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Using natural language processing to classify social work interventions

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Abstract

Objectives—Healthcare organizations are increasingly employing social workers to address patients' social needs. However, social work (SW) activities in healthcare settings are largely captured as text data within electronic health records (EHR), making measurement and analysis difficult. This study aims to extract and classify, from EHR notes, interventions intended to address patients' social needs using natural language processing (NLP) and machine learning (ML) algorithms.

Study Design and Methods—We extracted 815 SW encounter notes from the EHR system of a federally qualified health center (FQHC). We reviewed the literature to derive a 10-category

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classification scheme for SW interventions. We applied NLP and ML algorithms to categorize the documented SW interventions in EHR notes according to the 10-category classification scheme.

Results—Most of the SW notes (n=598; 73.4%) contained at least one SW intervention. The most frequent interventions offered by social workers included care coordination (21.5%), education (21.0%), financial planning (18.5%), referral to community services and organizations (17.1%), and supportive counseling (15.3%). High performing classification algorithms included the kernelized support vector machine (SVM; accuracy=0.97), logistic regression (accuracy=0.96), the linear SVM (accuracy=0.95), and Multinomial Naive Bayes classifier (accuracy=0.92).

Conclusion—NLP and ML can be utilized for automated identification and classification of SW interventions documented in EHRs. Healthcare administrators can leverage this automated approach to gain better insight into the most needed social interventions in the patient population served by their organizations. Such information can be applied in managerial decisions related to SW staffing, resource allocation, and patients' social needs.

Précis:

Natural language processing can be used for automated extraction of social work interventions from electronic health records, thereby supporting social work staffing and resource allocation decisions

Keywords

Social work intervention; Natural Language Processing; Machine Learning; Deep learning; Neural networks

INTRODUCTION

Traditionally, efforts to improve health outcomes have primarily focused on medical care services.[1] However, consistent evidence suggests that social needs and risk factors have a more profound effect on individual and population health than medical care.[2–5] Given their professional training and workflows, social workers within health care settings are uniquely positioned to deliver interventions to address patients' social needs.[6] Moreover, social workers are increasingly becoming embedded in healthcare organizations to help address patients' social needs.[7] However, tracking and evaluating interventions instituted by social workers remains challenging, since social work (SW) interventions are largely documented as unstructured text data within electronic health records (EHR)[8,9]. Unstructured documentation makes it difficult to systematically monitor and study SW interventions and services - as manual chart reviews are expensive, time-consuming, and often require expert reviewers.[10–12] These limitations underscore the need for using novel information extraction methods, such as natural language processing (NLP) and machine learning (ML), to identify and classify interventions documented in unstructured EHR notes such as SW notes.

Existing research has been successful in using NLP methods to identify and classify social needs with EHR data. Dorr et al[13] demonstrated that NLP could be used to identify chronic stress, social isolation, financial insecurity, and housing insecurity in the clinical notes of primary care doctors. Conway et al[14] developed the Moonstone system, which used rule-based classification to identify housing situations and social support within EHRs. Also, Cook et al[15] used NLP and ML techniques to predict suicidal ideation from a text message intervention. These studies demonstrated the feasibility and applicability of using NLP approaches to detect social needs and risks in unstructured clinical data. Although few studies have developed classification schemes for SW interventions using manual chart reviews, no study has sought to utilize NLP methods to identify and/or classify SW interventions.[16–21]

The purpose of this study was to extract and categorize SW interventions aimed at addressing patients' social needs by developing and applying NLP and ML algorithms. Development of such classification tools supports healthcare organizations' assessment and measurement of a growing part of the non-medical workforce. Additionally, this study highlights the methodological approaches to examine SW interventions in situations where only unstructured data are accessible. Healthcare organizations armed with data on SW interventions instituted on their patient population will make more informed resource-allocation, staffing, quality improvement, and program design decisions to address their patients' social needs. Moreover, automation of the classification of interventions will offer stakeholders an enhanced ability to quantify the specific impact of social workers' interventions on patients' health outcomes.

METHODS

We developed a classification scheme from the literature[16–21] to categorize interventions instituted by social workers to address patients' social needs at Eskenazi Health, an urban safety-net health system. Eskenazi Health employs in-house social workers to address patients' social needs. These needs are identified through multiple pathways. For example, physicians and nurse practitioners may identify patients' social needs during consultations and refer patients to social workers. Additionally, social workers may review records of patients with scheduled appointments to identify social needs.

We used NLP and ML algorithms for automated categorization of SW interventions based on the classification scheme we developed. Figure 1 describes, in brief, the process and pipeline used for this classification (see Appendix 1). This study is approved by the Indiana University Institutional Review Board.

Setting & Sample

We used patient record data from Eskenazi Health, a safety-net provider with a 300-bed hospital and a federally qualified health center (FQHC) serving the Indianapolis, IN metropolitan area. The study sample included 408 adult patients (≥18-year-old) with 815 SW encounters between October 1, 2016 and September 30, 2019.

Data

The study data were derived from Eskenazi Health's EHR (Epic). The EHR data included patients' clinical notes and their demographic and clinical characteristics. We obtained unstructured data containing free-text descriptions of the reason(s) for patient visits, the intervention(s) instituted by the social worker, and future visits or engagement plans from social workers' notes. We extracted SW notes, using an existing pipeline (nDepth[22]), by searching clinical notes for the following search terms: "social work" or "MSW" or "LCSW", or "LSW", or "LMSW", or "LBSW." nDepth, an NLP tool developed by the Regenstrief Institute, conducts information retrieval and extraction from textual documents by adapting its existing pipeline to customizable search queries. nDepth has been used in other clinical domains, including gastrointestinal diseases and sarcopenia.[23,24] For this study, nDepth was used to extract a sample of SW notes from the EHR. Our search with nDepth retrieved 1,289 clinical notes. Three abstractors (AB, HT, KW) manually reviewed the retrieved notes and categorized them into notes written by a social worker and notes written by other professionals. Notes were deemed as written by a social worker if they were signed off by a social worker, or if the wordings and structure of the notes clearly indicate documentation of activities by a social worker. The final sample for this study included 815 SW encounters with notes that were determined to be written by social workers during distinct SW encounters (see Appendix 2 for details and examples).

Three members of the research team (AB, HT, and KW) developed a classification scheme for SW interventions, which was derived based on literature review and expert consultations, with 10 non-mutually exclusive categories of SW interventions briefly defined as follows:

- **Financial planning:** resources for funding medications, treatment, or other care[25]
- **Supportive counseling:** emotional and mental health support services; addiction services[26]
- **Care coordination:** coordination of care continuity, case management, arranging and coordinating home visits[27]
- **Education:** health/wellness programs, crisis intervention, course planning[28]
- **Community service:** referrals to community, spiritual, and peer advocacy organizations; translational services; food assistance; clothing assistance[29]
- **Applications and reporting**: Help with filing applications, filing mandatory reports such as the Department of Child Services (DCS) reporting and the Adult Protective Services (APS) reporting
- **Housing**: Shelter provision, help with housing.
- **Transportation:** provision of transportation fares and passes; linkage with transportation services.
- **Durable Medical Equipment:** provision of medical equipment; repair, maintenance, and/or replacement of medical equipment
- **Legal:** Link to attorneys, law enforcement, and other legal services

Inspired by the ConText algorithm,[30] three coders (AB, HT, and KW) independently reviewed 100 randomly selected SW notes to identify verbs likely to indicate the presence of SW interventions in a sentence. The abstractors also identified contextual terms and negation terms associated with each verb, used to describe a social worker (social worker terms), as well as unique terms that map to each of the 10 intervention categories (see Appendix 3 and 4 for lexicon of terms). The abstractors manually coded the selected notes into their respective non-mutually exclusive SW intervention categories. We calculated the rate of agreement between the three coders using Fleiss's kappa coefficients (see Appendix 5).

Analysis

To categorize the notes based on our 10-category scheme, we used 1) Rule-based classification algorithms using Python's regular expressions[31]; 2) ML algorithms such as the multinomial Naive Bayes Classification algorithm[32] and multi-label (One Vs Rest, Binary Relevance, Classifier Chains, and Label Powerset)[33,34] classification algorithms using Logistic Regression[33] and Kernelized Support Vector Machine (SVM) with radial basis function;[35] and 3) a deep learning algorithm for multilabel classification: the Long Short-term Memory (LSTM) recurrent neural network with a sigmoid activation function and binary cross-entropy loss function.[36] The LSTM model has a single input layer, an embedding layer, one LSTM layer with 128 nodes, and one output layer with 10 nodes, with each node in the output dense layer representing one of the SW intervention categories.

For the rule-based algorithm, we used Python's[31] in-built regular expressions to extract sentences that include a social worker term and one of the intervention verb terms, where the verb term is not preceded by one of the negative-lookbehind terms for intervention and not followed by one of the negative-lookahead terms. A review of SW notes and consultation with clinical social workers revealed that these sentences are likely to contain information about the type of intervention instituted. A SW note was deemed to indicate the presence of an intervention category if the extracted sentences in the note also contain at least one of the intervention key terms for that category.

For the implementation of the ML and deep learning algorithms, we randomly divided the data into training (68%), validation (12%), and test (20%) sets. (see Figure 1). We preprocessed the text in each of these datasets as follows: we tokenized sentences in each SW note into individual words (tokens), removed stop words (e.g. one- and two-letter words, compositions, and prepositions), applied part of speech tagging to the tokens, and stemmed the tokens down to their root words. Next, for implementation of the ML algorithms, we created feature vectors using the term frequency-inverse document frequency (tf-idf) vectorizer with single words (unigrams), two consecutive words (bigrams), and three consecutive words (trigrams). Relatedly, For the LSTM model, we created word embeddings using the GloVe word embeddings[37] to convert text inputs to their numeric counterparts.

We used the preprocessed feature vectors (or word embeddings in case of the LSTM model) from the training dataset to initially train each classifier and the validation dataset to test the accuracy of the trained classifier. We implemented multiple iterations of training and validation for each classifier while tuning and optimizing the hyperparameters of the classification algorithm to attain higher accuracy. Upon achieving the highest accuracy score possible for each classifier, we coalesced the training and validation sets and trained a final classifier on them using the optimal hyperparameters. We also used 5-fold cross validation to evaluate the performance of the logistic regression, kernelized SVM, linear SVM, and multinomial Naive Bayes algorithms on the full training data (see Appendix 6A and 6B).

Finally, for each intervention category, we evaluated the performance of the rule-based, logistic regression, kernelized SVM, linear SVM, and multinomial Naive Bayes algorithms on test data using accuracy; precision or positive predictive value (PPV); recall (sensitivity); F1-score, which is the harmonic mean of precision (PPV) and recall (sensitivity); specificity; and area under the curve (AUC).

RESULTS

Our final sample included 408 patients with 815 SW encounters. Descriptive information about the sample and categories of social worker interventions is available in Appendix 7. Briefly, 43% of the patients were Hispanic; the mean age was 38.7 years; and the majority were female (64%).

Of the 815 SW encounters, the majority (n=598; 73.4%) contained at least one SW intervention. More specifically, 217 (26.6%) did not include any description of a SW intervention, 295 (36.2%) included one SW intervention, 207 (25.4%) included two interventions, and 96 (11.8%) included three or more interventions. The highest number of interventions in a single SW note was six, which was observed in only 5 of the 815 encounters. The most common SW interventions in the notes included: care coordination (21.5%), education (21.0%), financial planning (18.5%), referral to community services and organizations (17.1%), and supportive counseling (15.3%; Table 1).

Models with the highest accuracy included multilabel (One Vs Rest) classifier with kernelized SVM (accuracy=0.97), multilabel (One Vs Rest) classifier with logistic regression (accuracy=0.96), linear SVC (accuracy=0.95), and Multinomial Naive Bayes classifier (accuracy=0.92; see Appendix 9). Precision (PPV) score was generally higher than the recall (sensitivity) score in the kernelized SVM, logistic regression, and Linear SVM for most of the intervention categories (Table 2a and 2b). However, for the multinomial Naive Bayes classifier, the recall score was higher than the sensitivity score in financial planning, care coordination, community service, and education intervention categories. Moreover, the multinomial Naive Bayes classifier offered the highest recall scores for the financial planning (recall=0.86) and community service categories (recall=0.92; Table 2b). Linear SVM provided the best evaluation metrics for the financial planning category (accuracy=0.96, precision=0.91, recall=0.91, F1-score=0.91, specificity=0.98, AUC=0.94). The F1-scores for the logistic regression and kernelized SVM algorithms in the care coordination, community services, and transportation categories were high (0.82–0.94). The multinomial Naive Bayes algorithms had the worst F1-score (0.00) in the legal intervention category. Linear SVM offered the best evaluation metrics for the housing (accuracy=1.00, precision=1.00, recall=1.00, F1-score=1.00, specificity=1.00, AUC=1.00) and durable medical equipment category (accuracy=0.99, precision=0.80, recall=1.00, F1-score=0.89, specificity=0.99, AUC=0.90; see Tables 2A–2C)

DISCUSSION

This study described the extent and nature of SW activities in primary care using NLP algorithms. These findings illustrate the key roles social workers play in connecting patients to other aspects of the health care systems, brokering connections with non-health care related organizations, as well as providing patient education.

As brokers, social workers link patients to critically needed resources and services.[38,39] This "broker" function was evident in our study, where care coordination interventions and referrals to community based organizations were frequently offered. SW interventions require "brokering" services for patients between different organizations/providers, maintaining communication, and identifying needed resources from referral partners. These efforts may lead to improved clinical outcomes. For instance, Bronstein et al[40] found that social worker involvement in post-discharge care coordination, which involved directing patients to organizations that address food insecurity, clothing, and peer-advocacy needs, was associated with fewer 30-day hospital readmissions. Pruitt et al[41] showed that referrals to community-based organizations offered by social workers were associated with lower healthcare costs.[41] Our study provided evidence that social workers in primary care offer interventions known to aid health care organizations' efforts to improve quality of care, reduce costs, and effectively manage population health. We intend to investigate the value of SW interventions towards improving quality outcomes in our future studies.

In our study, social workers educated patients, in 21% of encounters, about the availability of resources and interpretation of medical information. Patient education contributes significantly towards better health outcomes.[42] The role of social workers as providers of patient education, thus, highlights the significance of social workers in primary care teams. Also, financial planning, which involves assisting patients with medication, insurance, and benefits, was a common SW intervention in this study. Similar to previous studies,[38,43] our study found that social workers primarily address the impact of finances on healthcare access by providing assistance with medication, insurance, and benefits, rather than directly providing monetary assistance.

Social workers are the largest providers of mental health services in the United States.[44] In Indiana, social workers can offer a wide range of mental health services, including counseling and treatment for substance use, provided they obtain a state license to practice mental health.[45] However, some authors have opined that social workers employed in healthcare settings may not have the time to directly provide mental health services, given the need to frequently coordinate and allocate resources for these patients.[38,46] For example, in a study on diabetic patients, Rabovsky et al[38] found that social workers did not directly address patients' mental health issues. Rather, they referred patients to mental health providers. The practice pattern and/or expertise of the social workers in Rabovsky et al[38] may explain why social workers outsourced counseling interventions to external organizations rather than providing the counseling services themselves. In our study, social workers addressed mental and behavioral health issues by directly providing supportive counseling interventions to patients. Thus, it is conceivable, given our findings, that social workers can multi-task and interchange roles, thereby providing patients in healthcare settings with direct counseling and tangible resources or referrals. Finally, in previous studies, the nature of the advocacy role of social workers was not evident and underexplored.[38,39,47] However, in our study, we found that social workers helped patients in completing and filing insurance coverage or housing applications and reporting child and adult domestic issues to the appropriate social agencies. This highlights the role of social workers as patient advocates, particularly for those most vulnerable.

Similar to the findings of and Pooler et al.,[47] we found that approximately two-fifths of the SW notes included more than one SW intervention, indicating that a substantial number of patients have co-occurring social needs.[47] The presence of a sizable proportion of patients receiving multiple social interventions indicates the need for effective SW staffing and differential use of more experienced social workers to manage patients with co-occurring social needs.

Although unstructured free-text narratives within EHRs are conducive to NLP- and ML-based classification methods, previous research suggests that social needs interventions are rarely explored using these methods.[11,16–21] Our study shows that NLP and ML can effectively be used to determine the types of SW interventions suggested by social workers operating within healthcare systems. Consistent with the findings of previous studies, ML- and deep learning -based classification algorithms performed better than rule-based classification methods.[48,49] However, the multilabel LSTM model did not perform as well as some ML approaches. This finding may be due to the small sample size in this study, as deep learning algorithms are known to perform poorly when sample size is small.[50]

This study has several limitations. First, although we derived our SW intervention categories from consultation with experts and peer-reviewed literature, our classification scheme may not be exhaustive. Second, the small nature of our sample may limit the performance of our classification algorithms on new test data. However, for most of the intervention categories our evaluation metrics are satisfactory. In addition, our models were trained using data from a single health system, which weakens the generalizability of our findings to other hospital systems or other diverse populations. Lastly, the range of intervention categories and their relative frequencies in this study may be a reflection of the characteristics of the population under study and/or the practice pattern of the social workers in our study site, rather than the general primary care population.

CONCLUSION

Contextual details of interventions instituted by social workers, which are available in EHR notes, highlight how social needs are addressed by social workers. NLP and ML can be utilized for automated identification and classification of SW interventions documented in EHRs. These methods have the advantage of being scalable and can be automated and integrated into EHR systems. Thus, NLP and ML can be leveraged by healthcare administrators to gain better insight into the most needed social interventions in their patient populations, thereby helping organizations make better decisions related to SW staffing, resource allocation, and patient’s social needs.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Take-Away Points:

Social work interventions are increasingly important in health care.

- Most of the social work notes examined in this study contained at least one social work intervention. In approximately 37% of social work notes, more than one intervention was identified, underscoring the need to address coexisting social needs among a sizable population.
- The most frequent social work interventions offered included care coordination, education, financial planning, referral to community services and organizations, and supportive counseling.
- NLP and ML are inexpensive tools for automated identification and classification of social work interventions.
- This automated identification can support managerial decisions related to social worker staffing and allocation of resources to address patients' social needs.

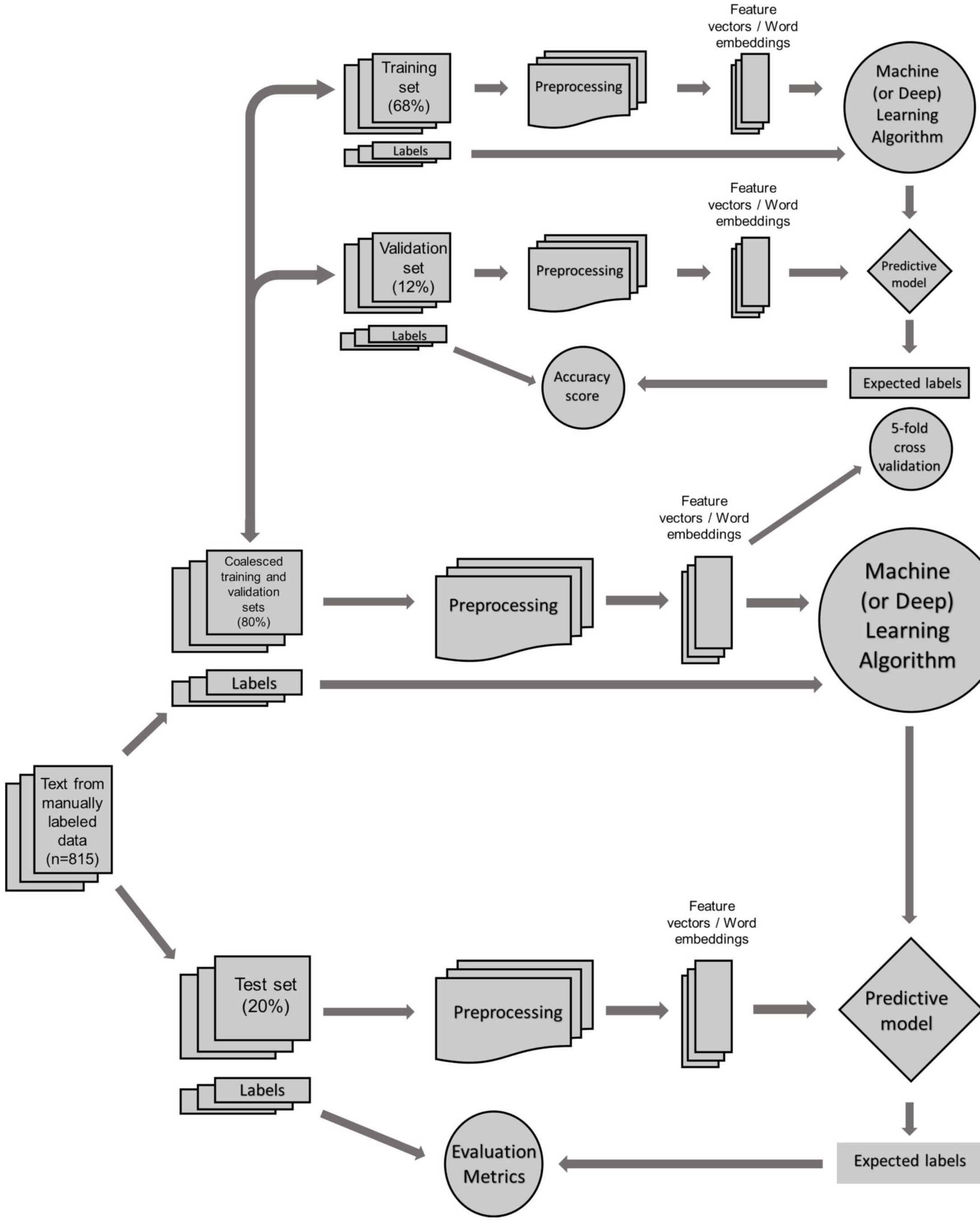

Figure 1.
Classification algorithm pipeline

Table 1:

Social interventions offered by social workers

Interventions	Frequency (%) (N=815)	Examples of social work note
Financial Planning	151 (18.5)	• SW provided a medication voucher for patient for the needed medications • SW provided $100 in TCC gift cards • SW submitted a new contingency form and verified with the pharmacy that mom had received patient's medication. • MSW also obtained approval from SW leadership to assist with the cost of the patient's prescriptions.
Care coordination	175 (21.5)	• SW will follow up with the Neuropsychiatric department to ensure the patient is scheduled for an evaluation. • SW met with physician to discuss case. • SW submitted home health referral • Social worker will continue to follow the patient and family towards developing an appropriate discharge plan. • SW completed and faxed a referral for a public health nurse home visit. • SW has sent message to provider to see if she will proceed to order the rehab and if it is to be outpatient or home based. • SW sent fax referral for patient to be evaluated by Neuropsychiatry as well
Community Service	139 (17.1)	• Completed referral to safe sleep program in order for patient to get a crib for baby. • Brief home visit today to provide Christmas gifts to patient and family donated by GRACE team. • SW referred the family to NACS for assistance • Social work -placed online referral to CICOA to see if they are able to assist.
Education	171 (21.0)	• SW provided [the] mother with resource information for the Downs Syndrome Indiana group. • Social worker informed patient of the team's recommendation for SAR • SW expressed understanding and educated mom and dad on the benefits of CSHCNS as supplemental insurance • Patient was provided a list of detox/in/outpatient services. • Social Worker educated patient on the therapy services hospice agency offers to deal with grief & loss
Supportive Counseling	125 (15.3)	• SW offered counseling and problem-solving to assist and patient agreed. • SW will provide individual therapy to address patient's active symptoms of depression by exploring cognitive distortions through Cognitive Behavioral Therapy and creating self-soothing techniques • Social worker provided behavioral management of pain • Patient seen for CBT for depressed mood. • SW offered grief counseling and problem-solving techniques • SW also offered counseling and problem-solving to assist and patient agreed. • SW processed coping strategies as well as discussed mother's supports. • SW provided supportive listening and gave pt resource for EMBRACE to have support for medical diagnoses.
Applications and Reporting	101 (12.4)	• SW placed call to FSSA to follow up on patient's application. • SW assisted mother with filing DCS report • SW will also follow up with APS • SW filed a 310 for communication with DCS • SW placed call to FSSA to follow up on patient's application. • Social worker phoned APS to inquire about the status of patients APS investigation.
Housing	39 (4.8)	• A cot was secured [for patient] at Wheeler Mission for Women • SW followed up on lodging accommodations which are serving pt and brother • Social work discussed housing options with patient • Provided patient with a subsidized housing list. • SW provided lodging and parking to patient
Transportation	90 (11.0)	• Social work assisted patient with finding the appropriate route for transportation through Indygo • Bus pass provided [by SW] • Patient was provided an all-day bus pass for transportation home at discharge. • Social work authorized yellow cab voucher to take patient to hospital- • SW discussed and received approval from Manager to use Airline donated tickets for the family to utilize.
Durable Medical Equipment	37 (4.5)	• Discussed with MD and received DME order for hospital bed. • SW is currently working on a hospital bed for patient • Social worker faxed order, facesheet, and progress notes to Community DME for wheelchair assistance • SW confirmed with the daughter that the raised toilet seat did get delivered. • SW received the order for patient's wheelchair cushions.
Legal	26 (3.2)	• SW provided mother with contact and resource information for Legal Aid • SW encouraged patient to follow up with police • SW referred patient to medical legal services to see if this is able to be expunged

Interventions	Frequency (%) (N=815)	Examples of social work note
		• SW referred patients to Medical Legal Partnership to evaluate the possibility of changing patient's immigration status. • SW left a message for patient's case manager to call back to reinforce need for pt to receive meds while in jail

Table 2a:

Evaluation metrics for logistic regression and kernelized SVM algorithms

	Logistic Regression						Kernelized Support Vector Machine (SVM)					
Performance Metrics	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**Specificity**	**AUC**	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**Specificity**	**AUC**
Financial Planning	0.95	1.0	0.73	0.85	1.00	0.87	0.95	1.00	0.73	0.85	1.00	0.87
Care coordination	0.93	0.89	0.89	0.89	0.98	0.93	0.96	0.89	0.89	0.89	0.98	0.94
Community Service	0.96	0.85	0.81	0.83	0.98	0.89	0.96	0.89	0.76	0.82	0.99	0.87
Education	0.93	1.0	0.63	0.77	1.00	0.81	0.96	1.00	0.74	0.85	1.00	0.87
Supportive Counseling	0.98	1.0	0.89	0.94	1.00	0.94	0.98	1.00	0.89	0.94	1.00	0.94
Filing Applications and Reporting	0.95	1.0	0.55	0.71	1.00	0.78	0.95	1.00	0.56	0.71	1.00	0.78
Housing	0.98	1.0	0.71	0.83	1.00	0.85	0.99	1.00	0.71	0.83	1.00	0.86
Transportation	0.96	1.0	0.70	0.82	1.00	0.84	0.96	1.00	0.70	0.82	1.00	0.85
Durable Medical Equipment	0.99	1.0	0.66	0.8	1.0	0.83	0.99	0.67	0.67	0.67	0.99	0.83
Legal	0.99	1.0	0.5	0.67	1.0	0.75	0.99	1.00	0.50	0.67	1.00	0.75

Table 2b:

Evaluation metrics for multinomial NB and linear SVM algorithms

	Multinomial Naive Bayes Model						Linear Support Vector Machine (SVM)					
Performance Metrics	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**Specificity**	**AUC**	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**Specificity**	**AUC**
Financial Planning	0.91	0.75	0.86	0.80	0.92	0.85	0.96	0.91	0.91	0.91	0.98	0.94
Care coordination	0.85	0.52	0.85	0.65	0.85	0.75	0.90	0.76	0.50	0.60	0.97	0.84
Community Service	0.89	0.58	0.92	0.71	0.88	0.78	0.94	0.79	0.79	0.79	0.96	0.88
Education	0.87	0.65	0.71	0.68	0.91	0.79	0.88	0.70	0.68	0.69	0.93	0.81
Supportive Counseling	0.91	0.89	0.68	0.77	0.99	0.92	0.93	0.88	0.60	0.71	0.99	0.91
Filing Applications and Reporting	0.89	0.57	0.57	0.57	0.94	0.75	0.94	0.89	0.89	0.89	0.75	0.88
Housing	0.98	0.75	0.60	0.67	0.99	0.87	1.00	1.00	1.00	1.00	1.00	1.00
Transportation	0.95	0.92	0.63	0.75	0.99	0.94	0.97	0.92	0.79	0.86	0.99	0.96
Durable Medical Equipment	0.96	0.67	0.25	0.36	0.99	0.81	0.99	0.80	1.00	0.89	0.99	0.90
Legal	0.95	0.00	0.00	0.00	1.0	0.95	0.96	0.75	0.38	0.50	0.99	0.85

Table 2c:

Evaluation metrics for rule-based algorithm

	Rule-based			
Performance Metrics	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**
Financial Planning	0.84	0.56	0.56	0.56
Care coordination	0.87	0.56	0.56	0.56
Community Service	0.94	0.66	0.66	0.66
Education	0.81	0.48	0.48	0.48
Supportive Counseling	0.52	0.27	0.27	0.27
Filing Applications and Reporting	0.96	0.61	0.61	0.61
Housing	0.96	0.63	0.63	0.63
Transportation	0.82	0.43	0.43	0.43
Durable Medical Equipment	0.99	0.71	0.71	0.71
Legal	0.95	0.32	0.32	0.32