Spring 2018

Evaluation of the Associations Between Unplanned Readmissions and the LACE Index and Other Variables

Cathy Stankiewicz, DNP, MSN, RN
George Washington University

Evaluation of the Associations Between Unplanned Readmissions and the LACE Index and Other Variables

Presented to the Faculty of the School of Nursing,

The George Washington University,

In partial fulfillment of the

requirements for the degree of

Doctor of Nursing Practice Degree

Cathy Stankiewicz, MSN, RN

Ellen T. Kurtzman, PhD, MPH, RN, FAAN

Patricia Robinson, PhD, ARNP, NE-BC, CCRP

Hong Tao, PhD, RN

Spring 2018

Abstract

Background: Unplanned readmissions, within 30 days following an inpatient hospital admission, are common and costly. Research has identified factors that predict readmissions, and predictive algorithms, such as the LACE index, have been studied and widely adopted by hospitals despite demonstrated variability in predictive ability.

Objectives: To examine the associations between unplanned readmissions and the LACE index, and other variables that reflect patient- and encounter-level factors not currently incorporated in the LACE index.

Methods: A retrospective analysis was conducted utilizing data from electronic health records of inpatients discharged from a large quaternary hospital located in the southeastern United States between January 1 and June 30, 2017. Associations between readmissions and each variable were separately examined utilizing chi-square test.

Results: Of the 17,082 inpatients, 1,695 (9.9%) patients were readmitted. Positive, statistically significant associations ($p<0.01$), were found between readmission and each of the following: LACE index, race, marital status, payer source, index disposition, and index Diagnosis-Related Group (DRG). No association was found with age, gender, or preferred language.

Conclusions: LACE index, race, marital status, payer source, index disposition, and DRG were associated with unplanned readmission. Utilizing other factors, in addition to the LACE index, may be clinically useful in better predicting readmissions and targeting resources to prevent them from occurring.

Evaluation of the Associations between Unplanned Readmissions and the LACE Index and Other Variables

A readmission is defined as an admission to the hospital within a defined timeframe after a patient is discharged following an inpatient admission. Nearly 20% of Medicare beneficiaries experience an unplanned readmission to the hospital within 30 days of discharge with an associated cost of $17.6 billion (Jencks, Williams, & Coleman, 2009). Historically in a fee-for-service reimbursement system, hospitals were reimbursed for services provided during a readmission; therefore, there was no financial incentive to reduce their occurrence (McIlvennan, Eapen, & Allen, 2015). However, given the tremendous cost of readmissions to payers, and hospitals' disincentive to reduce them, a provision of the Affordable Care Act (ACA) was enacted to discourage hospital readmissions by better aligning payment with performance. Specifically, the ACA established the Hospital Readmission Reduction Program (HRRP), which authorized the Centers for Medicare & Medicaid Services (CMS) to withhold up to three percent of Medicare reimbursement from hospitals with readmission rates that exceeded the national average for certain diagnoses (CMS, 2017, November 30). The program began in 2012 with readmission penalties for patients readmitted following an inpatient admission for heart failure, acute myocardial infarction, or pneumonia. In the first year of the HRRP, 2,225 hospitals were penalized $227 million, which quickly heightened hospitals' focus on reducing readmissions. The program has since expanded to include readmission penalties for patients with chronic obstructive pulmonary disease, hip and knee arthroplasty, and coronary artery bypass graft surgery. Fiscal year 2017 reimbursement penalties were forecasted to impact 2,597 hospitals and total $528 million (Bishop, 2016).

Under HRRP, a readmission is defined as any admission to the hospital within 30 days of discharge for the six specified conditions (CMS, 2017, November 30); however, readmissions that are planned—that is, those for bone marrow or organ transplant, maintenance chemotherapy, and other potentially planned procedures—are excluded (Yale New Haven Services Corporation Center for Outcomes Research & Evaluation [YNHHS/CORE], 2013). Hereafter the term "readmission" and "readmission rates" refer to only those readmissions that occur within 30 days and are unplanned based on this definition.

The study site is in the southeastern United States with over 1,200 beds, approximately 40,000 inpatient admissions and 5,000 readmissions annually. In fiscal year 2017, the study site's readmission rates for the six conditions included in the HRRP exceeded the national average (Table 1). The resulting penalties prompted prioritization of reducing its readmission rates to avoid future penalties by targeting rates below the national average

Because implementing effective interventions that are known to reduce readmissions, including advanced nurse practitioner discharge planning and nurse transition coaches, can be costly to implement (Kripalani, Theobald, Anctil, & Vasilevskis, 2014), hospitals often aim to target these interventions to the most high-risk patients (Futoma, Morris, & Lucas, 2015). Readmission risk prediction tools can be useful for this purpose (Swain & Kharrazi, 2015). Van Walraven et al. (2010) developed and validated a clinically useful tool, referred to as the LACE index, to quantify risk of death or readmission within 30 days after discharge from the hospital. The mnemonic stands for length of stay (L), acuity of admission (A), comorbidity (C), and emergency department (ED) use in six months prior to admission (E) (van Walraven et al., 2010).

Purpose, Aims, Research Questions

This study aimed to test the associations between readmissions within 30 days among adult inpatient discharges from the study site and the LACE index, as well as additional explanatory variables, separately. The LACE index has been adopted at the study site to categorize patients' risk of readmission (low, moderate, and high) and to tailor interventions based on the risk category. Because the Van Walraven et al. (2010) study was conducted in Canada, its generalizability to other populations—including the study site's patient population—may be limited. In addition, because the LACE index' results indicate that it is moderately predictive, and subsequent studies have identified poor predictive performance in certain populations (Cotter, Bhalla, Wallis, & Biram, 2012), there is value in measuring how the index performs at the study site and identifying whether there are additional variables associated with readmissions.

The specific research questions of interest included: (1) Was the LACE index score associated with readmissions within 30 days among adult inpatients at the study site? (2) Were additional explanatory variables, such as age, gender, race, preferred language, marital status, payer source, index disposition (location to which the patient is discharged for the index admission-home, skilled nursing facility, etc.), and DRG, independently associated with hospital readmissions within 30 days?

Significance

The National Quality Strategy targets readmissions as a key priority in shifting health care from volume to value (CMS, 2017, November 9). Readmission risk prediction is complex and the LACE index tool has demonstrated variability in its predictive ability (Cooksley et al., 2016; Cotter et al., 2012; Tong, Erdmann, Daldalian, Li, & Esposito, 2016; Wang et al., 2014). Cooksley, et al. (2016) opined that the heterogeneity of patient populations and health care systems may be a barrier to a simple and clinically useful tool and recommended that risk prediction tools be developed for specific populations. As discussed, by testing the LACE index' association with readmissions at the study site, and whether additional factors are associated with, and might strengthen, its predictive power, this study adds to what is known about the use of risk prediction tools, generally, and the use of the LACE index for this purpose, specifically. Additionally, by examining the association of other patient-level variables to readmissions, the research extends what is known about LACE and explores additional considerations that account for patient heterogeneity.

Literature Review

A search of the literature was conducted to review the research on the LACE index as a risk prediction model for readmissions. Medline and CINAHL were searched utilizing key words, MeSH terms, and Boolean modes: LACE AND readmission OR patient readmission. No limits were added. The search produced 64 articles, and after duplicates were removed, that number was reduced to 49. Abstracts of the 49 articles were reviewed and full text was examined for the 23 that were deemed most relevant. Ultimately, there were nine titles describing the derivation and/or validation of the LACE index, which were included in this review.

As previously described, the LACE index was developed to meet the need for a clinically useful tool to quantify risk of death or unplanned readmissions (Van Walraven et al., 2010). Four of almost 50 evaluated factors explained most of the variation in risk of early death or readmission as evidenced by their odds ratios (OR): length of stay (OR 1.47, 95% Confidence Interval [CI] 1.25-1.73); acute admission (OR 1.84, 95% CI 1.29-2.63); comorbidity (OR 1.21, 95% CI 1.10-1.33); and ED visits during previous six months, (OR1.56, 95% CI 1.27-1.92). Based on the value of these four covariates, points were assigned and combined to produce a

LACE index score ranging from 0 to 19 (Table 3) (Van Walraven et al., 2010). A concordance (C) statistic, which measures the accuracy of a predictive model based on a sample's prior outcomes and allows for estimation of the probability of a positive outcome in the future, was used to measure the ability of the LACE index to discriminate between patients who died, or were readmitted, and those who survived, or were not readmitted (Van Walraven et al., 2010, p.554). In this case, the C-statistic was measured in the derivation sample, the validation sample, and the entire cohort demonstrating that the LACE index had moderate discrimination for early death or readmission with a C-statistic (95% CI) of 0.71 (0.67-0.74) in the derivation, 0.69 (0.65-0.73) in the validation, and 0.70 (0.68-0.73) in the entire cohort. A poorly predictive model has a C-statistic less than 0.5, and a very good model has a C-statistic that approaches 1.0 (Hermansen, 2008).

External validation studies of the LACE index have been conducted in cohorts of medical, heart failure, elderly, primary care, and oncology patients and findings have been mixed (Cooksley et al., 2016; Cotter et al., 2012; Donovan, Turney, Emnett, Lamoreaux, & Portman, 2016; Garrison, Robelia, Pecina, & Dawson, 2016; Low, Liu, Ong, Ng, Ho, Thumboo, & Lee, 2017; Tong et al., 2016; Wang et al., 2014). As outlined in Table 2, the ability of the LACE index to predict patients at high risk of readmission varied from poor with a c statistic of 0.55 (95% CI 0.49-0.61) among elderly patients in the United Kingdom (Cotter et al., 2012) to moderate with a C-statistic of 0.68 (95% CI 0.67-0.69) among adult primary care patients in the United States (Garrison et al., 2016). The poor predictive ability found by Cotter, Bhalia, Wallis, and Biram (2012) in elderly patients, was later confirmed in a study by Cooksley et al. (2016) in which the predictive ability of the LACE index decreased with increasing age. Although Wang et al. (2014) found LACE to be a poor predictor of readmissions in heart failure patients; it was a better predictor of emergency department visits than readmissions following discharge. Two studies utilized the LACE index to stratify the population by score (Tan, Low, Yang, & Lee, 2013; Yian et al., 2016). A LACE index greater than 10 was associated with increased risk of readmission in medical patients in Singapore, OR 4.37, 95% CI 4.18-4.57 (Tan et al., 2013). Yian et al., 2016 also found that a LACE index greater than 10 increased the risk of readmission, OR 4.47, 95% CI 2.54-7.86, in patients following humerus repair in California.

Several of these validation studies also explored the benefit of adding variables to the LACE index, and found some positive associations between added variables and readmission. For example, Tong et al. (2016) found the following factors associated with a risk of readmission: admissions and emergency department visits within the prior six months to one year, Braden score, poly-pharmacy, employment status, index disposition, albumin level, malignancy, renal failure with hemodialysis, substance abuse history, dementia, and trauma. Yian et al. (2016) identified liver disease as significantly associated with readmissions.

In summary, the evidence indicates that the LACE index has demonstrated variability in external validation studies and may not be sufficiently predictive across all patient populations. Additional research is needed to examine the LACE index' power to predict readmissions, as well as, to identify additional variables that may improve hospitals' ability to predict readmissions.

Conceptual Framework and Variables

The conceptual framework for this study is the adaptation of the health services research framework by Vest, Gamm, Oxford, Gonzalez, and Slawson (2010). These authors utilized this framework in a systematic review of the literature to identify factors associated with preventable readmissions. The framework (Figure 1) organizes factors from two perspectives, population and clinical. From the population perspective, outcomes are derived from individual characteristics and the quality of their environment, and from clinical perspective, outcomes are related to processes and structure of health care encounters (Vest et al., 2010, p. 3).

Additionally, Vest et al. (2010) identified factors, associated with these perspectives that influence preventable readmissions and operate at four levels:

- Patient characteristics: demographics, socioeconomic standing, behaviors, and disease states.
- Encounter level: activities and events associated with the delivery of care for the index hospitalization
- Organization: factors not specific to a single encounter, but applicable to all encounters in the facility
- Environment: all factors external to the individual and provider

These levels were utilized to categorize the independent variables that were studied (Table 4).

Methods

This was a quantitative, correlational study using a retrospective analysis of electronic health record (EHR) data to examine the associations between unplanned 30-day readmissions and the LACE index and additional explanatory variables. The data were collected from the institution's EHR by the investigator then de-identified to preserve patient confidentiality. Descriptive and correlational statistics were used to examine unplanned readmission rates, LACE index, and other variables as well as their relationships.

Sample

A retrospective, population-based sample was drawn from the hospital's EHR and included adult inpatient discharges from the study site between January 1 and June 30, 2017. All inpatients, 18 years of age and older, were included in the sample. Exclusion criteria were closely aligned with the national measure for Hospital-Wide All-Cause Unplanned Readmission (HWR) specifications (YNHHS/CORE, 2013): observation patients, patients transferred to another acute care facility; patients who left against medical advice; and patients admitted for psychiatric diagnosis, rehabilitation, medical treatment of cancer, or obstetric diagnosis. Encounters for planned readmission were identified as no readmission. In addition, patients for whom a LACE index could not be calculated were excluded. After exclusions the sample included 17,082 inpatient discharges, which exceeded the minimum sample size needed to conduct the chi-square test with an effect size of 0.1, a desired statistical power level of 0.8, and significance level of 0.05 (QFAB Bioinformatics, 2017).

Setting

The study was conducted at a large major teaching hospital and quaternary care center with specialized and advanced services including neurosurgery, open-heart surgery, organ transplantation (bone marrow, kidney, liver, pancreas, heart, lung), left ventricular assist device implantation, and extracorporeal membrane oxygenation. The study site has over 1,200 inpatient beds including 305 intensive care beds. There are over 40,000 inpatient discharges annually, which made the six-month data time frame adequate to meet sample size requirements.

Instruments, Measurements and Data Collection

Two instruments were utilized for this study, the EHR and the LACE index. The study site utilizes Cerner as its EHR vendor. Patient data are entered and maintained in the EHR for all encounters and can be accessed retrospectively. The LACE index is an instrument comprised of four factors (LOS, acuity of admission, comorbidity, and ED visits), with assigned point values ranging from 0 to 19 (Table 3), indicating increasing risk of readmission as the score increases (Van Walraven et al., 2010).

Data Collection and Analysis

Patient data for this study were drawn from the study site's EHR. Variables, including age, gender, race, preferred language, marital status, payer source, index disposition, index DRG, and readmission were extracted from the EHR utilizing automated reporting tools. The investigator checked the data for missing and outlier values, as well as consistency by variable, due to risk of missing or invalid data associated with retrospective data not originally collected for research (Motheral, et al. 2003).

For purposes of analysis, the investigator manually reentered each variable into Excel (Appendix A) and transformed each variable's responses into analyzable values based on standardized, operational definitions (Table 4). For example, the gender variable was assigned a value = 0 if the patient was male and a value = 1 if the patient was female.

Patients' LACE index scores, which by definition can range from 0-19 (Table 3), were not documented in the EHR in their precise form and could not be directly extracted; instead, the four factors that comprise the index—i.e., length of stay, acuity of admission, comorbidities, and ED visits—were used to manually calculate the index. As is consistent with the literature, patients with higher LACE index scores were considered higher readmission risks (Van Walraven et al., 2010). Based on LACE scores, patients were categorized as low (0-6), moderate (7-10), or high (11-19) risk for readmission based on the study site's classification scheme.

Once all the data from the EHR were entered in this fashion, the investigator uploaded the Excel file into Statistical Package for the Social Sciences (SPSS, Version 24.0) for analysis.

As per the project timeline (Figure 2), the data were collected and prepared for analysis from December 1, 2017 through February 15, 2018.

All analyses were conducted in SPSS. First, pairwise deletion was applied and all remaining data were included. Descriptive statistics were summarized for each variable. Since the dependent variable was dichotomous (1=unplanned readmission; 0=no readmission), chi-square tests were performed to determine the association between readmission status and readmission risk based on the LACE index in its categorical form (low, moderate, high). Chi-square tests were also used to study the associations between readmission status and other patient and encounter variables, separately, including age, gender, race, preferred language, marital status, payer source, index disposition, and DRG, none of which contribute to the LACE index score.

The specific research questions were: (1) Was the LACE Index score associated with readmissions within 30 days among adult inpatients at the study site? (2) Were additional explanatory variables, such as age, gender, race, preferred language, marital status, payer source, index disposition, and DRG, independently associated with readmission to the hospital within 30 days? For each independent variable, the null hypothesis was that there was no association between the variable and unplanned readmissions. The null hypothesis was rejected for *p*-values less than or equal to 0.05. The results were interpreted, compared with other related evidence, and conclusions were drawn about the meaning, credibility, importance, and generalizability of the findings for the purposes of dissemination and presentation.

Ethical Considerations

To preserve patient confidentiality and privacy, the data were only accessible by the investigator and stored in a password protected Excel file on a restricted network drive. The data were de-identified when they were entered into the Excel data collection tool (Appendix A) prior to uploading to SPSS. The study (1070495-1) was approved by the study site's Institutional Review Board (IRB) as well as The George Washington University's IRB. A Waiver of Consent was approved based on the research involving no more than minimal risk to subjects.

Results

From January 1 to June 30, 2017, the study site had 17,082 inpatient adult discharges eligible for analysis based on inclusion and exclusion criteria. There were 1,695 readmissions within 30 days of discharge, representing a readmission rate of 9.9%. This rate reflects all adult inpatient readmissions as opposed to the condition specific rates included in the HRRP (Table 1). Nine demographic and clinical characteristics including each variable's association with readmission based on chi-square analysis are summarized in Table 5.

The composition of the inpatient sample was male (50.9%), married (44.2%), age 65 or older (44.6%), and English speaking (93.5%). The population was mixed racially including 69.3% White/Caucasian, 18.5% Black/African American, 1.2% Asian, and 10.9% other/unknown. Medicare was the payer source for a majority of these inpatients (51.9%) although approximately one-quarter (25.60%) of the sample was commercially insured. Nearly one-half of the sample (49.2%) had a moderate LACE index (7-10) and 19.0% had a high LACE index (11-19) and 31.80% had a low LACE index (0-7). The majority of the sample (63.3%) was discharged home without home health care. Table 5 lists the population's 10 most common DRGs.

Chi-square test was used to determine whether the characteristics of patients who were readmitted were similar to those who were not. The dependent variable was readmission and nine independent variables were analyzed separately, six of which demonstrated a positive association with readmission. As can be seen in Table 5, there was a significant relationship between readmissions and the following variables separately: LACE index, $\chi^2(2, N = 17{,}082) = 537.92$, $p = <0.01$; race, $\chi^2(4, N = 17{,}070) = 27.78$, $p < 0.01$; marital status, $\chi^2(4, N = 16{,}279) = 18.64$, $p = 0.01$); payer source, $\chi^2(4, N = 17{,}082) = 112.93$, $p < 0.01$; index disposition, $\chi^2(4, N = 17{,}082) = 79.136$, $p < 0.01$; and index DRG, $\chi^2(10, N = 17{,}082) = 126.62$, $p < 0.01$. Three of the variables studied did not show an association to readmission: age, $\chi^2(1, N = 17{,}082) = 2.48$, $p = 0.12$); gender, $\chi^2(1, N = 17{,}082) = 0.118$, $p = 0.73$); and preferred language, $\chi^2(2, N = 17{,}066) = 0.227$, $p = 0.80$).

Discussion

This was a quantitative, correlational study using a retrospective analysis of EHR data to examine the associations between unplanned 30-day readmissions and the LACE index, and additional explanatory patient- and encounter- level factors. In this study, we found the LACE index was associated with readmissions among adult inpatients at the study site; however, additional variables, such as race, marital status, payer source, index disposition, and DRG were also independently and significantly associated with readmissions.

Like other organizations, the LACE index was adopted at the study site in 2017 as the methodology to categorize patients' risk of readmission (low, moderate, and high) and target prevention interventions to patients at highest risk. This analysis confirmed that the LACE index was positively associated with readmissions in the study population at the study site. As such, our results, from a large cohort in the southeastern U.S., add to the broader generalizability of the LACE index beyond the Canadian population in which the LACE index was developed and validated (Van Walraven et al., 2010) and populations in Ireland, Singapore, and other regions of the U.S., where external validation studies were conducted (Cooksley et al., 2016; Tan et al., 2013; Yian et al., 2016). Logistic regression and C-statistic calculation were not pursued, so the magnitude to which LACE index predicts readmissions in this population is unknown.

We evaluated additional patient and encounter variables, separately, and found five variables, which are not included in the LACE index and easily extracted from the EHR; to be significantly correlated to readmission: race, marital status, payer, index disposition, and selected DRGs. Considering that the LACE index was developed to meet the need for a clinically useful tool to quantify risk of readmission (Van Walraven et al., 2010), it is reasonable to continue to identify variables, like we have in this study, that are readily available in the EHR to improve the predictability of the LACE index. Tong et al. (2016) for example, found that when additional variables (Braden score, poly-pharmacy, trauma, dementia, etc.) were utilized to augment the LACE index, predictability was improved (C-statistic increased from 0.65 to 0.73). With 11,645 index discharges—or approximately 2,000 discharges per month (68%)—in patients with a moderate or high LACE index, there is value in including what might be considered "modifiable" risk factors in the predictive scoring.

Limitations

There were several limitations in this study. First, this was a retrospective study of data from the EHR collected in the normal course of care, so there is risk to accuracy and completeness of the data. If the patients who had missing data were systematically different than those who had no missing data, selection bias may have been introduced. A second limitation is that this was a single center study capturing only readmissions to the study site, which may under-represent rates by not identifying patients as having a readmission who were readmitted to another hospital. As a result, generalizability may be limited. Lastly, a significant limitation is that this was a correlational study, and causal relationships were not evaluated. We examined each covariate separately rather than combining them in a single model necessary to (1) account for multiple influences on the outcome of interest and (2) determine which correlate has the greatest influence. In this way, our research is incomplete.

Implications and Recommendations

This research has important implications for improving practice by extending what is known about readmission risk prediction, specifically about the LACE index and additional variables that might improve its predictive power. We found five patient and encounter level variables, not currently incorporated into the LACE index, that are readily available during the course of care and are statistically significant correlates of readmission: race, marital status, payer, index discharge disposition, and selected DRGs. Cooksley et al. (2016) opined that good readmission risk prediction tools have a scoring system that is easily calculated, accurately stratify the population, and be clinically useful for targeting prevention interventions. We recommend augmenting the LACE index with the additional variables we found to be associated with readmission; this would improve the predictability of the LACE index, maintain ease of calculation, and improve stratification to target interventions.

Readmissions are complex with multiple influencers at the patient-, encounter-, organization-, and environment- levels as conceptually described by Vest et al. (2010) (Figure 1). Additional research is recommended to continually advance the understanding of readmission risk prediction, illuminate the full complement of factors that predict readmissions, and identify interventions that target at risk populations and effectively reduce readmissions. Based on the findings of this study, additional research is recommended to explore a broader array of possible covariates that can augment the LACE index to increase its predictive power and make it more clinically meaningful and actionable.

Policy should require the re-investment of HRRP penalty dollars, estimated at $528 million for fiscal year 2017 (Bishop, 2016), to support these research recommendations, as well as hospitals and the health care systems in the implementation of resource intensive, evidence-based practices that reduce readmissions.

Conclusions

In this quantitative, correlational study using a retrospective analysis of EHR data from 17,082 adult inpatient discharges from January 1 to June 30, 2017, LACE index, race, marital status, payer source, disposition, and DRG were separately associated with unplanned readmission. The LACE index, and the other patient- and encounter- level factors identified as being associated with readmission provide clinically useful information to target readmission reduction and improve quality of hospital care and transition at discharge.

References

Bishop, H. (2016). Medicare readmission penalties exceed $500M for FY 2017. Retrieved from http://health.wolterskluwerlb.com

Centers for Medicare & Medicaid. (2017, November 30). Readmissions Reduction Program. Retrieved January 22, 2017, from https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Readmissions-Reduction-Program.html

Centers for Medicare & Medicaid Services. (2017, November 9). What are value-based programs? Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/Value-Based-Programs/Value-Based-Programs.html

Cooksley, T., Nanayakkara, P. W., Nickel, C. H., Subbe, C. P., Kellett, J., Kidney, R., ... Braband, M. (2016). Readmissions of medical patients: An external validation of two existing prediction scores. *QJM: An International Journal of Medicine*, *109*(4), 245-248. http://dx.doi.org/10.1093/qjmed/hcv130

Cotter, P. E., Bhalla, V. K., Wallis, S. J., & Biram, R. W. (2012). Predicting readmissions: Poor performance of the LACE index in an older UK population. *Age & Ageing*, *41*(6), 784-789. http://dx.doi.org/10.1093/ageing/afs073

Donovan, K. A., Turney, M., Emnett, C. E., Lamoreaux, A., & Portman, D. G. (2016). Predicting hospital readmissions in the oncology population. *Journal of Clinical Oncology*, *34(29)*, 177. http://dx.doi.org/10.1200/jco.2016.34.26_suppl.177

Futoma, J., Morris, J., & Lucas, J. (2015). A comparison of models for predicting early hospital readmissions. *Journal of Biomedical Informatics*, *56*, 229-238. http://dx.doi.org/ 10.106/j.jbi.2015.05.016

Garrison, G., Robelia, P. M., Pecina, J. L., and Dawson, N. L. (2017). Comparing performance of 30-day readmission risk classifiers among hospitalized primary care patients. *Journal of Evaluation in Clinical Practice, 23*(3), 524-529.

Hermansen, S. W. (2008). Evaluating predictive models: Computing and interpreting the c statistic. Retrieved from http://www2.sas.com/proceedings/forum2008/143-2008.pdf

Jencks, S. F., Williams, M. V., & Coleman, E. A. (2009). Rehospitalizations among patients in the Medicare Fee-for-Service Program. *N Engl J Med*, *360*, 1418-1428. http://dx.doi.org/DOI: 10.1056/NEJMsa0803563

Kripalani, S., Theobald, C. N., Anctil, B., & Vasilevskis, E. E. (2014). Reducing readmission: Current strategies and future directions. *Annu Rev Med*, *65*, 471-485. http://dx.doi.org/doi:10.1146/annurev-med-022613-090415

Low, L. L., Liu, N., Ong, M. E., Ng, E. Y., Ho, A. F., Thumboo, J., and Lee, K. H. (2017). Performance of the LACE index to identify elderly patients at high risk for hospital readmission in Singapore. *Medicine, 96*(19), 1-6. doi: 10.1097/MD.0000000000006728

McIlvennan, C. K., Eapen, Z. J., & Allen, L. A. (2015). Hospital readmission reduction program. *Circulation*, *131(20*), 1796-1803. http://dx.doi.org/doi: 10.1161/CIRCULATIONAHA.114.010270

Motheral, B. Brooks, J. Clark, M.A., Crown, W., Davey, P. Hutchins, D., … Stang, P. (2003). A checklist for retrospective database studies- Report of the ISPOR Task Force on Retrospective Databases. *Value Health, 6,* 90-97.

QFAB Bioinformatics. (2017). ANZMTG statistical decision tree. Retrieved May 7, 2017, from https://www.anzmtg.org/stats/PowerCalculator/PowerChiSquare

Swain, M. J., & Kharrazi, H. (2015). Feasibility of 30-day hospital readmission prediction modeling based on health information exchange data. *International Journal of Medical Informatics*, *84(12*), 1048-1056. Retrieved from http://ck8gh5qu6z.search.serialssolutions.com.proxygw.wrlc.org

Tan, S. Y., Low, L. L., Yang, Y., & Lee, K. H. (2013). Applicability of a previously validated readmission predictive index in medical patients in Singapore: a retrospective study. *BMC Health Services Research*, 13(366), 1-6. Retrieved from http://www.biomedcentral.com/1472-6963/13/366

Tong, L., Erdmann, C., Daldalian, M., Li, J., & Esposito, T. (2016). Comparison of predictive modeling approaches for 30-day all-cause non-elective readmission risk. *BMC Medical Research Methodology*, 16(26), 1-8. http://dx.doi.org/10.1186/s12874-016-0128-0

Van Walraven, C., Dhalla, I. A., Bell, C., Etchells, E., Steill, I. G., Zarnke, K., … Forster, A. J. (2010). Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. *CMAJ*, *182*(6), 551-557. http://dx.doi.org/DOI: 10.1503/cmaj.091117

Vest, J. R., Gamm, L. D., Oxford, B. A., Gonzalez, M. I., & Slawson, K. M. (2010). Determinants of preventable readmissions in the United States: A systematic review. *Implementation Science*, *5*(88), 1-28. Retrieved from http://www.implementationscience.com/content/5/1/88

Wang, H., Robinson, R. D., Johnson, C., Zenarosa, N. R., Jayswal, R. D., Keithley, J., & Delaney, K. A. (2014). Using the LACE index to predict hospital readmissions in congestive heart failure patients. *BMC Cardiovascular Disorders*, 14(97), 1-8. Retrieved from http://www.biomedcentral.com/1471-2261/14/97

Yale New Haven Services Corporation Center for Outcomes Research & Evaluation. (2013, March). Centers for Medicare & Medicaid Services Planned Readmission Algorithm Version 2.1. . Retrieved from https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/Measure-Methodology.html

Yian, E., Zhou, H., Schreiber, A., Sodi, J., Navarro, R., Singh, A., & Bezrukov, N. (2016). Early hospital readmission and mortality risk after surgical treatment of proximal humerus fractures in a community-based health care organization. *Perm J*, 20(1), 47-52. http://dx.doi.org/10.7812/TPP/15-065

Tables

Table 1. FY2017 Risk-Standardized Readmission Rates Compared to National Average

Condition	FY2017 Study Site Rate	National Average	2017 Targets
Acute Myocardial Infarction	17.7%	16.6%	≤ 15.39%
Chronic Obstructive Pulmonary Disease	23.8%	20.0%	≤ 18.02%
Heart Failure	24.9%	21.9%	≤ 20.13%
Pneumonia	19.5%	17.2%	≤ 15.06%
Coronary Artery Bypass Graft Surgery	17.1%	14.2%	≤ 10.87%
Total Hip/Knee Arthroplasty	5.4%	4.5%	≤ 3.28%

Table 2. LACE External Validation Studies

Study	Population	Risk of Readmission
1. Cooksley et al., 2016	19,277 adult medical patients in Ireland	C-statistic 0.648 (95% CI 0.639-0.670
2. Cotter, Bhalla, Wallis, & Biram, 2012	507 elderly patients, mean age 85 years in United Kingdom	C-statistic 0.55 (95% CI 0.49-0.61)
3. Garrison, Robelia, Pecina, & Dawson, 2016	14,663 adult primary care patients with inpatient admission in United States	C-statistic 0.680 (98.75% CI 0.670-0.691)
4. Donovan, Turney, Emnett, Lamoreaux, & Portman, 2016	329 oncology patients in United States	C-statistic 0.45
5. Low, Liu, Ong, Ng, Ho, Thumboo, & Lee, 2017	17,006 adult inpatients age > 65 years discharged home in Singapore	C-statistic 0.628 (95% CI 0.615-0.642)
6. Tan, Low, Yang, & Lee, 2013	127,550 medical patients in Singapore	OR 4.37; CI=4.18-4.57 for LACE index $\geq$ 10
7. Tong, Erdmann, Daldalian, Li, & Esposito, 2016	80,000 adult inpatients in United States	C-statistic 0.655 (95% CI 0.652-0.659)
8. Wang et al., 2014	253 adult congestive heart failure patients	C-statistic 0.5610 (95% CI 0.4771-0.6447)
9. Yian et al., 2016	1387 surgical humerus fracture repair patients in United States	OR 4.47; CI=2.54-7.86 for LACE $\geq$ 10

Table 3. LACE Index

Factors		Values	Points
L: Length of stay (days)		0	0
		1	1
		2	2
		3	3
		4 to 6	4
		7 to 13	5
		14 or more	7
A: Acute (emergent) admission		Yes	3
C: Comorbidity (Charlson comorbidity index score)		1	1
History of myocardial infarction	1		
Peripheral vascular disease	1		
Cerebrovascular disease	1		
Diabetes without complications	1	2	2
Congestive heart failure	2		
Chronic obstructive pulmonary disease	2		
Mild liver disease	2		
Cancer	2	3	3
Dementia	3		
Connective tissue disease	3		
HIV infection	4	≥ 4	5
Moderate or severe liver disease	4		
Metastatic solid tumor	6		
E: Emergency department visits during previous six months		1	1
		2	2
		3	3
		> 4	4
LACE Index score*		0 (minimum) 19 (maximum)	

** total of the points assigned for each factor based on that factor's value*

Table 3. LACE index. Adapted from "Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community," by Van Walraven, C., Dhalla, I. A., Bell, C., Etchells, E., Steill, I. G., Zarnke, K., … Forster, A. J. (2010). *CMAJ*, *182*(6), 551-557.

Table 4. Variables of Interest

Variable	Form	Theoretical Definition	Operational Definition
Dependent Variable			
Unplanned readmission	Binary	Unplanned admission to hospital within 30 days after index admission discharge	Unplanned admission to hospital within 30 days after index admission discharge to any Florida Hospital campus. Day of discharge = day 0. 0= No unplanned readmission 1= Yes unplanned readmission
Independent Variables			
LACE index *Patient-level*	Categorical	Calculated score based on length of stay, acuity of admission, comorbidities, number of emergency visits in 6 months prior to index admission	LACE index score abstracted from the Cerner Electronic Health Record (EHR) on day of discharge. 1= LACE Index 1-6 (Low) 2= LACE Index 7-10 (Moderate) 3= LACE Index 11-19 (High)
Age *Patient-level*	Categorical	Chronological age in years	Date of discharge minus birth date abstracted from Cerner EHR. 1= 18-64 2= $\geq$ 65
Gender *Patient-level*	Binary	Biological sex	Male or female abstracted from Cerner EHR 0=Male 1=Female
Race *Patient-level*	Categorical	Group based on biological physical traits	Race abstracted from Cerner EHR. 1= White/Caucasian 2= Black/African-American 3= Asian 4= Other 5= Unknown
Preferred Language *Patient-level*	Categorical	Language identified as preferred	Preferred language abstracted from Cerner EHR. 1= English 2= Spanish 3= Other
Marital Status *Patient-level*	Categorical	Status of current relationship	Marital status abstracted from Cerner EHR 1= Single 2= Married or Life Partner

			3= Separated 4= Divorced 5= Widowed
Payer source *Encounter-level*	Categorical	Insurance type or self-pay	Payer abstracted from Cerner EHR. 1= Medicare 2= Medicaid 3= Commercial 4= Self Pay 5= Other
Index Disposition *Encounter-level*	Categorical	Location or services to which patient was discharged	Discharge disposition abstracted from Cerner EHR. 1= Home 2= Home with Home Health Care 3= Skilled Nursing Facility/Rehab/Long-term Acute Care 4= Psychiatric Hospital 5=Other
Index DRG *Encounter-level*	Categorical	Index admission DRG assignment	Final coded DRG abstracted from Cerner EHR Categorical 1 – 10 based on top 10 DRGs by volume. 11 = Other

Table 5. Population Demographics and Clinical Characteristics and Association to Readmission (N=17,082)

Characteristics		%	χ^2	df	*P*
LACE Index	0-7 (Low)	31.80%	537.92	2	<0.01
	7-10 (Moderate)	49.20%			
	11-19 (High)	19.00%			
Age	18-64	55.40%	2.480	1	0.12
	$\geq$ 65	44.60%			
Gender	Male	50.90%	0.12	1	0.73
	Female	49.10%			
Race	White/Caucasian	69.30%	27.782	4	<0.01
	Black/African-American	18.50%			
	Asian	1.20%			
	Other	9.40%			
	Unknown	1.50%			
Preferred Language	English	93.50%	0.45	2	0.80
	Spanish	5.10%			
	Other	1.40%			
Marital Status	Single	32.60%	18.64	4	<0.01
	Married/Life Partner	44.20%			
	Separated	2.40%			
	Divorced	9.90%			
	Widowed	10.90%			
Payer Source	Medicare	51.90%	112.925	4	<0.01
	Medicaid	9.50%			
	Commercial	25.60%			
	Self Pay	8.30%			
	Other	4.70%			
Index Disposition	Home	63.30%	79.136	4	<0.01
	Home with HHC	20.10%			
	Skilled Nursing Facility/Rehab/Long-term Acute	15.30%			
	Psych Hospital	0.90%			
	Other	0.40%			

Index DRG	247-Perc Cardiovasc Proc W Drug-Eluting Stent	2.20%			
	470-Major Joint Replace Or Reattach Of Lower Extremity	2.10%			
	392-Esophagitis, Gastroent & Misc Digest Disorders	2.10%			
	871-Septicemia Or Severe Sepsis W/O Mv 96+ Hours	2.00%			
	291-Heart Failure & Shock W Mcc	1.70%			
	460-Spinal Fusion Except Cervical W/O Mcc	1.50%	126.624	10	<0.01
	603-Cellulitis W/O Mcc	1.40%			
	494-Lower Extrem & Humer Proc Except Hip,Foot,Femur	1.30%			
	101-Seizures	1.10%			
	287-Circulatory Disorders Except Ami, W Card Cath	1.00%			
	Other	83.70%			

Figures

Figure 1. Conceptual Model of the Determinants of Preventable Readmissions

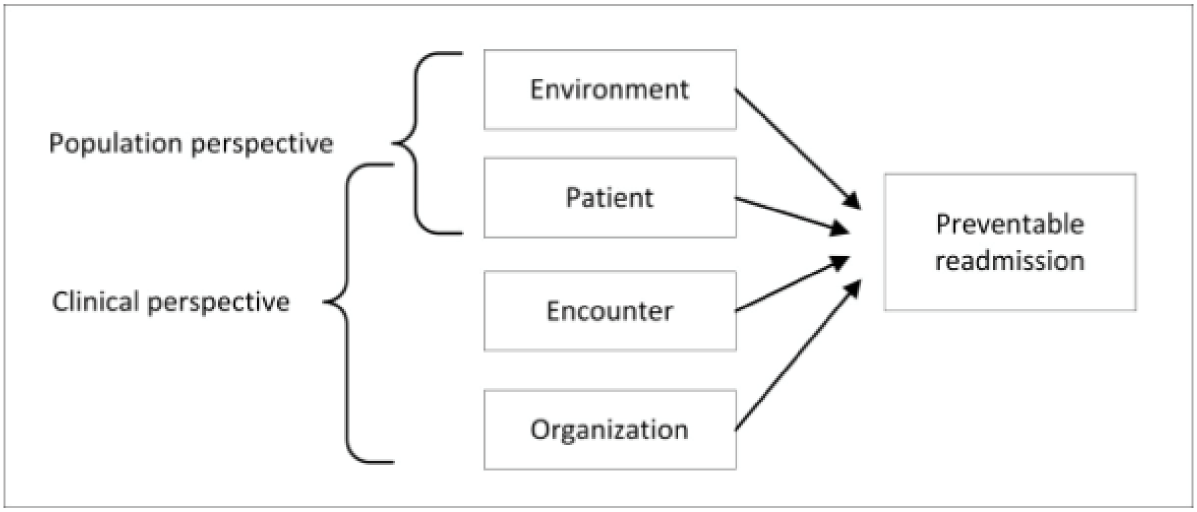
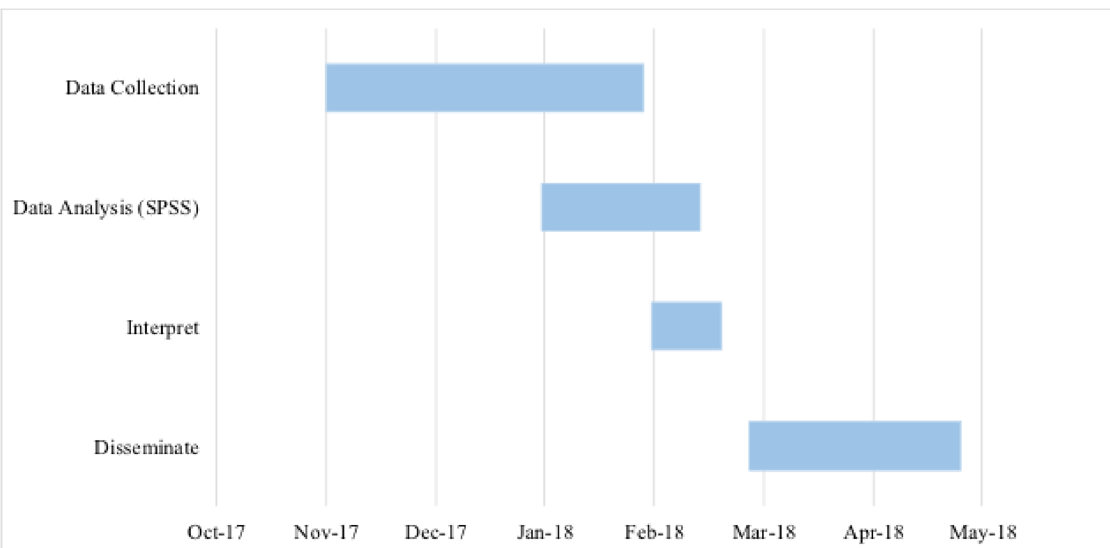


Figure 1. Model demonstrating the influence of population and clinical factors on preventable readmissions. Reprinted with permission from "Determinants of Preventable Readmissions in the United States: A Systematic Review," by J. R. Vest, L. D. Gamm, B. A. Oxford, M. I. Gonzalez, and K. M. Slawson, 2010, *Implementation Science*, *5*(88), p. 3. Copyright 2010 by Vest et al.; licensee BioMed Central Ltd. 2010.

Figure 2. Project Timeline



Appendix

Appendix A: De-identified Data Collection Spreadsheet

ID	LACE Index 1-3	Gender 0, 1	Age 1, 2	Race 1-5	Preferred Language 1-3	Marital Status 1-5	Payer 1- 5	Discharge Disposition 1-5	Index DRG 1-11	Unplanned Readmission 0, 1
0001										
0002										
0003										
0004										
0005										
0006										
0007										