

# EASTERN CONNECTICUT STATE UNIVERSITY

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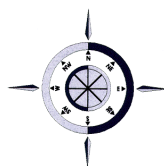
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## Introduction:

The United States health expenditure has been steadily increasing over the past few decades. In fact, the World Health Organization (WHO) announced that the average rate of global health expenditure increased 4.0% from 2000 to 2015 (Guan et al., 2020), citing it as a “key undesirable outcome of healthcare systems” (Wong et al., 2011). On top of this, The Commonwealth Fund Commission on a High-Performance Health System Scorecard gave the US healthcare system a 66/100, citing that the United States’ healthcare expenditure was far greater than any other industrialized country, though their healthcare performance was roughly the same as other countries (Berwick et al., 2008). This trend in performance has been noted in other relevant literature, such as *To Err is Human*. The study found that medical errors resulting from healthcare facilities were some of the leading causes of death, stating that, “it is as lethal as breast cancer, motor vehicle accidents, or AIDS,” (Berwick, 2002) and the study calls for change in the American Healthcare System. *To Err is Human* (2000) acted as a wakeup call to the American people, showing that the American Healthcare System needs to be redesigned for the 21<sup>st</sup> century, focusing on increasing quality and lowering costs (Berwick, 2002). Much of this increase in expenditure and mortality is in relation to complex patient care processes, outdated systems and policies, or a lack of insight into patient-centric care approaches (Berwick, 2002). According to *A User’s Manual for The IOM’s Quality Chasm Report*, most patient injuries arise from unrealistic reliance on human skills, as well as lack of information and communication infrastructure in an overly technological world (Berwick, 2002). To ensure a better future for the American Healthcare System, studies such as the IOM’s (Institute of Medicine) *Quality Chasm Report* (2002) call for a focus on six dimensions of healthcare quality; patient safety, effectiveness of healthcare, patient-centered healthcare, timeliness in healthcare performance, efficiency in healthcare, and equity in patient care (Berwick, 2002). The IOM has been cited

saying that, “in its current form, habits, and environment, American health care is incapable of providing the public with the quality health care it expects and deserves,” acting as a call to action for healthcare organizations and policymakers (Berwick, 2002). In addition to the IOM’s claims, *The Triple Aim: Care, Health, And Cost* (2008) proposes three interdependent pillars for healthcare success, those being a focus on improving individual experience of care, improving health populations, and reducing per-capita costs of care for populations (Berwick et al., 2008). These three goals are achievable through obtaining, understanding, and usage of healthcare performance metrics (Berwick et al., 2008).

To help combat an increase in spending and poor healthcare performance, legislation has been passed to better regulate healthcare facilities (Lewis et al., 2022). The Patient Protection and Affordable Care Act (2010), also known as “Obamacare,” has put policies in place to push organizations such as the Centers for Medicare and Medicaid Services (CMS) to cut reimbursement funds for hospitals with statistics in relation to outliers in performance metrics, such as excessive 30-day readmission rates in patients (Huang et al., 2022). In addition to the Affordable Care Act, The Hospital Readmissions Reduction Program (HRRP) was introduced to reduce hospital readmission rates among Medicare beneficiaries (Lu et al., 2021). Readmission, namely all-cause readmission, is defined as the percentage of admitted patients who return to the hospital within a number of days of discharge, say 30 or 90 days (Institute for Healthcare Management, 2023). Reduction of readmission rates was cited as one of the top strategic priorities of healthcare facilities and is one of the most universally used outcome variables when it comes to measuring hospital performance (Wong et al., 2011). In 2017 alone, roughly 8-30% of all hospital admissions were potentially preventable, costing upwards of 561.6 million USD (Lewis et al., 2022). In addition, studies have found that approximately 18-20% of Medicare patients are expected to be readmitted within 30 days of discharge (Baig et al., 2020; Reddy et

al., 2001; Huange et al., 2022; Luu et al., 2021), overall costing the Medicare program \$17 billion USD, roughly 20% of Medicare's total budget (Shams et al., 2015). Being able to reduce this rate through research on healthcare practices, quality of care, or other factors would be able to effectively lower the cost of care as well as help uphold the standard of quality established by the Affordable Care Act. Length of stay (LOS) is the amount of time a patient spends in a healthcare facility and is also crucial in the analysis of healthcare facility performance (Kalgotra & Sharda, 2021). In the relevant literature, LOS allows researchers to measure the success of different practices based on the average amount of time a patient spends in a healthcare facility (Thomson et al., 2015). These factors are used not only in measurement of general healthcare performance (Gu et al., 2019) but are also used to measure healthcare performance for specific diseases or illnesses.

Pneumonia is an acute viral infection that inflames the air sacs in the lungs, causing them to fill with fluid, resulting in coughing, fever, chills, and difficulty breathing (Mayo Clinic, 2020). Pneumonia is one of the leading causes of hospitalization in the United States (Lewis et al., 2022) and is the most common type of lower respiratory infection (Li et al., 2019). In addition to issues with healthcare outlined previously, pneumonia hospitalization continues to go up because of an increased antibiotic resistance as well as a population that continues to live longer, thus creating an older population (Huang et al., 2022). The economic burden amongst Medicare patients was \$13 billion in 2013 (Sato et al., 2013), and in 2008 became the leading infectious cause of death in the United States (Lin et al., 2016). Pneumonia is associated with high hospitalizations, mortality rates, and economic burden (Sato et al., 2013). There are roughly 5.6 million cases of Community-Acquired Pneumonia per year, with circa one quarter requiring hospitalization (Lewis et al., 2022). Of that, 30-day readmission rates are upwards of 20% (Sato et al., 2013).

Although there is research regarding the metrics of LOS, readmission rates, and healthcare cost for pneumonia patients, there is limited research done on the relationship between these factors. Thus, the goal of this research is to examine the relationship between the three key factors of pneumonia patients: (1) LOS, (2) readmission rates, and (3) healthcare costs. This research could help contribute to a great variety of stakeholders including academicians and practitioners who analyze these three factors of pneumonia condition. The findings can also be used by the state and federal level decision-makers who analyze pneumonia condition.

## **Methods:**

### Literature Review:

The process of literature review began in early May of 2023. This literature review was conducted based on the systematic literature review (SLR) flow chart, which outlines the process of planning review, conducting review, and reporting the review. As shown in Figure 1, our process first began with identifying the need for a systematic review. Next, we constructed our research question as follows: “Is there any statistically significant relationship between LOS, readmission rate, and healthcare costs for pneumonia patients admitted in a longitudinal perspective covering the years of 2010-2020?”



Figure 1: Systematic Literature Review Flowchart

Once the need for research and research question was established, the strategy for gathering resources was developed. Our strategy for gathering resources was to develop an inclusion and exclusion criteria for articles and use this in tandem with a list of keywords to search allowed us to ensure the quality and scope of the papers that were going to be read. A

second round of filtering would be done with the articles gathered to develop a final list of articles for literature review. This would involve taking notes on pertinent sections of the articles and formatting them into a note sheet containing the article title, year published, authors, research objectives, data used for research, methods used for data analysis, and the results yielded from the methods.

Table 1. Inclusion and exclusion criteria

Criteria	Items
<b>Inclusion criteria</b>	<ul style="list-style-type: none"> <li>• Full-text articles published in scholarly journals</li> <li>• Published in English between 1990 and 2023</li> <li>• The publications found in selected digital databases in primary search</li> <li>• The articles including identified key words: pneumonia, LOS, LOS, readmission, charge (cost) (discharge cost)</li> <li>• The articles used in the previous literature reviews (secondary search)</li> </ul>
<b>Exclusion criteria</b>	<ul style="list-style-type: none"> <li>• Articles published in non-scholarly journals</li> <li>• Not full-text articles</li> <li>• Materials published in languages other than English</li> <li>• Duplicated studies</li> <li>• Conference proceedings</li> </ul>

After developing the inclusion and exclusion criteria established in Table 1, we were able to start searching for the relevant literature. To gather large amounts of articles for filtering and analysis, digital databases were used in the SLR. These databases allow users to sort through their catalogue with a query system. This query system allows for the input of inclusion and exclusion criteria such as the ones outlined in Table 1, as well as allowing for the input of keywords to search by. This list of keywords is as follows: “Pneumonia”, “LOS”, “Readmission”, “Cost”, “Charge”. This list of keywords was then broken up into two different query searches. For each of the 9 databases searched (ABI/INFORM collection, Business Source Premier (EBSCO), LexisNexis, Science Direct, Professional Development Collection, PubMed,



Medline, CINAHL, SCOPUS) two query searches were done. As shown in Table 2, search 1 was done with the keywords pneumonia, LOS, readmission, and cost, while search 2 was done with pneumonia, LOS, readmission, and charge. The difference in keyword between the searches was to ensure the quality of our article gathering and was able to yield more relevant articles.

Table 2. Primary results in SLR – includes number of articles found per query search option.

Database	Search 1: pneumonia, LOS, readmission, cost	Search 2: pneumonia, LOS, readmission, charge
ABI/INFORM Collection	248	101
Business Source Premier (EBSCO)	132	59
LexisNexis	12	5
Science Direct	25	10
Professional Development Collection	14	8
PubMed	181	35
Medline	28	3
CINAHL	10	1
SCOPUS	264	27
Total	914	249

Once this list of articles was gathered, we were able to extract an Excel spreadsheet (.xls) file for each database search result. This spreadsheet provided multiple fields of information, namely the article title, keywords, publisher, year published, and abstract or summary. Using article titles, keywords, and the abstract or summary, a secondary search through the article list was conducted to further narrow down the scope of the literature, after which 60 articles remained from the search. Next, a full-text screening was conducted, taking notes on each of the articles, and further ensuring the quality of the literature gathered.

#### Literature Report:

LOS:

A study, including 227 pneumonia patients aged 18 or older between May 2011 and August 2014, shows that hospital LOS is associated with the Charlson Comorbidity Index Score, types of treatment, duration of treatment, mechanical ventilation, and ICU (Intensive Care Unit) admission (Tong et al., 2016). In addition to this, LOS has been linked to the severity of illness. A study used hospital discharge data from the 2018 NRD to find pneumonia patients under the age of 18, separating patients by severe or non-severe cases based on variables including presence of respiratory failure, sepsis, mechanical ventilation, dependence on long-term supplemental oxygen, and respiratory intubation. Using this study sample and the variables derived from them, descriptive and summary statistics were reported (Lewis et al., 2022). LOS has been shown to decrease based on resource utilization as well. In a study on the impact of an antibiotic restriction program for treatment of community-acquired pneumonia, researchers found that, after implementing the antibiotic restriction program, the average LOS was reduced from 7.6 days to 5.8 days (Mansouri et al., 2011). This study is further supported by other relevant literature. Multivariate analysis was conducted on factors potentially associated with LOS and 30-day mortality, as well as days of duration of therapy, the occurrence of adverse events and subsequent hospital admissions. This study arrived at the same conclusion (Viasus et al., 2017).

#### Readmission rates:

A study in the relevant literature used linear regression to evaluate associations between pneumonia severity and readmission rates, finding that the severity of an illness has a direct impact on readmission rates. The resulting conclusions were that severe pneumonia patients had a higher rate of 30-day readmission (8.7% versus 5.9%) (Lewis et al., 2022). In the aforementioned study on an antibiotic restriction program for community-acquired pneumonia

treatment, results also found that, upon implementing the restriction program, 30-day readmission rates decreased from 16.9% to 6.2% (Mansouri et al., 2011). Another article examining regional differences and risk factors for, among others, readmission rates for community-acquired pneumonia in Danish patients, found that gender and the Charlson comorbidity index score for patients were predictive risk factors, namely if the patient was male and if their index score was high. The Charlson comorbidity index predicts a patient's mortality based on having multiple health conditions. A lower score indicates that their mortality rate is lower, while a higher score indicates a higher rate of mortality (Klausen et al., 2012). In addition to these risk factors, other literature found that a patient's age has an impact on the potential for readmission. The study sought to analyze patterns of readmission following hospitalization for community-acquired pneumonia across different age groups and insurance payers and used the National Readmission Database to collect data. Patients aged 18 years and older, discharged alive after index hospitalization with primary diagnosis of pneumonia, and were hospitalized between 2013 and 2014 were used in the study. Ages 18-44 had a readmission rate of 12.4%, ages 45-64 had a readmission rate of 16.1%, and ages 65 and older had a readmission rate of 16.7%. When a risk-adjusted analysis was conducted, middle-aged adults had a higher likelihood of readmission (Jain et al., 2018).

## Healthcare cost:

According to the relevant literature, healthcare costs are calculated as the product of total charge and the hospital-specific cost-to-charge ratio, which is provided by the HCUP (Healthcare Cost and Utilization Project) family of databases (Lewis et al., 2022). A study on predictors of readmission rates found a relationship between disease severity and daily cost as a secondary outcome variable. Two groups of patients, severe and non-severe, had daily costs of \$3,246 USD and \$2,679 respectively (Lewis et al., 2022). Another study found comorbidity to be directly related to healthcare costs (Sato et al., 2013). The study found that another potentially related factor, age, mattered less than the potential risk of developing Community-Acquired pneumonia, such as if a patient was immunocompromised or had underlying conditions. As a result, regardless of age, the cost to treat pneumonia patients was determined to be high, as each age group had low, medium, and high-risk patients (Sato et al., 2013). Another article in the relevant literature found that healthcare costs depend on the condition and resources used. Through a large-scale literature review meant to identify the relationship between the two factors, the study found that the relationship between them is more complex and nuanced (Jamalabadi et al., 2020). In support of these findings, an article from the National Institute of Health found that a change in the cost of care is tied to the resources used. In a study comparing the effectiveness of ceftriaxone, an antibiotic used to treat pneumonia, versus using a combined approach with ceftriaxone and a macrolide, the combined approach was shown to decrease treatment costs for the age group of 5-17 years of age. Measured by using LOS and total healthcare costs, the study used children 1-17 years of age with pneumonia and analyzed the associations between the antibiotics used and LOS. The treatment costs were assessed with multivariable linear regression and propensity-score analyses (Leyenaar et al., 2014). In addition to resource use, resource utilization is a factor impacting healthcare cost. In the study on an antibiotic restriction program

for treatment of patients with community-acquired pneumonia, results found that restriction of antibiotic use saved the Veterans Affairs Medical Center (the location in which the study was conducted) roughly \$943 USD per patient treated (Mansouri et al., 2011). A population-based study done in Hong Kong using public hospital pneumonia patient data from 2011-2015 found that patients aged 65 years and older accounted for 75% of pneumonia related hospitalizations, 90% of deaths, and an overwhelming majority of healthcare costs (Li et al., 2019). Further supporting these findings, relevant literature found that patients that were between the ages of 45 and 65 had an average hospital stay cost of \$10,238.70 USD, and patients aged 65 and older had an average hospital stay cost of \$10,163.90 USD (Jain et al., 2018).

#### Connections Between Metrics:

Relevant literature supports the existence of a relationship between LOS and readmissions for patients with community-acquired pneumonia. In a study published in 2014, researchers sought to identify factors associated with readmissions among children previously hospitalized with pneumonia. Using multivariable regression models to identify patient and hospital characteristics as well as costs associated with readmission, the study found that readmission rates were higher in patients who, among other factors, had longer index hospitalizations (Neuman et al., 2014). According to other relevant literature, the risk of patient readmission is directly related to the LOS. The study, focused on developing a model for aggregated readmission risk over time using Markov chains, survival analysis, stochastic processes, and linear regression, used surgical patient data to better estimate readmission risk through predictors, such as LOS (Zhang et al., 2020). Another article focused on comparing the impact of practice guidelines for common inpatient disorder to hospital-based reorganization arrived at the same conclusion, analyzing hospital costs, LOS, patient mortality, and resource

use. The study found that hospitalist-based practices resulted in a significant decrease in LOS and that, “reduced LOS was associated with a borderline significant reduction in readmission rates (from 4.8% to 0.7%  $P = .055$ ).” This study also found that different interventions, such as the hospital-based one analyzed in the article, can help reduce cost, LOS, and readmission rates, all key metrics in determining program success (Reddy et al., 2001). Furthermore, an article published by BioMed Central used machine learning methods to predict 30-day hospital readmissions among US adults with pneumonia. Their study cohort consisted of patients 18 years and older with pneumonia from January 1<sup>st</sup>, 2016, to November 30<sup>th</sup>, 2016, through the National Readmissions Database. After modeling all-cause readmissions 30 days post-discharge and using a total of 61 clinically relevant variables to model it, the top risk-predictive rules captured by the rule-based algorithms included LOS (Huang et al., 2022). In contrast to these findings, a study analyzing the relationship between LOS, costs, and practice patterns for pneumonia antibiotic administration found that reductions in LOS weren’t associated with a difference in 30-day readmission rates (Christensen et al., 2019).

The relationship between LOS and cost has been contested by relevant literature. In an article published by the NIH, researchers sought to determine the effectiveness of ceftriaxone, an antibiotic treatment for pneumonia, compared to a combined approach using both ceftriaxone and a macrolide. Children aged 5-17 receiving the combined antibiotic approach had a shorter LOS with no significant change on cost compared to solely using ceftriaxone (Leyenaar et al., 2014). There is, however, other relevant literature that points to a relationship between LOS and healthcare costs. A study assessed the impact of changing from an antibiotic vancomycin to linezolid for community-acquired pneumonia treatment using LOS and healthcare costs. The resulting findings were that LOS was significantly associated with, among other factors, the type of treatment used, and linezolid treatment resulted in, on average, a shorter LOS and hospital

charge (\$25,900 USD versus \$32,100 USD) (Tong et al., 2016). In addition to this, relevant literature found that patients receiving antibiotics intravenously had a reduced LOS by 0.58 days, which was associated with a reduced average cost by \$1,332 USD (Christensen et al., 2019). In relation to antibiotic administration, the study on the antibiotic restriction program's performance for patients with community-acquired pneumonia found a relationship between the two factors, noting that, as LOS decreased due to the program implemented, costs declined, too (Mansouri et al., 2011). Another study analyzed community-acquired pneumonia patient data to find effective methods of lowering LOS while increasing financial performance. The study consisted of 10,512 primary admissions for adults (patients ages 18 and older) for community-acquired pneumonia to 97 different healthcare facilities from June of 2002 to December of 2003. The results showed that LOS had a relationship with cost, as practices related to LOS, such as lowering the time to oral antibiotic conversion in patients or time to ambulation, both factors contributing to an average \$456 USD in savings for per-patient care (Grote et al., 2007).

In the aforementioned study on readmission rates for children hospitalized with community-acquired pneumonia, results showed that readmission rates were associated with an increased cost, and readmissions occurred in 8% of total pneumonia patients but accounted for 16.3% of overall healthcare expenditure on pneumonia (Neuman et al., 2014).

Although we were able to find articles discussing relationships between the different variables pertinent to our study, very few articles in our literature review directly covered what our research would be discussing. As a result, our research is more novel, though that means there was less relevant literature in which to base our hypotheses on.

Once the literature review was conducted, we were able to discuss research questions as hypotheses for our topic. Based on an understanding after literature review, we hypothesized that:

Hypothesis 1: As LOS decreases, the 30-day readmission of patients would also decrease among pneumonia patients.

Hypothesis 2: As LOS decreases, healthcare costs would also decrease.

Hypothesis 3: As readmission rates increase, total healthcare costs increase.

#### Data Collection:

Data found on LOS, readmission rates, and healthcare costs is gathered from the National Readmission Database (NRD), which is part of the larger HCUP family of databases (National Readmissions Database, 2023). The NRD is a powerful database gathering patient data to support analysis and research regarding healthcare information. The HCUP family of databases and related software tools were developed through the Agency for Healthcare Research and Quality (AHRQ) (National Readmissions Database, 2023). The HCUP State Inpatient Databases provides verifiable patient data from 31 HCUP partners, which is used in the NRD. This data includes more than 100 clinical and nonclinical variables on a case-by-case basis, including readmission rates, patient demographic information, LOS, and healthcare costs (National Readmissions Database, 2023). This data has helped support research on topics such as readmissions by diagnosis, costs associated with readmissions, impact of healthcare policy and practice, as well as our own topic of study.

Our study cohort will consist of adults (aged 18 and older) with a primary diagnosis of pneumonia, based on ICD-9 codes (482.40, 482.41, 482.42, 482.49, 482.89, 482.9, 484.8, 485,



486, 510.0, 510.9, 513.0, or 513.1) from the National Readmission Database between 2010 to 2015 and ICD-10 codes (J09X1, J100, J1000, J1001, J1008, J110, J1100, J1108, J120, J121, J122, J123, J1281, J1282, J1289, J129, J13, J14, J15, J16, J17, J18, A221, A3701, A3711, A3781, A3791, A481, B250, B440, B7781) for years 2016 to 2020. Patients must be discharged alive from their respective healthcare facility. Excluded patients were those who died during hospitalization and have missing records regarding LOS, readmission rates, and healthcare cost. To pull records based on specified inclusion criteria, the NRD provides different HCUP data elements to differentiate between data. For our study, these will include elements for age, ICD-9 and ICD-10 codes, DRG codes, gender, total charges, LOS, year, payer, discharge type, elective vs nonelective status, zip code, hospital bed size, urban/rural status of hospital, and death.

#### Outcome Variables:

The primary outcome variables for our research will be the analysis of LOS, healthcare costs, and readmission rates in patients with the primary diagnosis of pneumonia. LOS will be defined as the number of calendar days spent in a healthcare facility. Healthcare costs are calculated as the product of total charge and the hospital-specific cost-to-charge ratio, as found in relevant literature (Lewis et al., 2022). Readmission rates will be defined as readmission to any hospital within 30 days of discharge from index hospitalization.

#### Data Analysis:

The reviewed studies show that the methods commonly used in analyzing different healthcare metrics included descriptive analytics, linear regression, logistic regression, t-tests, and Fisher's exact test in the literature. The most prevalent in relevant literature in examining the relationship between variables in healthcare performance was linear regression and forms of it, such as multiple linear regression and logistic regression.

Our proposed method for data analysis is using linear regression to find a relationship between our independent variables, LOS and healthcare costs, and our dependent variable, readmission rates. The other variables listed above will be considered control variables. Linear regression is a form of predictive analysis that allows for analysis of the ability to predict a dependent variable based on a set of independent variables, as well as determining the significance of those predictor variables in respect to the outcome. Our study will be using the software Minitab and STATA in tandem with Microsoft Excel in order to analyze and use data for statistical analysis.

For our regression equations, we have five proposed formulas or methods we will decide between. Our first formula measures readmission rates against LOS and a control variable.

$$\text{Readmission} = \beta_0 \text{LOS} + \beta_1 X_{i1} + \varepsilon \quad (1)$$

where  $\beta_0$  is the coefficient of LOS variable,  $\beta_1$  the coefficient of control variables, and  $\varepsilon$  is the error term.

Our second formula measures readmission rates against LOS, total charges, and another control variable.

$$\text{Readmission} = \beta_0 \text{Total Charges}_0 + \beta_1 X_{i1} + \varepsilon \quad (2)$$

where  $\beta_0$  is the coefficient of total charges variable,  $\beta_1$  the coefficient of control variables, and  $\varepsilon$  is the error term.

Our third formula measures readmission rates against total charges.

$$\text{LOS} = \beta_0 \text{Total Charges}_0 + \beta_1 X_{i1} + \varepsilon \quad (3)$$

where  $\beta_0$  is the coefficient of total charges variable,  $\beta_1$  the coefficient of control variables, and  $\varepsilon$  is the error term.

Our fourth formula measures LOS against a number of currently unspecified control variables.

$$\text{LOS} = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \varepsilon_i \quad (4)$$

where  $\beta_0$  is the coefficient of an unspecified variable variable,  $\beta_1$  and onward the coefficient of control variables, and  $\varepsilon$  is the error term.

Our final proposed means of statistical analysis is the use of machine learning. Though more research is needed to effectively use this method in our study, machine learning can allow us to analyze more complex and varied data in a faster amount of time. It can be applied to our study to determine the relationship between our three factors for pneumonia patients by use of neural networks and support vector machines. The main issues that come with this approach is the need for more research and learning in terms of how to use machine learning in our study, as well as being able to interpret results of machine learning, a key issue highlighted by the article *Machine learning methods to predict 30-day hospital readmission outcome among US adults with pneumonia: analysis of the national readmission database* (Huang et al., 2022). Their machine learning models used rule ensemble-based learning, which is a classification algorithm relying on a tree-based framework for rule generation and LASSO (Least Absolute Shrinkage and Selection Operator) for rule-pruning and compiling a result set from large datasets (Huang et al., 2022). According to the article, limited research using rule-based learning to predict readmissions factors has been conducted (Huang et al., 2022). This would add to the novel nature of our research at the cost of adding even more complexity, required research, and methods.

Gathering of data will start over winter break 2023, while research methods will be used on the gathered data spring semester 2024. Further research and findings will be gathered in the summer of 2024, and results will be presented in the fall semester 2024.

### **Anticipated Results:**

As mentioned before, the literature review yielded sparse information directly related to our topic, though some adjacently related findings have helped greatly with developing a better understanding of not only our topic, but the greater scope of the healthcare industry. The limited amount of literature review related to our research topic shows that there is a gap in the relevant literature to analyze the relationships between these three variables particularly for pneumonia patients: LOS, readmission rate, and healthcare costs. In light of this gap, our study will attempt to test the hypotheses by analyzing these three variables using NRD data sets in a longitudinal analysis including 11-year data provided by HCUP and AHRQ.

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