Social Support and Health Care Utilization

A Retrospective Cohort Study

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Abbreviations

C-TraIn: Care Transitions Intervention
ED: Emergency department
HRRP: Hospital Readmission Reductions Program
OHSU: Oregon Health and Science University
PAM: Patient Activation Measure
PHQ-2: Personal Health Questionaire-2 item form
SES: Socioeconomic status
SSQ: Social support questionnaire
SSQN: SSQ number score
SSQS: SSQ satisfaction score

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Abstract

Background: Hospital readmissions are common, costly, and associated with poorer quality of care. Existing models have not performed adequately in assessing hospital readmission risk and do not always account for social variables that may be important predictors of readmission risk, including social support.

Methods: We used the abbreviated Social Support Questionnaire (SSQ3) to generate measures of quality and quantity of social support for uninsured or low-income publically insured patients in the Portland metro area. Using logistic regression, we assessed whether social support quality or quantity was predictive of hospital readmission risk.

Results: Models of readmission risk at 30, 90, and 180 days were constructed with social support network size (SSQN) and quality (SSQS) as the primary variables of interest. Although several of the constructed models achieved overall statistical significance, social support measures were not significant in any of the models. As expected, the Charlson Index score, a measure of comorbidity was significantly associated with readmission risk.

Discussion: Overall, we did not find evidence that social support quality or quantity was associated with readmission risk at 30, 90, or 180 days. The implications of our findings are that social support may not be an independent predictor for readmission risk, but may work as an effect modifier in conjunction with other measures of medical comorbidity.

Background and rationale

Hospital readmission and health care utilization

In recent years, increasing emphasis has been placed on reducing the risk of hospital readmission. While hospital readmission rates vary from hospital to hospital, it is estimated that nearly 1 in 5 patients are readmitted to the hospital within 30 days of discharge, and that many of these readmissions are avoidable.[1,2] Hospital readmissions are costly to the health care system.[3] A study of Medicare patients estimated that the total cost of unplanned readmissions in 2004 exceeded $17 billion.[2]

The high frequency and cost of unplanned hospital readmissions have important implications for hospitals and national health care system. Several studies have presented evidence that unplanned readmissions are associated with poor quality of care. [4] Because of the relationship between care quality and unplanned hospital readmission, unplanned readmission rates are used as a hospital quality measure. Programs like the Hospital Readmission Reductions Program (HRRP) – a federal program that penalizes hospitals with higher than expected Medicare readmission rates – were motivated by the desire to improve care quality while reducing the cost of care.[5]

Because of the interest surrounding readmission rates, recent scholarship has attempted to understand the complex array of factors that lead to an increase in an individual's risk for hospital readmission. However, attempts to develop accurate predictive models for hospital readmission risk have been difficult to achieve. A 2011 systematic review of 30 risk prediction models found that most performed poorly, [6] An update to this review in 2016 found that an additional 73 models performed moderately better, but only two reported high discriminate ability.[7]

The limited ability to predict readmission risk with existing models suggests both that hospital readmission is a complex outcome, and that models may not include the variables most important for predicting readmission risk. Current models used to calculate the Medicare readmissions penalty do not include socioeconomic status (SES) and other social and demographic characteristics that may drive health outcomes and healthcare utilization, but this remains a contentious area within the field.[8,9] A 2016 study by Bernheim et al, found that hospitals caring for a higher proportion of low SES patients performed similarly on measures compared to hospitals with a higher SES population.[9] However, further research is needed to understand whether or not these factors are important in determining individual readmission risk.

Social Support

Within the body of readmission literature, social support is an often-mentioned but inconsistently utilized variable for predictive readmission models. Social support has been consistently linked to physical health outcomes[10–12], and multiple studies have suggested a link between health care utilization and lack of social support. For example, Broadhead et al found that lack of social support increased health care utilization in a family practice outpatient setting, where patients with low social support scores were more likely to have longer appointments with their physicians and spend more on health care over the course of a year.[13] These results were echoed in a similar study by Bosworth, et al, which found that individuals with lower perceived social support were more likely to visit the hospital than those with higher levels of social support.[14]

Qualitative studies of both patients and providers have described the lack of adequate social support as a barrier to successful post-hospital transition.[15–17]

Although often described as a single construct, social support has several component parts.[13] Domains of social support include instrumental and emotional social support, among others. Instrumental social support refers to concrete forms of assistance that are available from members of one's social network, including things like financial assistance, transportation assistance, and material goods. Emotional social support refers to individuals who provide love, encouragement, and concern for a person's well-being.[14,18] These domains of social support are hypothesized to serve different roles with regard to health promotion and health utilization. Both instrumental and emotional social support have positive effects on health outcomes.[13]

Social network size and quality have independent pathways to health.[19] An objective lack of social network members is termed "social isolation", while subjective feelings of dissatisfaction with one's social network is termed "loneliness". For certain health outcomes, loneliness may be more important than social isolation for determining beneficial health outcomes.[12] Those who report loneliness are at higher risk for mental health symptoms. However, individuals who are less socially isolated are more likely to engage in positive health behaviors and comply with medical regimens.[19] In some cases, both social isolation and loneliness can predict a given health outcome, but in other cases only one metric is associated. For example, Howard et al, demonstrated that quality of social support, but not quantity, was associated with decreased blood pressure in older adults.[20] Similar findings of the differential effects of quality and quantity of social support have been demonstrated in multiple settings.

Despite the known relationship between social support and health outcomes, social support is an inconsistently used variable in health research. Studies that seek to adjust for social support commonly use marital status as a proxy for social support. This was the case in a study of mortality and readmission risk for African Americans with heart failure, marital status and housing status were used to extrapolate one's social support.[8] Though this structural measure of social support is easily assessed and may capture some aspects of social support, it is a weak tool for assessing social support overall.[21] Other validated tools are better designed to more accurately assess the different domains of support and to provide more robust information.

Several studies have used validated tools to assess social support in total or component domains. One such tool is the Social Support Questionnaire (SSQ).[22] This validated 27-item questionnaire assesses both quantity and quality of multiple domains of social support. An abbreviated form of this questionnaire, the SSQ-3, has also been validated to provide similarly useful information about the number of relationships and quality of social support, focusing on the emotional domain.[23]

Although some measure of social support is frequently used as a potential covariate in analyses of hospital readmission risk, no studies have examined whether or not social support is a primary predictor of hospital readmissions.

Objectives

Our primary objective was to assess whether social support was a predictor of 30-day hospital readmission risk. We used two social support measures, derived from the Social Support Questionnaire:[23] (1) the social support questionnaire number, or SSQN representing the quantity of social support received; and (2) the social support questionnaire satisfaction, or SSQS, representing the quality of social support. Secondary outcomes included readmission risks at 90 and 180 days post-discharge. Additionally, we examined the relationship between social support satisfaction and Emergency Department (ED visits) at the same time points. To our knowledge, this is the first study to investigate the association between social support and risk of readmission to the hospital.

Methods

Study Design and Setting

This project used data from the Care Transitions Initiative (C-TraIn), a randomized controlled trial conducted at Oregon Health & Science University (OHSU) from November 2010 to January 2012.[24,25] The purpose of the original study was to evaluate the efficacy of an intervention designed to improve care transitions following hospital admission for uninsured and low-income, publically insured individuals.

The present analysis is designed as a retrospective cohort study. Using data from the C-TraIn study, baseline data on social support were utilized to predict readmission risk.

Participants

Study subjects for the present study included all participants enrolled in the C-TraIn intervention trial. All patients for the parent study were screened from patients admitted to the hospitalist service, the teaching service, or the inpatient cardiology service at OHSU between November, 2010, and January, 2012. After screening, eligible individuals (Table 1) were invited to participate and informed consent was obtained. In total, 382 individuals were enrolled in C-TraIn. Baseline surveys were completed for all study subjects, including questions on social support.

The present study utilizes social support data from these baseline surveys and readmission data from the follow-up period. For this study, we excluded 45 participants who either refused to complete the social support questionnaire or who completed it with non-numeric answers. Our final analysis data set consisted of 337 individuals.

Table 1: Inclusion and exclusion criteria for C-TraIn RCT

Inclusion Criteria ▪ Uninsured or low-income publically uninsured[1] ▪ Admitted to OHSU on one of seven teams (five general medicine teaching teams, one hospitalist team, and one inpatient cardiology team) ▪ Living in the tri-county area (Multnomah, Washington, or Clackamas counties) ▪ English speaking ▪ Access to working phone
Exclusion Criteria ▪ Non-community dwelling (i.e. long-term care facility) ▪ HIV positive ▪ Disabling mental illness ▪ Incomplete social support questionnaire

[1]Defined as <200% federal poverty level and using Medicaid or Medicare/Medicaid without supplemental insurance

Variables

Predictor Variables

We used two predictor variables for our analysis, both derived from the Social Support Questionnaire (SSQ3) [23]. The SSQ3 has three questions, each with two parts. The first part of each question dyad asks participants to count the number of individuals that can support them in a certain situation. The second part asks participants to rate their satisfaction with this source of support on a scale of 1-6. The number score, or SSQN, provides a numerical representation of a source of social support and is calculated by taking the average of three numerical items in the questionnaire. The satisfaction score, or SSQS, represents an individual's satisfaction with their level of social support and is calculated as the average of the three satisfaction ratings in the questionnaire.

These variables were analyzed as categorical variables divided into tertiles. Following descriptive analysis, we found that the SSQS scores were distributed toward the upper end of the scale – the 50th percentile of the SSQS scores were at 5.33 (out of 6). For SSQN, the 50th percentile was 5. Because of the clustering of these two scores and the small number of observations at the ends of the spectrum, we felt that utilizing these variables as continuous variables would not allow us to discriminate differences in our outcomes.

For this reason, we chose to categorize both the SSQN and the SSQS into three levels, and all analyses using these predictor variables were conducted using the categorized form of the variables. SSQN was cut into tertiles based on percentiles. In previous studies, SSQS has been found to be asymmetrically distributed, with a mean SSQS of 4-5.[26–28] We observed a similar distribution in our data. Based on this, we chose to categorize SSQS into three levels with the lower level representing SSQS cores of 1-3, the middle level representing SSQS scores of 4-5, and the upper level representing an SSQS score of 6.

Outcome variables

The primary outcome variable was readmission to the hospital within 30 days of the index admission. Secondary outcomes were hospital readmission within 90 and 180 days. Outcome data was collected from the Oregon Hospital Discharge Dataset, which provides information about hospital admissions and discharges in Oregon and two Southwest Washington hospitals for all insured and uninsured patients.

Covariates

Potential covariates are summarized in Table 2, and were selected based on the plausibility of their relationship to both social support and hospital readmission risk. Age (used as a continuous variable) and gender (used as a binary variable) were extracted from clinical chart review. Housing status, race/ethnicity data, substance use information, and education level were elicited during the initial baseline interview. The Patient Activation Measure (PAM) was calculated from a 13-item validated questionnaire administered as part of the baseline interview.[29] Depression screening was conducted using the Patient Health Questionnaire (PHQ-2).[30] Finally, the Charlson index was calculated as a score to indicate the severity of medical comorbidities for each participant.[31]

Table 2: Study variables

Demographics	Age	Categorical
	Gender	Binary
	Marginal housing	Binary
	Racial minority	Binary
	Education (high school or less)	Binary
Primary outcomes	30, 60, and 180-day hospital readmission	Binary
Predictor variables	Social Support Number	Categorical
	Social Support Satisfaction	Categorical
	Social Support Interaction	Categorical
Potential confounders	Patient Activation Measure	Continuous
	Depression screen	Binary
	Tobacco use	Binary
	Illicit drug use	Binary
	Prescription drug misuse	Binary
	Insurance status	Binary
	Charleson index	Continuous

Data sources

Baseline data

At the time of enrollment in the study, C-TraIn participants completed a survey that contained questions about demographics, access to care, medical comorbidities, PAM score, depression (using the PHQ-2), health literacy, substance use, and self-rated health. Questions on social support were also included in this baseline data, using the Social Support Questionnaire – 3.[23]

Social Support Questionnaire – 3 [23]

1. Who accepts you totally, including your worst and best points?
2. How satisfied are you with this source of support on a scale of 1-6 with 1 being very dissatisfied and 6 being very satisfied?
3. Who can you really count on to tell you, in a thoughtful way, when you need to improve in some way?
4. How satisfied are you with this source of support on a scale of 1-6 with 1 being very dissatisfied and 6 being very satisfied?
5. Who do you feel truly loves you deeply?
6. How satisfied are you with this source of support on a scale of 1-6 with 1 being very dissatisfied and 6 being very satisfied?

Figure 1: Questions from the Social Support Questionnaire

Follow-up data

All C-TraIn participants were contacted by phone 30 days after discharge to complete a survey to assess health care access and utilization since discharge, as well as to reassess several baseline data indicators including depression, patient activation, and their experience with care transition using the Care Transition Measure (CTM), a three-item questionnaire. Hospital utilization data, including primary outcomes for 30, 90, and 180 day hospital readmission and ED utilization, were collected from an OHSU research database and the Oregon Hospital Discharge Dataset.

Sample size

The original C-TraIn study was designed to detect a 50% reduction in readmissions from an assumed baseline rate of 25%, using an alpha of 0.05 with 82% power. Using these calculations, target enrollment was 200 intervention participants and 200 controls. Final study enrollment was 382 participants, with 173 control participants and 209 intervention participants.

To evaluate power and sample size for the present study, we developed two scenarios: one with a 30-day readmission rate of 25% as with the parent study, and a second with a 30-day readmission rate of 20%. We used Power Analysis and Sample Size calculation software (PASS Version 13, NCSS) to conduct these analyses. With a power of 80% and a fixed sample size of 337, we had sufficient power to detect a difference in readmissions with an OR of 1.37 at a significance level of 0.05. Using a conservative estimate of 0.15 to account for the effect of covariates in the model, this sample size would allow detection of an OR of 1.40, again with 80% power. Results from these analyses are summarized in Table 3.

Table 3: Power analysis

P0	P1	R-squared	Odds Ratio
0.20	0.260	0.00	1.403
0.20	0.261	0.05	1.415
0.20	0.263	0.10	1.429
0.20	0.265	0.15	1.444
0.25	0.313	0.00	1.367
0.25	0.315	0.05	1.378
0.25	0.317	0.10	1.391
0.25	0.319	0.15	1.404

P0: Baseline proportion of individuals readmitted; P1: Proportion detectable with sample size parameters; R-squared: effect of covariates

Statistical methods

Statistical analyses for this study were conducted using Stata/MP 13.1 (College Station, TX) [32]. Descriptive analyses of all variables included frequencies for categorical variables and frequencies, means, and standard deviations for continuous variables.

Prior to analysis, we calculated the social support scores to be used the analyses. SSQN was calculated as the average of the reported numerical score of supports given by each study participant. SSQS was calculated as the average of the reported satisfaction with each source of support, rated on a scale of 1-6. We conducted descriptive analysis of each of these variables, examining their distributions. Based on these data, we chose to categorize both the SSQN and the SSQS into three levels.

We used multiple logistic regression to examine the association between the primary and secondary outcomes (30-, 60-, and 180-day hospital readmission) and social support using Hosmer and Lemeshow's method for purposeful selection.[33] First, we conducted univariable analysis for all independent variables. Next, we built an initial model including any variables with a p-value of <0.2. Using this initial model, we constructed a smaller model using only covariates that were significant at the $p<0.05$ level. Each excluded variable was assessed for potential confounding by comparing the reduced model (without the potential confounder) to the model including the removed variable. Variables were considered to be confounders if they changed the estimate for the coefficients in the main effects model by greater than 20%. After inclusion of identified confounders, we reintroduced each excluded variable back into the main effects model to see if it had gained significance at the level of $p<0.05$.

We assessed the effects of potential interactions in this model as well. Because the goal of this study was to assess the role of social support in health care utilization we chose to only consider potential interactions with the predictor of interest – SSQS or SSQN. Literature review supported the testing of potential interaction between SSQS and SSQN with Charlson Index score.[34] After including any significant interactions, we conducted tests for goodness-of-fit using the Hosmer and Lemeshow test, and by constructing an ROC for each model.

Results

Participants

Of the 382 participants enrolled in the C-TraIn study, 337 (88%) completed the Social Support Questionnaire and were included our analysis. The characteristics of participants who completed the SSQ were similar to those who did not complete the questionnaire, except that those who did not complete the SSQ were more likely to use alcohol (29.7% vs 50.0%, p=0.07).

Participants were mostly male (57%) and white (73%), with an average age of 48 years. A summary of the demographic characteristics of participants in the study is presented below in Table 4.

Table 4: Demographic characteristics of study participants

	Full sample	**30 day readmission**
Current smoker (%)	103 (30.8)	30 (35.7)
Alcohol use (%)	98 (29.1)	18 (22.0)
Illicit drug use (%)	155 (46.1)	41 (26.5)
Male sex (%)	190 (57.6)	41 (29.3)
Prescription drug misuse (%)	35 (10.4)	9 (25.7)
Marginal housing (%)	98 (29.0)	31 (31.6)
Insurance (%)	201 (59.5)	55 (27.4)
High school or less education (%)	60 (17.8)	15 (25.0)
Racial minority (%)	92 (27.4)	24 (26.1)
Intervention (%)	188 (55.8)	48 (25.5)
Mean age (SD)	47.9 (14.4)	50.1 (14.5)
Mean PAM score (SD)	56.8 (10.6)	55.9 (11.7)
Mean Charlson index (SD)	2.24 (3.06)	2.72 (3.21)

Descriptive data

Data from the SSQ were used to generate two summary scores: the Social Support Number (SSQN) and the Social Support Satisfaction (SSQS) as described above. In this sample, the mean SSQN was 8.50 (SD 11.5, range 0-100). The mean SSQS was 4.84 (SD 1.39, range 1-6). Based on the distribution of the data, we chose to categorize the two variables into three levels. SSQN was divided into tertiles based on percentiles of the distribution. A summary of the SSQN levels is presented below (Table 5).

Table 5: Tertiles for SSQN

SSQN	Mean	Std. Dev.	Freq (%)
Low (ref)	2.07	0.97	116 (34.4)
Medium	5.24	1.08	113 (33.5)
High	18.8	15.8	108 (32.1)
Total	8.50	11.5	337

Past studies that have used the SSQ have found that SSQS is skewed to the left[22] with the mean SSQS score between 4-5.[23,28,35] For this reason, we chose to categorize our data into "low", "medium", and "high" levels for SSQS, with "low" representing those with an SSQS of 1-3, "medium" representing those with a score of 4-5, and "high" for those who reported an SSQS of 6 (Table 6).

Table 6: Levels for SSQS

SSQS level	Mean	Std. Dev.	Freq.
Low (ref)	2.40	1.07	64 (18.99)
Medium	5.02	0.53	163 (48.37)
High	6.00	0.00	110 (32.64)
Total	4.84	1.39	337

Outcome data

Participants in this study had a higher 30-day readmission rate than the national average at 25%.[5] Readmission rates for the samples as a whole at 90 and 180 days were 41% and 51%, respectively. We examined readmission rates at each time point by level of SSQN and SSQS (Table 7). Readmission rates did not vary significantly by level at any of the three time points for either variable.

Table 7
Summary of mean (SD) readmission rates at 30, 90, and 180 days by level of SSQS and SSQN

SSQS Level	30-day readmission	90-day readmission	180-day readmission
Low	17 (26.6)	26 (40.6)	33 (51.6)
Medium	40 (24.5)	67 (41.4)	87 (53.7)
High	28 (25.5)	45 (40.9)	54 (49.1)
Total	85 (25.2)	138 (41.1)	174 (51.8)

SSQN Level	30-day readmission	90-day readmission	180-day readmission
Low	33 (28.5)	51 (44.0)	64 (55.2)
Medium	30 (26.6)	43 (38.1)	54 (47.8)
High	22 (20.4)	44 (41.1)	56 (52.3)
Total	85 (25.2)	138 (41.1)	174 (51.8)

We also examined the percentage of the study population that visited the ED after the index admission. At 30, 90, and 180 days, 23%, 35%, and 53% of the study population respectively had a visit to the ED. When stratified by level of SSQS, there was evidence of decreasing use of the ED for individuals with higher social support satisfaction – for example, 27% of participants in the lowest level of SSQS visited the ED compared to 21% in the highest level. However, none of these trends were statistically significant.

Table 8: Summary of mean (SD) SSQS level with ED visits at 30, 90, and 180 days

SSQS level	30-day ED visit	90-day ED visit	180-day ED visit
Low	17 (26.6)	23 (35.9)	36 (56.3)
Medium	36 (22.1)	57 (35.2)	84 (51.9)
High	23 (20.9)	37 (33.6)	59 (53.6)
Total	76 (22.6)	117 (34.8)	179 (53.3)

Main results

Using SSQN as the primary predictor variable, we generated models for readmission risk at 30, 90, and 180 days using the variables listed in Table 1 as potential covariates. The results from these three multivariate logistic regressions are shown below (Table 9). All three models were statistically significant overall. However, in no model did SSQN as a variable achieve statistical significance. Moreover, there was no clear trend in the relationship between SSQN level and readmission at any of the three time points. Only Charlson Index was consistently significant as a covariate in all three models. In building these models, we tested potential interactions between social support and medical comorbidities, and this product term was found to be significant in the 30- and 90-day readmission models. ROC curves were constructed for each model. All three models had poor predictive capability with AUCs ranging from 65-68%.

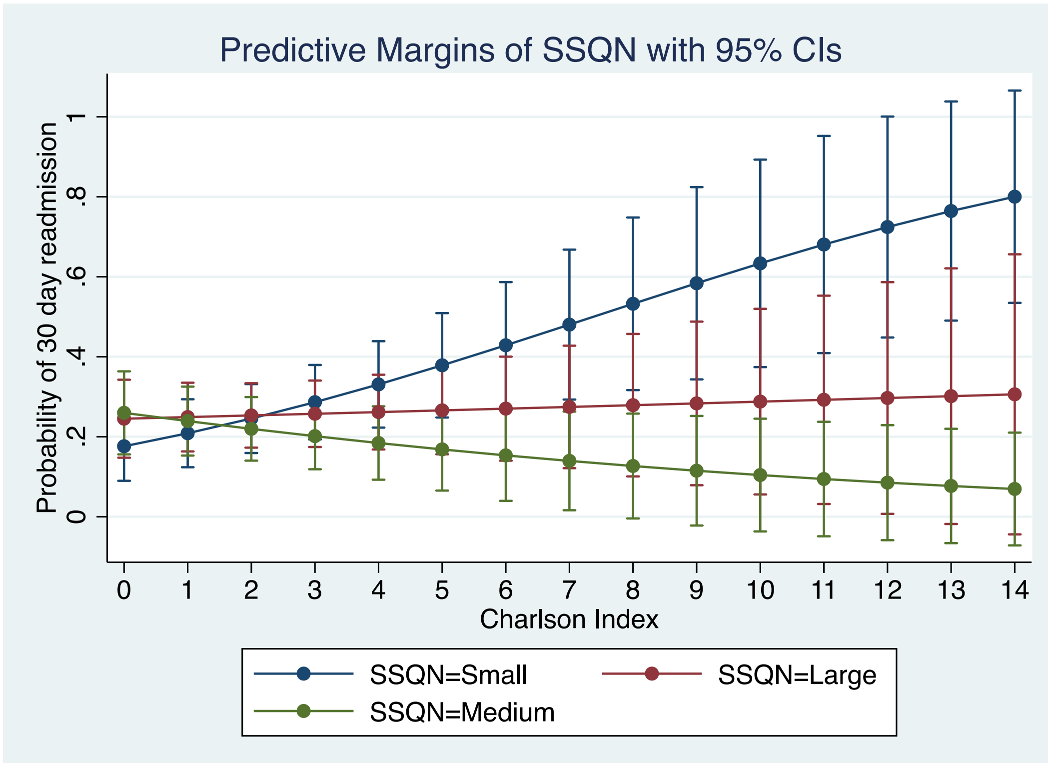
We explored the interactions using predictive margins, and plots of these interactions are displayed below. As shown, individuals in the highest level of SSQN had a decreased probability of hospital readmission for both time points compared to individuals in both the first and second level of social support number.

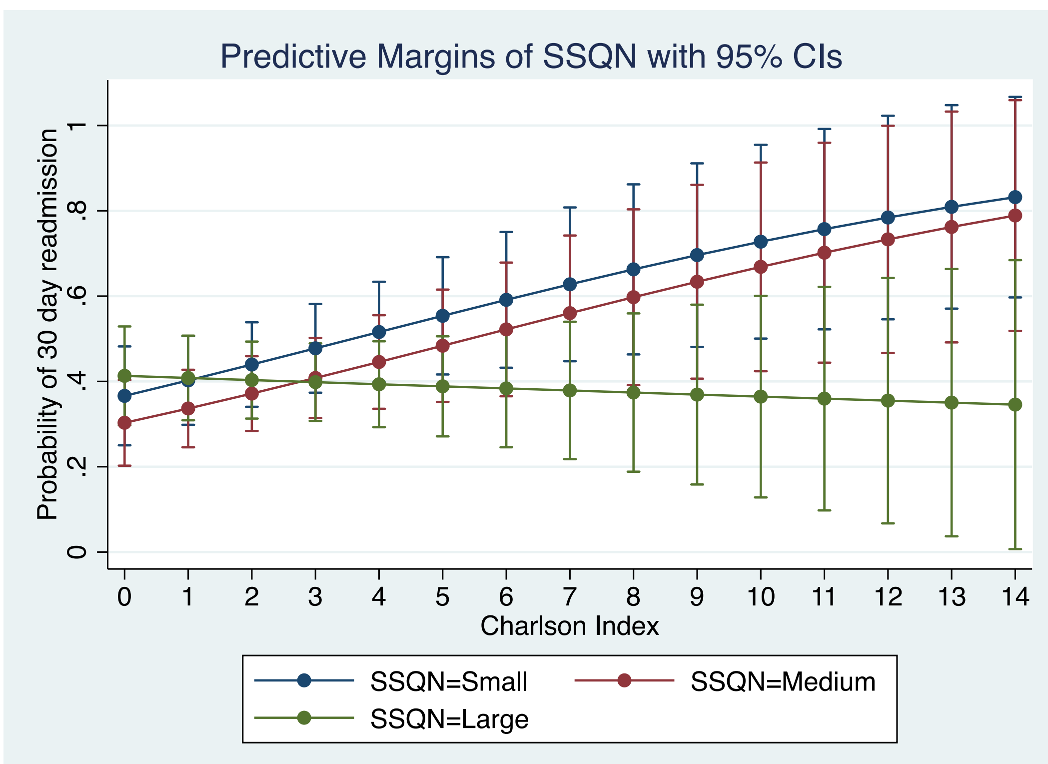
Table 9: Results of logistic regression models for SSQN at 30-, 90-, and 180-day hospital readmission

* Indicates statistical significance at the level of $p<0.05$

	30 day readmission		90 day readmission		180 day readmission	
	OR	**[95% Conf.**	**OR**	**[95% Conf.**	**OR**	**[95% Conf.**
Constant	0.073	(0.021 - 0.251)	1.62	(0.411 - 6.391)	1.61	(0.404 - 6.45)
SSQN						
2	1.53	(0.679 – 3.46)	0.746	(0.367 - 1.52)	1.26	(0.637 - 2.49)
3	1.66	(0.726 – 3.80)	1.23	(0.601 - 2.50)	1.19	(0.611 - 2.32)
Age	1.02	(0.997 - 1.04)				
Marginal housing	1.95*	(1.10 - 3.44)				
CI	1.24*	(1.07 - 1.43)	1.17*	(1.02 - 1.35)	1.12*	(1.03 - 1.22)
Insurance			1.74*	(1.05 - 2.87)	1.73*	(1.06 - 2.82)
PAM Score			0.976*	(0.955 - 0.998)	0.977*	(0.956 - 0.999)
Tobacco use					3.56*	(1.55 - 8.17)
SSQN * CI						
2	0.825	(0.677 - 1.01)	1.00	(0.824 - 1.21)		
3	0.721*	(0.576 - 0.901)	0.836	(0.693 - 1.01)		
	$\chi^2=20.76$, p=0.004		$\chi^2=23.8$, p=0.001		$\chi^2=33.1$, p<0.001	
HL test	0.897		0.881		0.964	
AUC (%)	65.7		65.2		68.1	

Figure 2: Predictive margins for readmission at 90 days by level of SSQN and Charlson Index Score, 30 and 90 day models





The second set of models generated used SSQS as the primary predictor variable for the same three follow-up periods. Overall models for 90 and 180 days readmission were significant with p<0.05; however, the model for 30-day readmission was not. The SSQS variable was not statistically significant in any of the three models, and no consistent trend across SSQS levels and hospital readmission risk were observed in any of the three follow-up periods investigated. None of the covariates considered were significant in all three models.

As with models including SSQN as the variable of interest, the AUC indicated poor performance for all three models of SSQS (69-68%). Again, only the interaction with Charlson Index was considered. This interaction with SSQS was not statistically significant in any of the three models.

Table 10: Results of logistic regression models for SSQS at 30-, 90-, and 180-day hospital readmission
* Indicates statistical significance at the level of p<0.05

	30 day readmission		90 day readmission		180 day readmission	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Constant	0.092	(0.028 - 0.302)	0.430	(0.237 - 0.782)	3.31	(0.756 - 14.5)
SSQS						
1	1.05	(0.53 - 2.11)	1.13	(0.620 - 2.06)	1.05	(0.562 - 1.95)
2	1.18	(0.57 - 2.47)	1.01	(0.534 - 1.90)	0.818	(0.417 - 1.60)
Age	1.02	(0.998 - 1.04)				
Marginal Housing	2.03*	(1.16 - 3.55)				
Charlson Index	1.06	(0.974 - 1.15)			1.14*	(1.05 - 1.23)
Insurance			1.99*	(1.26 - 3.12)		
Alcohol use					0.569*	(0.337 - 0.960)
Tobacco use					2.00*	(1.20 - 3.36)
PAM Score					0.98*	(0.953 - 0.997)
	χ^2=10.4, p=0.065		χ^2=8.82, p=0.032		χ^2=12.9, p<0.001	
HL test	0.136		0.957		0.773	
AUC (%)	61.5		58.8		66.7	

Other analyses

Finally, we built models for SSQ satisfaction and ED visits at 30, 90, and 180 days follow-up to assess the potential confounding effect of provider and system level factors driving health care utilization that may have masked the role of social support in readmission analyses. As shown below (Table 10), we saw that the 90- and 180-day models were significant overall, while the 30-day model was not. Again, SSQS was not statistically significant as part of the model, even after adjustment for other covariates. Performance of these models was similarly poor with AUC between 61 and 69%.

Table 10: Results of logistic regression models for SSQS at 30-, 90-, and 180-day ED visit

* Indicates statistical significance at the level of p<0.05

	30 day ED visit		90 day ED visit		180 day ED visit	
	OR	**95% CI**	**OR**	**95% CI**	**OR**	**95% CI**
Constant	0.094	(0.028 - 0.318)	0.295	(0.158 - 0.551)	0.676	(0.342 - 1.34)
SSQS						
1	0.910	(0.451 - 1.83)	1.07	(0.565 - 2.01)	0.896	(0.483 - 1.66)
2	0.886	(0.417 - 1.88)	1.07	(0.542 - 2.11)	1.08	(0.555 - 2.11)
Age	1.02*	(1.00 - 1.04)				
Marginal housing	1.89*	(1.07 - 3.34)	1.82*	(1.09 - 3.05)	2.60*	(1.53 - 4.43)
Charlson Index			1.16*	(1.07 - 1.25)	1.13*	(1.04 - 1.22)
Alcohol use					0.556*	(0.328 - 0.941)
Education					0.504*	(0.275 - 0.925)
Intervention					1.70*	(1.07 - 2.71)
	$\chi^2=10.4$, p=0.065		$\chi^2=8.82$, p=0.032		$\chi^2=12.9$, p<0.001	
HL test	0.136		0.957		0.773	
AUC (%)	61.5		58.8		66.7	

Discussion

Key Results

In these analyses, we did not find evidence that social support, as measured with either a quantitative score or a quality score by the Social Support Questionnaire-3 was a significant predictor of hospital readmission risk. We did not observe a trend across levels of either of these scores at multiple lengths of follow-up, 30, 60 and 180 days post admission. Furthermore, we did not find any evidence that social support was a predictor for ED visit risk.

We hypothesized that higher levels of social support would be protective against hospital readmission, and that the protective effect of social support would decrease over time as an individual moved further from the index hospitalization. As noted in previous work, individuals who are admitted to the hospital are at increased risk for readmission in the short term, but return to baseline levels of hospital use by one year from the index admission.[36] Based on these findings, we expected that the relative importance of social support on readmission risk would be stronger at the forefront, but wane over time. However, we did not find evidence in this study to support this hypothesis.

The relationship between social support and health outcomes and/or utilization is complex, leaving lingering questions about what variables should be included in risk prediction models for hospital readmission. Multiple studies posit that social factors, including social support is an important factor for hospital readmissions, noting that hospitals caring for a higher proportion of uninsured patients are more likely to be penalized for excess readmission, and there is some concern that failure to account for other factors may unfairly burden hospital for patients' social challenges [15,37]. However, in our analyses, we could not demonstrate that social support adds to the predictive models for readmission risk. Although the published literature on this specific potential association is limited, the available studies have similarly been unable to establish an increased risk of readmission based on socioeconomic factors[9] and if an association exists, the effect size may be very small. For example, a recent study of socioeconomic status and hospital readmission risk found that the risk of readmission changed approximately 0.1% after adjustment for socioeconomic status.[9]

Similarly, existing research provides evidence that not all social support is helpful, and that the utility of a social support depends on a variety of factors.[12,19] In a 2010 paper, Uchino et al. described a three-class model of factors that make social support helpful for promoting health. These include task related factors (whether or not the provided supports match the needs of the recipient), recipient-related factors (such as an individual's desire to receive a given type of support), and provider-related factors (such as the ability of an individual to provide useful support to another person).[38] In our population of socioeconomically vulnerable adults, it is possible that although participants reported a high level of satisfaction with their social support system, members in their network were unable to provide them with practical assistance that may have been helpful in influencing health care utilization.

Despite the lack of evidence that social support (in either quality of quantity) is predictive of readmission risk, we did find that there was a statistically significant interaction between social support and Charlson Index for 30- and 90- day readmission modeled with SSQN. Interestingly, this interaction showed a decreased risk of hospital readmission with increasing level of social support. It is possible that for healthier people, social support has little effect on readmission risk. However, for individuals with more comorbidities, social support may serve as a way to encourage an individual to seek health care.

Limitations

This study has several limitations. First, the SSQ3 primary asks questions that describe an individual's sources of emotional social support, but does not address instrumental social support. While there is evidence that multiple domains of social support have effects on health outcomes and health care utilization,[13,14] instrumental social support may eventually prove to be more helpful in averting unnecessary hospital readmissions.

A second limitation is that this study has a relatively small number of individuals who report very low satisfaction with their sources of social support. Because of our limited sample size, we may have been unable to distinguish the effects of low social support satisfaction on readmission risk. We chose to categorize SSQS and SSQN given the distribution of our data and from a desire to provide clinically meaningful data. In categorizing our predictor variables, we may have missed nuances of the data that may have been evident had we analyzed them as continuous variables. However, preceding our decision to categorize SSQS and SSQN we conducted univariable analyses with both of these variables in the continuous form, and we failed to observe an association in these analyses (data not shown). Therefore, we feel that the likelihood that our decision to categorize our variables masked an association between social support and readmission risk was low.

Finally, the C-TraIn parent study selected for a socioeconomically vulnerable population. This population may have had smaller social networks, or less satisfaction with their social network than a more socioeconomically diverse study population. The selection of this study population may have biased the results toward the null, by excluding the effect of a larger social network, or one with more ability to provide for an individual's needs. However, our study sample reported high satisfaction in their sources of social support, comparable in mean and distribution to other groups in which the SSQ has been used.[23,35]

Generalizability

Our cohort was recruited from the general patient population of the Medicine teams at OHSU's hospital. Although OHSU is an academic center and thus may have a more medically complex population with a more diverse profile of payers, the results of the social support questionnaire are likely generalizable to the general population. In our review of the literature we found that social network size, as represented by SSQN in this study, varies greatly based on the population in question. We chose to categorize this variable into tertiles based on percentiles (representing small, medium, and large social network size). As these cuts do not represent social network sizes in the broader population, findings from analyses with SSQN may not be generalizable outside of the study population.

Conclusions

In our analysis, we did not find evidence that social network size or quality, as measured by the social support questionnaire, were predictors of hospital readmission risk at 30, 90, or 180 days. These findings suggest that social support – especially emotional social support – may not be an important factor to include in future predictive models for assessing readmission risk. However, our analyses also found evidence that social support may act as an effect modifier in combination with medical comorbidity (as measured by Charlson Index).

To our knowledge, this is the first study to specifically look at the relationship between social support and hospital readmission risk. We focused on emotional social support, but the findings from this study should drive further, more rigorous research into social support and health care utilization in a number of domains with a special focus on instrumental social support and health care utilization. Specifically, future research should examine other domains of social support, especially instrumental social support, with regard to their relationship to readmission risk and healthcare utilization. Additionally, further investigation into the relationship between medical comorbidity and social support is warranted.

References

1. Hansen LO. Interventions to Reduce 30-Day Rehospitalization : A Systematic Review. *Ann Intern Med*. 2013;155(8):520-528.
2. Jencks SF, Williams M V, Coleman EA. Rehospitalizations among Patients in the Medicare Fee-for-Service Program. *N Engl J Med*. 2009;360:1412-1428.
3. Raven MC, Billings JC, Goldfrank LR, Manheimer ED, Gourevitch MN. Medicaid patients at high risk for frequent hospital admission: Real-time identification and remediable risks. *J Urban Heal*. 2009;86(2):230-241. doi:10.1007/s11524-008-9336-1.
4. Ashton CM, Del Junco DJ, Souchek J, Wray NP, Mansyur CL. The association between the quality of inpatient care and early readmission: a meta-analysis of the evidence. *Med Care*. 1997;35(10):1044-1059. http://www.ncbi.nlm.nih.gov/pubmed/9338530. Accessed April 5, 2017.
5. Boccuti C, Casillas G. *Aiming for Fewer Hospital U-Turns: The Medicare Hospital Readmission Reduction Program*. http://kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/.
6. Kansagara D, Englander H, Salanitro A, et al. Risk Prediction Models for Hospital Readmission. *JAMA*. 2011;306(15):1688. doi:10.1001/jama.2011.1515.
7. Zhou H, Della PR, Roberts P, Goh L, Dhaliwal SS. Utility of models to predict 28-day or 30-day unplanned hospital readmissions: an updated systematic review. *BMJ Open*. 2016;6(6):e011060. doi:10.1136/bmjopen-2016-011060.
8. Lu MLR, Davila CD, Shah M, et al. Marital status and living condition as predictors of mortality and readmissions among African Americans with heart failure. *Int J Cardiol*. 2016;222:313-318. doi:10.1016/j.ijcard.2016.07.185.
9. Bernheim SM, Parzynski CS, Horwitz L, et al. Accounting For Patients' Socioeconomic Status Does Not Change Hospital Readmission Rates. *Health Aff*. 2016;35(8):1461-1470.
10. House J, Landis K, Umberson D. Social relationships and health. *Science (80-)*. 1988;241(4865).
11. Holt-Lunstad J, Smith TB, Layton JB. Social Relationships and Mortality Risk: A Meta-analytic Review. *PLoS Med*. 2010;7(7). doi:10.1371/ journal.pmed.1000316 Academic.
12. Uchino BN. What a lifespan approach might tell us about why distinct measures of social support have differential links to physical health. doi:10.1177/0265407509105521.
13. Broadhead WE, Gehlbach SH, DeGruy F V., Kaplan BH. Functional versus Structural Social Support and Health Care Utilization in a Family Medicine Outpatient Practice. *Med Care*. 1989;27(3):221-233.
14. Bosworth HB, Schaie KW. The Relationship of Social Environment, Social Networks, and Health Outcomes in The Seattle Longitudinal Study: Two Analytical Approaches. *J Gerontol*. 1997;52(5):197-2.
15. Davis MM, Devoe M, Kansagara D, Nicolaidis C, Englander H. "Did I Do as Best

as the System Would Let Me?" Healthcare Professional Views on Hospital to Home Care Transitions. *J Gen Intern Med*. 2012;27(12):1649-1656. doi:10.1007/s11606-012-2169-3.
16. Strunin L, Stone M, Jack B. Understanding Rehospitalization Risk: Can Hospital Discharge Be Modified to Reduce Recurrent Hospitalization? *J Hosp Med*. 2007;2(5):297-304. doi:10.1002/jhm.206.
17. Kangovi S, Barg FK, Carter T, et al. Challenges faced by patients with low socioeconomic status during the post-hospital transition. *J Gen Intern Med*. 2014;29(2):283-289. doi:10.1007/s11606-013-2571-5.
18. Cyranowski JM, Zill N, Bode R, et al. Assessing social support, companionship, and distress: National Institute of Health (NIH) Toolbox Adult Social Relationship Scales. *Health Psychol*. 2013;32(3):293-301. doi:10.1037/a0028586.
19. Coyle CE, Dugan E. Social Isolation, Loneliness and Health Among Older Adults. *J Aging Health*. 2012;24(8):1346-1363. doi:10.1177/0898264312460275.
20. Howard S, Creaven A-M, Hughes BM, O'Leary ÉD, James JE. Perceived social support predicts lower cardiovascular reactivity to stress in older adults. *Biol Psychol*. 2017;125:70-75. doi:10.1016/j.biopsycho.2017.02.006.
21. Teo AR, Lerrigo R, Rogers MAM. The role of social isolation in social anxiety disorder: A systematic review and meta-analysis. *J Anxiety Disord*. 2013;27(4):353-364. doi:10.1016/j.janxdis.2013.03.010.
22. Sarason I, Levine H, Basham R, Sarason B. Assessing Social Support: The Social Support Questionnaire. *J Pers Soc Psychol*. 1983;44:127-139.
23. Sarason I, Sarason B, Shearin E, Pierce G. A Brief Measure of Social Support: practical and Theoretical Implications. *J Soc Pers Relat*. 1987;4:497-510.
24. Englander H, Kansagara D. Planning and Designing the Care Transitions Innovation (C-TraIn) for Uninsured and Medicaid Patients. 2012;000(000):1-6. doi:10.1002/jhm.1926.
25. Englander H, Michaels L, Chan B, Kansagara D. The Care Transitions Innovation (C-TraIn) for Socioeconomically Disadvantaged Adults: Results of a Cluster Randomized Controlled Trial. *J Gen Intern Med*. 2014;29(11):1460-1467. doi:10.1007/s11606-014-2903-0.
26. Barak-Levy Y, Atzaba-Poria N. The effects of familial risk and parental resolution on parenting a child with mild intellectual disability. *Res Dev Disabil*. 2015;47:106-116. doi:10.1016/j.ridd.2015.09.008.
27. Kohlbrenner V, Deuba K, Karki DK, Marrone G. Perceived Discrimination Is an Independent Risk Factor for Suicidal Ideation among Sexual and Gender Minorities in Nepal. *PLoS One*. 2016;11(7):e0159359. doi:10.1371/journal.pone.0159359.
28. Yoshikawa E, Nishi D, Matsuoka YJ, et al. Association between regular physical exercise and depressive symptoms mediated through social support and resilience in Japanese company workers: a cross-sectional study. *BMC Public Health*. 2016;16(1):553. doi:10.1186/s12889-016-3251-2.
29. Hibbard JH, Mahoney ER, Stockard J, Tusler M. Development and testing of a short form of the patient activation measure. *Health Serv Res*. 2005;40(6 Pt

1):1918-1930. doi:10.1111/j.1475-6773.2005.00438.x.
30. Corson K, Gerrity MS, Dobscha SK. Screening for depression and suicidality in a VA primary care setting: 2 items are better than 1 item. *Am J Manag Care*. 2004;10(11 Pt 2):839-845. http://www.ncbi.nlm.nih.gov/pubmed/15609737. Accessed April 14, 2017.
31. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation. *J Chronic Dis*. 1987;40(5):373-383.
32. Stata/MP 13.1. 2015.
33. Gortmaker SL, Hosmer DW, Lemeshow S. *Applied Logistic Regression.* Vol 23.; 1994. doi:10.2307/2074954.
34. Bisschop MI, Kriegsman DM., Beekman AT., Deeg DJ. Chronic diseases and depression: the modifying role of psychosocial resources. *Soc Sci Med*. 2004;59(4):721-733. doi:10.1016/j.socscimed.2003.11.038.
35. Mutumba M, Musiime V, Lepkowski JM, et al. Examining the relationship between psychological distress and adherence to anti-retroviral therapy among Ugandan adolescents living with HIV. *AIDS Care*. 2016;(February). doi:10.1080/09540121.2015.1131966.
36. Moore L, Stelfox HT, Turgeon AF, et al. Rates, Patterns, and Determinants of Unplanned Readmission After Traumatic Injury. *Ann Surg*. 2014;259(2):374-380. doi:10.1097/SLA.0b013e31828b0fae.
37. Kangovi S, Barg FK, Carter T, et al. Downloaded from content.healthaffairs.org by Health Affairs on April 9, 2014 at OREGON HEALTH SCI UNIV L593. 2013. doi:10.1377/hlthaff.2012.0825.
38. Uchino BN, Carlisle M, Birmingham W, Vaughn AA. Social support and the reactivity hypothesis: Conceptual issues in examining the efficacy of received support during acute psychological stress. *Biol Psychol*. 2010;86:137-142. doi:10.1016/j.biopsycho.2010.04.003.