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Research and Applications

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Clinical documentation variations and NLP system portability: a case study in asthma birth cohorts across institutions

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ABSTRACT

Objective: To assess clinical documentation variations across health care institutions using different electronic medical record systems and investigate how they affect natural language processing (NLP) system portability.
Materials and Methods: Birth cohorts from Mayo Clinic and Sanford Children's Hospital (SCH) were used in this study ($n = 298$ for each). Documentation variations regarding asthma between the 2 cohorts were examined in various aspects: (1) overall corpus at the word level (ie, lexical variation), (2) topics and asthma-related concepts (ie, semantic variation), and (3) clinical note types (ie, process variation). We compared those statistics and explored NLP system portability for asthma ascertainment in 2 stages: prototype and refinement.
Results: There exist notable lexical variations (word-level similarity = 0.669) and process variations (differences in major note types containing asthma-related concepts). However, semantic-level corpora were relatively homogeneous (topic similarity = 0.944, asthma-related concept similarity = 0.971). The NLP system for asthma ascertainment had an *F*-score of 0.937 at Mayo, and produced 0.813 (prototype) and 0.908 (refinement) when applied at SCH.
Discussion: The criteria for asthma ascertainment are largely dependent on asthma-related concepts. Therefore, we believe that semantic similarity is important to estimate NLP system portability. As the Mayo Clinic and SCH corpora were relatively homogeneous at a semantic level, the NLP system, developed at Mayo Clinic, was imported to SCH successfully with proper adjustments to deal with the intrinsic corpus heterogeneity.

Key words: documentation variation, natural language processing, portability, asthma, electronic medical records

BACKGROUND AND SIGNIFICANCE

The rapid adoption of electronic medical records (EMRs) provides a good opportunity to leverage clinical data for clinical research. Natural language processing (NLP), which can convert unstructured text to a structured format, has been shown to be a promising way to automate chart review to enable large-scale research studies that require information embedded in clinical narratives where labor-intensive manual chart review is infeasible.[1–4]

NLP techniques have been successfully applied in various clinical applications, including medication information extraction,[5] patient medical status identification,[6–8] sentiment analysis,[9] decision support,[10,11] genome-wide association studies,[12,13] and diagnosis code assignment.[14,15] Over the past decade, multiple clinical NLP systems have been developed and deployed, such as cTAKES,[16] YTEX,[17] MTERMS,[18] HiTEXT,[19] MedLEE,[20] and MedTagger.[21,22] Although clinical NLP systems have proven to be successful at various tasks, their performance often varies across institutions and sources of data.[23,24]

Clinical practice and workflow vary across institutions, which results in different practice settings and reporting schemes for generating EMRs (ie, process variation). Also, it has been demonstrated that clinical language is not homogeneous, but instead consists of heterogeneous sublanguage characteristics (eg, syntactic variation[25–29] or semantic variation[30,31]). Those variations need to be considered in the tool development process.[32] Implementation of an EMR system differs among institutions, and the clinical corpus also differs in its nature. That being said, questions arise whenever an NLP system developed in one corpus is applied to another corpus, such as: How similar are the 2 corpora? If 2 corpora differ, how does the difference affect NLP system portability?

A previous study suggested that the performance of a clinical NLP system may depend on the source of the clinical notes. Thus, the semantic and contextual information of the target notes should be seriously considered in the tool development process.[32] Liu et al.[33] compared the performance of an existing NLP system for smoking status across institutions and showed that customization was necessary to achieve desirable performance. Similarly, Carroll et al.[34] studied the portability of a phenotype algorithm using NLP for medical concept extraction in identifying rheumatoid arthritis. They found that the number of NLP-derived data elements varied among institutions and thus normalized it by International Classification of Diseases, Ninth Revision codes to produce consistent performance. Mehrabi et al.[35] developed a rule-based NLP system to identify patients with a family history of pancreatic cancer and showed that a rule-based NLP system relying on specific information extraction was portable across institutions. Additionally, Liu et al.[36] emphasized the importance of a semantic lexicon for extracting and encoding clinical information from EMRs to achieve semantic interoperability in developing NLP systems. Most studies of NLP system portability showed the validity of portability by comparing system performance but lacked a systematic analysis of the heterogeneity of the EMR corpus (ie, clinical documentation variations) among institutions and its impact on portability. A systematic comparison of EMR corpus characteristics across institutions would help us better understand the portability of NLP systems.

Mayo Clinic developed an NLP system[2] that processes clinical notes and automatically ascertains asthma status based on predetermined asthma criteria (PAC).[37] The original system has been restructured as the open source information extraction framework MedTaggerIE,[21] one of the 3 components in MedTagger,[21,22] and has been significantly refined to improve its performance.[1] The current system extracts asthma-related episodes or events from clinical notes and applies expert rules to determine a patient's asthma status.

In this study, we examined the clinical corpus of asthma birth cohorts using the different EMR systems at Mayo Clinic and Sanford Children's Hospital (SCH) in 3 aspects: (1) overall corpus at the word level (ie, lexical variation), (2) topics and asthma-related concepts (ie, semantic variation), and (3) clinical note types (ie, process variation). We compared those statistics and explored the NLP system's portability for asthma ascertainment.

METHODS AND MATERIALS

This study was approved by the Mayo Clinic and SCH institutional review boards.

Measures of clinical documentation variations

Variations in clinical documentation across institutions can be simply examined by basic corpus statistics, such as total number of documents/tokens, frequency of medical concepts, note types, and sections. Further, we explored corpus similarities between Mayo Clinic and SCH in terms of: (1) entire corpus, (2) medical concepts of interest, and (3) note types. For corpus and note similarity, we preprocessed the documents by using tokenization, removing stop words, and stemming. We created a vector space model for each case to compare similarities.

For each case, we calculated the cosine similarity, a measure between 2 vectors that quantifies the angle between them. It measures the orientation of 2 vectors, not magnitude, and is commonly used in high-dimensional positive space (eg, text mining) bounded in [0, 1], with 0 indicating orthogonality (decorrelation) and 1 meaning exactly the same. Thus, cosine similarity is useful to show how 2 documents or corpora are alike in terms of their subject matter.[38] The detailed descriptions of a vector representation are as follows:

(1) **Corpus**: The entire corpus of each institution was compared as a whole using $tf-idf$ (term frequency–inverse document frequency), $tf-ipf$ (term frequency–inverse patient frequency), and latent topic–based vector. In the $tf-idf$ setting, each corpus was represented by a normalized $tf-idf$ vector whose element consisted of the $tf-idf$ for each term t, defined by the summation of $tf(t)\cdot idf(t)$ for all documents in the corpus divided by the total number of documents in the corpus, ie, $\sum_i tf_i(t)\cdot idf(t)/N$, where

$$tf_i(t) = (\#\ \text{term}\ t\ \text{in the doc}\ i)/(\text{total}\ \#\ \text{terms in the doc}\ i)$$

$$idf(t) = \log(\text{total}\ \#\ \text{docs in the corpus}\ (N))/\\ (\#\ \text{docs with the term}\ t\ \ \text{in the corpus})$$

The $tf-ipf$ is a variation of $tf-idf$, designed to view the word distribution weighted at the patient level instead of the document level, in order to reflect the significance of words across patients. The $tf-ipf$ for the term t is defined by the summation of $tf(t)\cdot ipf(t)$ for all patients in the corpus divided by the total number of patients in the corpus, ie, $\sum_i tf_i(t)\cdot ipf(t)/P$, where

$$tf_i(t) = (\#\ \text{term}\ t\ \text{in the patient}\ i)/(\text{total}\ \#\ \text{terms in the patient}\ i)$$

$$ipf(t) = \log(\text{total}\ \#\ \text{patients in the corpus}\ (P))/\\ (\#\ \text{patients with the term}\ t\ \text{in the corpus})$$

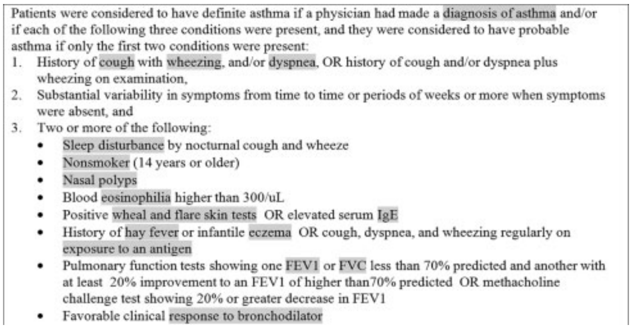
In order to compare the corpora by topic, we employed latent Dirichlet allocation[39,40] to generate the document distributions in the topic space, ie, $p(z_k|d_i)$. The topic z_k for the corpus C is defined as:

$$p(z_k|\mathrm{C}) = \sum_{d_i\in \mathrm{C}} p(z_k|d_i,\mathrm{C})p(d_i|\mathrm{C}) = \sum_{d_i\in \mathrm{C}} \frac{p(z_k|d_i)}{N}$$

(2) **Medical concepts**: The asthma-related concepts used in the PAC (Figure 1) were extracted and compared. Each concept consists of the corresponding keywords. A vector representation of asthma-related concepts for each corpus was created using the definition of $cf-idf$ (concept frequency–inverse document frequency) and $cf-ipf$ (concept frequency–inverse patient frequency). The $cf-idf$ for the concept c is defined by $cf(c)\cdot idf(c)$ where

$$cf(c) = (\#\ \text{concept}\ c\ \text{in the corpus})/\\ (\text{total}\ \#\ \text{concepts in the corpus})$$

$$idf(c) = \log(\text{total}\ \#\ \text{docs in the corpus}\ (N))/\\ (\#\ \text{docs with the concept}\ c\ \ \text{in the corpus})$$



Patients were considered to have definite asthma if a physician had made a diagnosis of asthma and/or if each of the following three conditions were present, and they were considered to have probable asthma if only the first two conditions were present:

1. History of cough with wheezing, and/or dyspnea, OR history of cough and/or dyspnea plus wheezing on examination,
2. Substantial variability in symptoms from time to time or periods of weeks or more when symptoms were absent, and
3. Two or more of the following:
   - Sleep disturbance by nocturnal cough and wheeze
   - Nonsmoker (14 years or older)
   - Nasal polyps
   - Blood eosinophilia higher than 300/uL
   - Positive wheal and flare skin tests OR elevated serum IgE
   - History of hay fever or infantile eczema OR cough, dyspnea, and wheezing regularly on exposure to an antigen
   - Pulmonary function tests showing one FEV1 or FVC less than 70% predicted and another with at least 20% improvement to an FEV1 of higher than70% predicted OR methacholine challenge test showing 20% or greater decrease in FEV1
   - Favorable clinical response to bronchodilator

Figure 1. Predetermined asthma criteria (PAC).

The $cf - ipf$ for the concept c is defined by $cf(c) \cdot ipf(c)$, where $cf(c)$ and $ipf(c)$ are defined as the same as above, but replacing document with patient frequency.

(3) **Note types:** Clinical documents have various note types based on the event (eg, admission, discharge, progression). Although there is commonality of note types among institutions, the detailed definitions of note types may differ and the same note type may contain heterogeneous topics. Therefore, it is interesting to compare topic distributions of note types between the 2 institutions. Similar to the latent topic vector representations for the corpus, the topic z_k for the clinical note type T is defined by

$$p(z_k|T) = \sum_{d_i \in T} \frac{p(z_k|d_i)}{N_T}$$

where N_T is the number of documents in the note type T.

A case study of NLP system portability in asthma birth cohorts

We examined clinical documentation variations in asthma birth cohorts of Mayo Clinic and SCH, which use different EMR systems, and compared the performance of the NLP asthma ascertainment system on the 2 corpora.

Patient cohorts

The patient cohorts used for corpus analysis were randomly selected from the birth cohort at each institution ($n = 298$ for each); the SCH cohort was born between 2011 and 2012 (male 54%), and the Mayo Clinic cohort was born between 1997 and 2007 (male 50%). As the Mayo Clinic cohort was followed up longer (median = 11.5 years, SD = 3.3) than the SCH cohort (median = 2.3 years, SD = 0.35), we adjusted the last follow-up date of Mayo Clinic subjects to match the same age as the SCH cohort in order to avoid age bias; ie, Mayo clinical notes were selected up to a certain date to match age with SCH.

EMR system at Mayo Clinic vs SCH

Mayo Clinic uses an in-house EMR system originated from GE. Mayo's clinical notes consist of predefined sections and each section contains specific content. SCH uses an Epic EMR system. Although there are section templates in the SCH EMR system, use of templates is not mandated. Therefore, there are many variations in section names and content. In this study, we used clinical notes exported as plain-text files from both EMR systems.

NLP asthma ascertainment system

The NLP asthma ascertainment system (NLP-PAC system) implements the predetermined asthma criteria, which are based on presence/absence of asthma-related concepts (Figure 1). It has been developed as an alternative to labor-intensive manual chart review and also to overcome noncomprehensive asthma identification by conventional approaches using structured data, such as International Classification of Diseases, Ninth and Tenth Revisions codes.[41–43] The NLP-PAC system was implemented in MedTaggerIE,[21] a resource-driven open source information extraction framework built under Apache Unstructured Information Management Architecture, which separates domain-specific NLP knowledge engineering from the generic NLP process. Domain-specific knowledge (ie, asthma-related events and episodes; concepts with shade in Figure 1) was defined in the customizable external resources and extracted from clinical notes using regular expression-based pattern match rules, assertion status (eg, nonnegated, associated with patients), and section constraint (eg, diagnosis section for physician-diagnosed asthma). Then, expert rules were implemented in a rule-engine program to ascertain asthma status (ie, asthma vs non-asthma) based on predetermined asthma criteria (see Figure 1).

The predetermined asthma criteria were originally developed by Yunginger et al.[37] and have been used extensively in research on asthma epidemiology.[44–48] In our study, probable and definite asthma types were combined, because most probable asthma becomes definite over time.[37,49]

Comparison of NLP asthma ascertainment

The NLP-PAC system was applied to both Mayo Clinic and SCH corpora, and the performance of asthma ascertainment against the gold standard (ie, manual chart review) was compared in sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and *F*-score.

RESULTS

We examined basic corpus statistics and corpus similarities between Mayo Clinic and SCH for a given study cohort ($n = 298$ for each institution) in terms of: (1) overall corpus at the word level (ie, lexical variation), (2) topics and asthma-related concepts (ie, semantic variations), and (3) clinical note types (ie, process variations). Corpus similarities were measured by the cosine similarity described earlier. The performance of the NLP-PAC system on both cohorts was also reported.

Corpus statistics of Mayo Clinic vs SCH

The basic corpus statistics of Mayo Clinic and SCH are included in Table 1. SCH has a larger number of documents than Mayo Clinic. SCH has certain note types (eg, Care Planning, Patient Instructions, and Clinical Team, consisting of 29% of the total documents) that are not used by Mayo Clinic; however, they are represented as sections within Mayo clinical notes. Also, there are multiple same note type documents in SCH, with a little extra or different text content, created on the same date but at different times, which is not the case at Mayo Clinic. These facts explain the major difference in total number of documents between the 2 institutions. SCH has a greater median number of asthma-related concepts per patient than Mayo Clinic. However, Mayo Clinic has greater median number of tokens and asthma-related concepts per document than SCH.

Table 1. Corpus statistics of Mayo Clinic and SCH ($n = 298$ patients each)

Category	Mayo	SCH
Total no. of documents	9604	30 589
Total no. of tokens	2 212 389	10 117 963
No. of documents/patient, median (IQR)	27 (18)	80 (69.8)
No. of tokens/document, median (IQR)	186 (210)	103 (331)
No. of asthma-related concepts[a]/patient, median (IQR)	19.5 (32.8)	65.5 (88)
No. of asthma-related concepts/document, median (IQR)	2 (3)	1 (2)
No. of note types	16	32
No. of sections	17	54

[a] Each concept consists of a set of keywords. IQR: interquartile range.

SCH has more segmented note types (eg, Anesthesia Pre-Procedure Evaluation, Anesthesia Post-Procedure Evaluation, Anesthesia Transfer of Care) than Mayo Clinic and thus has a higher number of note types. We were not able to obtain the exact SCH section statistics, since the section is not explicitly defined in the clinical notes. Instead, we examined frequent patterns of potential sections (eg, OBJECTIVE:, SUBJECTIVE:, EXAM:), parsed those sections in clinical notes, and obtained section statistics. It should be noted that these statistics represent only this cohort.

Figure 2 shows the distribution of asthma-related concepts (from PAC in Figure 1 and found in clinical notes in this study) between Mayo Clinic and SCH. The concept "cough" appears most frequently at both institutions. At Mayo Clinic, "asthma," "dyspnea," and "wheezing" concepts have similar distribution, but at SCH, "wheezing" is a lot more prevalent. Figures 3 and 4 show the distributions of note types and sections that contain any asthma-related concepts, respectively, for the 2 institutions. At Mayo Clinic, the Limited Exam note contains more than half of the asthma-related concepts. At SCH, 3 note types, Progress Note, Telephone Encounter, and Patient Instruction, contain most of the asthma-related concepts. However, it should be noted that asthma-related concepts in Patient Instruction do not represent actual medical conditions a patient presents, but are provided as an educational guide to handle possible events. As shown in Figure 4, major sections containing most asthma-related concepts differ between the 2 institutions, although History of Present Illness and the "plan" section (Impression/Report/Plan at Mayo Clinic and Plan at SCH) are used at both institutions.

Corpus similarities between Mayo Clinic and SCH

The similarities between Mayo Clinic and SCH corpora were examined in terms of the whole corpus and asthma-related concepts (Table 2). Although the word-level similarity (ie, corpus $tf-idf$ and $tf-ipf$) was mediocre, the topic similarity (ie, semantic similarity) of the 2 corpora was high (0.944). The similarity of asthma-related concepts (ie, semantic similarity) between the 2 institutions was 0.971 for $tf-idf$ and 0.855 for $tf-ipf$. Since asthma-related concepts can be considered as a topic, we did not measure the topic similarity of asthma-related concepts.

The similarity of note types (ie, process similarity) between Mayo Clinic and SCH corpora was compared based on topics. The note types with frequency ≥20 were compared and a clustered image map (ie, heat map) was plotted. In Figure 5, the color in the cell represents the degree of topic similarity (ie, cosine similarity) of the 2 note types. Euclidean distance was used to cluster rows and/or columns in the heat map. At SCH, Progress Notes and Telephone Encounter are major note types that contain asthma-related concepts. The top 3 notes similar to SCH's Telephone Encounter are Mayo's Test MIS, Supervisory, and Miscellaneous notes (similarity = 0.973, 0.948, 0.937, respectively); similar to SCH's Progress Note are Mayo's Test MIS, Supervisory, and Limited Exam notes (similarity = 0.897, 0.872, 0.856, respectively).

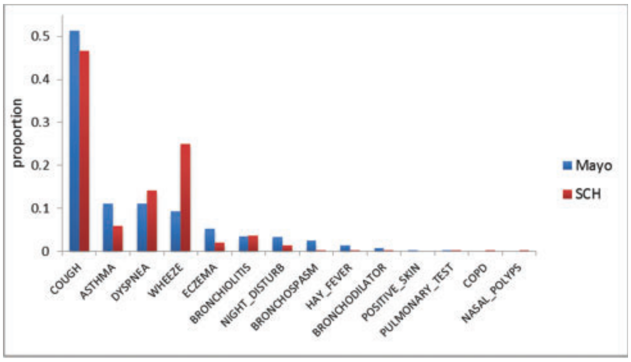
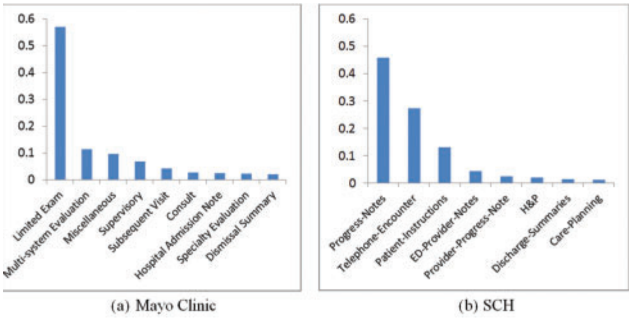
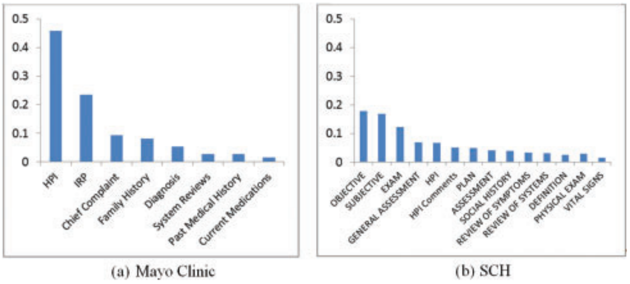


Figure 2. Distribution of asthma-related concepts.



(a) Mayo Clinic (b) SCH

Figure 3. Note types that contain asthma-related concepts (y axis is proportion of asthma-related concepts; includes note types with proportion ≥ 0.01).



(a) Mayo Clinic (b) SCH

Figure 4. Sections that contain asthma-related concepts (y axis is proportion of asthma-related concepts; includes sections with proportion ≥ 0.01).

Table 2. The similarities of Mayo Clinic and SCH corpora

Data source	$tf-idf$	$tf-ipf$	Topic
Whole corpus	0.669	0.581	0.944
Asthma-related concepts	0.971	0.855	NA

NA: not applicable.

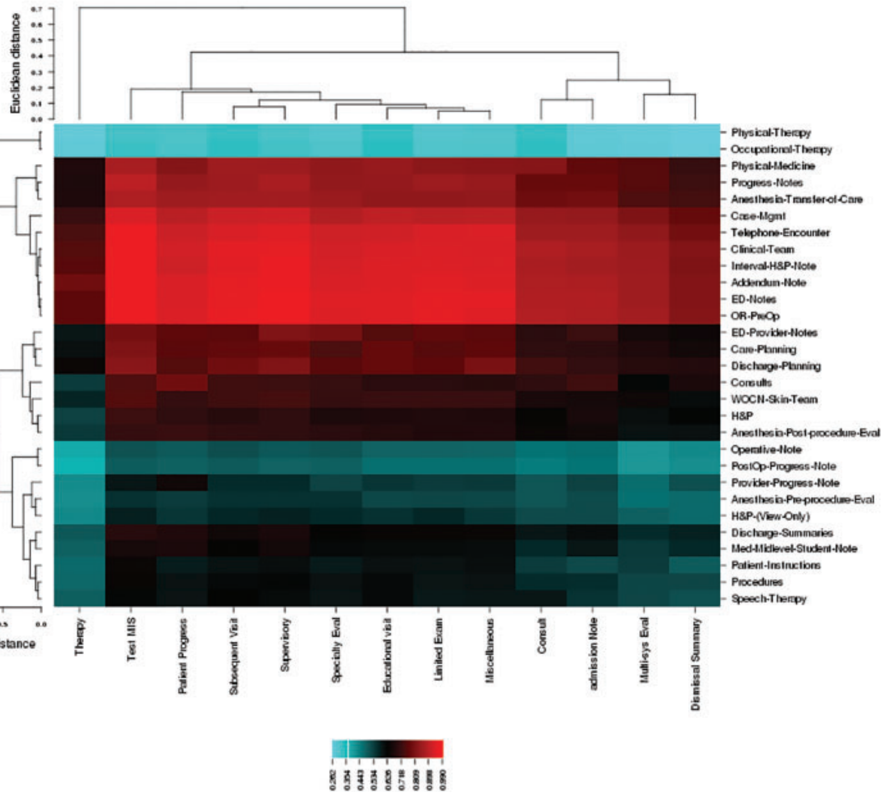


Figure 5. A heat map of note type similarity based on topics at Mayo (bottom label) and SCH (right label).

NLP-PAC asthma ascertainment

Portability of the NLP system to SCH has been examined in 2 stages: (1) prototype (stage 1), which required adjustments to be able to run the Mayo NLP-PAC system on the SCH cohort to deal with process variations due to different EMR generation, such as sentence parsing and section segmentation; and (2) refinement (stage 2), which further reduced process variations and refined assertion after error analysis based on the results of the prototype system; ie, selection of practice setting (note type) to be excluded (eg, Psychology, Care Conference, Speech Therapy), adjustment of assertion (eg, negated, possible) to cope with SCH description patterns.

Table 3 contains the NLP-PAC performance of Mayo Clinic and SCH stages 1 and 2. The data used at Mayo Clinic consisted of 497 subjects randomly selected from an Olmsted County birth cohort who had primary care at Mayo Clinic (independent from the data used in NLP-PAC development). The data used in SCH stage 1 are the same cohorts described previously (see Methods and Materials section). SCH stage 2 used another 298 subjects, independent from stage 1. The performance of SCH stage 1 (prototype) was considerably lower than Mayo Clinic, but after moderate refinement, stage 2 produced comparable performance to Mayo Clinic.

Table 3. NLP-PAC performance for asthma ascertainment

Metrics	Mayo	SCH Stage 1 (prototype)	SCH Stage 2 (refinement)
Sensitivity	0.972	0.840	0.920
Specificity	0.957	0.924	0.964
PPV	0.905	0.788	0.896
NPV	0.988	0.945	0.973
F-score	0.937	0.813	0.908

DISCUSSIONS

The corpus statistics of asthma birth cohorts between Mayo Clinic and SCH were analyzed and various aspects of their documentation variations were compared. The basic statistics differed in number (ie, number of documents, tokens, asthma-related concepts, note types, and sections), and word-level corpus similarities (ie, corpus $tf-idf$ and $tf-ipf$) were merely mediocre. However, at the concept level, the 2 corpora were relatively homogeneous (corpus topic similarity = 0.944; asthma-related concept similarity = 0.971). This may reflect that clinicians share common semantics to describe asthma episodes and events even though they have heterogeneous clinical sublanguage that shows up in different EMR systems; ie, there exist notable lexical variations to denote semantically similar concepts.

There are process variations across institutions in practice settings and reporting schemes for generating EMR data; ie, the distributions of note types and sections that contain asthma-related concepts differ. Regarding the distribution of asthma-related concepts, “cough,” “asthma,” “dyspnea,” and “wheezing” were dominant, making up 83% and 92% of total concepts at Mayo Clinic and SCH, respectively. Although cough is the most frequent asthma-related symptom, cough alone does not lead to an asthma diagnosis. It should be associated with wheezing in PAC to meet the definition of “asthmatic-cough.” At Mayo Clinic, the “asthma” concept (11%) appears in a similar proportion as “dyspnea” and “wheezing” (11% and 9%, respectively), while at SCH the “asthma” concept (6%) appears much less than “dyspnea” and "wheezing" (14% and 25%, respectively). There is also a 16% difference in the appearance of "wheezing" between the 2 institutions.

The major note types that contain asthma-related concepts were different between the 2 institutions: Limited Exam, Multi-System Evaluation, Miscellaneous (57%, 11%, and 10%, respectively) at Mayo Clinic; Progress Notes and Telephone Encounter (46% and 27%, respectively) at SCH, indicating a difference in the practice of recording asthma-related events and episodes in clinical notes. The major sections that contain asthma-related concepts also differed: 3 sections (History of Present Illness, Impression/Report/Plan, and Chief Complaint) contain almost 80% of asthma-related concepts at Mayo Clinic, but they were spread among many sections at SCH. There were some note types at SCH that were not similar to any of Mayo Clinic's note types (eg, Physical Therapy, Occupational Therapy, Post-Op Progress Note). However, most of Mayo Clinic's note types were similar in some degree to SCH notes.

The NLP system first applied to the SCH corpus (stage 1) is the one that dealt with required process variations to be technically operable. It produced an *F*-score of 0.813, ie, roughly 13% lower than the system's performance on the Mayo corpus. The error analysis showed that assertion identification (mostly negation detection) was a major source of error and needs to be adjusted accordingly to cope with SCH description patterns (ie, negation sublanguage characteristics). As noted by Wu et al.,[50] negation detection suffers when applied to a different corpus and requires domain adaptation. They revealed that negation detection is relatively easy to optimize for a specific corpus but difficult to generalize to an arbitrary clinical corpus. The structured section templates would be helpful to correctly identify sections at SCH, which would eliminate subsequent asthma ascertainment errors due to sectionization. After the refinement process (SCH stage 2) to reduce errors found in stage 1, the NLP-PAC showed comparable performance to Mayo Clinic, except sensitivity (0.972 at Mayo, 0.920 at SCH), suggesting that further effort may be required to analyze SCH data to capture additional asthma cases.

We also reapplied NLP-PAC used in SCH stage 2 on the Mayo data (in Table 3), but using Mayo specifications (ie, section, note type) due to the technical operability. It produced 0.973, 0.963, 0.917, and 0.988 for sensitivity, specificity, PPV, and NPV, respectively, which was a little better but very similar to the performance of the original Mayo NLP-PAC (see Table 3). Since the major adjustment at SCH is assertion (except required adjustment for technical operability), the revised NLP-PAC on the Mayo data was able to produce comparable asthma ascertainment without loss of performance.

There are limitations in this study. Mayo Clinic and SCH cohorts were matched by age, but the date ranges differ by approximately 10 years. There is potentially clinical practice change related to asthma. However, we believe that it would not have much effect on the outcome, because asthma prevalence did not change considerably over a decade (7.3% in 2001 to 8.4% in 2010).[51] The NLP-PAC system we evaluated is an expert system based on information extraction of medical concepts. Other NLP systems using different techniques may not hold the same notions we found. Lastly, this study was conducted on a specific domain, pediatric asthma at 2 institutions. Our findings may not be generalizable to other domains with different patient cohorts at other institutions.

We conducted this study on corpora across institutions using different EMR systems (GE-based *vs* Epic). In the future, it would also be interesting to conduct the same study on corpora across institutions using the same EMR system and explore how it differs from the current study in terms of clinical documentation variations and NLP system portability.

CONCLUSION

The different types of clinical documentation variations played different roles in assessing NLP system portability. The NLP system for asthma ascertainment is largely dependent on asthma-related concepts rather than individual word distributions. We believe that concept-wise similarity (ie, semantic similarity) should be emphasized to assess the portability of a knowledge-based NLP system that largely relies on information extraction, such as our NLP-PAC system. The Mayo Clinic and SCH corpora were relatively homogeneous in concepts, which shows good potential for NLP-PAC system portability. However, appropriate adjustments were necessary to deal with the intrinsic corpus heterogeneity, such as process and assertion variations, in order to produce a desirable performance of asthma ascertainment using NLP.

COMPETING INTERESTS

The authors have no competing interests to declare.

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CONTRIBUTORS

SS and HL conceived the study and design. SS and YW acquired the data and implemented the algorithms. SS performed the analysis and drafted the initial manuscript. All authors participated in interpretation of the data and contributed to manuscript revisions.

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