Use of a Natural Language Processing-Based Approach to Extract Depression Symptom Severity and Suicide Ideation from Clinical Notes to Support Depression Research

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Background

- Depression is a major public health concern, and new research is needed to improve patient outcomes[1,2]
- Electronic health records contain large amounts of data that could be used for depression research, but some critical data, such as depression symptom severity as measured by the Patient Health Questionnaire-9 (PHQ-9) and suicide ideation (SI), are recorded in clinical notes rather than in structured fields[3]
- Natural language processing (NLP) can be used to extract relevant information from clinical notes and could improve availability of information on depression symptom severity and suicide ideation in real-world data sources to support research and clinical care

Objective

This study aimed to determine the feasibility of extracting PHQ-9 scores and SI from clinical notes

Methods

Data Source

Data were drawn from the OM1 Real-World Data Cloud (OM1, Inc, Boston, MA, USA), continuously updated dataset of US patients derived from deterministically linked, de-identified, individual-level health care claims, EHR, and other data covering 2013 to present day

Two Study Cohorts

- The PHQ-9 cohort was restricted to patients from the OM1 Real World Data Cloud who had at least one clinical note that mentioned the PHQ-9
- The SI cohort was restricted to patients with at least one clinical note that mentioned suicide

Methods (continued)

Approach

- An NLP-based approach was used to extract PHQ-9 scores and SI
- The approach identifies collections of linguistic patterns used to record PHQ-9 scores and associated dates and SI or denial thereof in clinical notes
- Subject matter experts validated the patterns for each task to ensure reliability of the approach
- PHQ-9 total scores and associated dates were extracted.
- For SI, notes were categorized as one of the following:
  - Negations of SI (e.g., 'patient denies thoughts of suicide')
  - Affirmations (e.g., 'patient reports having thoughts of suicide')
  - Neither negations nor affirmations (e.g., notes that include medication label text about SI, family history)
  - Unknown (e.g., notes that mention suicide but do not indicate current SI)

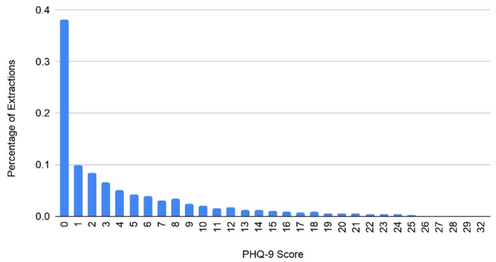
Results

- 1.1 million clinical notes were identified for inclusion in the PHQ-9 extraction cohort. Phrases validated by subject matter experts were used to extract 735,267 PHQ-9 scores
- The distribution of extracted PHQ-9 scores is shown in Figure 1
- 3.7 million clinical notes were identified for inclusion in the SI cohort. Phrases validated by subject matter experts were used to classify 2,088,144 clinical notes as having negation of SI and 25,255 clinical notes as having affirmation of SI (Table 1)
  - Of the 2,113,399 notes with either negation or affirmation of SI, 1.2% were affirmations and 98.8% were negations
- The remaining notes in the SI cohort were classified as neither negations nor affirmations or unknown

Table 1: SI Note Categorization

Category	Number of Notes Matched	Percent of All Notes
Negation	2,088,144	54.16%
Affirmation	25,255	0.66%
Neither	164,797	4.27%
Unknown	1,580,318	40.99%
Totals	3,858,514	

Figure 1: Distribution of Extracted PHQ-9 Scores



Conclusions

- PHQ-9 scores and SI can be extracted from clinical notes using a natural language processing-based approach
- The approach used in this study is a reproducible model for efficiently extracting concepts related to depression from unstructured clinical notes
- Future research should examine the performance of this approach in other data sources

Conference

ICPE 2021 Virtual Meeting

Employment

Noa Palmon, Pedro Alves, Safiyy Momen, Michelle B. Leavy, Gary Curhan, Costas Boussios, Cameron Jones, and Rich E. Gliklich are all employees of OM1, Inc., Boston, MA, USA

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