Cancer Research and Reports
An open access journal
eSciRes
ISSN: 2817-6324
Research Article
CRR-1-102

Automatically Identifying Financial Stress Information from Clinical Notes for Patients with Prostate Cancer

Zhu V*[1], Lenert L[1], Bunnell B[1], Obeid J[1], Jefferson M[2,3] and Halbert CH[2,3]

[1]Biomedical Informatics Center, Medical University of South Carolina, Charleston, South Carolina, United States
[2]Hollings Cancer Center, Medical University of South Carolina, Charleston, South Carolina, United States
[3]Department of Psychiatry and Behavioral Sciences, Medical University of South Carolina, Charleston, South Carolina, United States

Abstract

Background: Financial stress, one of the social determinants, is common among cancer patients because of high out-of-pocket costs for treatment, as well as indirect costs. The National Academy of Medicine (NAM) has advised providers to recognize and discuss cost concerns with patients in order to enhance shared decision-making for treatment and exploration of financial assistant programs. However, financial stress is rarely assessed in clinical practice or research, thus, under-coded and under-documented in clinical practice. Natural language processing (NLP) offers great potential that can automatically extract and process data on financial stress from clinical free text existing in the patient electronic health record (EHR). **Methods:** We developed and evaluated an NLP approach to identify financial stress from clinical narratives for patients with prostate cancer. Of 4,195 eligible prostate cancer patients, we randomly sampled 3,138 patients (75%) as a training dataset (150,990 documents) to develop a financial stress lexicon and NLP algorithms iteratively. The remaining 1,057 patients (25%) were used as a test dataset (55,516 documents) to evaluate the NLP algorithm performance. The common terms representing financial stress were "financial concerns," "unable to afford," "insurance issue," "unemployed," and "financial assistance." Negations were used to exclude false mentions of financial stress. **Results:** Applying both pre- and post-negation, the NLP algorithm identified 209 patients (6.0%) from the training sample and 66 patients (6.2%) with 161 notes from the test sample as having documented financial stress. Two independent domain experts manually reviewed all 161 notes with NLP identified positives and randomly selected 161 notes with NLP-identified negatives, the NLP algorithm yielded 0.86 for precision, 1 for recall, and 0.9.2 for F-score. **Conclusions:** Financial stress information is not commonly documented in the EHR, neither in structured format nor in clinical narratives. However, natural language processing can accurately extract financial stress information from clinical notes when such narrative information is available.

Keywords: Financial stress; Prostate cancer; Natural language processing; Electronic health record

Abbreviations

SD: Social Determinant; EHR: Electronic Health Records; NLP: Natural Language Processing; NAM: The National Academy of Medicine; MUSC: Medical University of South Carolina; RDW: Research Data Warehouse; I2E: Linguamatics I2E; GPRO: Group Physician Reporting Option; COST: Comprehensive Score for Financial Toxicity; UMLS: Unified Medical Language System; MRN: medical record number; IRB Institutional Review Board for Human Research

Introduction

The social determinants (SD) of health reflect the conditions in the environments in which individuals live, work, and play that contribute to disease risk and health care outcomes; economic issues are an essential component of these determinants [1]. Financial stress is one aspect of economic stability; within the context of health care, financial stress refers to the extent to which patients experience problems covering the costs of medical care [2]. Financial out-of-pocket costs for treatment, as well as indirect costs, such as loss of income and increased caregiver costs [3,4]. Evidence suggests that financial stress negatively affects cancer patients' treatment compliance, health outcomes, quality of life, and survival [5-8]. The National Academy of Medicine (NAM) has advised providers to recognize and discuss cost concerns with patients in order to enhance shared decision-making for treatment and exploration of financial assistant programs [9]. However, financial stress is rarely assessed in clinical practice or research, thus, under-coded and under-documented in clinical practice [10]. Researchers have called for the systematic and prospective collection of financial stress information as well as other SDs using specially designed questionnaires [11]. However, provider workflow and patient engagement are a challenge to such data collections [12]. One alternative is to automatically extract and process data on financial stress from clinical free text existing in the patient electronic health record (EHR) using natural language processing (NLP). NLP is a technique that uses both logical and statistical processes to parse free text and automatically convert those data to a structured format that can be stored in a database and applied in analytics [13]. NLP has been applied successfully for diagnoses, patient safety, clinical decision-making support, and quality performance reporting [14-16]. However, to date, few studies have evaluated the design or efficacy of NLP strategies to identify financial stress from EHR. Herein, we report the development and assessment of an NLP approach for extracting information on financial stress from a large dataset of clinical notes for patients with prostate cancer. We evaluated the NLP algorithm's performance using the current disciplinary gold standard, i.e., manual review by domain experts.

Materials and Methods

Study setting

The study setting was the Medical University of South Carolina (MUSC), an academic medical science center with inpatient, outpatient, and emergency facilities serving Charleston, South Carolina, and surrounding areas. MUSC has had the EpicCare EHR system (Epic Systems Corp., Verona, WI) in place for outpatient care since 2012 and for inpatient care since 2014. A Research Data Warehouse (RDW) copies the Epic data warehouse and serves as the data repository for clinical research. This study tests the feasibility of identifying mentions of financial stressing clinical notes using NLP for a defined population consisting of prostate cancer patients. The MUSC Intuitional Review Board approved the study.

NLP software

We used commercial NLP software (Linguamatics I2E version 5.3, Cambridge, United Kingdom) to index, parse, and query each clinical note. Linguamatics I2E (I2E) applies concept-based indexing techniques to identify keywords/phrases from text documents and electronically map them to concepts in the UMLS Metathesaurus. Then I2E queries retrieve information for reports, meeting a user-defined set of criteria through a user-friendly interface to define syntactic and semantic representations. In previous work using I2E, we abstracted numerator data for the Group Physician Reporting Option (GPRO) quality measure for fall risk assessment. The NLP algorithm identified 62 (of 144) patients for whom a fall risk screen was documented only in clinical notes and, thus, was not ICD coded. A manual review confirmed 59 patients as true positives and 77 patients as true negatives. That NLP approach scored 0.92 for precision, 0.95 for recall, and 0.93 for F- measure [17].

Data source

This study was conducted as part of a transdisciplinary center for precision medicine and minority men's health that is doing translational research in racial disparities in prostate cancer risk and outcomes. To be included in the NLP analysis of financial stress, patients were eligible if they were 18 years of age or older and were diagnosed with prostate cancer (ICD 10 codes: R97.21, D29.1, C61, D40.0) between January 1, 2014, and May 31, 2017. NLP pipelines identifying financial stress were developed via extraction of notes on progress, history and physical, consult, emergency department provider, telephone encounter, discharge summary, and plan of care. A de-identified subject-ID was used to link source documents and data across each patient's records. From 4,195 eligible prostate cancer patients, we randomly sampled 3,138 patients (75%) as a training dataset with 150,990 notes to develop the lexicon and NLP pipelines to detect financial stress mentions. The remaining 1,057 patients (25%) were used as a test dataset that provided 55,516 notes to evaluate NLP algorithm performance.

Development of the lexicon for financial stress

Financial stress is not commonly documented in the EHR, including within clinical notes. To generate an adequate lexicon that appropriately represents financial stress mentions, we relied on components of financial distress that are measured as part of validated instruments (e.g., Comprehensive Score for Financial Toxicity (COST) questionnaire) [18]. Domain experts' knowledge. The initial list of terms was provided by behavioral scientists who have extensive experience with research in health care quality and racial disparities. These terms included "feel financially stressed," "financial problems," "money problems," "difficulty paying," "lack of insurance coverage," "cannot work," "cost," "expenses," and "out-of-pocket medical expenses." Housing insecurity is one of the aspects of economic stability that has implications for financial stress [19]; therefore, we included "assistant house," "low-income housing program," and "Section 8" as the indicators of housing insecurity. However, we did not include "homelessness" because this represents a distinct socioeconomic status among individuals. Using I2E to query these seed terms against the training dataset, the NLP informatics team developed a draft enhanced terminology set consisting of three categories: financial issue, employment issue, and insurance issue (Table 1). For each term, we utilized the I2E morphologic and case variant functions and I2E built-in ontology to generate a set of spelling variants, acronyms, and abbreviations. We then queried these terms against clinical notes to extract any relevant lexical representations iteratively to form an enhanced and refined list. The domain expert and the NLP informatics team came to a consensus agreement, creating the final lexicon. To exclude false mentions of financial distress, we utilized I2E built-in pre- and post-negation, which is a collection of regular terms that are negative mentions (e.g., "no," deny," "negative"), as well as historical events or a family member as the experiencer.

Financial issue
Financial concern/issue/problem/assistence/difficulty/stress/distress/strain/insolvency/hardship/burden/toxicity, bankruptcy, money problem, no money, payment difficulty, economic loss/problem, low income, in debt, indebtedness, unable/inability to afford/cover cost/meet expenses, below poverty line, food stamp, SNAP (Supplemental Nutrition Assistance Program), Section 8, low income housing
Employment issue
unemployed/unemployment, lose job/employment, job/work dissatisfaction/problem/layoff, fired, reduction of workforce
Insurance issue
uninsured, insurance issue, loss insurance/Medicaid/Medicare, limited/lack of insurance coverage, out-of-pocket medical expenses

Table 1: Initial terms of financial stress.

Development of NLP algorithm to identify financial stress

To identify patients with financial stress, we developed a set of I2E queries to identify financial stress mentions in clinical notes using the following criteria: a) mentions of financial stress by the lexicon; and b) excluding financial stress mentions with negations. These I2E queries were designed to capture semantic information, syntactic patterns, and clinical negations in order to translate a documented financial stress to structured data elements including the following: 1) patient medical record number (MRN), 2) financial stress mention(s), 3) author type, 4) note ID, 5) date of document, and 6) type of clinical note. We used I2E 5.3 to index, query, flag, and count the number of query hits within each clinical note. We used all clinical notes in the training dataset to develop an NLP algorithm for each variable. We evaluated the results of the I2E queries independently and in combination against the gold standard of expert chart review. These chart review evaluations were completed independently by two domain experts who were blinded to the I2E query development. Discrepancies between query results and the manual expert review led the informatics team to conduct error analyses and iteratively refine the I2E query algorithms until sensitivity and specificity could not be improved. A multiple I2E query combining these six queries was established to produce a structured output table to store information extracted by the six queries.

NLP algorithm performance evaluation

Using clinical notes in the test dataset (55,516 notes from 1,057 patients), we compared the results generated from the I2E multiple query to the results from the gold standard. Two domain experts further validated the results for positive cases as well as a matched number of negative cases of NLP-detected financial stress by manual chart review. Furthermore, we calculated three standard performance measures for the NLP algorithm: the precision, recall, and F-measure, respectively. Precision (exactness) is the proportion of true positives among the total number of algorithm-identified cases; in contrast, recall (completeness) is the proportion of true positives retrieved by algorithms. Finally, for all false positives and negatives generated by the NLP algorithms, we manually determined and summarized the reasons for false classification to improve the algorithm.

Results

Financial stress lexicon

The training data set contained 150,990 documents from 3,138 patients. The average number of documents per patient was 48 (max: 994; minimum: 1). We developed a set of I2E queries to search the enhanced keywords representing financial stress against these documents. After iterative evaluations between the keywords hit and the original documents, we developed a lexicon of financial stress and negations. The final lexicon presented wide variations (Table 1). Without applying negation, 810 documents were identified as having financial stress mentions for 387 (12.3%) patients. A total of 163 terms (with morphologic and case variants) associated with financial stress were grouped to 30 keywords at the content level (Table 2).

Term	**Count** (%)		**Term**	**Count** (%)	
financial concerns	270	33.3	money problems	9	1.1
unable to afford	69	8.5	SNAP	8	1.0
insurance issues	62	7.7	no money	8	1.0
unemployed	51	6.3	financial stress	7	0.9
financial assistance	45	5.6	financial strain	6	0.7
bankruptcy	43	5.3	cover cost	5	0.6
lost job	38	4.7	low income	4	0.5
economic problems	30	3.7	Work Problems	4	0.5
uninsured	30	3.7	low income housing	4	0.5
food stamps	26	3.2	Section 8	3	0.4
debt	21	2.6	loss of insurance	2	0.2
financial issues	20	2.5	inability to afford	2	0.2
section 8	15	1.9	cannot afford	1	0.1
financial problems	15	1.9	job dissatisfaction	1	0.1
financial difficulties	10	1.2	work problems	1	0.1

Table 2: Financial stress lexicon.

The leading keywords were "financial concerns," "unable to afford," "insurance issue," "unemployed," and "financial assistance." Pre-negation indicators include "denies," "without," and "no," which presented in 15 documents. Post-negation indicators include "none" and "no" presented in 218 documents, which "none" as the answer to "financial concerns" in 216 documents. Most commonly, these instances occurred in progress notes (389), plan of care (236) notes, and telephone encounter notes (44); the most common author types were physician (255), case manager (288), social worker (121), nurse practitioner (37), psychologist (37), and physician assistant (30). After we applied both the pre-and post-negation, the NLP algorithm identified 188 (6% of the training sample) unique patients who had financial stress mention(s) in 530 documents (357 for a financial issue, 94 for employment issue, and 93 for insurance issue). Table 3 shows the association between financial stress identified by the NLP algorithm and racial background and health insurance status. Based on T-test or Chi-square test results (p-value <0.05), patients with NLP identified financial stress were more likely to be African Americans (6% more than White). They were more likely having a younger age at prostate cancer diagnosis and being Medicare/Medicaid beneficiaries.

	Positives	**Negatives**
Number of patient (%)	276 (6.5%)	3,918 (93.4%)
Age at prostate cancer diagnosis	66.8 ± 8.7	70.8 ± 8.8
Race		
White	124 (4.6%)	2,559 (95.4%)
African American	146 (10.4%)	1,257 (89.6%)
Other	6 (5.6%)	102 (94.4%)
Insurance Type		
Commercial	41(6.2%)	617 (93.8%)
Medicaid/Medicare	201(7.2%)	2602 (92.8%)
Other	34 (4.6%)	699 (95.4%)

Table 3: Demographics for financial stress groups.

The multiple I2E query combined six I2E queries and produced a structured output table that extracted a patient's MRN, financial stress mention, the sentences where keywords hit, note type, author type, and note creation date. The output table also provided a link to the original document, which the NLP developer and domain experts could review during the development and evaluation phases (Figure 1). Among 55,516 notes from 1,057 patients in the test dataset, the I2E query identified 161 notes with a likely mention of financial stress from 67 patients (6.2%). Among these 161 NLP identified notes with a financial stress mention, two domain experts' manual review confirmed that 138 notes from 53 patients had a financial stress mention and identified 23 notes as false positives from 13 patients. Two domain experts also manually reviewed 161 notes randomly selected from patients who had no financial stress mention identified by NLP algorithms and confirmed there were no financial stress mentions in these notes. Counting on the document level, the I2E query for financial stress had a precision of 0.86, a recall of 1.0, and an F-measure of 0.92 (Figure 2). We identified major reasons for false positives: a) our NLP approach could not entirely exclude some false financial stress mentions that had no sufficient information to be excluded or included; and b) some terms represented another meaning that was not associated with financial stress (e.g., "sleep debt") (Table 4).

Pre-negation	finanicial issue Ins..	Post-Negation no	NOTE_TYPE	AUTHOR_TYPE	#Docs	Doc	#Hits	Hit
	bankruptcy		progress notes	Physician	31	107840	1	... to having to file for bankruptcy.
	Financial Concerns	none	progress notes	Case Manager	1	70170	1	... cane, straight;commode Financial Concerns: none How will patient obtain meds ...
			progress notes	Case Manager	1	68822	1	... home: cane, straight Financial Concerns: patient cannot afford out ...
	insurance issues		progress notes	Physician	9	23960	2	... 11/2013 due to insurance issues (next dose given in ...
				Physician	1	102734	1	Due to insurance issues, Mr. Maury had a ...
	unable to afford		progress notes	Physician	9	104617	1	... the patient reports he is unable to afford the medication at home.
	Financial Concerns	none	plan of care	Case Manager	1	106952	1	... while in recliner,not always) Financial Concerns none How will patient obtain meds ...
	financially difficulties		discharge summaries	Physician	1	49556	1	As patient had financially difficulties affording home IV antibiotics, ...
	inability to afford		discharge summaries	Physician	1	105739	1	... day course inpatient due to inability to afford home VI abx.
	Money Problems		progress notes	Psychologist	1	108015	1	... Anxiety Burnout Aches / Pains Money Problems Worry Boredom Low Energy Thoughts ...
	money problems		progress notes	Psychologist	1	101496	1	... regretted later I have had money problems because of my drinking or ...
	unemployed		plan of care	Case Manager	1	106952	1	... Financial Employment Status disabled;unemployed (oversees farm/hunting ...
	Work Problems		progress notes	Psychologist	1	108015	1	... Others Guilt Anger Sleep Problems Work Problems Anxiety Burnout Aches / Pains ...
	financial assistance		telephone encounter	Social Worker	2	6324	1	... enquiring about community agencies for financial assistance.
	economic problems		progress notes	Physician	5	104699	1	Axis IV: economic problems, other psychosocial or environmental ...

Figure 1: Example of I2E query output.

Unable to determine
Change in income or financial concerns?
Employment Status: Working. Unemployed. Disabled.
Financial Concerns: Unable to determine at this time.
Financial Concerns: Aetna Medicare
Any current financial concerns? No. Yes.
Financial Concerns (patient has Medicare A&B and American)
Missed post-negation
FINANCIAL Issues: No known issues
Keyword has another meaning
1–urgency, 0–weak stream 0 debt straining, 2–nocturia
apnea as well as sleep debt
obstructive sleep apnea and sleep debt
Insurance issues - Mr. Abdul Malik expressed concern that his insurance will/may be changed

Table 4: Examples of false positives of NLP identified financial stress.

	NLP algorithm	
Gold standard	positive	negatives
positives	138 (TP)	0 (FN)
negatives	23(FP)	161 (TN)

Precision = TP/(TP + FP) = 138/(138+23) = 138/161=0.86
Recall = TP/(TP+FN) = 161/(161+0) = 161/161 = 1
F-measure = 2*precision*recall/(precision + recall)
= 2*0.86*1/(0.86+1)=0.92
*TP=true positive; FP=false positive; FN=false negative; TN=true negative.

Figure 2: Results of manual review and I2E algorithm.

Discussion

The main finding of this study is that NLP can accurately extract evidence of financial stress from clinical documents, which is usually underrepresented or absent in coded form. To the best of our knowledge, this study is the first to develop and evaluate an NLP strategy for identifying financial stress information from clinical narratives for cancer patients. Patients with cancer commonly experience considerable financial costs; however, financial stress is rarely assessed in clinical practice or research. As our results indicate, although both ICD 9 and ICD 10 have standard codes ('Z59.9', 'V60.9') to represent financial related problems (another linguistic representation of financial stress), financial stress is not adequately documented in the EHR unlike other findings in clinical domains. In our study, among three-year longitudinal structured data for more than 4,000 prostate cancer patients, we could not find any patients with an ICD10 or ICD9 code recorded for a financial problem. However, by utilizing NLP strategies, we found that 12.3% of prostate cancer patients had conversations about financial stress with their providers documented in clinical notes. This low percentage is consistent with the previous observation that financial stress is usually not addressed as part of delivering cancer care services. However, among the patients in our study who had conversations with providers about financial stress, 50% had documented evidence of their financial stress in clinical notes. This finding parallels patient-survey evidence in the literature that cancer patients have a high prevalence (20-48%) of financial stress [5,20]. Although the impact of social determinants, including financial stress, are increasingly recognized, implementation of EHR-based approaches for SD data collection is still in the early stage. The conventional way to obtain financial stress data is to use instruments that prospectively collect information outside clinical practice through selected population-specific studies. NLP strategies started developing more robust approaches; a recent study reported that 8.3% of hospitalized patients had documented evidence of financial problems from clinical notes using an NLP approach [21]. Our findings also demonstrate that NLP-identified evidence of financial stress obtained from clinical notes can be used as a potential data source when coded data is not available or insightful, and when prospective data collection is not feasible for clinical practice or research.

The automatic extraction of financial stress information is challenging because of the lack of documentation standards and diverse lexicon representations. The NAM defined four sub-domains for financial resource strain, including employment insecurity, income insecurity, housing insecurity, and food insecurity. The semantic representations of those subdomains guided the lexicon and NLP algorithm development for financial stress. The Comprehensive Score for Financial Toxicity (COST), an instrument specifically designed for cancer patients, provides validated statements and terms to measure financial stress [18]. In addition, standard terminologies, such as SNOMED-CT and MESH, include a broad array of terms with the full coverage of medical specialties. Those methodologies also can guide data extraction from clinical notes. However, we anticipated a discrepancy with the lexical presentation of financial stress in clinical notes because providers commonly document the notes as natural language. Therefore, just examining standard terminology or using terms identified from such instruments may miss important information embedded in clinical notes. In our study, "financial concerns," "unable to afford," and "insurance issue" were suggested by domain experts and are the most common terms identified from clinical notes; however, none of them were included in instruments or SNOMED/MESH. Moreover, the SNOMED concept, "financial problem," "financial stress," and "bankruptcy," were present in clinical notes yet with modest frequency. Similarly, "food insecurity" and "housing instability" are important measures for financial stress defined by the NAM; however, in our study, they are not the most common measures identified from clinical notes. Because the lexicon generated from our current study combines standard concepts and domain expert knowledge, our approach offers a complete data extraction method. Another challenge is that clinical notes do not always follow standard grammar and format. Although our NLP algorithms maximally mimic a common way that providers document financial stress, false positives are inevitable. For example, "financial concerns" may represent an incidence ("Dose held due to financial concern," "The patient-reported financial concerns related to transplant"), or a question or topic ("Financial Concerns: Aetna Medicare," "Financial Concerns (patient has Medicare A&B and American)," "Financial Concerns: Unable to determine at this time"). Our NLP algorithm could not tell if those mentions related to financial stress based on the following information. Because financial stress is not commonly recorded in the EHR, we sought to develop a highly sensitive NLP algorithm that avoids false negatives by sacrificing specificity. After iterative evaluation and refinement, our final I2E algorithm achieved 0.86 precision and 1.0 recall, which indicated that our NLP approach could effectively identify financial stress when such information is available in clinical notes.

Limitations

This study has several potential limitations that should be considered. First, this study only included prostate cancer patients at a single academic medical center in the United States. Our lexicon and NLP algorithms may not be generalizable to other populations with different diseases or other academic medical centers or community health care systems. Secondly, our study population (prostate cancer patients) are male-only; recent studies have demonstrated that females report feeling considerably more financial stress than males, and women almost always report more negative feelings about the cost [22]. Therefore, the lexicon of financial stress developed from male patients' clinical notes may not completely and accurately reflect concerns from female patients. Finally, we developed a highly accurate NLP approach to extract financial stress from clinical notes. However, we remain cautious about claiming an NLP determinant for the prevalence of financial stress that we detected in patients with prostate cancer because the majority of subjects in our database have no evidence of financial stress conversation in either coded data or clinical narratives.

Conclusions

Financial stress information is not commonly documented in the EHR, neither in structured format nor in clinical narratives. However, natural language processing can accurately extract financial stress information from clinical notes when such narrative information is available.

Ethics approval and consent to participate

This study was approved as a secondary analysis of existing clinical data by the Institutional Review Board for Human Research (IRB) at MUSC (reference number:

Pro00067144). MUSC IRB waived the need for informed consent since this study did not involve subject recruitment, and the participants were not be provided information about their study participation.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author (VZ) on a reasonable request.

Competing interesting

None of the authors has any competing interests.

Funding

This research was supported in part by NIH grants (NIMHD1U54MD010706-01, NCATS 5UL1TR000062-05, and NIDA 2K12DA031794-06A1) to the Medical University of South Carolina.

Authors' Contributions

VZ participated in literature research, study design, data analysis/interpretation, and manuscript preparation. LL participated in study design and data analysis/interpretation. BB, JO, and MJ participated in study design and data analysis. CHH led the manuscript definition of intellectual content, study design, and manuscript preparation. All authors read and approved the final manuscript.

References

1. Healthy People 2020 (2020) Social determinants of health.
2. National Cancer Institute (2018) NCI's dictionary of cancer terms.
3. Stump TK, Eghan N, Egleston BL, et al. (2013) Cost concerns of patients with cancer. J Oncol Pract 9(5): 251-257.
4. O'Connor JM, Kircher SM, de Souza JA (2016) Financial toxicity in cancer care. J Community Support Oncol 14(3): 101-106.
5. Zafar SY, McNeil RB, Thomas CM, et al. (2015) Population-based assessment of cancer survivors' financial burden and quality of life: A prospective cohort study. J Oncol Pract 11(2): 145-150.
6. Lathan CS, Cronin A, Tucker-Seeley R, et al. (2016) Association of financial strain with symptom burden and quality of life for patients with lung or colorectal cancer. J Clin Oncol 34(15): 1732-1740.
7. Neugut AI, Subar M, Wilde ET, et al. (2011) Association between prescription co-payment amount and compliance with adjuvant hormonal therapy in women with early-stage breast cancer. J Clin Oncol 29(18): 2534-2542.
8. Ramsey SD, Bansal A, Fedorenko CR, et al. (2016) Financial insolvency as a risk factor for early mortality among patients with cancer. J Clin Oncol 34(9): 980-986.
9. Zafar SY (2015) Financial toxicity of cancer care: It's time to intervene. J Natl Cancer Inst 108(5).
10. Zafar SY, Peppercorn JM, Schrag D, et al. (2013) The financial toxicity of cancer treatment: A pilot study assessing out-of-pocket expenses and the insured cancer patient's experience. Oncologist 18(4): 381-390.
11. Hripcsak G, Forrest CB, Brennan PF, et al. (2015) Informatics to support the IOM social and behavioral domains and measures. J Am Med Inform Assoc 22(4): 921-924.
12. Boonstra A, Broekhuis M (2010) Barriers to the acceptance of electronic medical records by physicians from systematic review to taxonomy and interventions. BMC Health Serv Res10: 231.
13. Friedman C, Hripcsak G (1999) Natural language processing and it's future in medicine. Acad Med 74(8): 890-895.
14. Demner-Fushman D, Chapman WW, McDonald CJ (2009) What can natural language processing do for clinical decision support? J Biomed Inform 42(5): 760-772.
15. Melton GB, Hripcsak G (2005) Automated detection of adverse events using natural language processing of discharge summaries. J Am Med Inform Assoc 12(4): 448-457.
16. Pons E, Braun LM, Hunink MG, et al. (2016) Natural language processing in radiology: A systematic review. Radiology 279(2): 329-343.
17. Zhu V, Tina D Walker, Robert W Warren, et al. (2017) Identifying falls risk screenings not documented with administrative codes using natural language processing. AMIA Annu Symp Proc.
18. De Souza JA, Yap BJ, Wroblewski K, et al. (2017) Measuring financial toxicity as a clinically relevant patient-reported outcome: The validation of the Comprehensive Score for financial Toxicity (COST). Cancer 123(3): 476-484.
19. Stahre M, VanEenwyk J, Siegel P, et al. (2015) Housing insecurity and the association with health outcomes and unhealthy behaviors, Washington State, 2011. Prev Chronic Dis 12.
20. Gordon LG, Walker SM, Mervin MC, et al. (2017) Financial toxicity: A potential side effect of prostate cancer treatment among Australian men. Eur J Cancer Care (Engl) 26(1).
21. Greenwald JL, Cronin PR, Carballo V, et al. (2017) A novel model for predicting rehospitalization risk incorporating physical function, cognitive status, and psychosocial support using natural language processing. Med Care 55(3): 261-266.
22. Sharf S (2018) Struggling to take control of personal finances.

***Corresponding author:** Vivienne Zhu, MD, MS, Biomedical Informatics Center, Medical University of South Carolina, Charleston, South Carolina, United States; Email: zhuv@musc.edu

Received date: February 25, 2020; **Accepted date:** March 04, 2020; **Published date:** March 05, 2020

Citation: Zhu V, Lenert L, Bunnell B, Obeid J, Jefferson M, Halbert CH (2020) Automatically Identifying Financial Stress Information from Clinical Notes for Patients with Prostate Cancer. *Cancer Res Rep* 1(1): 102.