances of clinical context semantic relations to their target CIG constructs as a set of rules. We used the openEHR Guideline Definition Language (GDL)[29] as our target CIG; GDL leverages the designs of openEHR Archetype Model that we used in the pattern detection step.

Although the clinical context mapping is still a manual task to be done by the knowledge engineer, it can be fully automated if the medical expert modeller used a standard naming convention for the clinical data structures used in the clinical context pattern detection component.

Our evaluation was based on measuring the precision, sensitivity/recall, and specificity of the extracted drug recommendation and procedure recommendation rules form the input recommendation sentences. The precision, sensitivity/recall, and specificity are measured based on the correctness of our framework in finding instances for the UIMA Ruta patterns defined by the medical expert. More formally, assume that I is the set of all sentences in a CPG and I_G denotes the subset of I that contains sentences with a medication and a disorder, or sentences with a procedure and a disorder; $I_{G'}$ denotes for all sentences in I that are not in I_G; I_F denotes the set of sentences extracted by our framework; $I_{F'}$ denotes set of sentences not extracted by our framework

$$Precision = \frac{|I_G \cap I_F|}{|I_F|} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Recall\ /\ sensitivity = \frac{|I_G \cap I_F|}{|I_G|} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$Specificity = \frac{|I_{F'}|}{|I_{F'} \cup \{I_F \cap I_{G'}\}|} = \frac{True\ Negative}{False\ Positive + True\ Negative}$$

Table 3. Recommendation sentences classification evaluation.

Recommendation	Precision (%)	Sensitivity/recall (%)	Specificity (%)
Chemical & Drugs	78	71	73
Procedure	70	75	79
Average	74	73	76

Table 4. Extracted rules' accuracy.

Recommendation	Accuracy (%)
Chemical & Drugs	87
Procedure	81
Average	84

Results

We implemented our formalization framework in JAVA (version 1.7) and integrated it with the GDL editor.[29] Due to the lack of access to independent human modellers, we could not measure the manual effort saving introduced by our framework; nevertheless, we evaluated the accuracy of the knowledge extracted by our framework for the drug recommendation and the procedure recommendation clinical contexts. To build our gold standard for the drug recommendation clinical context to measure against, we used all recommendations from the 'Management of chronic pain' CPG[26] and the 'Management of lung cancer' CPG,[30] and then we manually tagged each recommendation as either drug/procedure recommendation or non-drug/procedure recommendation. The resulted test data set is composed of 169 recommendation sentences. In Table 3, we show the accuracy of our framework on classifying the 169 recommendation sentences.

We evaluated the correctness of the formalized recommendations by manually checking the extracted rules and we assigned a coefficient of 1 for rules that are correctly coded and complete, 0.5 for rules that are correct but partial (e.g. not all elements of the rule conditions are captured), and 0 for rules that are wrong. In Table 4, we show the accuracy of the extracted rules based on the described metric. There are two main sources of errors for the wrong rules: either wrong MetaMap annotations or wrong classification from our clinical context filtering component using logistic regression.

Discussion

Using information extraction, techniques to extract biomedical knowledge have been applied in other non-CPG biomedical documents.[31,32] The proposed framework is tailored to the specific needs of CPGs where the granularity of clinical knowledge differs between different types of CPGs; therefore, we designed the framework to enable the human modeller to control the granularity of the extracted clinical knowledge.

The proposed framework is based on a clinical context pattern detection component using UIMA Ruta, a rule-based information extraction mechanism to extract text fragments that contain the minimum necessary features of the clinical recommendation type in question. We believe that extracting clinical recommendations a by following a top-down approach[15] where only general rules that cover as many possible instances of clinical recommendation need to be defined is suitable for CPG formalization. General extraction rules tend to be in small numbers and are simple to define

making the rule authoring task a good fit for medical experts who usually lack extensive knowledge in rule authoring. Although general information extraction rules result in high coverage, they have a poor precision; therefore, we added the clinical context filtering component using logistic regression to filter out false-positives introduced by general information extraction rules defined in the clinical context pattern detection component. The framework was tested on extracting only two clinical context types due to the lack of pre-annotated test data sets. In the following discussion, we analyse the achieved results:

The precision is impacted by the size and the quality of our training data set; in the presented example, we used a training data set made of 117 recommendation sentences extracted from YGRC which is small to provide high precision. This issue could be lessened by feeding the outputted rules of the framework back to the training data set, a step that requires a minor manual tagging of which rules are correctly extracted and which ones are wrongly extracted.

The sensitivity/recall is impacted by how we split our CPG into smaller text chunks, for example, in the presented example we split CPG into sentences, but some drug recommendations within the CPG have the drug and the medication located in two separate sentences, and therefore, these ones are missed by our extraction rules. This issue could be lessened by changing the size of our unit of analysis from one sentence to two consecutive sentences or to the whole paragraph, but such a modification would hurt the precision unless we add more rules to handle cross-sentence extraction. Different cross-sentence extraction approaches can be applied. One approach would be to perform cross-sentence extraction when a sentence only contains one part of the clinical context such as a sentence with only a disease, followed by a sentence that only contains the other part of the clinical context such as a sentence with only a medication. This approach is very conservative and would not impact the precision of the in-sentence extraction rule. Incorporating other cross-sentence extraction approaches that have more coverage would likely interfere with other in-sentence extraction rules. Therefore, with every cross-sentence extraction approach, we need to evaluate the cross-sentence extraction precision gain to the in-sentence precision loss.

The specificity is impacted by how strict are our conditions for tagging a sentence with a specific semantic relation. In the presented example, we achieved high specificity because our conditions for tagging drug medication semantic relations are very strict.

The proposed framework can be effectively used to formalize the drug recommendation and procedure recommendation clinical contexts of CPGs into CDSS-friendly format. More significantly, it provides human modellers with a methodology to extend the framework to formalize other clinical context of CPGs. The framework is focused on automating the CPG common formalization steps while allowing the human modeller to stay in control of all the knowledge extraction steps. By configuring the *clinical context detection pattern* component, the human modeller could define how CPG text would be split into smaller chunks for analysis and control the level of granularity of the clinical knowledge extracted. This control balances generality and specificity in order to maximize usefulness of the extracted knowledge. If the extracted knowledge is too specific/expressive, it unnecessarily complicates the extraction rules. We believe that such configuration capabilities in our framework would help reduce the human modeller's annoyance and dissatisfaction accompanied with either the lengthy manual CPG formalization steps or the inflexibility of other automated CPG formalization approaches.

Declaration of Conflicting Interests

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