Extraction of Sleep Information from Clinical Notes of Alzheimer’s Disease Patients Using Natural Language Processing

Haneef Ahamed Mohammad†1, Sonish Sivarajkumar†2, Samuel Viggiano1, David Oniani1, Shyam Visweswaran, MD, PhD2,3, Yanshan Wang, PhD1,2,3†
1Department of Health Information Management, University of Pittsburgh, Pittsburgh, PA; 2Intelligent Systems Program, University of Pittsburgh, Pittsburgh, PA; 3Department of Biomedical Informatics, University of Pittsburgh, Pittsburgh, PA

Abstract
Alzheimer’s Disease (AD) is the most common form of dementia in the United States. Sleep is one of the lifestyle-related factors that has been shown critical for optimal cognitive function in old age. However, there is a lack of research studying the association between sleep and AD incidence. A major bottleneck for conducting such research is that the traditional way to acquire sleep information is time-consuming, inefficient, non-scalable, and limited to patients’ subjective experience. In this study, we developed a rule-based NLP algorithm and machine learning models to automate the extraction of sleep-related concepts, including snoring, napping, sleep problem, bad sleep quality, daytime sleepiness, night wakings, and sleep duration, from the clinical notes of patients diagnosed with AD. We trained and validated the proposed models on the clinical notes retrieved from the University of Pittsburgh Medical Center (UPMC). The results show that the rule-based NLP algorithm consistently achieved the best performance for all sleep concepts.

Introduction
Alzheimer’s Disease (AD) is the most common form of dementia in the United States (U.S.), which affects at least 5.7 million Americans with a projected increase to 13.8 million by mid-century due to a global aging population11–13. In 2015, official death certificates recorded more than 110 thousand deaths from AD, making it the sixth leading cause of death in the U.S. and the fifth leading cause of death in Americans 65 years of age or older1. Unlike deaths from stroke and heart disease, which decreased between 2000 and 2015, deaths from AD increased 123%. By the year 2050, 13.8 million Americans are expected to have AD with an associated cost of $1.2 trillion U.S. dollars, not including unpaid caretaker hours. Postponing dementia onset by even one year could result in nine million fewer cases worldwide than predicted by 20504 and a reduction in care costs. Therefore, early intervention to reduce the risk of AD will have a better population health impact.

Social and behavioral determinants of health (SDOH) are modifiable factors and offer opportunities for reducing the risk of AD3. Sleep is one of the lifestyle-related SDOH factors that has been shown critical for optimal cognitive function in old age6. However, the association between sleep and AD incidence is complex, as shown in the literature. On the one hand, previous studies suggest that sleep problems, such as insomnia7, excessive daytime sleepiness8,9, snoring10, sleep duration11, poor sleep quality12, and difficulties maintaining sleep13, are associated with an increased risk of incident cognitive impairment and could be an early predictor of future AD dementia13. On the other hand, some studies find no association between sleep variables (e.g., sleep duration, sleep difficulties, and snoring) and cognitive function14. Moreover, a bi-directional relationship is seen between sleep and cognitive function decline in the elderly with underlying AD; in other words, AD also causes circadian and sleep disturbances. Despite a growing interest in studying sleep-AD relationship, longitudinal epidemiological research in a large cohort is still needed to understand the relationship. A major bottleneck for conducting such research is that the traditional way to acquire sleep and AD data through multi-year follow-ups is time-consuming, inefficient, non-scalable, and limited to patients’ subjective experience.

Large volumes of electronic health records (EHRs) collected by healthcare organizations offer an opportunity to use a large sample size to investigate intervention outcomes in routine care, such as predictors of response, safety, comparative effectiveness, and health economic evaluations15. EHRs have become popular in AD research, such as resource use in AD care16, comorbidities17,18, case capture efficiency18, and health disparities19. However, EHRs remain

* Co-first authors
† Corresponding author: Yanshan Wang, PhD, FAMIA; yanshan.wang@pitt.edu

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underused in collecting sleep information for AD research. A major barrier that hinders the use of sleep information from EHRs for AD research is that most of the sleep information in EHRs is embedded in clinical narratives. Natural language processing (NLP), a technique in computational linguistics that uses computational models for understanding natural language, has been used to extract meaningful information from clinical narratives. However, there existed no NLP algorithms in the literature to extract sleep information from clinical notes, particularly for patients with AD, to the best of our knowledge. In this study, we developed both rule-based NLP algorithm and machine learning-based NLP models to automate the extraction of sleep-related concepts, including snoring, napping sleep problem, poor sleep quality, daytime sleepiness, night wakings, and sleep duration, from the clinical narratives of patients diagnosed with AD. We trained and validated the proposed models on the clinical notes retrieved from the University of Pittsburgh Medical Center (UPMC). The results show that the rule-based NLP algorithm achieved consistently the best performance for all sleep concepts.

Background

Several prior studies have used the EHR data for the sleep information, most of which utilized structured EHR data, such as the International Classification of Diseases (ICD) diagnostic codes. For example, Felder et al. used ICD codes to identify sleep disorders and study the association between sleep disorders and preterm birth. Hsiao et al. identified patients with sleep disorders using ICD-9 codes 307.4 and 780.5x and explored the association between sleep disorders and autoimmune diseases. ICD codes have also been used to identify obstructive sleep apnea. However, it has been shown that sleep disorders are poorly coded in structured EHR data. ICD codes for identifying a sleep disorder from inpatient EHR data has only 79.2% sensitivity and 28.4% specificity. A study also found that manual chart review of unstructured EHR data was able to identify 50% more individuals with insomnia and 68% more individuals with sleep problems, compared to using only ICD code. Therefore, unstructured EHR data (e.g., clinical notes) is valuable for identifying sleep information.

Despite the rich sleep information embedded in unstructured EHRs, only a limited number of studies are found in the literature applying NLP and machine learning methods to automatically extract sleep information from unstructured EHRs. Divita et al. applied a keyword matching approach to extract general symptoms that includes sleepiness from VA clinical notes. Similarly, a few studies used NLP to extract disturbed sleep and insomnia from clinical notes to study the association between sleep and mental disorders. For example, Zhou et al. used sleep-related symptoms to identify patients with depression, and Irving et al. considered insomnia and distributed sleep in clinical notes to predict psychosis. Kartoun et al. used text mention of sleep disorders in clinical notes to predict insomnia and found superior performance in identifying insomnia patients compared to ICD codes. Other studies used sleep-related reactions, such as sleeplessness and sleepy, from clinical notes or adverse event reports of adverse drug events. However, none of the studies focused on automated methods of extracting a comprehensive list of sleep variables related to the AD.

Methods

Data Collection

We first defined a cohort of patients diagnosed with AD (ICD-10 codes: G30.0, G30.1, G30.8, and G30.9) between January 1st, 2020 and December 31st, 2020 at UPMC. We collected all their clinical notes that were created between January 1st, 2016 and December 31st, 2020, through the data service provided by the University of Pittsburgh Health Record Research Request (R3). The University of Pittsburgh’s Institutional Review Board (IRB) reviewed and approved this study’s protocol.

Data Preprocessing

A total of 7,266 patients were identified, and approximately 1.1 million de-identified clinical documents were retrieved. Since these clinical documents were auto-populated in the EHR system, we developed a data preprocessing algorithm to clean the clinical text. Specifically, we integrated clinical documents with the same document ID regardless of the line number ID and removed duplicated clinical documents. Although some documents are not duplicated, most contents in those documents are overlapped due to the nature of data population. For example, a physician digitally signing a clinical document will generate a duplicated document with just the addition of “Digitally signed by…” one or two days later. Therefore, we applied a surface lexical similarity approach to identify the highly similar documents. Suppose that V is a set of unique words that occurred in documents $D_1$ and $D_2$. $D_1$ and $D_2$ can be represented in the same vector space as $d_1$ and $d_2$ respectively where each component corresponds to the word in V and the value is the word frequency. Then we calculated the cosine similarity between two document vectors. If the
similarity score is greater than 0.9, we will randomly remove one of the duplicated documents. After the data preprocessing, the total number of clinical documents was 379k.

Another challenge in extracting sleep information from clinical notes is that not every clinical note records relevant information. To identify relevant documents, we used information retrieval (IR) to select the documents. We applied fuzzy search that returns the documents containing keywords related to sleep regardless of the morphological format. The keywords used in our search are shown in Table 1. As a result, 192k (51%) out of 379k documents were returned for further investigation in this project. This set of 192k documents is called adSLEEP corpus hereafter.

Table 1. Sleep-related keywords used to retrieve relevant clinical note documents.

| 'snore', 'snoring', 'wheeze', 'wheezing', 'sleep', 'sleepiness', 'sleeping', 'sleepless', 'sleeplessness', 'apnea', 'hypopnea', 'osa', 'insomnia', 'nap', 'napping', 'narcolepsy', 'nocturnal', 'somnolence', 'somnolent', 'dizziness', 'hypersomnia', 'rem', 'nrem', 'wake', 'wakefulness', 'waking', 'polysomnography' |
|---------------------------------------------------------------------------------------------------------------|

Table 2. Definitions and examples of sleep-related concepts.

| Concept Category       | Definition                                      | Example                                      |
|------------------------|-------------------------------------------------|----------------------------------------------|
| Snoring                | Snoring or snoring synonyms                     | “snoring”                                    |
|                        |                                                 | “sleep apnea”                                |
| Napping                | Napping during daytime                          | “napping”                                    |
|                        |                                                 | “doze”                                       |
| Sleep problem          | Sleep problem                                   | “sleep disorder”, “insomnia”, “hypersomnia”  |
|                        | Specific sleep disorder/condition/disease        |                                              |
|                        | mentioned in the note                           |                                              |
| Bad sleep quality      | Any mention related to bad sleep quality in the  | “sleeplessness”                              |
|                        | note                                            | “couldn’t sleep during night”                |
|                        |                                                 | “staying up all night”                       |
| Daytime sleepiness     | Sleepiness during daytime                       | “sleep a lot through out the day”            |
|                        |                                                 | “excessive daytime sleepiness”               |
| Night wakeings         | Night time wakeings                              | “frequent night waking”                      |
|                        |                                                 | “waking up in the middle”                    |
|                        |                                                 | “waking up 3-5 times”                        |
| Sleep duration         | Duration of night time sleep                    | “sleeps 4-5 hours” --&gt; Short              |
|                        | (Short &lt;=6h, Medium 6-8h, or Long &gt;=8h)    | “sleep more than 12 hours” --&gt; Long       |

Gold Standard Data Annotation

We randomly sampled 320 clinical note documents from the adSLEEP corpus for manual annotation to create the gold standard dataset. Two health informatics students annotated this sampled dataset. The annotator was directed to annotate mentions of seven sleep-related categories in each clinical note, including snoring, napping, sleep problem, sleep quality, daytime sleepiness, night wakings, sleep duration. These sleep-related concept categories are defined based on previous sleep studies for patients with AD. Table 2 shows the detailed definitions for each of the classes. Then a judge aggregated the concept annotations in a clinical note to a document-level label. Initially, a batch
of 20 documents was given to the annotators to refine the annotation guidelines and to discuss the discrepancies to reach consensus on the concept definition. We repeated this process on another batch of 20 documents until an inter-annotator agreement (IAA) above 0.60 in terms of Cohen’s Kappa was achieved. These 40 documents were used to measure a final IAA. Then we annotated the remaining 200 clinical notes using the updated annotation guidelines.

**Rule-based NLP Algorithm**

We developed a rule-based NLP algorithm named nlp4sleep for sleep information extraction using MedTagger\(^3\), a clinical NLP tool based on the Unstructured Information Management Architecture (UIMA) framework\(^6\). The MedTagger software is publicly available at GitHub\(^7\).

We first used top-down and bottom-up approaches to identify the keywords in the rules for each sleep concept extraction. For the top-down approach, we searched the synonyms for each concept in the medical terminologies and ontologies, including Unified Medical Language System (UMLS) Metathesaurus. For the bottom-up approach, we used word embeddings trained from the clinical corpus to find the top 3 most similar terms. Then we used 70% (200 documents) of the gold standard dataset as training data to develop regular expression rules for the NLP algorithm. Since MedTagger includes the negation detection and hypothetical mention detection, we didn’t specify negation rules unless we saw undetected negations in the training data. Table 3 lists the regular expression rules used in the nlp4sleep algorithm to extract sleep concepts. The NLP system extracted sleep concepts from each clinical document and assigned a document-level classification for each concept. If there were multiple mentions one of a concept in a document, we applied majority voting strategy to obtain the final document label. The NLP algorithm is publicly available through the Open Health Natural Language Processing (OHNLP) consortium at GitHub (https://github.com/OHNLP/nlp4sleep).

| Concept Category | Keywords and Regular Expressions |
|------------------|----------------------------------|
| Snoring          | snor(es|ing(e)?; snorings; sleep apnea; osa; obstructive sleep apnea |
| Napping          | nap(s|ping)? |
| Sleep problem    | insomnia; sleeplessness; sleep (disorders?|problems?); hypersonnia; parasomnia; osa; obstructive sleep apnea; sleep apnea; hypersonmolence |
| Bad sleep quality| staying up; (trouble|irritable|tense) (?S+s+)\{0,5\}(sleep(ing)?|asleep); sleep(s|ing)? poorly; sleep is poor; restless sleep; ca(n’t|not) sleep; sleep issues?; sleep(ing)? (?S+s+)\{0,5\}(problems?|problematic); sleeps? a lot; difficulty (?S+s+)\{0,5\}(asleep|sleep(ing)?)?; sleep disturbance; disturbance in sleep; sleep quality: (fair|bad); not sleeping; no sleep; sleep difficulty; nocturnal agitation; up (during|at) night; nocturnal; often awake |
| Daytime sleepiness| (excessive )?daytime sleep(iness|inesses)?; (excessive )?daytime somnolence; sleep(sing)ness at times; sleep(s|iness)? in (?S+s+)\{0,2\}day(time)?; sleep(s|iness) during (?S+s+)\{0,2\}day(time)?; sleep all day |
| Night wakings    | night (wakings|awakenings), wak(e|es|ing up) (?S+s+)\{0,5\}night; awake(ning|n)? (from|during|at) night(mares)? |
| Sleep duration   | Short: sleep(s|ing)? (less than|up to) (1|2|3|4|5|6) hours |
|                  | Medium: sleep(s|ing)? (?S+s+)\{0,5\}(6|7|8)-6(7|8) hours |
|                  | Long: sleep(s|ing)? (?S+s+)\{0,5\}more than (8|9|10|11|12|13|14|15|16|17|18|19|20) hours; sleep(s|ing)? (?S+s+)\{0,5\}(8|9|10|11|12|13|14|15|16|17|18|19|20) hours |

3. https://github.com/OHNLP/MedTagger
Machine Learning Models

We compared the rule-based NLP algorithm with machine learning models. Five major machine learning-based clinical text classification models, namely Gradient Boosting Machine (GBM), Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF), were trained and tested for each sleep concept. Since real-world clinical text data may be inadequate and inconsistent for machine learning-based NLP models to comprehend, we adopted multiple preprocessing steps before feeding the text data to the machine learning models. After converting into lower case, the text was tokenized to break the sentences into tokens, including words, phrases, symbols, or other meaningful elements. Stop words and non-numeric were removed from the token lists. The tokens were then lemmatized to the base forms to reduce the complexity of the text. Then we converted the entire document to a numeric vector using Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. The experiments were conducted as a binary text classification task, with positive and negative predictions for each concept category. The same training and test datasets were used as in the rule-based NLP algorithm, and the performance on the test dataset was reported.

Evaluation

We used 30% (120 documents) of the gold standard dataset as the testing data to validate the rule-based NLP algorithm and machine learning models. All models were evaluated using sensitivity, specificity, positive predictive value (PPV), and F1 score. Since our dataset is imbalanced, we report the weighted-averaged F1 score. The definitions of the evaluation metrics are shown below:

\[
\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}
\]

\[
\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}
\]

\[
\text{PPV} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}
\]

\[
F1\text{ score} = \frac{2 \cdot \text{True Positive}}{2 \cdot \text{True Positive} + \text{False Positive} + \text{False Negative}}
\]

Results

Table 4 shows the demographics of the AD cohort of 7,266 patients. Patients were primarily white (91%), female (64%), and not Hispanic or Latino (95%), with a mean age of 85 years. The demographics of this cohort are similar to the demographics of the population in western Pennsylvania.

Table 5 lists the number of documents for each sleep concept in the annotated training and test datasets. As shown in the table, the frequency of these sleep concepts is low in the gold standard dataset. Though the clinical documents were identified by using a list of relevant keywords, most documents do not contain any sleep-related concepts. The reason might be that some keywords may not be only related to sleep; for example, wheezing might be related to respiratory diseases.

The performance of the rule-based NLP algorithm and machine learning models is listed in Table 6. The result for the sleep duration concept is ignored since there are no annotations in the test dataset. As shown in Table XX, we can clearly see that the rule-based NLP algorithm outperform the machine learning models for all six sleep-related concepts. For identifying snoring, the rule-based NLP algorithm achieved the best performance of 0.97 and 0.89 in terms of F1 score and PPV, respectively, and a specificity of 0.97 that is close to the best specificity of 0.98 achieved by GBM. RF had the best sensitivity of 1.00 but a low PPV and F1 score. LR, KNN, and SVM had zero F1 scores since they failed to identify the positive cases. This is also the reason why we observed many zero F1 scores as the machine learning models could not learn patterns effectively from the training dataset with only a few positive cases. For the napping concept, the rule-based NLP algorithm achieved the best

| Table 4. Demographics of the AD cohort. |
|----------------------------------------|
| Demographics                          | Total (n=7,266) |
| Age, years                            | 85 (79.91)     |
| Sex                                    |                |
| Female                                | 4,649 (64%)    |
| Male                                  | 2,617 (36%)    |
| Race                                   |                |
| White                                 | 6,628 (91%)    |
| Black                                 | 482 (6.6%)     |
| Asian                                 | 67 (1.1%)      |
| Others                                | 67 (1.1%)      |
| Not Specified                         | 22 (0.3%)      |
| Ethnicity                             |                |
| Hispanic or Latino                    | 33 (0.5%)      |
| Not Hispanic or Latino                | 6,900 (95%)    |
| Not Specified                         | 333 (4.5%)     |
performance in terms of four metrics while all the machine learning models failed to identify the positive cases. We can observe the same results for the night wakings concept. The rule-based NLP algorithm achieved the best performance consistently for sleep problem, bad sleep quality, and daytime sleepiness. SVM had a comparable performance for sleep problem and daytime sleepiness in terms of sensitivity and specificity and couldn’t accurately identify positive cases, which resulted in low PPVs and F1 scores. These results are consistent with previous studies\textsuperscript{37, 38} that machine learning models might not be effective in clinical text classification when the size of the annotated training dataset is small, and the concepts of interest are sparse and infrequent in the documents.

Table 5. Number of clinical documents for each sleep concept in the annotated training and test datasets.

| Concept Category      | # Documents in Training (Yes/No) | # Documents in Test (Yes/No) |
|-----------------------|----------------------------------|------------------------------|
| Snoring               | 30 / 170                         | 14 / 106                     |
| Napping               | 4 / 196                          | 1 / 119                      |
| Sleep problem         | 35 / 165                         | 20 / 100                     |
| Bad sleep quality     | 20 / 180                         | 8 / 112                      |
| Daytime sleepiness    | 9 / 191                          | 1 / 119                      |
| Night wakings         | 2 / 198                          | 2 / 118                      |
| Sleep duration        | 0 (Short) / 1 (Medium) / 2 (Long)| 0 (Short) / 0 (Medium) / 0 (Long) |

Table 6. Performance of the rule-based NLP algorithm and machine learning models.

| Sensitivity | Specificity | PPV | F1  |
|-------------|-------------|-----|-----|
|             | Snoring     | Napping | Sleep Problem | Bad Sleep Quality | Daytime Sleepiness | Night Wakings |
| Rule-based NLP | 0.94 | 0.97 | 0.99 | 0.95 | 0.98 | 0.85 | 0.93 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
| GBM         | 0.88 | 0.98 | 0.97 | 0.89 | 0.95 | 0.75 | 0.77 | 0.90 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
| LR          | 0.86 | 0.99 | 0.98 | 0.88 | 0.95 | 0.75 | 0.77 | 0.90 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
| KNN         | 0.86 | 0.99 | 0.97 | 0.86 | 0.95 | 0.75 | 0.77 | 0.90 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
| SVM         | 0.86 | 0.99 | 0.97 | 0.86 | 0.95 | 0.75 | 0.77 | 0.90 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
| RF          | 1.00 | 0.87 | 0.99 | 0.86 | 0.95 | 0.75 | 0.77 | 0.90 | 0.91 | 0.62 | 0.51 | 0.85 | 0.93 | 0.91 | 1.00 | 1.00 | 1.00 |
Error Analysis of the rule-based NLP algorithm

We conducted an error analysis of the documents misclassified by the rule-based NLP algorithm and analyzed the causes of the false positives and false negatives for each sleep concept. Some false positives were due to our annotators failing to annotate the information. For example, in the text “Histories Past Medical History Combined Chronic Systolic/Diastolic CHF COPD (industrial exposure) CAD s/p stents PMH Right Ocular Stroke - chronic visual defect BPH Type 2 DM OSA on BiPAP”, the rule-based NLP algorithm identified OSA as snoring and sleep problem. However, the concept had not been annotated. Many semi-structured clinical text auto-populated in the EHR system is difficult for the annotator to read and annotate. In another false positive, the sentence “He had episodes yesterday in which he became confused after waking up from a nap” indicates that the patient had a nap that may not be related to sleep pattern. In another false positive case for sleep problem “Depression screen done 7/2017, PHQ9 score 16 points for sleep problem which seems better now”, the NLP algorithm couldn’t identify that this sentence was not about a positive sleep problem. In a false positive case for bad sleep quality, the sentence “Take Melatonin 5 mg at bedtime every night for 3-4 weeks for difficulty falling asleep” was a suggestion for the patient.

Some false negatives are due to errors in negation detection. For example, in the sentence “The patient's daughter states that she has not been complaining of her back pain or of her leg cramps we discussed the fact that she is doing less and does nap during the day”, the algorithm incorrectly identified this mention as negated since it failed to identify two sentences. In another example for sleep problem “Change in social contacts/activities? No Patient Active Problem List Diagnosis Primary open angle glaucoma Urge incontinence Backache, unspecified Pneumonia, organism unspecified Insomnia”, the NLP algorithm incorrectly split the sentence into “Change in social contacts/activities?” and “No Patient Active Problem List Diagnosis Primary open angle glaucoma Urge incontinence Backache, unspecified Pneumonia, organism unspecified Insomnia” and wrongly identified the negation. The semi-structured clinical text also confused the NLP algorithm in detecting sentences and negations.

Discussion

Detailed descriptions of SDOH are usually captured in unstructured clinical text; however, the SDOH information may be sparsely documented due to the lack of clinical practice guidelines for documenting such information. Our study shows that sleep information is infrequently recorded in clinical notes for patients with AD. For example, in the gold standard dataset, only 14% of clinical documents recorded snoring concepts, 1.6% napping, 17.2% sleep problem, 8.8% bad sleep quality, 3.1% daytime sleepiness, 1.3% night wakings, and 1% sleep duration. This observation raises the question of whether such under-documented SDOH information in clinical notes will be useful for downstream statistical analysis in a cohort study or an epidemiology study.

Another challenge we encountered during the project was the definition of sleep-related concepts. We initially considered eight concepts, including sleep disorder, sleep problem symptoms, snoring, napping, sleep quality, daytime sleepiness, night wakings, and sleep duration, with detailed granularity according to the relevant sleep research in the literature. For example, there were four categories associated with snoring or daytime sleepiness: negated, positive, sometimes, and all the time. There were three categories for night wakings: 0, 1-2, and >2. However, during the annotation process, we found that the granular categories for each concept were rarely used and there were significant overlaps between sleep problem symptoms and other concepts. For example, phrases like “staying up all night” meet the description of insomnia, but the patient was never diagnosed with insomnia. Likewise, snoring and sleep apnea shared concept-likeness but are not always annotated similarly. For example, the concept of snoring is annotated as snoring but not sleep apnea. However, the concept of sleep apnea is annotated as a sleep problem and snoring because the concept meets both definitions. Thus, we simplified the concept definition and the categories for each concept.

Since SDOH comprises more conditions related to socioeconomic status, living environment, housing, education, food, community, it might be more challenging to define these SDOH concepts. It is also questionable whether such information is adequately documented in EHRs and whether such information from EHRs would be useful for research. Thus, a feasibility study of assessing the availability of SDOH in EHRs for a certain cohort of patients might be necessary before algorithm development. In addition, it is also a tedious and time-consuming process to manually annotate a gold standard dataset. A potential beginning point of building automated systems to extract SDOH from EHRs might be a community effort to build an SDOH ontology and terminology.

Additionally, sleep information is infrequently documented in the clinical notes and keywords are shared with concepts. Although we used IR to select the documents with keywords related to sleep, keywords including wheeze, wheezing, and apnea appear often but are unrelated to the patient’s sleep. For example, physicians commonly check a patient’s respiratory health and record the presence of wheezing in the clinical notes. Wheezing, a shared concept
between respiratory health and sleep, was found problematic when retrieving sleep-specific documents. Although sleep information is infrequently documented in the clinical notes, the proposed rule-based NLP algorithm still achieved promising results. In comparison, the machine learning and deep learning based approaches didn’t achieve good results, which is due to the small size of sleep information in the training data. This study focused on the clinical notes of patients with AD, but could be extended to general sleep information extraction for other diseases.

Limitations

There are several limitations in this study. First, the ICD codes used to define AD may not be optimal. However, a more comprehensive way to define AD is out of scope of this study. Second, the initial search keywords used to retrieve sleep-related clinical notes may not be complete and could miss some documents. However, this could be a common problem for SDOH information extraction due to the sparse and infrequent documentation in clinical notes. Third, the gold standard dataset is relatively small due to the time-consuming and expensive manual annotation. Last, we didn’t consider sleep information in other EHR data types, such as diagnosis codes, survey data, questionnaire data, sleep studies such as polysomnography, and sleep tests such as multiple sleep latency test (MSLT), which should be considered for further cohort studies or epidemiology studies.

Future Work

In future work, we plan to explore more sophisticated methods in retrieving relevant documents to the considered medical concepts with high precision. This might be a key challenge in collecting a corpus for studying an SDOH concept. In addition, we will also investigate novel machine learning methods that require less or no data for training.

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