THE ROLE OF SOCIAL WORKERS IN ADDRESSING PATIENTS' UNMET SOCIAL NEEDS IN THE PRIMARY CARE SETTING

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DEDICATION

I dedicate my dissertation to my late grandma, Halima Sanda Baba. I wish she were here to rejoice this success. To my parents, I thank you for the sacrifices you made in guiding me through my life and academic journey. To my siblings and friends, I thank you for your invaluable support. To my teachers and mentors, at each stage in my academic life, you dedicated your time and energy to improve my knowledge and character. Without your dedication and sacrifices, it would not have been possible for me to reach this academic milestone. I especially dedicate this work to my wife, Maryam, and son, Umar. I hope that you will forgive me for all the moments I was physically away from you, in pursuit of my degree.

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Unmet social needs pose significant risk to both patients and healthcare organizations by increasing morbidity, mortality, utilization, and costs. Health care delivery organizations are increasingly employing social workers to address social needs, given the growing number of policies mandating them to identify and address their patients' social needs. However, social workers largely document their activities using unstructured or semi-structured textual descriptions, which may not provide information that is useful for modeling, decision-making, and evaluation. Therefore, without the ability to convert these social work documentations into usable information, the utility of these textual descriptions may be limited. While manual reviews are costly, time-consuming, and require technical skills, text mining algorithms such as natural language processing (NLP) and machine learning (ML) offer cheap and scalable solutions to extracting meaningful information from large text data. Moreover, the ability to extract information on social needs and social work interventions from free-text data within electronic health records (EHR) offers the opportunity to comprehensively evaluate the outcomes specific social work interventions. However, the use of text mining tools to convert these text data into usable information has not been well explored. Furthermore, only few studies sought to comprehensively investigate the outcomes of specific social work interventions in a safety-net population.

To investigate the role of social workers in addressing patients' social needs, this dissertation: 1) utilizes NLP, to extract and categorize the social needs that lead to referral to social workers, and market basket analysis (MBA), to investigate the co-occurrence of these social needs; 2) applies NLP, ML, and deep learning techniques to extract and categorize the interventions instituted by social workers to address patients' social needs; and 3) measures the effects of receiving a specific social work intervention type on healthcare utilization outcomes.

Joshua R Vest, PhD, MPH, Chair

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Chapter One: Introduction

Traditional health care delivery models often overlook the contributions of non-medical factors towards health outcomes, thereby mainly focusing on biomedical determinants as the sole motivators of health outcomes.[1] However, empirical evidence suggests that non-medical factors, such as social risk factors and social needs, have more profound effects on health outcomes than medical care.[2–5] Social risk factors and social needs are common and costly to patients, healthcare organizations, and the larger society. For individuals and the society, social risk factors and social needs have been associated with increased morbidity, mortality, health care utilization, and health care cost, as well as poor access to medical care.[6–9] For health care organizations, social needs and risk factors may cause resource wastages through missed appointments, thereby complicating care delivery, and /or increasing the risk of treatment non-adherence.[10,11]

Social determinants, social risk factors, and social needs currently dominate the health care discourse, as evidenced by their frequent mention in trade association publications and websites.[12] Moreover, policymakers and payers are increasingly requiring health care organizations to become more attentive to patients' needs due to social risk factors.[7,13,14] Consequently, health care organizations are increasingly paying attention to social risk factors and social needs.[7,13,14] Truly, if health care organizations and policymakers want to improve health and wellbeing, social needs must be a priority.

Social determinants of health (SDoH), social risk factors, and social needs

SDoH, social risk factors, and social needs have been inconsistently defined in the literature, and many authors wrongly use these distinct, but related, terms Interchangeably.[13,15–18] However, based on the framework developed by the Health Care

Transformation Task Force (HCTTF),[19] SDoH are the underlying community-level, rather than individual-level, socioeconomic conditions that can positively or negatively influence health. Essentially, SDoH are the conditions into which people are born, grow, work, live, and age, including the overarching systems and forces that shape these conditions such as social policies, social norms, political systems, development agendas, and economic policies.[7] In contrast, social risk factors are those adverse socioeconomic conditions that are associated with poor health outcomes.[19] Examples of such social risk factors include financial and housing instability, exposure to violence, environmental hazards, unsafe living conditions, transportation barriers, social isolation, poor health behaviors, language barriers, and inadequate health literacy.[20–22] Social needs, however, encompass those social risk factors that are of immediate concern to an individual.[19] In essence, the concept of social needs emphasizes patients' concerns, thereby encouraging patient engagement in their care process.

Of note, the seemingly trivial semantic confusion in the precise and accurate usage of these terminologies has relevant practical implications. For example, emphasizing social needs, instead of social risk factors, accentuates the need for shared decision-making in health care, as well as the need for patients to participate in the identification and prioritization of the social interventions they critically need. To illustrate this point, a health organization may use screening tools to identify the social risk factors affecting their patients, however, the organization may fail to provide those patients the social interventions they critically need if the organization emphasizes social risk factors, rather than social needs. In other words, if health care organizations focus only on identifying the social risk factors affecting their patients, they may fail to prioritize those social risk factors that are of immediate concern to their patients. In fact, multiple studies have shown that the social risk factors identified by social screening tools fail to identify patients' immediate social needs.[23–26] Therefore, it is important to precisely delineate the meanings of each of these terms to motivate a rich contextual discussion.

Policies addressing social needs

In addition to the cost and health implications of social needs and social risk factors, health care organizations face several institutional pressures to better address social needs and social risk factors. At the federal level, the Patient Protection and Affordable Care Act (ACA) requires nonprofit hospitals to conduct a community health needs assessment (CHNA) every 3 years to retain their tax-exempt status.[27,28] Although the ACA does not provide specific incentives for hospitals to successfully address the needs identified during CHNA, the fact that CHNAs, by design, involve collaboration with community stakeholders will provide incentive for hospitals to address social needs of the communities they serve.[27,28]

Additionally, the Center for Medicare and Medicaid Innovation (CMMI), which was established by the ACA, developed many innovative models to address social needs. For example, the CMMI's "Accountable Health Communities" model (AHCM) awards healthcare organizations to serve as community hubs that screen Medicare and Medicaid beneficiaries for social needs; provide referral services; address unmet social needs – such as housing, food, transportation, and interpersonal violence; provide community navigation services; and serve as bridges connecting health care organizations with providers of community services.[29,30] Additionally, states receiving grants from CMMI's State Innovation Model (SIM) are establishing various policies and initiatives to address social needs and risk factors, and in so doing, advancing population and public health.[31] Such initiatives and programs include, among others, those seeking to link primary care patients with needed social services and those seeking to create formal feedback and referral protocols to connect healthcare providers with social services providers.[31] In addition to these initiatives, many state Medicaid programs and Medicaid Managed Care Organizations (MCOs) are developing programs to address social needs and social risk factors. These programs include those that provide employment services[32,33] and housing and/or food assistance to Medicaid beneficiaries,[34–37] as well as those that provide incentives for healthcare providers to address the social needs of Medicaid enrollees.[34] Fortunately, these policies are yielding good results, as a recent Kaiser Family Foundation (KFF) research suggests that 91 percent of MCOs are engaged in activities aimed at addressing patients' social needs.[14]

Healthcare organizations' response to social needs and risk factors

With policymakers and payers increasingly pressing on healthcare organizations to address social needs, healthcare providers are increasingly introducing procedures to identify and address these needs.[7,13,14] In terms of identifying patients' needs, the most common approach is the use of one of the numerous patient-facing screening tools.[29,38–41] A recent survey of over 300 hospitals and health systems suggested that approximately 88 percent of hospitals screen patients for one or more social needs.[42] Specifically, hospitals are more likely to engage in social needs screening and social interventions in the inpatient settings and among high-utilizer populations, compared to outpatient and community settings.[42]

Once social needs are identified using these screening tools, healthcare organizations must make the vital decision of allocating the responsibility of addressing these social needs to the appropriate cadre of staff. Ordinarily, physicians bear the primary responsibility of patients' care, however, physicians may not be the best cadre of staff to address social needs and social risks. For example, due to their workflow, training, and reimbursement, physicians may lack the time to pay attention to social needs, or the skill to address them.[43–47] Patients' accounts also indicate the incongruity of assigning physicians the responsibility of identifying and addressing social needs. In one survey study assessing patients' perceptions on integration of care, more than 40 percent of the study participants reported that their family physician was not aware of their personal struggles, including the ability to pay for their medication, how they feed themselves, or how they transport themselves to clinics.[48,49] Another study in Canada revealed that only about 14 percent of women were asked about potential intimate partner violence, even after presenting with bruises and broken bones[50].

Unlike physicians, social workers are in a unique position to effectively address patients' social risks and needs.[51–53] Social workers' training and workflow put them in a better position to address the complexities of social needs.[54] Notably, social workers address patients' social needs from the vantage point of multiple perspectives, including the person-in-environment, ecological, and biopsychosocial perspectives. The person-in-environment (PIE) perspective is the key philosophical cornerstone of social work practice.[55] The PIE perspective posits that a person's behavior can be understood by looking at the past and present environment(s) of that individual.[55] The ecological perspective posits that individuals function within larger systems,[56] whereas the biopsychosocial perspective suggests that understanding health, illness, and health care delivery requires the systematic consideration of biological, psychological, and social factors, including their complex interactions.[57] These perspectives shape social workers' panoramic way of viewing social needs as products of the larger environment within which individuals are born, live, and work. Consequently, social workers are better able to identify and address more social needs of patients than other health professionals.[58] Social workers address social needs by connecting patients to community resources, providing patients with counseling and support, offering care coordination services, and aiding patients' transitions between providers.[8,51,59] Among other roles, social workers serve as counsellors, helping patients in addressing personal issues; as advocates for poor and socially excluded patients; and as case managers, linking and referring patients to needed services and resources in the community.[60] Moreover, the presence of social workers in health care organizations has been associated with improved care coordination, lower hospital admission rates, fewer emergency visits, shorter lengths of stay, and cost savings.[52,61] Expectedly, the number of social workers employed in health care organizations, especially in outpatient care delivery settings, is growing.[53,62] However, increasing the number of social workers in healthcare organizations will not yield meaningful results if healthcare organizations cannot consistently, comprehensively, and systematically track and evaluate the activities of social workers.

The challenge of measuring social work activities

Because social workers largely document their activities using unstructured text data, tracking and evaluating their activities – such as the interventions they institute – remains challenging.[63,64] Given that manual chart reviews are expensive, time-consuming, and often require expert reviewers, using novel information extraction methods – such as NLP and ML, to convert these rich text data into meaningful information useful for modeling, evaluation, and decision-making – offers a viable alternative for systematic evaluation of social work activities.[48,65,66]

Furthermore, although previous studies were conducted to investigate the outcomes of social work interventions, these studies largely treated social work interventions as binary phenomena, thereby investigating the aggregate effect of providing one or more social work interventions to patients without necessarily untangling the specific social work activities driving the health outcomes.[67–74] The ability to use information extraction tools, such as NLP and ML, to identify social needs and social work interventions from text data, therefore, opens up the opportunity to comprehensively investigate the outcomes of specific social work interventions in the healthcare setting.

Overview of the dissertation

The primary objective of this dissertation is to investigate the role of social workers in addressing patients’ social needs. This dissertation encompasses three related studies examining the role of social workers in addressing patients’ social needs. The first study examined the array of patients’ needs that lead to referral to social workers in a primary care setting. Using EHR data containing free-text descriptions of the reasons for referral to social workers, we applied NLP to categorize social needs that lead to referral to social workers, and market basket analysis to identify co-occurring social needs.

The second study investigates the interventions instituted by social workers in a primary care setting. Using EHR data containing social workers' notes, we applied NLP, ML, and deep learning techniques to categorize the interventions instituted by social workers to address patients' social needs.

The third study measures the association between specific social work interventions and healthcare utilization outcomes. We used the conditional Poisson regression model, and for robustness check, the conditional negative binomial regression model, and the fixed-effects linear model, to examine the relationship between specific social work intervention types and healthcare utilization measures such as inpatient visits, emergency department (ED) visits, and missed outpatient appointments.

Chapter Two: Reasons for Social Work Referral in an Urban Safety-net Primary Care Setting

Background

The role social risk factors and contexts play in patients' health is increasingly important to health care delivery organizations. Needs arising from material conditions, social networks, and living situations result in financial and housing instability, exposure to violence, environmental hazards, unsafe living conditions, transportation barriers, social isolation, poor health behaviors, language barriers, and inadequate health literacy.[20–22] For the society, these social risk factors increase morbidity, mortality, utilization and costs, as well as create barriers in access to care.[6–9] For health care delivery organizations, unmet social needs wastes resources through missed appointments, complicates care delivery, increases the risk of treatment non-adherence, are a source of frustration to clinical staff, and put organizations at financial risk.[10,11] Moreover, the likelihood of these negative outcomes is high, because unmet social needs are exceptionally common. This is particularly true among patients seeking care from safety-net providers, where the majority of patients face one or more social risk.[48,63] Furthermore, policymakers, professional organizations, and payers are all emphasizing the importance of identifying and addressing patients' needs due to social factors.[7,13,14] Unmet social needs ultimately have negative effects on patients' health. Also, surveys and qualitative data repeatedly indicate that physicians see the importance of social risk factors and believe these risks should be addressed.[75–77] Nevertheless, physicians are likely not the best professionals to address these risks. Physicians may lack the time during office visits to address social risk factors.[78] Many medical specialties do not specifically train practitioners to deal with social needs and risk factors.[11] Additionally, most health care organizations do not have sufficient referral mechanisms in place to enable physicians to get patients to needed services.[26,79] As a result physicians may feel unable or unprepared to address patients' social risk factors and needs.[80]

In contrast, social workers are positioned to effectively address patients' social risks and needs.[51–53] Social workers' training and workflows puts them in a better position to address the complexities of social needs.[54] Social workers can address social risks and needs by connecting patients to community resources, providing counseling and support, care coordination and transitions to other providers.[8,51,59] Among other roles, social workers serve as counsellors helping patients in addressing personal issues; as advocates for poor and socially excluded patients; and as case managers linking and referring patients to needed services and resources in the community.[60] Moreover, the presence of social workers in health care organizations has been associated with improved care coordination, lower hospital admission rates, fewer emergency visits, shorter lengths of patient stay, and cost savings.[52,61] Moreover, the number of social workers employed in health care organizations, especially outpatient care delivery settings, is growing.[53,62]

Given the potential role of social workers in addressing patients' social needs, we sought to comprehensively describe both patients receiving social work services and the needs addressed by social workers. Specifically, we describe the array of patient needs addressed by social workers in a primary care setting. We then describe the patient characteristics associated with multiple social needs. A better understanding of the services and needs addressed by social workers, will help health care organizations better plan and staff their organizations to meet patients' needs. Health care organizations may also be able to design social intervention packages to address social problems that co-occur frequently.

Methods

Using a combination of natural language processing (NLP) and market basket analysis (MBA), we describe the social needs that lead to referral to a social worker and the patient socio-demographic and clinical factors associated with referrals in an urban, safety-net health system.

Setting and Sample

The study sample included adult patients (n = 33,683) who sought care at Eskenazi Health outpatient clinics between 2011 and 2016. Eskenazi Health is a safety-net provider with a 300-bed hospital and a federally qualified health center (FQHC) serving the Indianapolis, IN area metropolitan area. Of those patients, 7,328 (22%) had an encounter with an onsite social worker at Eskenazi Health, which employs social workers in outpatient clinics.

Data

All study data were derived from Eskenazi Health's electronic health record (EHR) and from the local health information exchange (HIE) system database. The EHR data included the free-text description of electronic orders for social work referral as well as structured patient demographic information. Each electronic order included a short (2 – 3 sentence) justification, reason(s), and/or explanation of the circumstances that led to the referral. The 7,328 patients had 9,473 associated electronic orders. The Indiana Network for Patient Care (INPC) is the local HIE database, which includes diagnosis and encounter data from more than 100 hospitals in the state.

Derivation of social needs categories

We used the following search terms in Medline (Ovid) to search for articles discussing social work referral in healthcare settings: "(social work$ or social problem$ or social service$ or social need$).ti,ab AND "referral.mp. or "Referral and Consultation"/." Our search yielded 1,276 articles. We read the title and abstract of each article to identify articles for full text review. We included only articles discussing social work referral or consultations in healthcare settings for full text review. We reviewed the full text of 88 articles out of which only 9 articles provided a classification for social problems and/or social services offered in a healthcare setting (see Table 1 below).

Table 1. List of Social work Referral Categories Identified from the Literature

Caufman, 1974	**Matthieu, 2014**	**Rabovsky, 2017**	**Ratoff, 1970**	**Rempel, 2017**	**Volland, 1979**	**Wrenn, 1994**	**Zielinski, 2017**	**Zittel, 2005**
Employment	Mental Health	Financial	Poverty	Psychiatric Problem	Family	Elderly	Education	Health Related
Financial	Substance Abuse	Employment	Housing	Relationship	Living Conditions	Alcohol	Employment	Financial
Food	Aging	Housing	Single Parent	Emotional	Illness	Child Abuse	Smoking	Mental Health
Family	Homelessness	Social support	Matrimonial Problems	Ill-Health	Financial Issues	Home Services	Drug Abuse	Transportation
Government	Employment	Transport	Emotional Problems	Food Security	Insurance	Domestic Violence	Alcohol Abuse	Housing
Housing	Justice system	Psychiatric Issues	Psychiatric		Mood Disturbance	Rape	Sadness	Legal
Legal	Education	Food					Domestic Violence	
Law Enforcement	Military	Stress					Day care need	
Clothing	Benefits	Addiction					Homelessness	
Consumer Protection	Policy	Child Development					Food Insecurity	
Recreation		Social Exclusion						
Household Essentials								
Transportation								
Insurance								

Two researchers reordered the categories obtained from previous studies, merging, and splitting some categories based on recommendations from two social work experts. We derived 17 social needs categories through this literature review process (see Table 2).

Table 2. Description of social work referral categories

Social need category	**Description**
Financial	Issues related to helping patients apply for financial assistance, medication assistance programs, indigent medical care, assistance from Veterans Affairs, drug reimbursement program, supplemental security Income, Medicaid, medical grant, or health insurance.[81,82]
Food /Food Insecurity	Issues related to referral for access to food pantry services, Supplemental Nutrition Assistance Program (SNAP) benefits, food stamp, Meals on Wheels, or nutrition education services.[82,83]
Violence and safety	Act(s) of commission or omission that led to failure to protect patient from harm or potential harm, reported experience of act(s) of physical or sexual violence by a former or current marital or sexual partner.[84,85]
Housing	Issues related to assistance with finding a house/apartment/shelter, help with paying rent, or utility bill application/assistance.[82]
Legal	Issues related to assistance with legal services or conviction/jail.[82]
Transportation	Issues related to assistance with public transportation, linkage to community transportation and Medicaid transportation services, or ability to arrive at appointments and walk/ exercise in safe environments.[82,86]
Behavioral Health	Issues related to behavioral health illnesses, drug abuse, linkage to behavioral health counselor or clinic, linkage to behavioral health support group, and behavioral health treatment.[82]
Aging	Issues related to linkage to community services for the elderly and other aging-related services.[87]
Education	Issues related to linkage to education services, including postsecondary education, life skills, and community education.[87]
Employment	Issues related to linkage to employment/career services, discrimination in workplace, stress in the workplace, and other workplace issues.[86,87]
Family/Social Support	Issues related to the impact that tangible and emotional support systems involving family and friends have on health.[86]
Pregnancy	Issues related to assessment of needs and concerns during pregnancy, and other issues related to labor and delivery.
Language services	Issues related to need for language and interpretation services
Disability	Issues related to need for disability services and assistance with resources and supplies for people with disability.
Community Resources	Issues related to the need for linkage to community resources
Adherence	Issues related to adherence to medications and treatment

Measures: Patients' social work needs

Following a five-step process, we used NLP to categorize the free-text descriptions in the electronic orders into 17 different types of social needs requiring social worker service: 1) Using RapidMiner,[88] we cleaned the free-text of all stop words (e.g. one- and two-letter words, compositions and prepositions). 2) Using RapidMiner, we tokenized the sentences into individual words, and using the Porter (2008) stemming algorithm,[89] we reduced the length of words and decreased the overall number of individual tokens (words). 3) We manually reviewed all tokens with frequency of occurrence of 10 or more (1149 out of 7624 unique tokens) to identify keywords that uniquely match to one the 17 literature-derived social needs categories (see Table 3). 4) We built text association rules to categorize each referral note into social-work-referral categories. While each token could be only applied to a single category (e.g., the token "bus" was uniquely associated with the "transportation" social needs category), a referral note could be assigned to multiple categories (e.g., a referral note that mentioned "bus" and "addiction" would be associated with the "transportation" category as well as the "behavioural health" category).

Table 3. Example of keywords and tokens for each social work service category

Category	Tokens
Financial	Insur afford finance Medicaid advantage copay pay medicar bill coverag mone income poor suppl financ ssi cost poverty fund secur expens purchas voucher charit uninsur paid price benefit buy acquir spendown "spend down" "united christmas service" "patient assistance program"
behavioral health	Depress counsel anxiety stress rehab sleep alcohol behavioral psych bipolar dementia drug stressor depression schizophrenia substance addict memori cocaine anxiety council adhd suicide marijuana anger counsellor retard mood grief griev ptsd iq alzheim narcot cognit "panic attack" "anger m"
Legal	Legal attorn custod appeal court incarcer jail inmate
Housing	Hous homeles liv leav shelter rent evict landlord tenant
Food /Food Insecurity	Food meal wheel stamp pantr
Aging	Elderl "assisted living" seniors geriatr
Family /Social support	famil daughter husband mother mom son caregiv children sister wife baby friend relationship partner kid father parent cousin brother singl "respite care" alone
Employment	Employ job
Education	School stud college ged class
Transportation	Transport cab indigo taxi bus ride indygo indigo drive
Violence / Safety	Abus safet domest violenc sexual assault threat abuse neglect "legacy house" "home service" "home care" "home visit" "home nurs"
Language	Interpret spanish language
Pregnancy	deliv partum preg "needs and concerns during pregnancy" natal
Disability	disab bath walker mobilit powerchair gait paresis amput
Community Resources	commun resourc
Home Health	"home health" "home PT"
Adherence	complian adheren adhering comply

To check the performance of the classification rules, we manually coded, and applied the classification rules to a 5% random sample of referral notes. Agreement between manual and automated classification rule coding was high: Cohen's kappa > 0.90 for 16 categories and 0.75 for the remaining category (see Table 4). Consequently, we categorized all the referral notes using the automated text classification rules.

Table 4. Level of agreement between manual and automated classification rule coding

Categories	Kappa	95% CI of Kappa	Precision	Recall	Accuracy	F1-Score
Financial	0.96	0.93 - 0.99	0.95	0.99	0.99	0.97
Behavioral Health	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Legal	0.93	0.80 -1.00	0.88	1.00	1.00	0.93
Housing	0.96	0.90 - 1.00	1.00	0.92	1.00	0.96
Food	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Aging	0.92	0.77 - 1.00	0.86	1.00	1.00	0.92
Family	0.99	0.96 - 1.00	0.98	1.00	1.00	0.99
Education	0.75	0.41 - 1.00	0.60	1.00	1.00	0.75
Employment	0.97	0.92 - 1.00	1.00	0.95	1.00	0.97
Transportation	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Domestic Violence	0.96	0.88 - 1.00	1.00	0.92	1.00	0.96
Language	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Pregnancy	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Disability	1	1.00 - 1.00	1.00	1.00	1.00	1.00
Home Health	0.97	0.94 - 1.00	0.98	0.98	1.00	0.98
Community	0.99	0.98 - 1.00	--	0.00	1.00	0.00
Adherence	1	1.00 - 1.00	1.00	1.00	1.00	1.00

Analysis

We compared patients with referrals to social workers to patients not referred by demographic and clinical characteristics using percentages and means. Next, we identified the most common social needs that lead to referral, i.e., social need categories. To identify co-occurrence of social need categories, we utilized MBA techniques. MBA is an approach to identify goods or services that are purchased, or occur, together in a transaction.[90] In the context of health care, MBA has been applied to investigate drug use initiation sequences[91] and the common nursing interventions used for aging adults with developmental disabilities.[92]

In MBA, co-occurrence is described using association rules. Each association rule has a form: A => B, or Left-Hand Side (LHS) => Right-Hand Side (RHS). Also, MBA provides multiple measures to evaluate the strength and relevance of association rules:[93] 1) *Support* is a measure of the probability that a transaction contains both A (the Item on LHS of a rule) and B (the Item on the right-hand side (RHS) of the rule); 2) *Confidence* is a measure of the conditional probability that a transaction contains item B (Item on the right hand side (RHS)), given that item A (the Item on the left hand side(LHS)) is already in the transaction; and 3) *Lift* is a measure of correlation between item A and item B. If an association rule between item A and item B has a lift of 1, then item A and item B are independent of each other. If the lift measure is greater than 1, then the presence of item A is positively correlated with the presence of item B with the degree of correlation being represented by the lift value. A lift measure that is less than 1 indicates that the presence of item A is negatively correlated with the presence of item B. In this study, we limited the co-occurrence analysis to only two categories of social needs, i.e. we applied a two-category association rule to each order. We calculated three measures of association to describe and identify the co-occurrence of social needs that lead to a referral to a social worker: support, confidence, and lift.[93] In the context of this study, *support* is a measure of the probability that an order contains both social needs categories; c*onfidence* is a measure of the conditional probability that an order contains the second need category, given the presence of the first need category; and *lift* is a measure of the likelihood that a transaction containing the first category also contains the second category. To conduct our MBA, we used the APRIORI algorithm,[93] to mine association rules. The goal of association rules mining using the APRIORI algorithm is to identify rules that have support and confidence values greater than or equal to predetermined minimum values (minimum-support and minimum confidence). In the case of our study, we mined association rules with support of at least 0.001 and confidence of at least 0.1. We used the "arules" extension package of the open-source R statistical analysis software[94] to implement the apriori algorithm.

Results

About 22% of adult patients were referred to a social worker (Table 5). Compared to patients not referred to a social worker, those referred to a social worker tended to be younger and female. A higher proportion of patients referred to social workers were Hispanic, and those referred had higher Charlson comorbidity index scores.

Table 5. Comparison of adult safety-net patients by social worker referral status

Characteristic	All patients	Patients not referred to social worker	Patients referred to social worker
Age, mean	52.1	52.7	50.0***
Sex, (%)			
Female	68.7	66.8	75.6***
Male	31.3	33.2	24.4***
Race-Ethnicity, (%)			
Hispanic	16.6	14.9	22.6***
African American Non-Hispanic	40.4	41.8	35.2
White Non-Hispanic	29.6	30.0	28.3
Other Non-Hispanic	4.6	4.5	4.9
Unknown Race or Ethnicity	8.8	8.8	9.0
Charlson, mean	1.15	1.14	1.2**
Total, n	33683	26355	7328

* significant at p < 0.05; ** significant at p < 0.01; *** significant at p < 0.001

The two most common social needs that led to referral to a social worker were financial needs (25%) and pregnancy-related needs (25%; Figure 1). Behavioral health needs, which included substance misuse and referral to treatment services, accounted for 16% of all referrals. Social needs related to family and social support (9%), home health needs (9%), language limitations (8%), and transportation needs (8%) were also common. Among those patients with an order for a social worker referral, demographic characteristics varied by category of service (see Table 6.1 and 6.2). For example, patients with a referral for aging, home health, disability, food insecurity, and medication adherence issues had higher mean ages than other categories. In contrast, patients referred for the pregnancy category were understandably younger. More women were referred in every category, except medication adherence issues. Higher average comorbidity scores were observed among patients referred to the categories of home health, transportation, disability, food insecurity, aging, and medication adherence issues.

Figure 1. Reasons for referrals to a social worker in a primary care setting

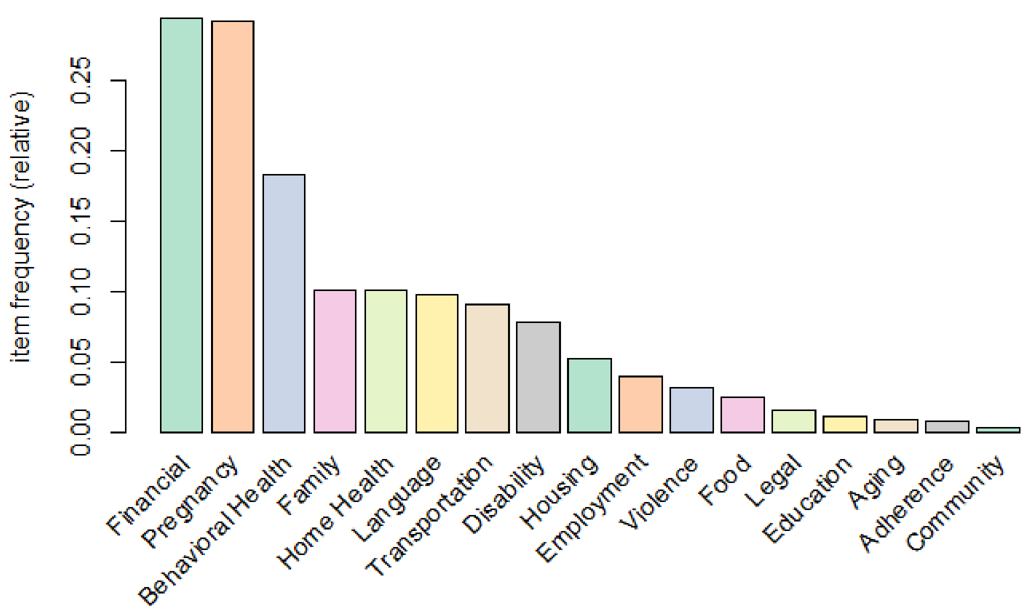


Table 6.1. Demographic and clinical characteristics of patients by social need category

Characteristic	Financial	Pregnancy	behavioral	Family	Home Health	Language	Transportation	Disability	Housing
Age, mean	57.3	33.7	51.2	55	69.1	38.7	61.5	62.8	54.7
Sex, (%)									
Female	60.4	99.5	72.4	75.5	69.1	94.7	66.4	66.5	64.4
Male	39.6	0.5	27.6	24.5	30.9	5.3	33.6	33.5	35.6
Race-Ethnicity, (%)									
Hispanic	8.7	50.9	9.4	17.0	4.3	85.4	5.2	6.5	8.1
African American Non-Hispanic	40.1	23.0	35.4	38.8	52.4	2.5	37.7	43.7	37.8
White Non-Hispanic	38.7	9.7	37.5	31.4	30.6	0.6	43.9	35.5	41.4
Other Non-Hispanic	3.2	8.4	41.2	3.9	2.2	3.7	3.3	3	2.2
Unknown Race or Ethnicity	9.3	8.0	13.5	8.8	10.5	7.8	10.0	11.3	10.5
Charlson, mean	1.7	0.2	1.2	1.5	2.9	0.3	2.0	2.4	1.7
Total, n	2358	2336	1464	816	810	787	733	629	418

Table 6.2. Demographic and clinical characteristics of patients by social need category (contd.)

Characteristic	Employment	Violence	Food	Legal	Education	Aging	Adherence	Community Resources
Age, mean	50.4	50.2	62.3	53.2	36.9	74.7	64.5	59.0
Sex, (%)								
Female	61.1	84	64.9	63.3	73.2	64.9	47.8	64.3
Male	38.9	16	35.1	36.7	26.8	35.1	52.2	35.7
Race-Ethnicity, (%)								
Hispanic	15.3	19.9	19.9	18.0	24.7	4.1	8.7	7.1
African American Non-Hispanic	44.6	25.4	25.4	32.0	40.2	40.5	43.5	35.7
White Non-Hispanic	31.2	42.6	42.6	36.7	17.5	43.2	36.2	46.4
Other Non-Hispanic	3.4	2.3	2.3	2.3	5.2	0	2.9	0.0
Unknown Race or Ethnicity	5.6	9.8	9.8	11.0	12.4	12.2	8.7	10.7
Charlson, mean	1.1	1.0	2.1	1.2	0.7	2.7	3.1	1.9
Total, n	321	256	205	128	97	74	69	28

About 22% of referrals to a social worker encompassed at least two different categories of social need. The most common co-occurring needs were pregnancy and language limitation (Table 7). Although only 7% of referrals had both pregnancy and language limitation needs (support = 0.07), patients with pregnancy needs had a high probability of also reporting language limitations (confidence = 0.78, lift = 2.69). Other issues that frequently co-occurred were behavioral health with family and social support (support = 0.03; confidence = 0.28; Lift = 1.63); financial with behavioral health (support = 0.025; confidence = 0.14; Lift = 0.47); and home health needs with disability (support = 0.02; confidence = 0.26; Lift = 2.57). Referral for financial needs were common given food insecurity (confidence=0.42), employment (confidence=0.37) and legal needs (confidence=0.35).

Table 7. Co-occurrence of reasons for adult primary care referrals to a social worker

Category 1	**Category 2**	**Support**	**Confidence**	**Lift**	**Count**
Language	Pregnancy	0.077	0.784	2.693	617
Family	Behavioral Health	0.030	0.297	1.625	242
Family	Financial	0.025	0.246	0.838	201
Behavioral Health	Financial	0.025	0.137	0.467	201
Disability	Home Health	0.020	0.259	2.567	163
Transportation	Financial	0.020	0.220	0.747	161
Disability	Financial	0.020	0.253	0.860	159
Housing	Financial	0.017	0.321	1.091	134
Employment	Financial	0.015	0.368	1.251	118
Home Health	Family	0.015	0.146	1.432	118
Home Health	Financial	0.012	0.120	0.407	97
Home Health	Behavioral Health	0.012	0.115	0.629	93
Food	Financial	0.011	0.420	1.427	86
Violence	Family	0.010	0.328	3.226	84
Housing	Family	0.010	0.199	1.952	83
Violence	Behavioral Health	0.010	0.313	1.713	80
Disability	Family	0.009	0.114	1.125	72
Employment	Family	0.009	0.221	2.175	71
Employment	Behavioral Health	0.008	0.206	1.127	66
Housing	Behavioral Health	0.007	0.141	0.774	59
Legal	Financial	0.006	0.352	1.196	45
Legal	Family	0.005	0.344	3.380	44
Education	Family	0.005	0.423	4.156	41

Discussion

More than one-fifth of adult primary care patients were referred to a social worker, which suggests a substantial level of need for services among this safety-net population. The high number of referrals, as well as the diversity of reasons for referral, indicate a potentially important and unique role for social workers in ensuring patients' health and well-being. As health care organizations plan to better address social needs and risk factors, understanding the leading needs and co-occurring needs is essential for effective staffing decisions and the design of effective intervention packages. A key component of many health care organizations' social and population health strategies is to increase social needs and risk factor screening efforts.[79,95] As would be expected, screening studies have similarly documented many of the needs that were observed in this study, including: financial needs, food insecurity, transport needs, language, social support, violence and safety, employment, and housing instability.[26,96] The similarity between social needs addressed by social workers as documented in previous studies and reasons for social work referral observed in our study suggests that once organizations identify patients with these types of social needs and risks through screening, social workers would be the logical provider to serve patients. In addition, our literature-derived categorization strategy and referral-based measurement approach highlighted the role of social workers in providing pregnancy support and behavioral health related services, which are categories of needs included in some, but not all, social risk screening tools.[29,39,97] The role of social workers in supporting pregnant women is particularly notable as pregnancy is linked with other psychosocial issues such as addiction, depression, and domestic violence.[98–100] In addition, pregnancy frequently co-occurred with language service needs. Because language need can be a significant barrier to health care access,[101] the frequent co-occurrence is another reminder that organizations serving diverse populations require a multilingual environment.

Additionally, our use of MBA identified other social needs that frequently co-occurred. The identification of co-occurring needs and services is a strength of MBA in that the approach provides a comprehensive view of the challenges facing organizations in developing effective interventions.[90,92] For example, there is growing evidence suggesting that patients with financial needs are more likely to have other psychosocial needs.[102,103] Furthermore, studies have shown that patients who receive financial assistance have better health outcomes.[104–106] Therefore, healthcare organizations cannot view social needs individually. Instead, patients will require packages of interventions that simultaneously address co-occurring needs. For example, the common co-occurrence of the financial category with such diverse needs as transportation, family and social support, and disability indicates that any organization trying to address these needs will have to include an underlying financial component.

In this study, social workers were addressing patient needs and risks best handled by non-medical care professionals. However, simply having social workers on staff to accept referrals is a necessary, but insufficient requirement for effective workflows. As social workers become more common in healthcare settings and address key patient risks – and given that most social work services are not reimbursable – organizations will be tasked with determining methods to most effectively and efficiently leverage the capabilities of social workers. Incorporating social needs into risk stratification and including referrals within clinical decision support systems could assist social workers in primary care practices to more effectively and efficiently address patients' social needs.[107] Additionally, simply knowing the chance of co-occurrence of social needs can prompt additional screening and interviews once one need is identified. Likewise, the reasons for referral categories and the NLP approach developed in this study could support efficient workflows. For example, this categorization scheme could be incorporated into a structured referral order form within the electronic health record to quickly communicate the nature of the social needs to a social worker, as well as to improve the analysis, evaluation, and reporting of patients' social needs and social worker' activities. Likewise, similar NLP approaches could be applied to social work referral notes within the organization, or to external community organizations, to better measure patient needs.

Limitations

This study has limitations related to measurement and generalizability. First, while our categories for referral reasons are derived from the literature, it is not exhaustive of every reason a patient is referred to a social worker. Other methods of categorizing referrals exist. Second, we relied on NLP to classify referral notes, which could result in misclassification. However, the agreement between the NLP algorithm and our manual coding was high. Third, we purposefully limited the MBA to two-category co-occurrence rules only. We made this decision to facilitate interpretation and because few of the orders included more than two categories. Using longer documents than order texts, like clinical notes, might allow for identification of three or more co-occurrences. Fourth, in this design we are not able to establish causal relationships (i.e., whether one need precipitates another need), nor were we able to determine if patient needs were resolved. Lastly, our patient sample was drawn from an FQHC with on-site social workers. As a result, findings may not reflect other patient populations or providers without such on-site social work services.

Conclusions

This study, which has been published in the Journal of Social Service Research,[108] demonstrated the utility of market basket analysis in understanding the co-occurring social needs that lead to referral to a social worker, as well as the patient characteristics associated with these social needs. By closely interacting with patients, social workers could provide hospitals with key insights into social needs of their communities. As health care organizations plan to better address social needs and risk factors, understanding the leading and co-occurring patients’ social needs will be essential for effective staffing decisions and for designing effective social intervention packages. Moreover, by closely interacting with patients, social workers could provide hospitals with key insights into social needs of their communities. The findings of our research will be valuable for designing a decision support algorithm to help social workers address patients’ social needs more efficiently and effectively.

Chapter Three: Identification and Classification of Social Work Interventions Using Natural Language Processing

Background

Traditionally, efforts to improve health outcomes have primarily focused on medical care services.[1] However, empirical evidence consistently suggest 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.[54] Moreover, social workers are increasingly becoming embedded in healthcare organizations to help address patients' social needs.[109] However, tracking and evaluating interventions instituted by social workers remains challenging, since social work interventions are largely documented as unstructured text data within electronic health records (EHR)[63,64]. Unstructured documentation makes it difficult to systematically monitor and study social work interventions and services - as manual chart reviews are expensive, time-consuming, and often require expert reviewers.[48,65,66] 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 social work notes.

Existing research has been successful in using NLP methods to identify social needs with EHR data. Dorr et al[110] demonstrated that NLP methods 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[111] developed the Moonstone system, which used rule-based classification to identify housing situations and social support within EHRs. Also, Cook et al[112] used NLP and machine learning 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 social work interventions using manual chart reviews, no study has sought to utilize NLP methods to identify and / or classify the interventions that social workers offer during clinical appointments.[113–118] The purpose of this study is to extract and categorize social work 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 social work interventions in situations where only unstructured data are accessible. Healthcare organizations armed with data on social work 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 impact of specific social work interventions on patients' health outcomes.

Methods

We developed a classification scheme from the literature[113–118] to categorize interventions instituted by social workers to address patients' social needs in an urban, safety-net health system. We used NLP and ML algorithms for automated categorization of social work interventions based on this classification scheme. Figure 2 describes, in brief, the process and pipeline used for this classification and figure 3 provides details of the text preprocessing steps. This study is approved by the Indiana University's Institutional Review Board.

Figure 2. Classification algorithm pipeline

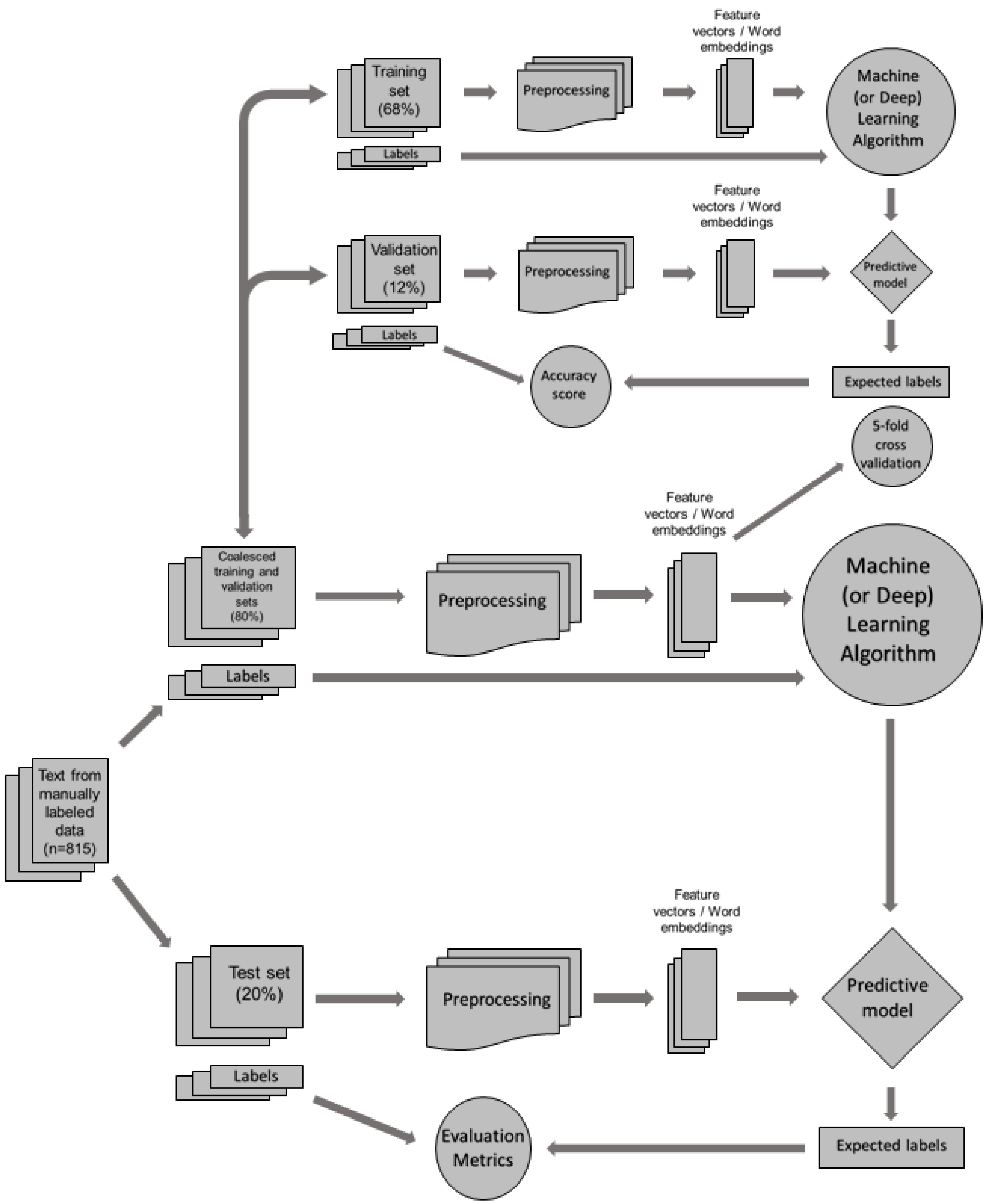
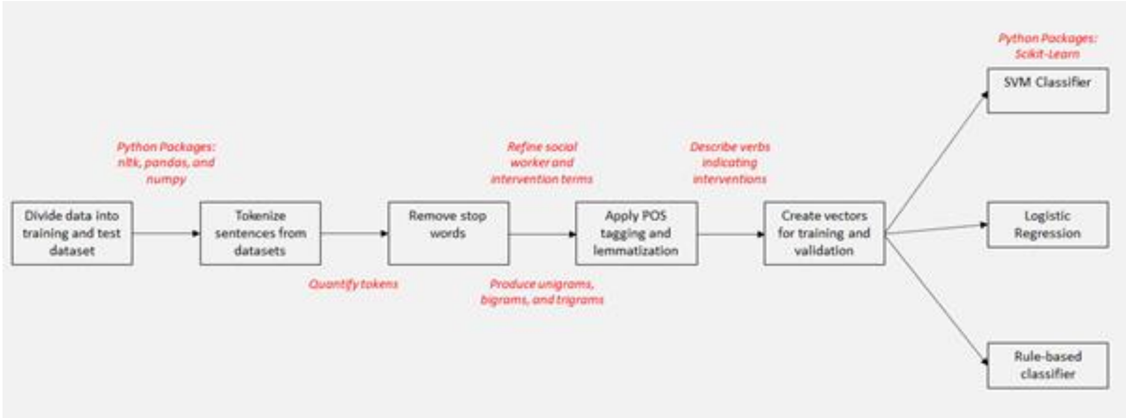


Figure 3. Social needs intervention text preprocessing



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 patients with 815 social work encounters between October 1, 2016 and September 30, 2019.

Data

The study data were derived from Eskenazi Health's EHR. The EHR data included patients' clinical notes and their demographic and clinical characteristics. We obtained unstructured data containing free-text description of the reason(s) for patient visits, the intervention(s) instituted by the social worker, and plans for future visits or engagement from social workers' notes. We extracted social workers' notes, using an existing pipeline (nDepth), by searching clinical notes for the following search terms: "social work" or "MSW" or "LCSW", or "LSW", or "LMSW", or "LBSW". nDepth, a natural language processing tool[119] developed by the Regenstrief Institute, conducts both 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.[120,121] For this study, nDepth was used to extract a sample of social work clinical notes from the EHR. The nDepth search retrieved 1,289 clinical notes containing our search terms. Three abstractors (AB, HT, KW) manually reviewed the retrieved notes and categorized them into notes that were actually written by a social worker and notes written by other professionals.

The final sample for this study included 815 notes that were determined to be written by social workers. 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. Of the 815 notes determined to be social work notes, 735 were duly signed off by a social worker. We determined that the remaining 80 notes were written by the social worker because the wordings and structure of these notes clearly indicate documentation of activities by a social worker, and thus, conform with the duly signed notes. The wordings we looked for included phrases like "This social worker met with patient…," "social work assessment: (at the beginning of the note)," and the like. Also, if the structure of the unsigned note is that of a standard social work assessment, with the writer of the notes mainly identifying social needs and/or documenting social work interventions, we decided that the note was written by a social worker. Sections of a standard social work assessment include: Patient demographics, diagnosis, biopsychosocial assessment, health literacy assessment, living arrangements, social support, activities of daily living and functional status, socioeconomic needs, income source, transportation, legal information, and risk of abuse. Of note, we further reviewed the notes with HM, who is an expert in the field of social work, to resolve coding ambiguities.

Measures

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

- **Financial planning:** Provision of resources for funding medications, treatment, or other care[122]
- **Supportive counseling:** Provision of emotional and mental health support services, addiction services, among others[123]
- **Care coordination:** Includes discharge planning, coordination of care continuity, transition of care, case management, and arrangement and coordination of home visits[124]
- **Education:** Includes health/wellness programs, crisis intervention, and course planning[125]
- **Community service:** Involves referrals to community, spiritual, and peer advocacy organizations, as well as translational services, food assistance, and clothing assistance[126]
- **Applications and reporting**: Include help with filling applications, filing mandatory reports such as the Department of Child Services (DCS) reporting and the Adult Protective Services (APS) reporting
- **Housing**: Encompasses shelter provision and other housing assistance.
- **Transportation:** Provision of transportation fares and passes, as well as links to transportation services.

- **Durable Medical Equipment:** Provision, repair, maintenance, and/or replacement of medical equipment
- **Legal:** Assistance with link to attorneys, law enforcement, and other legal services

Further, the three coders independently reviewed 100 randomly selected social work notes to identify verbs likely to indicate the presence of social work interventions in a sentence. The abstractors also identified contextual and negation terms associated with each verb, as well as unique terms that map to each of the 10 intervention categories. The abstractors, thereupon, manually coded the selected notes into their respective non-mutually exclusive social work intervention categories. We calculated the rate of agreement between the three coders using Fleiss's kappa coefficients, and after resolving differences, the three coders manually coded the rest of the data. The lexicon of verb and intervention terms is available in Table 8 and 9**,** and the initial Fleiss's Kappa for each intervention category is available in Table 10.

Table 8: Key terms for intervention categories used in rule-based algorithm

Social intervention Categories	**Key terms**
Financial Planning	anthem, insurance, medicare, advantage, financial counsel, sliding scale, self-pay, self pay, selfpay, medicaid(not medicaid cab), coverage, ssi , money, pay, free of charge, foc , HIP, ssdi, entitlements, united health, supplemental security, fund, worker(s) comp, christmas assistance, gas assistance, gas card, power account, cost, fee , waived, TANF, IMPACT, walmart card, employment, job, gift spend, CSHCS, FSSA, cash, ADAP
Care coordination	Physical therapy, PT, home health, hh, hha, hhc, care coordination, hha, plan (not followed by ":"), assisted living, nursing home, long-term care, long term care, longterm care, day care,daycare, personal care, home visit, nurse visit, referral, end of life, sleep, palliative, study, schedule appointment, referral, transition, transitional, alternative living, medication, outpatient therapy, linking to a pcp, transition, SAR, VNS
Supportive counseling and services	Psych, bereavement, crisis intervention, alcohol, substance abuse, culture, coping, adjustment, comorbid, chaplain, sexualit, rehabilitation, counsel(not financial counsel), behavioral management, problem-solving, depression, individual therapy, behavior, cogniti, soothing, relaxation CD, supportive, emotional support, couples counseling, supportive listening.
Education	class, information, educat, school, GED, guardianship, transition checklist, provided resource, list of facilit, facilit + list, explain, discuss, encourage, literacy, pamphlet, answer questions, EIP, handout,
Community/In-house services	food, food pantries, clothing meal(s), home podiatry, SNAP, M.O.wheels (meals on wheels), Caregivers, BABES coupon, voucher, open-door, care coordination, vocation, lifeline, department of aging, obama phone, school supplies, shoes, nacs, RMH, first steps,cshsc, chw, NCCS, Julian Center, Ronald McDonald house, Associations, organizations, support group, living center, senior care, creative change program, Healthy families, community action, group, St. Vincent DePaul, dip-in, ALS, GRACE team, Brooke's Place, safe sleep program, YMCA,CICOA
Applications and Reporting	POST form, ROI form, Family authorization form, Release of information, advanced directive, FMLA, documentation/identification, pre-cert, birth certificate, IPA Agreement, Client Conduct Statement, and Duty to Warm Statement, child support report, adult protective service report, dcs, aps, CW
Housing	Lodging, housing, parking, feeling safe (in-home), safe at home, electricity, running water, power, Homeless Initiative Program, pedigo, shelter, HUD, accomodation, florence house
Transport	medicaid cab, cab, indigo, bus, taxi, transport, travel arrangement, shuttle
DME	medical equipment, cane, walker, manual chair, wheelchair, electric chair, shower chair, test strips, meter, compression hose, bracelet, rollator, cpap
Legal	Mlp, legal, court, jail, law, lawyer, crime victims assist, police, prison

Table 9: Other lexical categories used in rule-based algorithm

Lexical category	**Key terms**
Social Worker terms	social worker, soc worker, soc. worker, s worker, s. worker, sw, social service coordinator, writer, ssc
Intervention (verb) terms	provided, informed, suggested, contacted, talked, sent, offered, assessed, discussed, inquired, assisted, suggested, delivered, informed, asked, contacted, updated, collaborated, demonstrated, gave, patient was given, pt was given, pt. was given, reviewed, explained, verified, spoke, notified, consulted, linked, educated, helped, requested, referred, reached, called, placed
Forward negative assertion terms for intervention verb terms	social worker, soc worker, soc. worker, s worker, s. worker, sw, social service coordinator, writer, ssc, by patient, by pt, by pt., by mom, by mum, by doctor, by nurse, by rn, by dad, by mother, by father, by son, by daughter, by friend, by uncle, by aunt
Backward negative assertion terms for intervention verb terms	social worker was, sw was, social service coordinator was, ssc was, writer was, soc worker was, s. worker was, s worker was, socal worker was, patient, pt, pt., mom, doctor, nurse, rn, dad, mother, father, son, daughter, friend, uncle, aunt, not, n't, nt

Table 10: Inter-rater agreement for manual coding

Interventions	**Kappa**
Financial Planning	0.65
Care coordination	0.64
Community Service	0.76
Education	0.52
Supportive Counseling	0.66
Filing Applications and Reporting	0.77
Housing	0.69
Transportation	0.69
Durable Medical Equipment	0.73
Legal	0.76

Analysis

To categorize the notes based on our 10-category scheme, we used 1) Rule-based classification algorithms using Python's regular expressions; 2) machine learning algorithms such as multinomial Naive Bayes Classification algorithm[127] and multi-label (One Vs Rest, Binary Relevance, Classifier Chains, and Label Powerset)[128,129] classification algorithms using Logistic Regression[128] and Kernelized Support Vector Machine (SVM) with radial basis function;[130] and 3) a deep learning algorithm for multilabel classification: the Long Short-term memory (LSTM) recurrent neural network.[131].

For the rule-based algorithm, we used Python's in-built regular expressions capabilities to extract sentences that include a social worker term and one of the intervention verb terms (see Table 9)**,** 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. Social work notes review and consultation with clinical social workers revealed that these sentences are likely to contain information about the type of intervention instituted. A social work note was deemed to indicate the presence of an intervention category if the extracted sentences in the note also contain 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 2). We preprocessed the text in each of these datasets as follows: we tokenized sentences in each social work 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[132] 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. 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 the 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 815 charts for encounters that were identified as being written by a social worker. Descriptive information about the sample and categories of social worker interventions is available in Table 11. Briefly, 43% were Hispanic (43%), the mean age was 38.7 years, and the majority were female (64%**).**

Table 11: Patient demographic characteristics by social work intervention type

Characteristic	All Categories	Financial Planning	Discharge Planning	Community Service	Education	Supportive Counseling	Applications and Reporting	Housing	Transportation	Durable Medical Equipment	Legal
Age, mean (SD)	38.7 (21.4)	36.6 (18.9)	35.5 (21.9)	39.5 (20.8)	38.9 (20.6)	36.9 (22.0)	33.8 (19.1)	32.9 (18.5)	34.7 (19.9)	39.3 (19.7)	42.9 (17.9)
Sex, (%)											
Female	63.5	65.7	60.6	59.4	61	57.3	60	70.6	65.9	57.1	64.7
Male	36.5	34.3	39.4	40.6	39	42.7	40	29.4	34.1	42.9	35.3
Race-Ethnicity, (%)											
Hispanic	42.9	46.3	42.6	37.7	51.2	45.3	46.7	41.2	39	42.9	47.1
African American Non-Hispanic	35.8	31.3	36.2	39	34.2	37.3	28.9	35.3	36.6	19	35.3
White Non-Hispanic	18.6	20.9	19.2	20.3	13.4	10.7	22.2	23.5	22	28.6	17.6
Other Non-Hispanic	1	0	1	1.5	1.2	1.7	2.2	0	2.4	9.5	0
Unknown Race or Ethnicity	1.7	1.5	1	1.5	0	4	0	0	0	0	0
Elixhauser score, mean (S.D)	3.14 (2.6)	2.4 (2.3)	3.4 (2.6)	3.1 (2.2)	3.1 (2.5)	3.2 (2.6)	2.6 (2.4)	2.6 (2.4)	2.8 (2.1)	3.2 (2.2)	3.9 (2.8)
Total, n	408	67	94	69	82	75	45	17	41	21	17

Of the 815 social work notes, the majority (n=598; 73.4%) contained at least one social work intervention. More specifically, 217 (26.6%) did not include any description of a social work intervention, 295 (36.2%) included one social work intervention, 207 (25.4%) included two interventions, and 96 (11.8%) included three or more interventions. The highest number of interventions in a single social work note was six, which was observed in only 5 of the 815 notes. The most common social work interventions in the notes included: discharge planning (21.5%), education (21.0%), financial planning (18.5%), referral to community services and organizations (17.1%), and supportive counseling (15.3%; Table 12).

Table 12.1: 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.

Table 12.2: Social interventions offered by social workers (contd.)

Interventions	Frequency (%) (N=815)	Examples of social work note
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 ● 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

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 Table 13).

Table 13: Average accuracy for all classification algorithms

Model	Macro-average Accuracy
Multilabel (On Vs Rest) kernelized SVM with radial basis function	0.97
Multilabel (One Vs Rest) Logistic Regression	0.96
Linear SVM	0.95
Multinomial Naïve Bayes classifier	0.92
Multilabel LSTM	0.88
Rule-based	0.87
Multilabel (Label Powerset) kernelized SVM with radial basis function	0.82
Multilabel (Classifier Chains) kernelized SVM with radial basis function	0.81
Multilabel (Binary Relevance) kernelized SVM with radial basis function	0.8
Multilabel (Binary Relevance) Gaussian Naïve Bayes Classifier	0.79
Multilabel K-Nearest Neighbor	0.41

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 14.1 and 14.2). However, for the multinomial Naive Bayes classifier, the recall score was higher than the sensitivity score in financial planning, discharge planning, 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 14.2). 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-score, which is the harmonic mean of precision (positive predictive value) and recall (sensitivity), was high (0.82 - 0.94) using the logistic regression and kernelized SVM algorithms for the discharge planning, community services, and transportation categories. 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 14.1 - 14.3)

Table 14.1: 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 14.2: 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 14.3: 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

The results of the 5-fold cross validation score are available in table 15.1 and 15.2 and generally showed that the models performed well for all the social work intervention categories, with the highest performance, for most categories observed in the kernelized SVM.

Table 15.1: Five-fold Cross validation metrics for logistic regression and kernelized SVM algorithms

	Logistic Regression					**Kernelized Support Vector Machine (SVM)**				
Performance Metrics	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**AUC**	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**AUC**
Financial Planning	0.96	0.98	0.82	0.89	0.98	0.97	0.98	0.88	0.93	0.97
Discharge Planning	0.94	0.94	0.77	0.84	0.97	0.94	0.93	0.77	0.84	0.97
Community Service	0.94	0.93	0.69	0.79	0.94	0.93	0.93	0.68	0.78	0.94
Education	0.92	0.88	0.70	0.77	0.91	0.91	0.86	0.69	0.76	0.91
Supportive Counseling	0.94	0.94	0.66	0.77	0.95	0.94	0.91	0.66	0.76	0.94
Filing Applications and Reporting	0.95	0.89	0.61	0.72	0.94	0.94	0.86	0.61	0.71	0.94
Housing	0.98	0.97	0.73	0.82	0.99	0.98	0.93	0.73	0.81	0.98
Transportation	0.96	1.00	0.58	0.73	0.97	0.95	0.94	0.58	0.71	0.98
Durable Medical Equipment	0.98	0.97	0.60	0.70	0.93	0.98	0.97	0.60	0.70	0.93
Legal	0.99	1.00	0.55	0.66	0.91	0.99	1.00	0.55	0.66	0.93

Table 15.2: Five-fold Cross validation metrics for multinomial NB and linear SVM algorithms

	Naive Bayes Model						Linear Support Vector Machine (SVM)			
Interventions	**Accurac y**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**AUC**	**Accuracy**	**Precision (PPV)**	**Recall (sensitivity)**	**F1-score**	**AUC**
Financial Planning	0.85	0.58	0.75	0.65	0.86	0.89	0.73	0.68	0.74	0.85
Discharge Planning	0.83	0.60	0.83	0.69	0.89	0.88	0.78	0.73	0.74	0.89
Community Service	0.81	0.48	0.82	0.60	0.85	0.87	0.64	0.65	0.60	0.85
Education	0.79	0.51	0.69	0.58	0.80	0.82	0.66	0.68	0.62	0.82
Supportive Counseling	0.89	0.65	0.61	0.63	0.82	0.92	0.70	0.69	0.68	0.82
Filing Applications and Reporting	0.87	0.49	0.69	0.57	0.85	0.91	0.67	0.55	0.57	0.85
Housing	0.96	0.69	0.45	0.53	0.84	0.96	0.73	0.56	0.59	0.87
Transportation	0.91	0.61	0.54	0.57	0.85	0.94	0.71	0.64	0.68	0.86
Durable Medical Equipment	0.96	0.51	0.34	0.40	0.87	0.98	0.71	0.63	0.60	0.87
Legal	0.97	0.13	0.10	0.11	0.63	0.97	0.21	0.23	0.26	0.66

Discussion

This study described the extent and nature of social work activities in primary care using NLP methods. 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[86,133] This "broker" function was evident in the primary care setting through the frequent activities of care coordination interventions and referrals to community-based organizations. These interventions require coordinating services for patients between different organizations / providers, maintaining communication, and identifying needed resources from referral partners. A study by Bronstein et al[134] showed that involvement of social workers in provision of post discharge care, a discharge planning intervention, was associated with fewer 30-day hospital readmissions. These referral activities included directing patients to organizations that address food insecurity, clothing, spiritual, and peer-advocacy needs. Pruitt et al. showed that referrals to community-based organizations offered by social workers are associated with lower healthcare costs[135]. Our study shows that social workers in primary care were offering interventions that are known to help health care organizations' efforts to improve quality of care, reduce costs, effectively manage population health, and thus, attain the Institute of Healthcare Improvement's Triple Aim). We intend to investigate the value of social work interventions towards improving quality outcomes in our future studies.

Social workers frequently educated patients about the availability of resources and interpretation of medical information. Given that patient education is known to contribute significantly towards better health outcomes,[136] the fact that social workers provide patient education 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 social intervention instituted by social workers in this study. Similar to previous studies,[51,86] our study findings indicated that social workers primarily address the impact of finances on healthcare access through provision of assistance with medication, insurance, and benefits, rather than by directly providing monetary assistance. In a study on diabetic patients, Rabovsky et al found that social workers addressed mental health issues in 12% of cases by referring patients to mental health providers.[86] In our study, social workers addressed mental and behavioral health issues by directly providing supportive counseling intervention to patients. This finding conflicts with the opinion that the time-consuming role of providing patients with tangible resources detracts social workers from their counselor role. Also, this finding suggests that the practice pattern and/or expertise of the social workers in Rabovsky et al may be the main reason why social workers outsourced counseling interventions to external organizations rather than providing the counseling services themselves. Finally, in previous studies, the nature of the advocacy role of social workers was not evident. However, in this study, 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 in advocating for patients, particularly the most vulnerable, a role that was not well explored in previous studies.[86,133,137]

Like Pooler et al,[137] we found that approximately two-fifths of the social worker notes included more than one social work intervention. Among this safety-net population, a substantial number of patients have co-occurring social needs.[137] The presence of a sizable proportion of patients receiving multiple social interventions indicates the need for effective social work staffing and differential use of more experienced social workers to manage patients with co-occurring social needs.

Previous research suggests that social needs interventions are rarely explored using NLP methods and machine learning methods, even though unstructured free-text narratives within EHRs are conducive to NLP- and ML-based classification methods.[66] NLP can effectively be used to determine the types of social work interventions suggested by social workers operating within healthcare systems. Consistent with the findings of previous studies, machine learning- and deep learning -based classification algorithms performed better than rule-based classification methods.[138,139] Also, the multilabel LSTM, a deep learning approach did not perform as well as some machine learning 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.[140]

Limitations

This study, which has been published by the American Journal of Managed Care,[141] has several limitations. First, even though we derived the social intervention categories in this study from consultation with experts and peer-reviewed literature, our classification scheme interventions 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 reflect 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.

Conclusions

Contextual details of interventions instituted by social workers, which are available in notes within EHRs, highlight how social needs are addressed by social workers. NLP and ML can be utilized for automated identification and classification of social work interventions documented in EHRs. Thus, these methods 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 social work staffing, resource allocation, and patient's social needs.

Chapter Four: The Impact of Social Work Interventions on Healthcare Utilization Outcomes

Background

As the US healthcare system transitions to value-based care model, policymakers and payers are increasingly requiring health care delivery organizations to address their patients' social needs and social risk factors.[142,143] Initiatives established under the Patient Protection and Affordable Care Act (ACA) of 2010 – such as the Accountable Health Communities model, the Health Homes programs, and the requirement on not-for-profit hospitals to conduct a community health needs assessment (CHNA) once every three years – are notable examples of health policies aimed at encouraging healthcare organizations to address their patients' social risk factors and needs.[7,13,14,30,31,144] In response, health care organizations are adopting numerous strategies to address their patients' social needs. Among other strategies, health care organizations have invested in affordable housing;[145] established their own food pantries;[146] engaged in community partnerships with rideshare companies;[147] increased screening of their patients for social needs;[42] and are increasingly employing social workers to address their patients' social needs.[86,108]

Social workers are uniquely positioned to address patients' social needs, owing to their training, skills, philosophical perspective, and workflow.[52–54] In general, evidence suggests that social workers operating within health care organizations can positively affect patients' health and outcomes. For example, Matalon et al[70] found that provision of biopsychosocial intervention by a care team that included social workers led to modification of illness behavior and decreased cost of medical investigations. Rose et al[69] studied the effect of provision of a set of interventions by social workers, in collaboration with primary care team members, to patients with increased inpatient and emergency department (ED) use. The researchers found that these interventions led to a decrease in admissions and ED utilization with significant cost savings. Furthermore, Frank et al[106] found that patients who received financial interventions had lower cost of care. Also, a study by Bronstein et al[134] showed that involvement of social workers in provision of post discharge care was associated with fewer 30-day hospital readmissions.

These previous studies have broadly highlighted the effectiveness of interventions offered by social workers, yet, they have not comprehensively explored the idea of untwining the specific interventions driving these outcomes. Specifically, evaluations have mainly treated social work interventions in health care settings as binary phenomena, whereby researchers investigate the outcome(s) of providing one or more social work interventions to patients without necessarily untangling the specific social work activities/interventions driving the health outcomes.[67–70,71–74] Concurring with findings of previous studies,[113–118,137] our previous works showed that patients commonly have multiple co-occurring social needs, and that social workers may offer multiple interventions to address the needs of patients with multiple co-occurring social needs.[108,141] Given that social workers offer various types of interventions to patients with multiple co-occurring social needs, untangling the specific set of social work activities driving healthcare utilization outcomes may inform resource allocation decisions related to social workers, guide social workers' workflow, and potentially inform reinforcement, or otherwise, of certain social work activities.

The aim of this study is to assess the association between receiving social work interventions and relevant health care utilization outcomes. Moreover, we aim to provide greater conceptual clarity by introducing more detailed measurements of actual social work activities. Strong evidence about the effectiveness of social work interventions is critical as more health care organizations consider employing social workers for their expertise in social needs and social risk factors. Moreover, identifying the specific social work interventions driving health outcomes will help towards shaping social workers' workflow as well as supporting managerial decisions related to resource allocation for social workers. Understanding the effectiveness of social work interventions is also important as policy discussions around reimbursement for social workers continue thriving.

Methods

In an unbalanced panel design, we measured the association between receiving social work intervention(s) and patients' count of ED and /or inpatient admission, as well as the rate of missed outpatient appointment.

Setting and sample

The study population comes from patients served by Eskenazi Health, a public safety-net provider with a 300-bed hospital and a federally qualified health center (FQHC) serving the Indianapolis, Indiana metropolitan area. Our study sample included 282 patients who had received at least one social work intervention between October 1, 2017 and September 30, 2019. The 282 patients had a total of 487 social work encounters.

Data

Our primary data source was Eskenazi Health's EHR system, which provided encounter, diagnosis, and patient demographic information. To obtain patient encounter and diagnosis information from patients' visits to non-Eskenazi providers, we complemented Eskenazi's EHR data with the Indiana Network for Patient Care (INPC) data. INPC is the oldest and largest health information exchange system in the United States, combining clinical data from more than 100 hospitals, 14,000 practices, and 40,000 providers.

Measures

We used nDepth,[119] a natural language processing tool developed by the Regenstrief Institute, to retrieve social work notes from Ezkenazi Health's EHR. nDepth allows users to conduct customizable search queries with text data. We extracted social work notes using the following search terms: "social work" or "MSW" or "LCSW", or "LSW", or "LMSW", or "LBSW." In consultation with social work experts, we developed a literature-based classification scheme for social work interventions. We then categorized the retrieved social work notes into non-mutually exclusive social work intervention categories. A full description of the extraction and categorization process for social work interventions is available in our previous work.[141]

Furthermore, we calculated the average Elixhauser score for each patient in the year they received their first social work intervention. Elixhauser score is a measure of comorbidity that has been widely used in predicting health outcomes such as 30-day mortality and 30-day readmission rates.[148–153]

Independent variables

The main independent variables were a set of dummy variables indicating whether a patient received one of the following social work intervention categories in the previous month:

- Financial planning: Includes provision of resources for funding medications, treatments, or other care, as well as assistance with obtaining insurance and/or benefits[122]
- Supportive counseling: Involves the provision of emotional and mental health support services[123]
- Care coordination: Involves coordination of care continuity, discharge planning, transition of care, case management, linking patients with primary care providers, arranging follow up visits, making follow up calls, and arranging home visits for discharged patients.[124]
- Education: encompasses health/wellness programs, provision of health information, crisis intervention, and course planning[125]
- Community service: Involves referrals to community organization, peer advocacy groups, spiritual organizations, translational services, and food assistance programs[126]
- Transportation: Includes provision of transportation fares and passes and other transportation assistance.
- Others: Encompasses assistance with housing, durable medical equipment, and legal issues, as well as reporting to adult and child protective services, among others.

Of note, these intervention categories are not mutually exclusive as patients may receive more than one intervention at any given point in time.

Dependent variables

The primary dependent variables were the total number of ED visits and/or inpatient visits per month and the rate of missed outpatient appointments in a month. We defined the rate of missed appointments as the number of no shows per scheduled primary care visits.

Analysis

We used conditional (fixed-effects) Poisson regression model, with robust standard errors, to investigate the within-patient effects of receiving a specific social work intervention type on the monthly count of ED and /or inpatient visits, as well as the monthly rate of missed outpatient appointments. In this fixed-effects approach, each patient served as their own control, which effectively accounted for all unobservable time-invariant patient characteristics. As robustness checks, we modeled these same within-patient effects using the linear model with individual-level fixed effects and robust standard errors, as well as conditional (fixed effects) negative binomial regression models with bias corrected bootstrapped standard errors. We used Bonferroni correction to account for multiple comparisons. For all our data analysis, we used STATA 16.1.[154] We considered 0.05 as the alpha level of significance.

Results

The mean age of the patients was 37.2 years. Most of the patients were female, and Hispanics constituted about 44% of the patients. The mean Elixhauser score among the patients was 2.7. Care coordination and education were the most frequently offered social work interventions (Table 16).

Table 16: Patient characteristics and social work interventions offered

Patient Characteristics and social work interventions	**Any social work intervention (n=282)**
Age, mean (S.D)	37.2 (21.0)
Gender (%)	
Female	62.1
Male	37.9
Race / Ethnicity (%)	
Hispanic	44.3
African American non-Hispanic	35.8
White non-Hispanic	17.0
Other non-Hispanic	1.5
Unknown	1.4
Elixhauser score, mean (S.D)	2.7 (1.9)
Monthly inpatient and ED encounters, mean (S.D)	3.7 (6.8)
Monthly rate of missed appointment, mean (S.D)	0.2 (0.2)
Social work interventions (% Yes)	
Financial	23.8
Care Coordination	32.0
Education	29.1
Community Services	23.0
Transport	14.5
Counseling	24.4
Others	30.1

Note: The social work intervention categories are not mutually exclusive

In the adjusted conditional (fixed effects) Poisson regression model, receiving care coordination intervention in the previous month was associated with a lower count of inpatient and / or ED visits (Table 17). Furthermore, receiving care coordination intervention in the previous months was associated with a higher rate of missed appointments (Table 18). However, in the bivariate Poisson regression models, the aggregate measure of association between provision of any type of social work intervention and utilization outcomes was not statistically significant (Tables 17 and 18). No other social work intervention was associated with outcomes.

Our robustness checks (Tables 19 and 20) provided consistent results, with the notable exception of education intervention in the adjusted fixed-effects negative binomial regression model. In this model, receiving care coordination intervention in the previous month was associated with a lower count of inpatient and / or ED visits and a higher rate of missed appointments (Table 19). Similarly, the adjusted fixed-effects linear model showed that receiving care coordination intervention was associated with a lower likelihood of post-discharge inpatient and /or ED visits and a higher likelihood of post-discharge missed outpatient appointments (Table 20). Similar to the bivariate Poisson models (Tables 17 and 18), the bivariate fixed-effects linear models and the bivariate conditional negative binomial regression model did not show evidence of a significant association between aggregate provision of any type of social work intervention and the count of ED and inpatient visits (Tables 19 and 20). While receiving education intervention was associated with a higher count of post-discharge utilization, the association was not statistically significant after Bonferroni correction (Table 21). The significance of other associations in all the adjusted models did not change after

Bonferroni correction (Tables 21 and 22).

Table 17: Poisson regression model coefficients and 95% confidence intervals (CI) for count of ED and inpatient visits per month

Social work intervention categories	Bivariate association (I)	Adjusted model (II)
Any social work intervention	-0.15 (-0.37, 0.06)	--
Categories		
Financial	0.15 (-0.35, 0.65)	0.13 (-0.32, 0.59)
Care Coordination	-0.51 (-0.89, -0.12) *	-0.66 (-1.07, -0.26) **
Education	0.04 (-0.27, 0.35)	0.33 (-0.09, 0.76)
Community Services	0.09 (-0.31, 0.50)	0.01 (-0.49, 0.50)
Transportation	-0.06 (-0.49, 0.37)	-0.32 (-0.80, 0.17)
Counseling	-0.10 (-0.63, 0.43)	-0.18 (-0.76, 0.41)
Others	0.18 (-0.13, 0.50)	0.33 (-0.04, 0.70)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Table 18: Poisson regression model coefficients and 95% confidence intervals (CI) for rate of missed outpatient appointments

Social work intervention categories	Bivariate association (I)	Adjusted model (II)
Any social work intervention	0.93 (0.69, 1.16) ***	--
Categories		
Financial	0.81 (0.32, 1.30) **	0.36 (-0.23, 0.95)
Care Coordination	1.43 (1.02, 1.85) ***	1.19 (0.74, 1.65) ***
Education	1.17 (0.70, 1.64) ***	0.39 (-0.16, 0.93)
Community Services	1.00 (0.52, 1.47) ***	0.13 (-0.50, 0.77)
Transportation	1.16 (0.69, 1.62) ***	0.61 (-0.03, 1.25)
Counseling	0.88 (0.43, 1.32) ***	0.51 (-0.03, 1.05)
Others	0.70 (0.24, 1.16) **	-0.03 (-0.54, 0.47)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Table 19: Robustness check – conditional negative binomial model coefficients and 95% confidence intervals (CI) for outcome variables

Social work intervention categories	**Count of ED/inpatient visits**		**Rate of missed appointments**	
	Bivariate association (I)	Adjusted model (II)	Bivariate association (I)	Adjusted model (II)
Any social work intervention	-0.19 (-0.44, 0.06)	--	0.93 (0.58, 1.27) ***	--
Categories				
Financial	0.07 (-0.47, 0.60)	0.09 (-0.47, 0.66)	0.81 (0.14, 1.50) *	0.36 (-0.45, 1.16)
Care Coordination	-0.47 (-0.88, -0.06) *	-0.63 (-1.07, -0.19) **	1.43 (0.81, 2.05) ***	1.19 (0.51, 1.87)**
Education	0.17 (-0.22, 0.57)	0.51 (0.04, 0.98) *	1.17 (0.50, 1.84) **	0.39 (-0.42, 1.20)
Community Services	-0.05 (-0.56, 0.46)	-0.01 (-0.62, 0.60)	1.00 (0.35, 1.64) **	0.13 (-0.73, 1.00)
Transportation	-0.27 (-0.84, 0.30)	-0.45 (-1.08, 0.18)	1.16 (0.41, 1.91) **	0.61 (-0.27, 1.50)
Counseling	-0.17 (-0.78, 0.45)	-0.24 (-0.92, 0.44)	0.88 (0.18, 1.57) *	0.51 (-0.29, 1.31)
Others	0.06 (-0.41, 0.53)	0.24 (-0.27, 0.75)	0.70 (0.04, 1.34) *	- 0.03 (-0.83, 0.76)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Table 20: Robustness check – fixed-effects linear regression model coefficients and 95% confidence intervals (CI) for outcome variables

Social work intervention categories	Count of ED/inpatient visits		Rate of missed appointments	
	Bivariate association (I)	Adjusted model (II)	Bivariate association (I)	Adjusted model (II)
Any social work intervention	-0.08 (-0.17, 0.21)	--	0.10 (0.07, 0.13)***	--
Categories				
Financial	0.05 (-0.14, 0.25)	0.05 (-0.17, 0.27)	0.10 (0.02, 0.17) *	0.04 (-0.03, 0.11)
Care Coordination	-0.29 (-0.47, -0.12) **	-0.36 (-0.55, -0.17) ***	0.14 (0.08, 0.20) ***	0.11 (0.05, 0.17) **
Education	0.03 (-0.18, 0.24)	0.09 (-0.13, 0.31)	0.11 (0.04, 0.17) ***	0.03 (-0.03, 0.09)
Community Services	0.05 (-0.18, 0.28)	0.05 (-0.17, 0.27)	0.13 (0.04, 0.21) **	0.05 (-0.03, 0.13)
Transportation	-0.06 (-0.46, 0.35)	-0.11 (-0.51, 0.29)	0.17 (0.07, 0.27) **	0.10 (-0.001, 0.21)
Counseling	-0.03 (-0.18, 0.12)	-0.03 (-0.19, 0.13)	0.09 (0.03, 0.16) **	0.05 (-0.02, 0.11)
Others	0.11 (-0.13, 0.35)	0.18 (-0.06, 0.42)	0.09 (0.02, 0.16) *	0.002 (-0.07, 0.07)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Table 21: Bonferroni corrected model coefficients and 98.3% confidence intervals (CI) for count of ED/inpatient visits

Social work intervention categories	Fixed-effects Poisson Regression	Fixed-Effects Linear Regression	Fixed-Effects Negative Binomial Regression
Financial	0.13 (-0.43, 0.69)	0.05 (-0.22, 0.32)	0.09 (-0.59, 0.78)
Care Coordination	-0.66 (-1.16, -0.17) **	-0.36 (-0.59, -0.13) ***	-0.63 (-1.17, -0.10) **
Education	0.33 (-0.19, 0.85)	0.09 (-0.18, 0.36)	0.51 (-0.06, 1.08)
Community Services	0.01 (-0.60, 0.61)	0.05 (-0.21, 0.32)	-0.01 (-0.75, 0.74)
Transportation	-0.32 (-0.91, 0.27)	-0.11 (-0.60, 0.38)	-0.45 (-1.21, 0.32)
Counseling	-0.18 (-0.89, 0.54)	-0.03 (-0.23, 0.16)	-0.24 (-1.07, 0.60)
Others	0.33 (-0.12, 0.78)	0.18 (-0.11, 0.48)	0.24 (-0.39, 0.87)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Table 22: Bonferroni corrected model coefficients and 98.3% confidence intervals (CI) for rate of missed outpatient appointments

Social work intervention categories	Fixed-effects Poisson Regression (I)	Fixed-Effects Linear Regression	Fixed-Effects Negative Binomial Regression
Financial	0.36 (-0.36, 1.10)	0.04 (-0.05, 0.13)	0.36 (-0.62, 1.34)
Care Coordination	1.19 (0.64, 1.75) ***	0.11 (0.03, 0.18) **	1.19 (0.36, 2.02)**
Education	0.39 (-0.28, 1.05)	0.03 (-0.05, 0.11)	0.39 (-0.60, 1.38)
Community Services	0.13 (-0.65, 0.91)	0.05 (-0.05, 0.15)	0.13 (-0.92, 1.18)
Transportation	0.61 (-0.17, 1.40)	0.10 (-0.02, 0.23)	0.61 (-0.47, 1.70)
Counseling	0.51 (-0.15, 1.17)	0.05 (-0.03, 0.12)	0.51 (-0.47, 1.50)
Others	-0.03 (-0.65, 0.58)	0.002 (-0.08, 0.08)	- 0.03 (-1.01, 0.94)

p-values – * < 0.05; ** < 0.01; *** < 0.001; The social work intervention categories are not mutually exclusive

Discussion

Overall, social workers offered multiple interventions for patients. Social worker delivered care coordination interventions were associated with lower subsequent inpatient and ED utilization in the safety-net primary care setting. However, for other services there was no indication of association with reduced utilization. Notably, the aggregate measure of the bivariate association between provision of any type of social work intervention and all the health care utilization outcomes was not statistically significant.   This helps illustrate why treating social work interventions as binary phenomena may lead to wrong conclusions about the impact of social work interventions and why more specific measurement strategies are valuable in evaluating social work interventions.

The care coordination interventions offered by social workers in this study included discharge planning, linking patients with primary care providers, arranging follow up visits, making follow up calls, and arranging home visits for discharged patients. Previous researchers have termed social workers providing these types of interventions as "transition coaches."[155,156] It has been suggested that using social workers to provide care coordination-related interventions may be more cost-effective and less redundant than using other healthcare personnel.[155–157] This might be due to the ability of social workers to serve multiple functions within the health care setting, as well as their ability to address complex patients' social needs. The findings of this study provide evidence to support the use of social workers in pursuing care coordination efforts among safety net healthcare providers intending to reduce early post-discharge rehospitalizations and ED visits among their patients. Moreover, the fact that our study shows that care coordination interventions are associated with reduced inpatient and ED visits suggests that the use of social workers to provide these services may be a cost-effective solution to attaining the Institute of Healthcare Improvement's (IHI) "triple aim" of improving quality of care, reducing costs, and effectively managing population health.

Our study showed that care coordination intervention is significantly associated with a higher rate of missed outpatient appointments. This finding, however, should be interpreted within the context of the care coordination intervention offered in our study setting. In this study, care coordination intervention was largely provided to inpatients in the form of discharge planning and arrangement of home visits and follow-up visits. Therefore, it is conceivable that care coordinators might have been scheduling more post-discharge appointments for admitted patients, and the patients are not keeping up with the scheduled outpatient appointments. As such, the fact that care coordination was significantly associated with a higher rate of missed outpatient appointments might reflect a high rate of missed post-discharge appointments among patients in this study, rather than the impact of care coordination intervention itself. Because missed appointments have been shown to worsen health outcomes and complicate the care delivery process,[10,11,158–160] future studies should investigate the factors associated with missed appointments among patients receiving care coordination intervention.

Furthermore, our study showed that other social work interventions such as financial, counseling, education, and transportation were not significantly associated with inpatient and ED visits or rate of missed appointments. While these interventions may not be associated with the utilization outcomes considered in this study, they may be associated with other outcomes. Future studies should, therefore, explore other health outcomes that may be associated with specific social work interventions. Notably, the fact that this study identified care coordination intervention as the only social work intervention associated with lower inpatient and ED utilization means that health care organizations should allocate more resources to help social workers provide better care coordination services for their patients. Moreover, finding the specific social work intervention potentially driving utilization outcomes will guide policymakers in making decisions related to optimal utilization of social workers in clinical care.

Limitations

This study has limitations related to measurement and generalizability. Our study participants are limited to patients from a single FQHC. The findings of our study may, therefore, not be generalizable to the larger Indiana or US population. Furthermore, although the social work intervention categories used in this study were derived from the literature, the categorization process may not be exhaustive, making the omission of certain interventions from our analysis likely. Also, although our fixed effects approach controlled for observable and unobservable time-invariant covariates, certain unobserved time-varying covariates may confound the findings of our study. However, the likelihood of confounding by a time-varying covariate is reduced by the fact that we limited our analysis to a period of 3 months before and 3 months after receiving a social work intervention.

Conclusions

Social workers offer various types of interventions to address patients' social needs. Care coordination intervention offered by social workers provides an efficient path to attaining the IHI's "triple aim" of improving quality of care, reducing costs, and effectively managing population health. The findings of this study provide evidence to support the use of social workers in pursuing care coordination efforts among safety net healthcare providers intending to reduce early post-discharge rehospitalizations and ED visits among their patients. Moreover, this study will inform policy makers on designing workflows for social workers that assures optimum allocation of social work resources to improve healthcare utilization outcomes.

Chapter Five: Conclusion

The purpose of this dissertation was to investigate the role of social workers in addressing patients' social needs. To accomplish this, I derived a literature-based categorization scheme for the social needs that lead to referral to social workers in a safety net population; automated the categorization process using NLP; and evaluated co-occurrence of the social needs using MBA. Next, I derived a literature-based categorization scheme for social work interventions and used NLP, ML, and deep learning to automate the classification process. Finally, I measured the impact of these literature-derived social work intervention types on healthcare utilization outcomes, mainly the count of inpatient and ED visits and the rate of missed outpatient appointments. Each of these individual studies provided specific insights into social needs and the provision of social work interventions in the health care setting. However, three cross-cutting themes derived from these individual studies are relevant to current health care practice and policy:

1. The ubiquity and diversity of the social needs leading to referral to social workers in this study indicate a requirement for substantial level of organizational efforts to address social needs. Furthermore, given that social needs commonly co-occur, and patients with multiple co-occurring needs have worse health outcomes than patients with single needs,[137,161,162] health care organizations could improve their ability to address social needs by developing packages of interventions that simultaneously address co-occurring social needs. Moreover, as recommended by the National Association of Social Workers (NASW),[163] patients with multiple and complex social needs require differential use of more

educated, skilled, and experienced social workers. Therefore, as health care organizations continue employing social workers, in their efforts to comply with the ever increasing mandates requiring them to address social needs,[7,13,14,53,62] determining the methods that will help them most effectively and efficiently leverage the capabilities of social workers becomes paramount.

2. This study proves that text mining and data mining algorithms, such as NLP, ML, and MBA, could improve health care organizations' ability to harness the capabilities of social workers to address patients' complex social needs. To illustrate, the social needs extraction and co-occurrence algorithms developed in this study could be incorporated into an appropriate decision support system to facilitate social workers' ability to identify patients' needs more efficiently, thereby improving the workflow of social workers. For example, once one need is identified the decision support system can prompt additional screening for other potentially co-occurring social needs. Additionally, this study proves that automated extraction of social work interventions could potentially facilitate organizational efforts to evaluate the impact of social work activities. In this study, I developed a literature-based classification scheme for social work interventions, which I automated using text mining algorithms, and used the classification scheme to analyze the outcomes of specific social work interventions. Therefore, organizations can develop algorithms to extract social work interventions from social workers' documentations, which are largely in unstructured format,[63,64] and use those algorithms to make decisions related social work resource allocation and social work staffing. Also, the automated algorithm

can facilitate quick evaluation of the impact of specific social work interventions. Importantly, however, the data I used to develop these algorithms came from a single health system. Consequently, the generalizability of the findings of this study is limited. Future studies should, therefore, explore using representative samples to develop extraction algorithms for social needs and social work interventions. Potentially, these generalizable algorithms can be incorporated into decision support systems of major EHR vendors to aid organizational efforts to address social needs.

3. This study contributes to a growing body of literature demonstrating the impact of social work interventions on health outcomes. As the number of social workers employed in the health care settings continues growing,[53,62] indicating organizational efforts to utilize social workers' expertise to address social needs, and as policy debates around social workers' reimbursement assumes greater prominence, the need for conceptual clarity regarding the specific social work activities driving population health becomes pivotal. The findings of this study suggest that provision of care coordination intervention by social workers is associated with lower post-discharge inpatient and ED utilization. This finding offers support for the use of social workers in pursuing care coordination efforts among safety net healthcare providers intending to reduce early post-discharge rehospitalizations and ED visits among their patients. Because care coordination in this study comprises multiple types of interventions, including discharge planning, home visits, and case management. Future studies should investigate the specific aspects of care coordination that are driving healthcare utilization

outcomes. Future studies should also investigate the impact of care coordination, as well as other social work interventions, on other health outcomes such as cost of care, length of stay, and mortality, among others.

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Curriculum Vitae

Abdulaziz Tijjani Bako

Education

2016-2021 PhD. in Health Policy and Management (*Biostatistics minor)*

Indiana University–Purdue University, Indianapolis – April 2021

Dissertation title: *The role of social workers in addressing patients' social needs in a primary care setting.*

2014-2015 Master of Public Health, *Health Policy and Management*

Texas A&M University – December 2015

2003-2011 Bachelor of Medicine, Bachelor of Surgery (MBBS)

Bayero University Kano – March 2011

Professional Experience

2020- *Post Doctoral Fellow*

Houston Methodist Hospital

2016-2020 *Research Assistant*

Indiana University Richard M. Fairbanks School of Public Health, Indianapolis

2015-2016 *Research Assistant*

Center for Health Organization Transformation, Texas A&M

2014 *Student intern*

Rural and Community Health Institute, College Station, Texas.

2013 *Medical Officer*

General Hospital, Bichi LGA, Kano State, Nigeria

Voluntary Services

2017-Present *Volunteer health correspondent*

Voice of America Radio Station

2015-2016 *Epi-Assist volunteer*

Community Assessment for Public Health Emergency Response (CASPER) surveys

2014-2015 *Graduate student leader*

Dementia Service-Learning Project, College of Education and Human Development, Texas A&M University.

2014-2016 *Graduate student leader*

Texas A&M University's Aggies Invent Program

2013 *Physician Volunteer*

World Health Organization (WHO) & United Nations Children's Fund (UNICEF)

Peer-Reviewed Publications

1. **Bako, A. T.,** Taylor, H. L., Wiley, K. J., Zheng, J., Walter-McCabe, H. A., Kasthurirathne, S. N., & & Vest, J. R. (n.d.). Using natural language processing to classify social work interventions. *The American Journal of Managed Care*.
2. **Bako, A. T.,** Walter-McCabe, H., Kasthurirathne, S. N., Halverson, P. K., Vest, J, R. (2020). *Reasons for social work referrals in an urban, safety-net population*. December 2019.
3. Dayyab, F. M., Iliyasu, G., Ahmad, B. G., **Bako, A. T**., Ngamariju, S. S., & Habib, A. G. (2020). Hepatitis B vaccine knowledge and self-reported vaccination status among healthcare workers in a conflict region in northeastern Nigeria. *Therapeutic Advances in Vaccines and Immunotherapy*, *8*, 2515135519900743.
4. Ferdinand, A. O., Cheon, O**., Bako, A. T**., & Kash, B. A. (2019). Interventions aimed at addressing unplanned hospital readmissions in the US: A systematic review. Journal of Hospital Administration, 8(1).
5. Vest, J. R., Freedman, S., Unruh, M. A., Bako, A. T., & Simon, K. (2020). Strategic use of health information exchange and market share, payer mix, and operating margins. Health Care Management Review. https://doi.org/10.1097/HMR.0000000000000293

Conference Presentations

1. **Bako, A. T.,** & Vest, J. R. (2019). Reasons for Referral to Social Worker in a Primary Healthcare Setting: A Market Basket Analysis and Natural Language Processing Approach. AcademyHealth 2019 Annual Research Meeting. Washington, DC. June 2-4, 2019.
2. Ferdinand, A.O., Cheon, O., Bako, A.T., Kash, B. (2018). Avoidable Hospital Readmissions: Top Three Interventions Used Versus Top Three Most Effective Interventions. Center for Health Organization Transformation Compendium, 2018.
3. Vest JR, **Bako A. T.**, Kasthurirathne SN, Grannis S. Services for Social Determinants of Health Delivered in Primary Care Settings: Measurement & Prevalence. AcademyHealth 2017 Annual Research Meeting. New Orleans, LA. June 25-27, 2017
4. **Bako A,** Apathy N, Harle CA, Menachemi N, Vest JR. User Concerns Following Replacement of a Legacy Electronic Health Record: A Longitudinal Qualitative Study. AcademyHealth 2017 Annual Research Meeting. New Orleans, LA. June 25-27, 2017.
5. Ferdinand, A. O., Sasangohar, F., **Bako, A. T.,** Mack S. (2016). Avoidable Admissions: The Role of Non-Urgent Emergency Visits. CHOT 2016 Spring IAB Meeting. Houston, TX. April 7-8, 2016.
6. Sumners, C. B., **Bako A. T.,** Fabian, O., Martel, I., Molar-Candanosa, R., Gastel, B. (2016). Communicating Science with Integrity, Effectiveness, Humor, and More: Some Highlights of the 2016 AAAS Annual Meeting

7. Sunusi A., Lawan U. M., Bako, A. T. Hospital Costs and Utilization Pattern for Paediatric Patients with Sickle Cell Disease Attending a Tertiary Health Institution: Northern Nigeria – **Won Travel award for** Presentation at the Geneva Health Forum, April 2012.
8. Ferdinand, A. O., **Bako, A. T.,** The Role of Disparities in 30-Day Readmission Rates. A webinar recorded on July 7, 2016

Research Support

Robert Wood Johnson Foundation: Vest & Halverson (Co-PI) 8/2018-7/2020

Addressing upstream determinants of health through collaboration and analytics (RWJF-75549)

Role: Research Assistant

$1,000,000

Teaching Experience

- Teaching Assistant, Population & Public Health (MHA course)
- Guest Lecturer, Health Systems Around the World
- Guest Lecturer, Health Administration Ethics
- Guest Lecturer, Chronic & Long-Term Care Administration

Certification Courses and Trainings Completed

- Base SAS online certification course (offered by SAS Institute)

- R Programming (provided by John Hopkins University, through Coursera)
- IHI certificate in healthcare quality
- Training on Exepron Critical Chain Project Management software
- Lean Six Sigma white belt certificate

Leadership Activities

2015-2015 School of Public Health Representative, Texas A&M Graduate and Professional Council

2015-2015 School of Public Health Representative, Texas A&M Health Science Centre's Student Government Board

2015-2015 Graduate Student Mentor, Aggies Invent Program, Texas A&M University

2007- Present Co-founder and Public Relations Officer, Masterpiece Health and Development Organization

2015-Present Board of Trustees Member, Kano Education Foundation (an Association of over 5,000 international students studying in various countries)

2010-2010 Chairman, Electoral Committee, Kano State Medical Students Association

2008-2009 Treasurer, National Association of Kano State Students (NAKSS)

2004-2005 Public Relations Officer, Kano State Medical Students Association (KAMSA National Body)

- Headed the publication of KAMSA Medical Journal

2004-2005 Senator, National Association of Kano State Students

Professional Affiliations

Peer reviewer, American Medical Informatics Association Annual Symposium (2016-date), American Journal of Managed Care

Student member, Institute of Healthcare Improvement

Student member, AcademyHealth

Student member, American Medical Informatics Association