Use of Billing and Electronic Health Record Data to define an Alternative Payment Model for the Management of Acute Pancreatitis

THESIS

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Abstract

Acute pancreatitis (AP) is a common cause of abdominal pain for which patients seek medical care. Most patients are treated conservatively and discharged without incident. The routine use of cross sectional imaging, endoscopic procedures and antibiotics are not required. AP presents similarly to other causes of abdominal pain, so evaluation of AP and ruling out competing diagnoses can lead to overutilization of tests and procedures. In this study we aim to define an alternative payment model (APM) for AP. We analyze information from two sources- claims data and electronic health care record (EHR) data to explore resource utilization in the management of AP with a focus on balancing the often competing aims of appropriate treatment and reducing unnecessary procedures.

Our claims data analysis revealed that the majority (93%) of care in AP is delivered in the acute care setting (Emergency Department and Hospital Inpatient). Physician fees and imaging were the two most expensive services (29% and 21% respectively). Exploratory data analysis of the EHR data showed a positive correlation between CT utilization and the LOS and early MRI utilization and cost. There was utilization of cross sectional imaging and antibiotics in encounters with very short length of stay (LOS) where it was unlikely that these would have altered management. We found that 48% of abdominal CTs and 58% of abdominal MRIs were used within 24 hours of admission even when the diagnostic criteria for AP have been met.

We define two types of complicated encounters - suspected biliary pancreatitis and those who develop adverse outcomes such as mechanical ventilation, parenteral nutrition, acute kidney injury and late endoscopic biliary procedures. Both conditions were found to have significantly higher cost, LOS and utilization of antibiotics.

We constructed a predictive model to predict the risk adverse events based on early clinical information to allow providers to determine the appropriate emergency department (ED) disposition. Three learning methods were used- Decision Trees, Rule based classifier and Naïve Bayes. The models correctly identified 29 to 39% of encounters where these adverse events occurred. The sensitivity of the models for normal encounters was 91 to 93% with a positive predictive value of 83 to 86%.

We propose an APM using the percentage of encounters using early cross sectional imaging, antibiotic use and the administration intravenous (IV) fluids as quality metrics. To reduce the variability of total charges, a LOS >7 days, endoscopic procedures, surgery and biliary pancreatitis should serve as some of the exclusion criteria.

In summary, there are opportunities to reduce healthcare resource utilization in the management of AP. APMs are one such way utilization could be safely reduced because it can be defined according to society guidelines and may be tied to reimbursement. A predictive model may help identify uncomplicated cases and help provide appropriate ED disposition. These types of studies could be useful to healthcare institutions to help quantify the amount of risk and develop suitable APMs that make sense to both providers and payers.

Dedication

This document is dedicated to my wife Tatum Hontiveros who undertook the immense task of taking care of our two children Diego and Gregorio while I pursue this graduate degree while doing my clinical fellowship in Gastroenterology.

I would also like to thank the Division of Gastroenterology under the leadership of Dr. Darwin Conwell and Dr. Marty Meyer for allowing me to pursue this graduate degree during my fellowship. Special thanks as well to Dr. Gregg Gascon for the mentorship in population health management.

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Fields of Study

Major Field: Public Health

Concentrations: Biomedical informatics, Health care Analytics, Data Mining

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Introduction

Acute pancreatitis (AP) is the third most common gastrointestinal cause of hospitalization in the United States.[1] Severe epigastric abdominal pain associated with nausea and vomiting, along with at least a threefold elevation in the serum lipase or inflammation of the pancreas on cross sectional imaging (CT and MRI) are the diagnostic hallmarks of acute pancreatitis. [2] However, AP can look like a number of other conditions, creating physician ordering patterns that rely heavily on diagnostic tests to both confirm and rule out competing diagnoses. Once AP is diagnosed, the evidence-based protocol is simple – fluids, pain control and avoidance of oral intake (i.e., *nil per os* (nothing by mouth) or NPO). In practice, however, patients are often subjected to numerous tests and procedures even after a clear diagnosis is made – leading to both unnecessary medical costs and non-patient centered care. As a result, the process of diagnosing and treating AP can result in a number of unnecessary medical services.

While the dominant model for reimbursement of hospital procedures is fee-for-service, there is a growing interest in APMs. In a fee-for -service environment, providers are compensated based on production either through the number of patients seen, procedures performed or through medication administration. Because of what is perceived as the unsustainable trajectory of healthcare expenditures, healthcare payers are beginning to explore APMs to control costs and manage risk.

The use of electronic health records (EHR) has made it feasible to explore the variances in practice associated with the treatment of medical conditions. EHR data can also offer insights into the geographic and demographic disparities that may become opportunities for outreach and identify social determinants of health in patients with AP.

The overall goal of this study is to define an APM for the management of AP. The model aims to balance the often competing aims of appropriate treatment and unnecessary resource utilization.

We will obtain insights from both claims data and EHR derived data. We will avoid using manual chart review and instead utilize discrete data elements with a goal of being able to scale up these methods for use in large health care delivery systems.

Background and Literature Review

Acute Pancreatitis

Acute pancreatitis is one of the most common causes of abdominal pain for which patients urgently seek medical care. [1] It presents similarly to other common conditions such as peptic ulcer disease or an impacted gallstone in the cystic duct (i.e. acute cholecystitis). The presentation of AP is not unique and as a result, the evaluation for suspected AP can create physician ordering patterns that can rely heavily on diagnostic tests to both confirm and rule out competing diagnoses.

Once a diagnosis of AP is made, initial supportive care should include at a minimum aggressive fluid resuscitation, avoidance of oral intake, pain control and correction of electrolyte abnormalities. Initiating appropriate therapy is crucial within the first 24 hours after presentation. [3] [4] Injury to the pancreas causes a systemic inflammatory response and fluid resuscitation is performed to prevent further ischemic injury which may lead to pancreatic necrosis. [5] AP is not a homogenous condition. Patients with mild AP are expected to recover quickly while those moderately severe and severe AP are expected to have prolonged and complicated hospital stay. [6]

The most common precipitants of AP are gallstones and alcohol. Gallstones cause AP by causing transient or persistent obstruction to the outflow of pancreatic enzymes. Premature activation of enzymes within the gland can cause injury through autodigestion. [7] To prevent further episodes of gallstone pancreatitis, it is recommended that the gallbladder be surgically removed. The timing of surgery is still a subject of intense debate. [8, 9]. In most cases the obstruction is transient. Unrelieved obstruction may lead to an infection of the biliary tract called cholangitis. This condition requires antibiotic coverage and urgent bile duct decompression through a procedure called an endoscopic retrograde cholangiopancreatography (ERCP). [10] This procedure has a high complication rate including causing AP in 1.6 to 15.7% of cases. To avoid the risks of ERCP, endoscopic ultrasonography (EUS) can be done to confirm the presence of obstruction prior to decompression. [11]

Socioeconomic factors may predispose some patients to develop AP more than others. Alcohol use is the second most common cause of AP. Alcohol induces oxidative stress and transcription of pro-inflammatory cytokines with in the pancreas which can cause pancreatic necrosis. [12] [13] [14] Obesity is a known risk factor for gallstone formation and is associated with worse outcomes in AP. [15] [16] These factors may predispose patients to higher complication rates and subsequently higher resource utilization.

The revised Atlanta classification grades the severity of AP as mild, moderate or severe based on the presence of organ injury (renal, respiratory of cardiac), local complications identified through imaging (fluid collections, necrosis), and exacerbation of pre-existing comorbidities. [6] Patients with mild AP have no organ failure, local complications or exacerbation of comorbid conditions. Moderately severe AP is defined by transient organ failure, local complications or exacerbation of comorbid disease. Severe acute pancreatitis is defined by the presence of persistent organ failure

Targets for resource optimization in AP

The diagnosis of AP is made when two of the following three criteria are met – 1) severe epigastric abdominal pain associated with nausea and vomiting, 2) at least a threefold elevation in the serum lipase or 3) inflammation of the pancreas on cross sectional imaging (CT and MRI). In practice, patients are often subjected to numerous tests and procedures, even after a clear diagnosis is made – leading to both unnecessary medical costs and non-evidence based care. The utilization of cross sectional imaging is one potential avenue for resource optimization. Abdominal ultrasonography is the preferred initial imaging study because it is highly sensitive and specific for the detection of gallstones and biliary obstruction. [17] However, it is not uncommon to find cross-sectional imaging such as computed tomography (CT) or magnetic resonance imaging (MRI) as part of the initial diagnostic workup on patients who present in the emergency department. MRI and CT studies are more costly and hence are recommended when there is diagnostic uncertainty, to confirm of severity based on clinical predictors of severe AP, or when patients fail to respond to conservative treatment or in the setting of clinical deterioration. The optimal timing for initial CT assessment is at least 72 to 96 hours after the onset of symptoms. [17] When the diagnosis of AP is established through the first two criteria, confirmatory cross sectional imaging is often unnecessary and rarely provides information that would change patient management.

The use of antibiotics is another potential target for resource optimization. In AP, the routine use of antibiotics in the absence of biliary or extra pancreatic sources of infection is not recommended. This is because the inflammatory response seen in AP is often not due to an infectious process. [17] There are efforts to curb the use of antibiotics in multiple healthcare settings due to some of the unintended consequences of antibiotic exposure such as the development of antimicrobial resistance and clostridium difficile infections. [18-20]

Because of the rising costs of inpatient care, payers have incentivized providers to shift care to hospital outpatient departments and ambulatory settings. Hospital inpatient units are set up deploy expensive interventions and hence cost more. In AP, some patients may require ICU care, invasive procedures or require alternative methods for nutrition for several days. Triaging less complex patients to observation units and reserving inpatient care to those at risk for complications have been shown in other conditions to reduce cost without reduction in quality of care. [21, 22] Identification of patients unlikely to require inpatient admission would be a useful cost containment strategy.

Payment models in healthcare

While the dominant model for healthcare reimbursement is fee-for-service (FFS), there is a growing interest in APMs. In FFS, healthcare providers are compensated for performing a discrete set of services such as outpatient visits, consultations, procedures or medication administration. [23] Because providers are paid per service, there is an incentive to do more to increase reimbursement. In FFS there is little incentive to improve the quality care and reduce unnecessary resource utilization. FFS reimbursement is thought to be one of the reasons that healthcare in the United States is inefficient. [24]

Because of the ever rising cost of care, there is a lot of pressure on providers, payers and government to come up with effective solutions to delay or even reverse the upward trend of healthcare costs. Health maintenance organizations (HMOs) were popular in the 1980s and 1990s as a way to control escalating healthcare costs. In a

HMO the payer and healthcare provider are a single entity. Patients pay a set premium to the HMO in return for medical care and providers are then paid by the HMO for their services. In this scenario there is an incentive for the entire organization to make care cost less and still be effective. Primary care providers serve as the principal point of contact to receive healthcare. They also function as gatekeepers to often more expensive specialist care. Emphasis on care coordination, wellness and limits on out of network care are some of the ways where HMOs control cost.

Recently, APMs are being proposed to change the way care is paid in a way that emphasizes high quality and cost efficient care. Accountable care organizations (ACO) and episode based payments are examples of APMs that incentivize quality by shifting some risk to healthcare providers. Providers in (ACOs) are reimbursed on both their ability to generate efficiencies that reduce costs and meeting quality metrics. [25] Episode based payments (EBP) also known as bundled payments, seek to reimburse a provider or group of providers a single payment for all services related to an episode of care. In this context, providers have incentives to eliminate unnecessary services and reduce expensive complications to reduce costs.[26] These arrangements are growing in popularity because of what is perceived as the unsustainable trajectory of healthcare expenditures.

State of Ohio Episode Based Payment Model

The state of Ohio currently ranks 29th out of 50 in healthcare spending per capita. Because of this, the Governor's Office in Health Transformation has taken steps in defining two APMs- episode based payments and accountable care organizations to shift care from fee-for-service into value-based care.[27] EBPs are ideal for acute procedures, inpatient stays and acute outpatient care where a single lump sum is offered to treat a specific condition. The State of Ohio EBP model mechanics are described below.

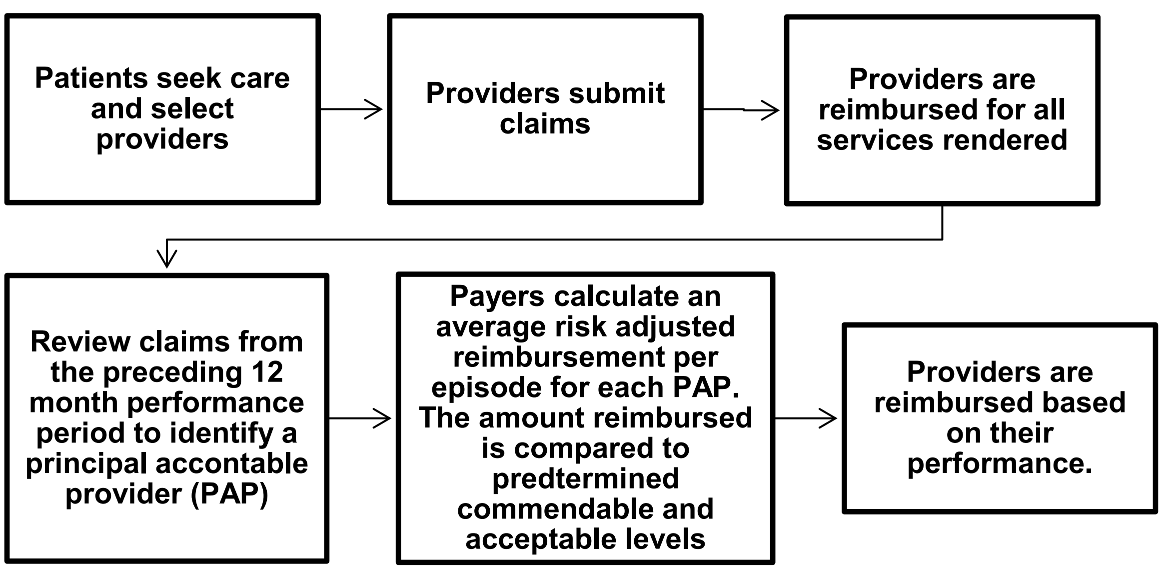

Figure 1. State of Ohio Retrospective Episode Model Mechanics

Briefly, this EBP model is a retrospective model using claims data which aims to reimburse providers based on their performance from the previous 12-month period. During the performance monitoring period, providers are reimbursed as in the fee-for-service model. After the 12-month performance period ends, claims data are reviewed to identify a principal accountable provider (PAP) who is responsible for the episode of care. To provide a level playing field, risk adjustment is performed by removing encounters that meet a set of exclusion criteria prior to calculation of the mean cost of care. The adjusted mean cost of care per provider is then compared to others. Payers then calculate an average risk adjusted reimbursement for per episode for each PAP. Providers could share in the savings if their average cost is below commendable levels and if quality metrics are met. Alternatively providers could get a reduction in their reimbursement if their average costs are above the acceptable level or see no impact if their average costs is between commendable and acceptable levels. An episode of care is defined by the following seven elements.

1. Episode trigger- A set of diagnoses or procedures and corresponding claim types and/or settings that define a potential episode of care
2. Episode window – A time period whereby all relevant care would be included in the episode. This time period is defined by the following criteria:

    Pre-trigger window – defined as the time period prior to the trigger event whereby all relevant care for an episode is included. Some episodes may not have a trigger window.

Trigger window- Duration of the trigger event. All relevant care within the episode is included.

Post trigger window- Time period following trigger event where by all relevant care is included in the episode.

3. Claims included – All claims for reimbursement relevant to the episode that are included in the payment bundle. Relevant claims are not billed separately.
4. Principal accountable provider- Provider or entity who is in the best position to assume principal accountability for the episode. Provider assignment is based on decision making responsibilities, influence over other providers and portion of the episode spend
5. Quality metrics-A set of measures to evaluate quality of care delivered during an episode of care. The quality metrics linked to incentive payments must be met in addition to having a less than commendable average cost to receive it. There are some quality metrics that are for reporting only.
6. Potential risk factors – Patient characteristics, comorbidities, diagnoses or procedures that may potentially indicate an increased level of risk for a given patient in a specific episode.
7. Episode level exclusions – patient characteristics, comorbidities, diagnoses or procedures that may potentially indicate an increased level of risk that due to its complexity, cost, or other factors, should be excluded rather than adjusted. Clinical exclusions refer to the medical characteristics of the patient or episodes

that confer increased risk. Business exclusions are non-clinical reasons for excluding an episode.

Electronic Health Record Data and Claims data

Healthcare claims data are itemized billing statements of services provided and paid for by healthcare payers. Healthcare claims data represent a holistic view of services rendered whether it is delivered in the hospital, rehabilitation facility or the home. Healthcare claims data also provide information on medication use and compliance. However, claims data has its limitations namely that no additional clinical information aside from diagnoses, procedures and medications can be obtained.

Electronic health record data is data primarily collected and stored to facilitate healthcare delivery. It is rich with clinical information such as labs, clinical assessments and vital signs. Secondary use of electronic healthcare data refers to the use of health data aside from direct patient care. [28] Secondary use of electronic healthcare data has the potential to accelerate research discoveries, improve public health surveillance and improve healthcare quality. [29] The rise of electronic medical records has made it feasible to explore the variances in practice associated with the treatment of medical conditions. One of the drawbacks of EHR data is the inability to obtain information on care delivered outside the healthcare institution. Information on care delivered in an independent rehabilitation facility for example cannot be obtained from a hospital EHR.

Data from EHRs and billing claims data can be complementary. Claims data captures the costs of care from multiple healthcare providers but suffers from the lack of clinical information while EHR data is rich with clinical information but is limited to a single healthcare provider. The use of both claims and EHR data can inform us where and how structure a quality improvement project. [30] Quality improvement projects using data from EHR queries and/or claims data is also likely to be easier to scale into a larger number of patients and be implemented independent of clinician oversight. Further, EHR data can offer insight into the geographic and demographic disparities that may become the opportunities for outreach and identify social determinants of health in patients with AP.

Summary of the Problem

AP is a common cause of abdominal pain for which patients seek medical care. It presents similarly to other conditions, so evaluation of AP and ruling out competing diagnoses can lead to overutilization of tests and procedures. The management of uncomplicated conditions is simple- there is often no need for cross sectional imaging, antibiotics or procedures.

The current trajectory of healthcare costs is unsustainable hence payers are looking to alternatives to the current FFS system. APMs reimburse providers based on their ability to reduce cost while meeting quality metrics. As a consequence, these models shift some of the financial risk to providers. Hence it would be prudent to study the impact of such models prior to implementation. Analysis of both claims and EHR data can be complementary in evaluating the drivers of healthcare utilization and cost which is critical to refine any APM so it accomplishes its goals of maintaining quality and reducing cost. Careful evaluation of healthcare data can be used define an optimal APM that can be successfully implemented.

Materials and Methods

Overview

We aim to develop an EBP model for AP using the template proposed by the Ohio Governor's Office of Health Transformation. Using claims data obtained from the OSU Health Plan we obtained summary statistics to determine which service areas and healthcare services were possible drivers of cost. We used the claims data analysis and literature review to narrow the data elements to obtain from the Ohio State University Medical Center (OSUMC) EHR. We then query these data elements from AP encounters during the study period. Exploratory data analysis was then performed on the EHR data to identify practice patterns of resource over utilization. Using the EHR data, we developed a predictive model with the goal of identifying high and low risk patients to enable triage either to inpatient or observation status. We then used the information obtained in this study to propose an EBP model for AP. All data pre-processing and analysis was performed using the R statistical package (Version 3.3.0, Vienna, Austria). Predictive modeling was accomplished using the Weka library of machine learning algorithms (Version 3.8.0, Waikato, New Zealand). Data visualization was performed using the R statistical package and Tableau (Seattle, Washington).

Data

We obtained claims data from all episodes of AP serviced by the OSU Health Plan (OSUHP) from 2011 to 2015. There were 117 episodes of acute pancreatitis identified using an episode grouper developed by Truven Health Analytics (Ann Arbor, MI), part of IBM Watson Health. The claims data contained basic patient demographics, dates of service, diagnosis codes, procedure codes, revenue codes, place of service, provider names and amounts paid.

We selected discrete data elements from the OSUMC EHR obtained from all acute care encounters for AP between 1/1/2014 to 7/31/2016. Patients were retrospectively identified using the ICD-10-CM diagnosis codes for AP (577.0, K85.0, K85.1, K85.2, K85.3, K85.8, K85.9). The author of this study and a Clarity database (Verona, WI) specialist together identified the table elements and logical conditions of the database queries to ensure the correct data was obtained. The dataset was composed of 64 attributes, 629 unique patients representing 799 patient encounters. Patient encounters instead of individual patients were the unit of analysis because the EBP proposed by the State of Ohio uses patient encounters and does not exclude repeat admissions. The three types of acute patient encounters captured include-inpatient which is an encounter requiring a hospital stay greater than two midnights, emergency – an encounter requiring an emergency room evaluation or observation which is an encounter where an individual is placed on observation status for a period less than two midnights. A patient in observation could either be discharged or transitioned to inpatient care depending on provider preferences.

Basic laboratory work such as complete blood counts (CBC) and electrolyte panels were obtained at both admission and at 36 hours to capture evidence of evolving biliary pathology that would require additional cross-sectional imaging or endoscopic procedures. Imaging (abdominal CT, MRI and US), endoscopic procedures (EUS and ERCP) and antibiotic use were of particular interest because these resources have specific recommendations for utilization by specialty societies [17, 31] Procedure, antibiotic and imaging utilization was obtained at 24 and 96 hours because the median length of stay (LOS) of the cohort was 4 days or 96 hours.

To incorporate a measure of comorbidity, the admission problem list was abstracted and used to compute a single Charlson score for each encounter using the ICD package in R. [32, 33] The original Charlson score was published in 1984 and since then has been updated in 2011 to reflect changes in chronic disease management. The Charlson score is computed from of 12 disease categories associated with increased 1 year mortality and healthcare costs.[34, 35] Each disease category has an associated weight between 1 and 6. One shortcoming of the Charlson score is that it does not incorporate psychiatric comorbidities or substance abuse into the score and this has been shown to be independently associated with increased cost and short term mortality. [36] [37, 38] Using the same admission problem list, we used the mappings described in the Elixhauser index to determine whether an individual has ICD-9-CM diagnosis codes for alcohol abuse, drug abuse, psychoses and depression. [39] This was then incorporated into the dataset as a single variable indicating the presence or absence of these comorbidities. Although there is a modification of the Elixhauser index into a single score that could have been used in this study, there are more studies of the Charlson score being predictive of higher costs. [34, 40]

Analytic Approach

We summarize our analytic approach using the diagram below **(Figure 2)**

Phase	Aim	Procedures	Outputs
Literature Review	Review guide lines to determine the optimal medical management for AP.	Review literature on management of acute pancreatitis focusing on the recommended care protocol.	List resources that may are potentially over utilized during the care of patients with AP.
OSUHP Claims Data Analysis	The state of Ohio EBP model uses a risk adjusted mean cost of care derived from claims data to determine incentives and penalties. To implement such a model we would need to explore claims data to determine what could be incorporated into a feasible model.	Obtain claims data from the OSU Health Plan and summarize by amounts paid per service area and amounts paid per service.	Summary tables of amounts paid by service and service area.
OSUMC EHR Data Analysis	Study resource utilization at OSUMC to determine practice patterns that are not supported by guideline recommendations and may be drivers of increased cost. Determine relationship between utilization, LOS and total charges.	Perform exploratory data analysis on the EHR dataset. Plot utilization against percentiles of LOS to demonstrate timing of utilization. Plot utilization against percentiles of total charges to show the relationship of resource utilization and a measure of cost.	Tables and charts showing the relationship of resource utilization, total charges and LOS.
Predictive Model	Provide a cost containment strategy by allowing providers to safely triage low risk patients to observation status.	Construct a predictive model using EHR data that enables providers to risk stratify patients into high and low risk for adverse outcomes	Predictive model that uses EHR derived information to enable early risk stratification
Propose EBP for AP	Define an EBP model that can accomplish the goal of cost containment and use claims data.	Construct the EBP model by defining episode triggers, measures of quality and exclusion criteria using information from EHR and claims data analysis. Ensure that the information can be obtained using claims data alone.	An EBP model as defined by the State of Ohio

Figure 2. Flow chart depicting the analytic approach utilized in this study.

The EBP model prosed by the Ohio Governor's Office of Health Transformation utilizes claims data to assign reimbursements. To begin the analysis, we obtained claims data from the OSU Health Plan. Using the claims data, we obtain the sum of the allowed amounts stratified by place of service and type of service provided. The allowed amounts are the dollar amounts paid by the payer for services rendered. The most expensive place of service or type of service may be a variable that could be further analyzed using more detailed EHR data.

The EHR data was used to explore the practice patterns in AP management at the OSUMC. Patient encounters were used as the unit of analysis in order to refine an EBP model which utilizes individual encounters and does not exclude repeat admissions. We reported medians and means for continuous variables and percentages for categorical variables. Means were used for variables with normal distributions while medians were used for non-normal distributions. To compare the concordance of admission and discharge diagnoses, all discharge diagnoses related to AP and its complications were counted and reported as a percentage of the total number of encounters.

It is well known that increased utilization of imaging, procedures and length of stay increase the cost of care. [41] [42] In this study, we specifically examined the distribution of imaging, antibiotic and procedure utilization in relation to strata representing increasing percentiles of LOS and total charges since these resources are potential targets for optimization. Society guidelines for the management of AP have specific recommendations on the conditions and timing of resource utilization. [17] [31] By using this approach, we could visualize the timing of utilization in relation to LOS. We examined the distribution of resource utilization using a discretized LOS and total charges using the 25^{th}, 50^{th}, 75^{th}, 90^{th} and 99^{th} percentiles as cutoffs. Attributes that do not have a positive correlation with increasing percentiles of total charges or LOS are not expected to be drivers LOS or charges while those with a positive correlation are the opposite. Using a cut off of 0.05, we reported the significance of the Kendall's tau test for trend for every resource being analyzed this way. A p value ≤ 0.05 indicates a significant correlation. The decision to use these resources as targets for optimization are based on the results of the initial claims data analysis and insights from APA guidelines for the management of AP. [17]

In this study we use total charges as a surrogate for cost of care. The total charges in this study represent the amount billed for the services rendered and not the actual cost of care. In general, the actual cost of care for any medical condition is difficult to ascertain from billed charges. There are various contractual arrangements between healthcare providers and payers so each payer pays a different amount for the same services rendered.

Because the number of comorbidities may be a driver of LOS and cost, we examine the distribution of the average Charlson scores within these defined strata. Higher average scores in the highest percentiles of cost and LOS may suggest that patients with more comorbidities may have more expensive and more complicated hospitalizations whereas similar average scores between the strata would suggest no effect of these comorbidities.

We defined and examined two potentially complicating conditions- suspected biliary pancreatitis and the development of adverse events. Suspected biliary pancreatitis is defined in this study as any encounter where the admission serum bilirubin is greater than 1.8 mg/dL and the AST is greater the three times the upper limit of normal. Encounters with adverse events are defined by the occurrence of any of the following- use of non-invasive positive pressure ventilation (NIPPV), mechanical ventilation, use of TPN, ERCP after 4 days or renal impairment 24 hours after admission. The definition of renal impairment in this study is a glomerular filtration rate (GFR) that is < 60 ml/min. [43] Biliary pancreatitis occurs when there is full or partial bile duct obstruction causing impairment of the flow of pancreatic secretions leading to premature activation of digestive enzymes within the gland. [44] Clinically this is determined by combining clues from the patient's history, labs or imaging. A bilirubin of 1.8 mg/dL to 4 mg/dL is one of the strong predictors of gallstones in the bile duct which may lead to AP. [45] [46] [47] To compare encounters with and without these complications, we report *p* values computed using the Wilcoxon Rank Sum Test. The *p* values indicate the probability that the distributions of the values being compared are equal. In this study a P value < 0.05 suggests that the groups being compared are not equivalent with respect to the attribute being tested.

Predictive modeling in healthcare improves medical practice by identifying patients who are at risk for adverse events so that providers have an opportunity to take corrective action.[48] Identification of high risk patients in AP may encourage providers be more aggressive with fluid resuscitation, triage patients to higher acuity care or seek earlier expert consultation. Low risk patients could be triaged to hospital outpatient units, treated conservatively and be expected to be discharged quickly. Following this logic, a predictive model was developed to predict the risk of adverse events defined previously. For this study we utilized three simple machine learning methods– Decision Trees, Rule-based classifiers and Naïve Bayes. These methods were chosen because the models are intuitive enough to explain to both administrators and clinicians. Implementing these models would not require adaptation of complex learning algorithms in an EHR. Encounters where patients were discharged prior to these assessments were excluded prior to model building and testing. This was done because these patients were no longer at risk for developing the outcome of interest. Validation of the model was performed using 10-fold cross validation [49] We report the accuracy, sensitivity, positive predictive value and area under the receiver operating curve (AUROC) for each model. A higher AUROC indicates a higher true positive rate and a smaller false positive rate.

Results

OSUHP Claims Data Analysis

Analysis of the claims data demonstrated that care delivered in the inpatient setting accounted for 50% of the costs associated with episodes of AP. Outpatient hospital care such as those delivered in emergency rooms/observation units (32%) and hospital associated emergency room care (11%) were the next most costly. Together, acute care encounters represent 93% of the cost for AP. **(Table 1)** When broken down by the types of services rendered; physician fees and miscellaneous fees were the most costly, followed by imaging and facility fees. **(Table 2)**

Table 1. Sum of the amounts paid by each service area in identified episodes of acute pancreatitis from 2011-2015 using billing data.

Service Area	**Sum of Allowed Amounts (%)**
Ambulance (land)	16978.7 (3)
Ambulatory Surgical Center	730 (0)
Emergency Room – Hospital	62733.36 (11)
Independent Laboratory	4708.56 (1)
Inpatient Hospital	290997.69 (50)
Office	20057.39 (3)
Outpatient Hospital	185210.1 (32)
Patient Home	1984.29 (0)
Unclassified	330.53 (0)
Total	**583730.62**
Allowed Amounts expressed in US dollars	

Table 2. Sum of amounts paid by each type of service from 2011 to 2015 using billing data.	
Service	**Sum of Allowed Amounts (%)**
Imaging (CT/MRI/Ultrasound/Echocardiography)	121635.9 (21)
Labs/Pathology	76053.44 (13)
Medications/Pharmacy	67279.13 (12)
Facility Fees	80902.0 (14)
Emergency services	65957.9 (11)
Physician services/others	171902.3 (29)
Total	**583730.62**
Allowed Amounts expressed in US dollars	

OSUMC EHR Data Analysis

The claims data analysis revealed that most dollars were spent in acute care settings (inpatient hospital, emergency department, and outpatient hospital). Physician fees and imaging studies were notably the most expensive services. These findings suggest that resource optimization is most likely beneficial when applied to acute care encounters. Using this information we obtained two years of the most recent data available from all acute care encounters for AP during the study period from the OSUMC EHR for a more detailed utilization analysis. The APA practice guidelines for the management of AP make specific recommendations on the conditions and timing of imaging, antibiotics and procedures hence we chose to study the utilization of these services. [17]

During the study period the cohort had a mean age of 49 years and the majority of patients were Caucasian (70%). Most patients received inpatient care (94%) and the median cost of care was $26,366. On admission, twenty-seven percent of patients had an abdominal CT study while 7 percent had an abdominal MRI study. The median length of stay was four days and eighty-four percent of the discharge diagnoses were related AP and its complications. The median number of hours patients were fasting (NPO) was 21 hours. The median cost of care was highest for inpatient stays followed by observation and emergency room care. **(Table 3)**

Table 3. Demographic, labs and utilization characteristics of the patient cohort derived from the OSU EHR.

Total	**N=799 (%)**
Unique patients	**629 (79)**
Age (mean)	**49 years**
Race	
Caucasian	**559 (70)**
African American	**205 (25.7)**
Others	**35 (4.4)**
Discharge diagnoses related to AP and complications	**673 (84)**
Encounter type (%)	
Inpatient	**749 (93.7)**
Emergency Department	**29 (3.6)**
Observation	**21 (2.6)**
Length of Stay (median, days)	**4**
Total Hours NPO [&] (median)	**21**
Charlson score (median)	**0**
Psychiatric comorbidity or substance abuse [$]	**201 (32)**
Admission Labs *	

Lipase (median)	**237**
AST (median)	**30**
ALT(median)	**90**
Total Bilirubin (median)	**0.7**
BUN (median)	**12**
Hematocrit (median)	**39**
Admission Imaging and Antibiotic use (24 hours)	
CT	**214 (26.7)**
MRI	**57 (7.1)**
Abdominal Ultrasound	**305 (38.2)**
Antibiotic use	**230 (28.8)**
Procedures on admission	
Endoscopic ultrasound	**6(0.7)**
ERCP	**9 (1.1)**
Labs at 36 hours **	
AST (median)	**43.0**
ALT(median)	**57.0**
Total Bilirubin (median)	**0.90**
BUN (median)	**33.0**
Hematocrit (median)	**34.5**
Imaging and Antibiotic use at 4 days***	
CT	**283 (35.4)**
MRI	**112 (14.0)**
Abdominal Ultrasound	**341 (42.7)**
Antibiotic use	**314 (39.3)**
Procedures at 4 days (96 hours) ***	
Endoscopic ultrasound	**46(5.8)**
ERCP	**51 (6.4)**
Cost of care (median, USD)	

Emergency	**7396.9**
Observation	**10394.4**
Inpatient	**27527.2**
Overall	**26366.4**
Cost percentiles (USD)	
25^{th}	**16366.6**
50^{th}	**26366.4**
75^{th}	**48948.4**
90^{th}	**98818.8**
99^{th}	**405348.2**

&- total number of hours NPO
*Admission labs defined as those obtained within 24 hours of admission were available for 761 patients
** AST,ALT,Bilirubin available for 200 patients, Hematocrit available for 390 patients, BUN available for 418 patients
***includes those at 24 hours
$ percentage computed with 629 unique patients

Using the patient's address of record, we mapped out the patient zip codes overlying a map of the United States. Most patients in the EHR cohort are from State of Ohio and most are from the immediate surrounding communities of the Ohio State University. There is also a noticeable concentration of patients originating from northwest and southeast Ohio. A diagram of the map was not included to protect patient confidentiality.

A boxplot of the discretized charges variable against the LOS show encounters in the lowest percentiles of total charges in general have shorter LOS. The mean length of stay progressively increases when going from the lowest to the highest percentiles of total charges but there is still considerable overlap in range of LOS between encounters in different percentiles. Encounters in the lowest percentiles of charges have a much narrower range of LOS compared to those in the highest percentiles. **(Figure 3)** This suggests that LOS may not be the sole driver of increased costs especially in the higher cost encounters. We arbitrarily define short LOS as a LOS less than the median which is 4 days.

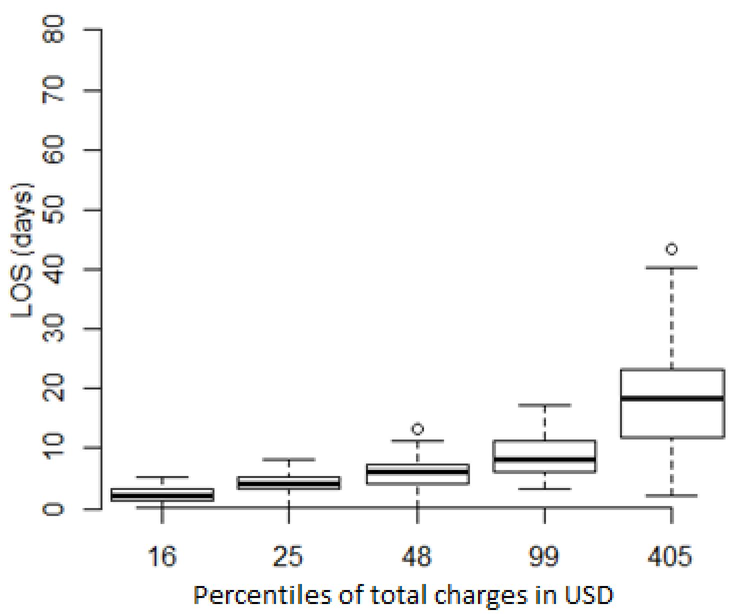

Figure 3. LOS vs percentiles of total charges (USD) in AP encounters identified in the OSU EHR. LOS is displayed in the Y axis and is expressed in days. The discretized total charges are the 25^{th}, 50^{th} , 75^{th},90^{th} and 99^{th} percentiles expressed in USD.

Imaging Utilization

Using the percentiles of total charges as strata, we examine the pattern of imaging utilization at 24 and 96 hours after admission. Overall, ultrasound was the most utilized imaging study followed by CT and MRI. Utilization of imaging was higher in the four highest strata compared to the lowest strata. The percent increase in imaging utilization between 24 and 96 hours was higher in the four highest strata compared to the lowest strata. Except for the MRI utilization at 24 hours, there was no significant positive correlation between the percentiles of total charges and the utilization of imaging. **(Table 4)**

When the percentiles of LOS are used as strata, we can see a similar pattern where in general imaging utilization in the lowest strata is lower compared the four next highest strata. There was a significant positive correlation between percentiles of LOS and utilization of CT at both 24 and 96 hours but not in the utilization of the other imaging modalities. The percentage increase in imaging utilization appears to be higher between 24 and 96 hours in encounters with longer LOS. **(Table 5)**

Both tables suggest that utilization of US is unlikely related to the eventual LOS and total charges. Between 23 and 27% of encounters with short LOS had utilization of CT while between 4 and 14% of encounters with short LOS utilized abdominal MRI. Because there was a significant positive correlation between CT utilization and LOS and MRI utilization at 24 hours and cost, early cross-sectional imaging utilization may be a marker of increased complexity of care and cost.

Table 4. Utilization of imaging modalities by percentiles of total charges in AP encounters identified in the OSU EHR.

Total charges percentiles (N=795, 4 missing)	**CT at 24 h (%) P=0.40**	**CT at 96 h (%) P=0.12**	**% increase**	**MRI at 24 h (%) P=0.01**	**MRI at 96 h (%) P=0.40**	**% increase**	**US at 24 h (%) P=0.22**	**US at 96 h (%) P=0.22**	**% increase**
<25th (N=200)	21 (11)	25 (13)	19.0	9 (5)	11 (6)	22.2	70 (35)	74 (37)	5.7
25th-50th (N=199)	74 (37)	83 (42)	12.2	14 (7)	30 (15)	114.3	79 (40)	90 (45)	13.9
50th-75th (N=200)	60 (30)	89 (45)	48.3	16 (8)	40 (20)	150.0	72 (36)	81 (41)	12.5
75th– 90th (N=120)	35 (29)	51 (43)	45.7	9 (8)	21 (18)	133.3	55 (46)	63 (53)	14.5
>90th (N=80)	24 (30)	35 (44)	45.8	9 (11)	10 (13)	11.1	29 (36)	33 (41)	13.8

Percentages are computed from baseline. Numbers in parenthesis indicate percentages. P values indicate the probability of no correlation between utilization and percentiles of cost.

Table 5. Utilization of imaging modalities by percentiles of LOS in AP encounters identified in the OSU EHR.									
LOS percentiles (N=795, 4 missing)	**CT at 24 hours P=0.04**	**CT at 96 hours P<0.01**	**% increase**	**MRI at 24 hours P=0.11**	**MRI at 96 hours P=0.10**	**% increase**	**US at 24 hours P=0.12**	**US at 96 hours P=0.22**	**% increase**
<3 days (N=164)	37 (23)	41 (25)	10.8	7 (4)	8 (5)	14.3	54 (33)	57 (35)	5.5
3-4 days (N=125)	30 (24)	34 (27)	13.3	10 (8)	17 (14)	70	45 (36)	49 (39)	8.8
5-6 days (N=280)	86 (31)	109 (39)	26.7	24 (9)	49 (18)	104.2	115 (41)	130 (46)	13.0
7-12 days (N=146)	37 (25)	61 (42)	64.9	8 (5)	26 (18)	225	61 (42)	69 (47)	13.1
>13 days (N=80)	24 (30)	38 (48)	58.3	8 (10)	12 (15)	50	30 (37)	36 (45)	20
Percentages are computed from baseline. P values indicate the probability of no correlation between utilization and percentiles of LOS.									

A situation where cross sectional imaging might be necessary is when it is needed to make the diagnosis of AP. One such situation is when the serum lipase is not at least three times the upper limit of normal . This situation could occur when patients have delayed presentations where the serum lipase has had time to trend down . Cross sectional imaging may be used to confirm severity based upon clinical predictors of AP or to evaluate reasons for failure to respond to conservatve treament if clinical deterioration occurs. The recommended timing of initial CT assesment is at least 72 to 96 hours after onset of symptoms. [17]

Tables 6 and 7 show CT and MRI utilization stratified by a diagnostic and non-diagnostic lipase. It is assumed that the majority of these patients came to the hospital with abdominal complaints otherwise imaging would have not been obtained. Fourty eight percent of abdominal CT and 58 percent of abdominal MRI were obtained when the lipase was diagnostic for AP. Additional cross sectional imaging at 96 hours regardless of serum lipase levels may have neen obtained to assess why patients failed to respond to therapy or if clinical deterioration had occurred.

Table 6. CT utilization at 24 and at 96 hours for patients with diagnostic and non-diagnostic serum lipase levels in AP encounters identified in the OSU EHR.

	Lipase not diagnostic (%)	**Lipase diagnostic (%)**
CT within 24 hours	111 (52)	103 (48)
CT within 96 hours	151(53)	132 (47)

Diagnostic serum lipase defined as >= 240 mg/dL. Numbers in parenthesis indicate percentages.

Table 7. MRI utilization at 24 and at 96 hours for patients with diagnostic and non-diagnostic serum lipase levels in AP encounters identified in the OSU EHR.		
	Lipase not diagnostic (%)	**Lipase diagnostic (%)**
MRI within 24 hours	24 (42)	33 (58)
MRI within 96 hours	52(46)	60 (54)
Diagnostic serum lipase defined as >= 240 mg/dL. Numbers in parenthesis indicate percentages.		

Antibiotic use

We examine antibiotic utilization using the same strata of total charges and LOS defined previously. Unlike imaging utilization, there was a significant positive correlation between the strata of total charges and antibiotic utilization at both 24 and 96 hours. **(Table 8)** A significant positive correlation is also seen between antibiotic utilization and strata of LOS at both 24 and 96 hours **(Table 9).** This suggests that the use or decision to use antibiotics may be surrogate for increased cost and complexity of hospitalization.

Between 20 to 32% of short stay encounters utilized of antibiotics. Ideally, antibiotics should be given on admission if there is concern for an infectious source of the systemic inflammatory response. In AP, antibiotics may be administred in patients who have associated cholangitis, bacterial pneumonia or bacteremia [17] However, the routine use of prophylactic antibiotics to prevent infection is discouraged because often the inflammatory response in AP is not from an infectious source.

Table 8 Antibiotic use at 24 and 96 hours by percentiles of total charges in AP encounters identified in the OSU EHR.			
Total charges percentiles (N=795, 4 missing)	**Antibiotic use 24 hours P<0.01**	**Antibiotic use 96 hours P<0.01**	**% increase**
<25th (N=200)	27 (14)	31 (16)	14.8
25th-50th (N=199)	43 (22)	62 (31)	44.1
50th-75th (N=200)	68 (34)	97 (49)	42.6
75th–90th (N=120)	50 (42)	69 (58)	38.0
>90th (N=80)	42 (53)	55 (69)	30.9
Numbers in parenthesis indicate percentages. P values indicate the probability of no correlation between utilization and percentiles of cost.			

Table 9. Antibiotic use by percentiles of LOS in AP encounters identified in the OSU EHR.			
LOS percentiles (N=795, 4 missing)	**Antibiotic use 24 hours P<0.01**	**Antibiotic use 96 hours P<0.01**	**difference**
<3 days (N=164)	32 (20)	35 (21)	3
3-4 days (N=125)	31 (25)	40 (32)	9
5-6 days (N=280)	79 (28)	116 (41)	37
7-12 days (N=146)	51 (35)	75 (51)	24
>13 days (N=80)	37 (46)	48 (60)	11
Numbers in parenthesis indicate percentages. P values indicate the probability of no correlation between utilization and percentiles of LOS.			

Procedure Utilization

At the OSUMC, endoscopic procedures are generally performed the day after a patient is admitted to the hospital unless they are emergent. This practice is common because patients are required to fast prior to endoscopy to prevent the aspiration of food laden gastric contents during the procedure. [50] We can see that endoscopic procedures in general are much less utilized compared to imaging. Very few endoscopic procedures were performed by 24 hours of admission. Looking at endoscopic procedure utilization by 96 hours shows a similar pattern where the patients belonging to the highest percentiles of total charges had higher rates of utilization. However aside from EUS utilization at 96 hours, there was no significant positive correlation between procedure utilization and total charges. **(Table 10)** Similarly using the percentiles of LOS show we can see that utilization is higher in the highest percentiles of LOS but there was no significant correlation at both 24 and 96 hours after admission.

Table 10. Utilization of endoscopic procedures by percentiles of total charges in AP encounters identified in the OSU EHR.

Total charges percentiles (N=795, 4 missing)	**ERCP at 24 hours P=0.15**	**ERCP at 96 hours P=0.12**	**Difference**	**EUS at 24 hours P=0.15**	**EUS at 96 hours P=0.04**	**Difference**
<25th (N=200)	0 (0)	1 (0.5)	1	1 (0.5)	7 (4)	6
25th-50th (N=199)	2 (1)	4 (2)	2	2 (1)	9 (5)	7
50th-75th (N=200)	4 (2)	17 (9)	13	1 (0.5)	14 (7)	13
75th–90th (N=120)	2 (2)	23 (19)	21	1 (0.8)	7 (6)	6
>90th	1 (1)	6 (8)	5	1 (1)	9 (11)	8

(N=80)						
Numbers in parenthesis indicate percentages. P values indicate the probability of no correlation between utilization and percentiles of LOS.						

Table 11. Utilization of endoscopic procedures by LOS percentile in AP encounters identified in the OSU EHR.

LOS percentiles (N=794, 5 missing)	**ERCP at 24 hours P=0.20**	**ERCP at 96 hours P=0.41**	**Difference**	**EUS at 24 hours P=0.28**	**EUS at 96 hours P=0.24**	**Difference**
<3 days (N=164)	2 (1)	3 (2)	1	2 (1)	6 (4)	4
3-4 days (N=125)	2 (2)	7 (6)	5	1 (0)	4 (3)	3
5-6 days (N=280)	3 (1)	27 (10)	24	0 (0)	19 (7)	19
7-12 days (N=146)	1 (1)	10 (7)	9	2 (1)	13 (9)	11
>13 days (N=80)	1 (1)	4 (5)	3	1 (1)	4 (5)	3

Numbers parentheses indicate percentages. P values indicate the probability of no correlation between LOS and percentiles of LOS.

Effect of comorbid conditions

Using strata of LOS and cost we found no significant positive correlation between the average Charlson score and percentiles of LOS nor the average Charlson score and the percentiles of total charges. **(Table 12)**

Table 12.Average Charlson scores by percentiles of total charges and LOS in AP encounters identified in the OSU EHR.			
LOS percentiles (N=794, 5 missing)	**Average Charlson score P=0.39**	**Total charges percentiles (N=794, 5 missing)**	**Average Charlson score P=0.15**
<3 days (N=164)	1.0	<25 (N=195)	0.9
3-4 days (N=125)	1.1	25-50 (N=199)	1.1
5-6 days (N=280)	1.0	50-75 (N=200)	1.3
7-12 days (N=146)	1.4	75-90 (N=120)	0.9
>13 days (N=80)	1.0	>90 (N=80)	1.3
P values indicate the probability of no correlation between Charlson scores and percentiles of LOS or percentiles of cost.			

Effect of Psychiatric comorbidities

Previous studies have demonstrated that the presence of psychiatric comorbidities is associated with increased costs of hospitalization and LOS. [37, 51] Many reasons have been hypothesized to account for this observation including increased risk for delirium, delays in diagnosis or delays in treatment. [52] Using the same strata as used previously we can see that there is no significant trend between the percentage of patients with psychiatric comorbidities with increasing percentiles of total charges and LOS. (**Table 13)**

Table 13. Psychiatric comorbidities by LOS and percentiles of total charges in AP encounters identified in the OSU EHR.			
LOS percentiles (N=794, 5 missing)	**Alcohol, drug abuse or psychiatric comorbidities (%) P=0.75**	**Total charges percentiles (N=794, 5 missing)**	**Alcohol, drug abuse or psychiatric comorbidities (%) P=0.95**
<3 days (N=164)	57(35)	<25th (N=200)	71 (43)
3-4 days (N=125)	40 (32)	25th-50th (N=199)	78 (62)
5-6 days (N=280)	120 (43)	50th-75th (N=200)	92 (46)
7-12 days (N=146)	53 (36)	75th–90th (N=120)	34 (28)
>13 days (N=80)	25 (31)	>90th (N=80)	22 (27)
P values indicate the probability of no correlation between the percentage of psychiatric comorbidities and percentiles of LOS and cost.			

Complicating conditions

Biliary pancreatitis

A subset analysis of patients with suspected biliary pancreatitis demonstrate that these patients are have significantly longer hospital stays, higher total charges, higher rate of antibiotic use, higher use of early CT, ultrasound and ERCP at 4 days compared to patients who did not have biliary pancreatitis. **(Table 14)**

Table 14.Characteristics of patients with suspected biliary pancreatitis AP encounters identified in the OSU EHR.			
Variables	**Suspected biliary pancreatitis (N=36)***	**No suspected biliary pancreatitis (N=763)***	**P-value**
Age (mean, years)	53	49	0.13
Total charges (median, USD)	52973.9	25153	<0.01
LOS (median, days)	6	4	<0.01
Charlson score (median)	1	0	0.04
Admission Labs**			
Lipase (median)	235	239	0.24
AST (median)	109.5	29.0	<0.01
ALT(median)	181	87	<0.01
Total Bilirubin (median)	3.4	0.6	<0.01
BUN (median)	13.5	12.0	0.10
Hematocrit (median)	37.4	39	0.86
Admission Imaging and Antibiotic use			
CT	11(30.5)	203(26.6)	<0.01
MRI	3(8.3)	54 (7)	0.77
Abdominal Ultrasound	20 (55.5)	285 (37.3)	0.03
Antibiotic use	19 (52.7)	211(27.7)	<0.01
Procedures on admission			
Endoscopic ultrasound	0(0.0)	6 (0.7)	0.6
ERCP	1(2.7)	8 (1)	0.3
Imaging and Antibiotic use at 4 days			
CT	13 (36.1)	270 (35.4)	0.92
MRI	5 (13.8)	107 (14.0)	0.98
Abdominal Ultrasound	22 (42.7)	319 (41.8)	0.02
Antibiotic use	28 (77.7)	286 (37.5)	<0.01

Procedures at 4 days			
Endoscopic ultrasound	2 (5.5)	6 (0.7)	0.96
ERCP	6 (16.6)	8 (1.0)	<0.01
P values denote the probability that the means of the two groups are equal. *Suspected biliary pancreatitis based on a total bilirubin >=1.8 mg/dL and an ALT > 3 times the upper limit of normal (145 based on local lab values) either on admission or at 36 hours **None of the lab values for 200 encounters met the criteria for suspected biliary pancreatitis at 36 hours			

Patients who develop adverse events

To evaluate the characteristics patients who have a complicated disease course, we define encounters where adverse events as those requiring or having any of the following -non-invasive positive pressure ventilation, mechanical ventilation, TPN, renal impairment after 36 hours of hospitalization (GFR < 60 ml/min) or endoscopic procedures after hospital day four. This definition using discrete EHR data elements approximates the condition of severe AP based on the Atlanta classification. [6] A subset analysis of patients with adverse events have a significantly longer LOS of 8 days, higher total charges, higher antibiotic use, higher use of EUS on admission compared to those who did not develop these complications**.** The admission BUN, total bilirubin and hematocrit were also significantly different **(Table 15)**

Table 15. Patients who develop adverse events in AP encounters identified in the OSU EHR.			
Variables	**Patients with adverse events (N=158) (%)**	**Patients without adverse events (N=641) (%)**	**P value**
Age (mean, years)	55	48	<0.01
Total charges (median, USD)	63023.0	23295	<0.01
LOS (median, days)	8	4	<0.01
Charlson score (median)	0	0	0.17
Suspected biliary pancreatitis	11 (7)	25 (4)	0.10
Admission Labs**			
Lipase (median)	237	238	0.62
AST (median)	41	29	0.06
ALT(median)	109	90	0.04
Total Bilirubin (median)	0.8	0.6	<0.01
BUN (median)	19	12	<0.01
Hematocrit (median)	35.0	39.5	<0.01
Admission Imaging and Antibiotic use			
CT	48 (30)	166 (26)	0.25
MRI	12 (7.6)	45 (7.0)	0.09
Abdominal Ultrasound	69 (43.7)	79 (12.3)	0.11
Antibiotic use	72 (45.6)	91 (14.2)	<0.01
Imaging and Antibiotic use at 4 days			
CT	65 (41.1)	218 (34.0)	0.09
MRI	22 (13.9)	90 (14.0)	0.97
Abdominal Ultrasound	79 (50.0)	262 (40.9)	0.04
Antibiotic use	91 (57.6)	223 (34.8)	<0.01
Procedures utilization on admission			
Endoscopic ultrasound	12 (7.6)	2 (0.3)	<0.01

ERCP	13 (8.3)	8 (1.2)	0.51
Procedures utilization after 4 days			
Endoscopic ultrasound	9 (5.7)	34 (5.3)	0.27
ERCP	11 (7.0)	38 (5.9)	0.26
Adverse events are defined as non-invasive positive pressure ventilation, mechanical ventilation, total parenteral nutrition, experience renal impairment after 36 hours of hospitalization or require endoscopic procedures after hospital day 4. P values denote the probability that the means of the two groups are equal.			

The exploratory data analysis of the EHR data suggest that the most likely drivers of cost in AP are overuse of imaging, overuse of antibiotics, long LOS, the occurrence of adverse events and suspected biliary pancreatitis. A higher Charlson score, the presence of a psychiatric comorbidity and alcohol use are not expected to be strong contributors to the cost of care.

Predictive Model

The goal of the predictive model was to provide risk stratification so that patients could be appropriately triaged to inpatient hospitalization or observation status. Observation status is typically less expensive and may be appropriate for low risk patients who are expected to be discharged quickly. [53] The outcome of interest in this study was the risk of adverse events as defined in this study. For model building, encounters with a LOS < 3 days are excluded because these patients were not at risk for developing the outcome of interest. There were 775 patient encounters of which 158

(20%) were noted to have developed adverse events. The variables utilized in both datasets are listed in Table 16. To prevent multicollinearity, the BUN at 36 hours was not used in classification for the models utilizing the data at 96 hours because this is related to the GFR 36 hours after admission which was one of the defining criteria for adverse events.

Table 17 lists the performance of the different models using the two different datasets. The models using the data available at 24 hours and 96 hours had relatively similar performance however; the models using data available at 24 hours had a higher AUROC. **(Table 17)** Using the data available at 24 hours**,** 617 were normal encounters while 158 were encounters where adverse events occurred. Four encounters were not used because they did not have the information to enable classification into a normal versus one where adverse events occurred. Assuming every encounter is predicted to be normal then the overall accuracy would be around 80%. Using the predictive model had little to marginal improvement in overall accuracy to identify those who develop adverse events (79 to 81%). The models had a sensitivity of 28 to 39 percent to identify patients who develop adverse events. The positive predictive value was 46 to 55%. The models performed better in identifying patients who will have no adverse events with a sensitivity of 91 percent to 93 percent and positive predictive value of 83 percent to 86 percent. **(Table 17)**

Table 16. Attributes used in models to predict the likelihood of an adverse event in AP encounters identified in the OSU EHR.

After 24 hours of admission	After 96 hours of admission
Age	Age
Charlson Score	Charlson Score
Admission Lipase	Admission Lipase
Admission BUN	Admission BUN
Admission Hematocrit	Admission Hematocrit
Admission AST	Admission AST
Admission AST	Admission AST
Admission Total Bilirubin	Admission Total Bilirubin
Utilization of cross sectional imaging (MRI/CT)	Hematocrit after 36 hours
Number of hours NPO	AST after 36 hours
Antibiotic use at 24 hours (Y/N)	AST after 36 hours
Suspected biliary pancreatitis (Y/N)	Total Bilirubin after 36 hours
Presence of psychiatric comorbidities (Y/N)	Utilization of advanced imaging (CT/MRI) after 96 hours *
US abdomen (Y/N)	US abdomen (Y/N)
	Number of hours NPO
	Antibiotic use at 96 hours *
	Suspected biliary pancreatitis
	Presence of psychiatric comorbidities

*imaging and antibiotic utilization at 96 hours includes those used at 24 hours.

Table 17. Comparison of classifier performance at 24 vs 96 hours to predict the likelihood of adverse events in AP encounters identified in the OSU EHR.

	24 hours (N=779)			96 hours (N=510)		
	DT*	**RBC**	**NB**	**DT***	**RBC**	**NB**
Accuracy	79%	81%	79%	74%	75%	75%
Precision **(PPV)**	0-84%	0-86%	0-83%	0-78%	0-79%	0-78%

	1-48%	1-55%	1-46%	1-52%	1-55%	1-55%
Recall **(sensitivity)**	0-92% 1-29%	0-91% 1-39%	0-91% 1-28%	0-89% 1-32%	0-90% 1-35%	0-91% 1-29%
AUROC**	0-0.71 1-0.70	0-0.65 1-0.66	0-0.74 1-0.73	0-0.69 1-0.69	0-0.62 1-0.63	0-0.70 1-0.70
DT – decision trees, RBC- rule based classifier, NB- naïve bayes. 0- patients who do not develop adverse events, 1- patients who develop adverse events *minimum leaf size for the DT model is 15 instances. **AUROC- area under the receiver operator curve						

The rules developed by the decision rule classifier are meant to be interpreted sequentially until the default case is reached. **(Figure 3)** Encounters that fulfill the conditions in the rules are classified as being at high risk for developing the adverse events. If an encounter does not fulfil the conditions of any rule they are classified as being at low risk for adverse events (default class). The decision rule-based classifier classifies encounters with an admission BUN ≥ 24 mg/dL and ALT ≥ 65 as being at risk for adverse events **(Figure 4).** The decision tree classifier meanwhile uses admission BUN value, admission hematocrit and use of antibiotics on admission and as conditions to classify encounters as being high risk for adverse events. Encounters where the admission BUN ≥ 25 and use of antibiotics on admission or an admission BUN ≥ 25 and an admission hematocrit ≥ 37.3 are those classified as high risk for developing adverse events. **(Figure 5)**

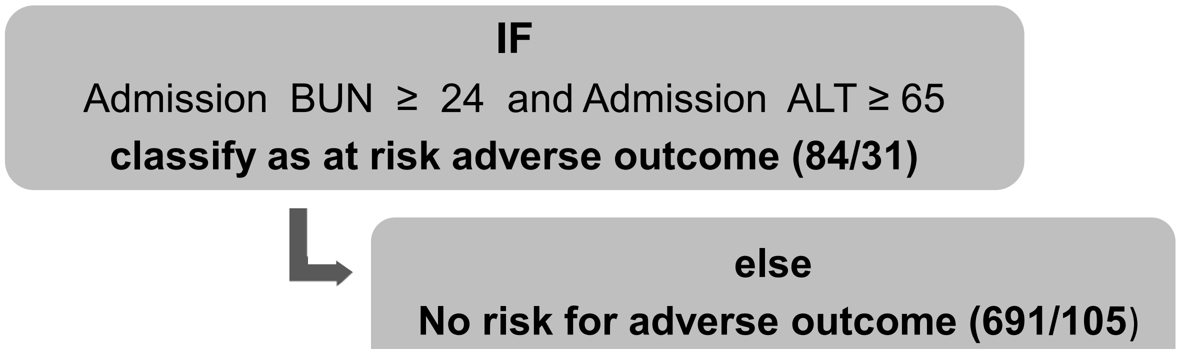

Figure 4. Decision rules to predict if patient is at risk for adverse outcomes during an episode of AP. Numbers in parenthesis show number of instances the rule covers followed by the number misclassified.

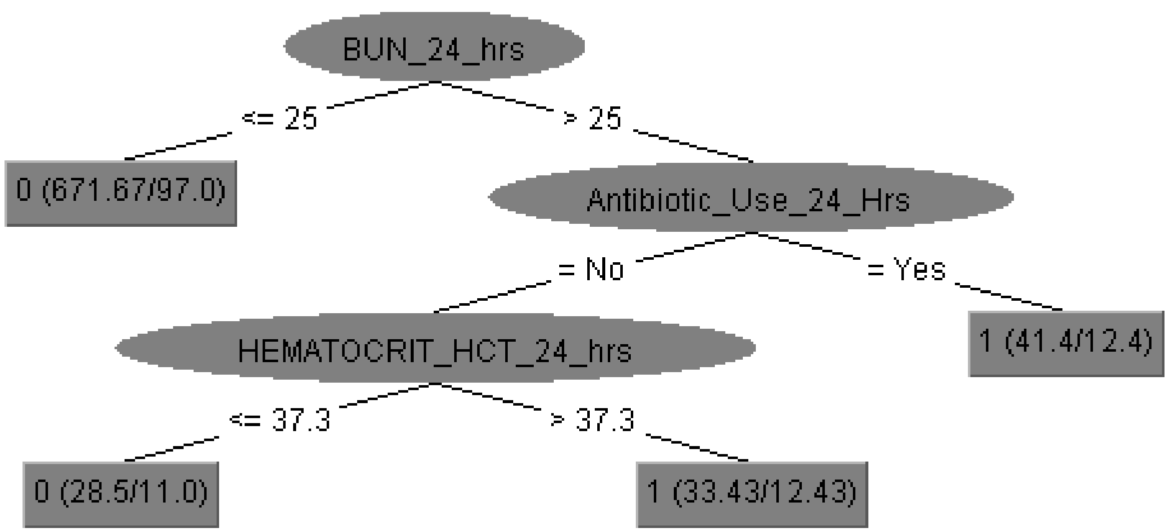

Figure 5. Decision tree classifier to predict if patient is at risk for adverse outcomes during an episode of AP. Numbers in parenthesis show how many were correctly classified followed by the number incorrectly classified.

Unlike the previous two algorithms, Naïve Bayes uses all the available attributes to construct the model. The probability of an outcome is equal to the product of the individual marginal probabilities of each of the predictors given the outcomes divided by the probability of the outcome overall. **(Table 18)** For numeric attributes, the density function using the mean (μ) and standard deviation (σ) is used to estimate the marginal probabilities for each attribute. **(Figure 6)**

$$f(x) = \frac{1}{\sqrt{(2\pi\sigma)}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Figure 6. Density function used to compute the marginal probability (f(x)) for continuous attributes. x- attribute value, μ- mean, σ – standard deviation.

Although all the attributes are used, we can see we can see that the means of the admission BUN between patients who are at risk for adverse events (b) and those not at risk (a) do not overlap. Hence, the admission BUN is likely to be a significant predictor of risk.

Table 18. Marginal probabilities of the Naïve Bayes classifier used to predict the risk of an adverse event in patients presenting with AP.

	Age		Charlson		Lipase		BUN		Hematocrit	
	A	B	A	B	A	B	A	B	A	B
0	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
1	**47.5**	**54.9**	**1.05**	**1.2**	**242.4**	**236.6**	**13.6**	**26.02**	**39.4**	**35.9**
	sd	**sd**	**sd**	**sd**	**sd**	**sd**	**sd**	**sd**	**sd**	**sd**
	15.4	**16.04**	**1.6**	**1.7**	**154.4**	**145.2**	**9.0**	**20.6**	**6.2**	**7.1**

	AST		ALT		Total Bilirubin		Number of hours NPO		Cross sectional imaging	
	A	B	A	B	A	B	A	B	A	B
0	Mean 71.8	Mean 97.3	Mean 97.7	Mean 108.1	Mean 1.2	Mean 1.4	Mean 6.4	Mean 9.9	0.67	0.64
1	sd 107.3	sd 182.5	sd 107.3	sd 182.5	sd 1.8	sd 1.9	sd 11.0	sd 33.8	0.33	0.36

	US abdomen		Antibiotic use		Biliary Pancreatitis		Psychiatric Comorbidity	
	A	B	A	B	A	B	A	B
0	0.38	0.44	0.75	0.54	0.96	0.92	0.62	0.64
1	0.62	0.56	0.25	0.46	0.04	0.08	0.38	0.36

The marginal probabilities were derived using data obtained during the first 24 hours of admission. Nominal attributes -cross sectional imaging, US abdomen, antibiotic use, biliary pancreatitis and the presence of psychiatric comorbidities. Letters A and B indicate the outcome – no adverse event (A) adverse event (B) . The row values 0 and 1 are used for nominal attributes- 1 - present or 0- absent

Discussion

The aim of this study was to develop an APM for episodes of AP. Beginning with an analysis of the claims data, it was determined that the majority of the dollars spent on AP were spent in acute care encounters. This suggests that to implement an APM for AP, one must implement it in the acute care setting. The claims data also suggest that imaging is a major driver of cost and hence further exploration of imaging utilization is warranted. The next phase of the study began by obtaining information from the OSUMC EHR to determine the data elements necessary to evaluate the question of resource utilization. Using zip code information overlaid on a map, we determined that the majority of the patients seen at the OSUMC live within the state of Ohio. There was a heavy concentration of patients who lived in the northwest and southeast portions of the state which is likely indicative of transfers or referrals from areas without a nearby large academic healthcare institution. Patients from the northeast and southwest areas of the state are likely served by the nearby academic centers of the Cleveland Clinic and University of Cincinnati respectively. The northwest area of the state is also likely served by the University of Toledo and University of Michigan. Because of the wide catchment area and large number of referrals to the OSUMC for AP management, optimizing the cost per episode may attract payers and increase referrals for management of pancreatic disease.

Imaging, antibiotic and endoscopic procedure utilization were the resources selected for exploration based on the findings of the claims data analysis and recommendations published in practice guidelines. In AP, the routine early use of cross sectional imaging and antibiotics are generally discouraged because they do not alter initial management. [17] In this study, the frequency and percentages of utilization were tabulated by the percentiles of LOS and total charges. By presenting the data in this format, the timing of resource utilization was clearly visible. This format also enables us to see the relationship of resource utilization and total charges which in this study serves as a surrogate for cost. Administrators looking for ways to reduce utilization and cost could monitor the frequency of utilization by the percentiles of LOS and total charges before and after a practice change to see if the intended outcome of the intervention was achieved.

Our results show that there was a significant positive correlation between the percentiles of LOS and CT utilization which suggest that early CT utilization may be marker for increased complexity of hospitalization. Between 23 and 27% of encounters with short lengths of stay (< 4 days) utilized CT on admission where it is not expected that these studies would have been necessary. Forty eight percent of all CTs and fifty eight percent of MRIs ordered in the first 24 hours were obtained in patients with diagnostic serum lipase levels. These studies were unlikely necessary to make the diagnosis of AP and would have not changed early management. Similar findings were seen in a retrospective study using clinical chart review and data from a radiology information system, which showed that factors associated with AP severity such as longer LOS, higher APACHE score, prior episodes of AP and drug induced AP, were associated with increased utilization of cross sectional imaging. The study went on to conclude that despite the higher utilization of cross sectional imaging, there was no improvement in patient outcomes. [54] In this study, there was a positive correlation between the percentiles of LOS and total charges with antibiotic utilization which is suggestive that early antibiotic use may also be a marker of increased cost. Similar to imaging, there was also evidence of unnecessary early antibiotic use in patients with very short LOS. Several studies have shown that the use of prophylactic antibiotics have shown no improvement in the development of pancreatic infection, mortality or need for surgery even in severe acute necrotizing pancreatitis. [55, 56]

We examined two conditions which can complicate the management of AP-biliary pancreatitis and the development of adverse events as defined in this study. In both conditions patients developing these complicating conditions had significantly longer LOS, higher total charges and antibiotic use. Patients with suspected biliary pancreatitis had significantly higher utilization of CT on admission and ERCP by day 4. Patients who develop adverse events had significantly higher EUS utilization and lower admission hematocrit. Although not specifically identified by labs that would be suggestive of choledocholithiasis, patients who develop adverse events also have significantly higher total bilirubin and ALT similar to those with suspected biliary pancreatitis. The data suggest that encounters with lab values suggestive of biliary obstruction such as an elevated bilirubin and ALT, utilization of procedures that either treat or identify biliary obstruction or early antibiotic use may be markers of increased cost and complexity.

We were able to construct a predictive model that could be used to risk stratify patients to more or less aggressive care. The outcome of interest was the development of adverse events. The composite outcome occurred in 20% of these encounters. All three models predicted that an admission BUN >24-25 is the strongest predictor for the development of adverse events. The rule based classifier used a BUN ≥ 24 and an ALT ≥ 65 as the criteria to classify encounters as high risk. The decision tree model used an admission BUN ≥ 25 and use of antibiotics on admission or an admission BUN ≥ 25 and an admission hematocrit ≥ 37.3 to classify encounters at high risk for developing adverse events. The results of this modeling exercise are consistent with what is known about the prognosis of episodes of AP. A high BUN and hematocrit are markers of the degree of third spacing which is directly related to the severity of an episode of AP. [57] A BUN > 25 mg/dL was one of the five variables associated with in hospital mortality in a large population based study of AP. [48] A high admission hematocrit has been also shown to be a predictor of severe acute pancreatitis. [49] A high ALT is the strongest predictor for biliary pancreatitis.[45] One shortcoming of our predictive models is the poor sensitivity and positive predictive value to identify high risk encounters. The models had better performance when identifying normal encounters. The information obtained from these models could be used to risk stratify patient encounters into those that could be managed in an outpatient observation unit and those who may require an inpatient stay. Those who are predicted to be at risk for adverse outcomes for example could have a lower threshold for repeat imaging while those who predicted to be at lower risk could have a higher threshold for procedures, imaging and antibiotics. Studies in other medical conditions such as acute atrial fibrillation, syncope and chest pain show that triage of low risk patients to observation units may avoid costly inpatient admission and reduce overall healthcare costs. [58] [59] [60]

The study has several advantages. It uses two complementary data sources and that it avoids the use of manual chart review to produce actionable information. The study demonstrated there was generally good agreement between the admission and discharge diagnosis in AP hence using the admission diagnosis to identify episodes of

AP is a reliable way to capture these encounters. This was important to ensure in this study because discrepancies in admission and discharge diagnoses could account for as much as a 0.76 day increase in LOS. [61]

The overutilization of imaging in medicine has driven up costs. Defensive medicine, fee-for-service reimbursement and patient preferences are some of the factors that contribute to imaging over utilization. Compared to many industrialized countries, utilization of cross sectional imaging is highest in the U.S., with 91.2 MRI exams and 227.9 CT exams per 1,000 population. [62] AP is a condition where medical society guidelines have delineated unambiguous conditions to utilize cross sectional imaging. This study clearly demonstrates that there is overutilization of imaging in patients who have short LOS and in those who have met the criteria for AP. The utilization of cross sectional imaging prior to 72 to 90 hours after admission in the setting of a diagnostic serum lipase and high clinical suspicion of AP may be a good quality metric in an APM for AP.

Similar conclusions may be reached with the use of antibiotics in the management of AP. The use of antibiotics in AP is clearly defined in medical society recommendations. [17] Because of the lack of sufficient detail, the cost of antibiotic use cannot be assessed using the claims data alone. Using the EHR data, we found that antibiotics were used in 29 percent of encounters. When examining the use of antibiotics against percentiles of LOS we found that antibiotics were utilized in patients with relatively short lengths of stay. Patients who had short lengths of stay are highly unlikely to have an infectious complication of AP. Conversely, antibiotics should be used in patients with suspected cholangitis or other infectious conditions. The early use of antibiotics in AP may also serve as a quality metric for an APM for AP.

Both the Charlson score and the presence of psychiatric comorbidities both assessed through the admission problem list were not associated with increased total charges and LOS. Examination of the Charlson score in the overall cohort and the two high risk subsets (suspected biliary pancreatitis and patients who developed adverse events) shows that the median Charlson scores remain low. This suggests that patients who present with AP have very few comorbidities associated with increased mortality.

This study has several limitations. The claims data analysis is limited in generalizability because it was obtained from a small payer servicing a population of university employees which may impart a healthy worker bias. None of the patients in our claims data analysis were discharged to rehab facilities or used a substantial amount of home health during the defined episodes (within 90 days of the episode start). These services can increase the cost of care beyond the care used in the hospital. [63, 64] Our study cannot account for clinical factors which have led clinicians to utilize antibiotics and imaging in patients who in retrospect may have not needed these interventions. We were unable to obtain data about the main intervention for AP- namely, the administration resuscitation fluids. The type and amount of fluid given initially during an episode of AP has been shown to be correlated with outcomes. [65-67] We were also unable to obtain the vital signs and changes to the labs beyond 36 hours. The changes in these labs may have been related to the increased utilization seen in the patients who had longer LOS or total charges. Obtaining these values may improve the discriminatory capability of the models.

Proposed Episode Based Payment Model

The results of the study suggest that the drivers of cost in AP are overuse of imaging, overuse of antibiotics, long LOS, the occurrence of adverse events and clinical information that suggest biliary obstruction as an etiology. Given the insights obtained from this study, we propose the following EBP model for acute pancreatitis as suggested by the Ohio Governor's Office of Health Transformation. The components of this EBP were chosen because these are obtainable using claims data alone and this is how the incentives would be computed.

1. Episode trigger
    - A discharge diagnosis of AP because this is more accurate than the admission diagnosis.
2. Episode window
    - Pre-trigger window – because patients present acutely, there is no pre-trigger window.
    - Trigger window- Duration of hospital admission
    - Post trigger window- 30 days after hospital discharge.
3. Claims included

- Relevant care and complications including diagnoses, procedures, labs, and pharmacy claims
- Readmissions except those not relevant to the episode
- Claims from the physician or physician group responsible for the episode

4. Principal accountable provider (PAP)- Emergency room physician or group, Hospitalist physician or group, healthcare facility.
5. Quality metrics
    - Administration of IV fluids on day 1
    - Percentage of encounters utilizing early cross sectional imaging (within 24 hours of admission). Using the information in this study, the goal percentage could be arbitrarily set to < 23% which is percentage of imaging utilization in patients with a LOS < 3 days.
    - Rate of early abdominal ultrasonography. It is recommended that all patients who present with AP receive abdominal ultrasonography as the preferred initial imaging modality.
    - Avoidance of antibiotics unless indicated for another infection such as a urinary tract infection, bacterial pneumonia or cholangitis. This could be abstracted from claims data using the discharge codes.
    - Percent of episodes with follow up visit within 30 days after hospital discharge.
6. Potential risk factors

- History of heart failure, chronic kidney disease or chronic liver disease which could limit the amount of fluid resuscitation
- Chronic pancreatitis, tobacco use, alcohol abuse and morbid obesity which may increase the risk of recurrent admissions

7. Episode level exclusions
   - Clinical- biliary (gallstone) pancreatitis, cholangitis, need for endoscopic procedures or surgery, LOS ≥ 7days, active malignancy, acute coronary syndrome, AIDS, organ transplant recipients, need for ICU care, Death in hospital, left AMA
   - Business- Members under 1 years old or above 64 years old, third party liability, inconsistent enrollment, PAP out of State, no PAP, dual eligibility, long-term care, long hospitalization, missing All Patients Refined Diagnosis Related Groups (APR-DRG), and incomplete episodes , episode's risk adjusted spend is three standard deviations above the risk adjusted mean (after business and clinical exclusions).

Being a retrospective model using claims data to assign the level of reimbursement limits the level of clinical detail in identifying the episodes of care, relevant claims, satisfaction of quality metrics and identification of exclusion criteria. The use of discharge diagnoses to identify potential episodes of care improves accuracy over using the admission diagnoses. The quality metrics chosen are potential areas of overutilization as demonstrated in this study.

The episode level exclusions are conditions which could lead to the removal of an episode from the provider level cost computation due to its complexity, cost, or other factors. These conditions have to be selected carefully so that they are not too restrictive and that they are applicable to most episodes of care. In this study, we found adverse events and biliary pancreatitis as complicated conditions which on average have longer LOS, higher imaging, procedure and antibiotic utilization hence are worthy of exclusion. These conditions and other exclusion clinical exclusion criteria can be identified using a combination of ICD9 and 10 codes. [68]

Figure 7 demonstrates that the percentiles of total charges are related to ranges of LOS. Switching the axes allows us to determine the percentiles of LOS where the range of total charges is relatively constant. Figure 7 shows that the ranges of total charges of the 1st to 3rd percentile corresponding to a LOS of 0-6 days overlap. There is also overlap among the outlier values of total charges. We could therefore estimate that by excluding an LOS ≥ 7 days we can reliably predict the range of total charges and use this as the basis of the per episode charge.

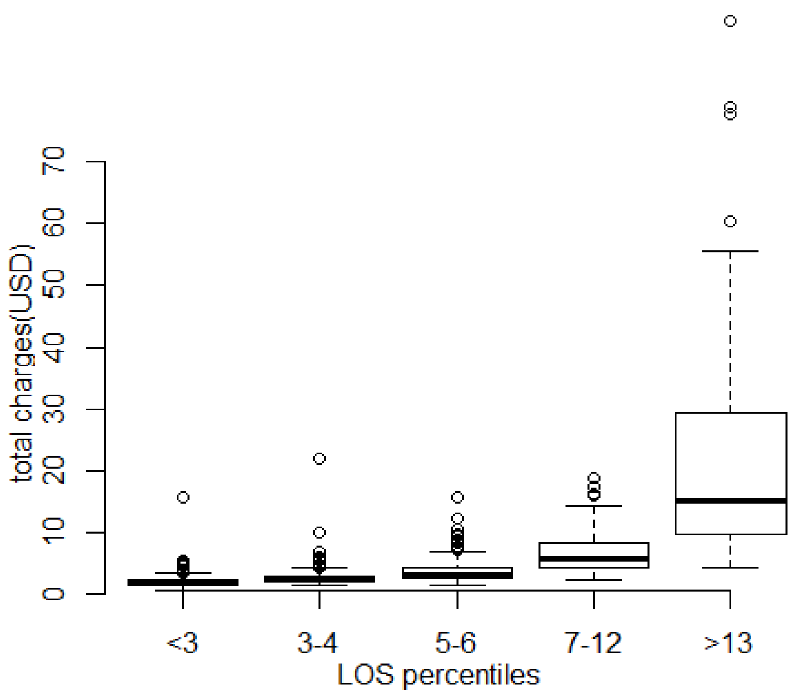

Figure 7. Total charges versus percentiles of LOS in AP encounters identified in the OSU EHR . Total charges are in the Y axis in increments of $10,000. The percentiles of LOS (days) are in the X axis.

Conclusion

In summary, we can produce actionable information on healthcare resource utilization using discrete elements from insurance claims data and EHR data without resorting to manual chart review. This study shows that we can define a meaningful APM that adheres to society guidelines by reviewing the relevant literature and through careful analysis of complementary claims and EHR data. To reduce expensive inpatient utilization, a predictive model may help triage low risk cases observation units and reserve inpatient admission for higher risk cases. The results of this study demonstrate both billing data and EHR data could be used together to inform and quantify the amount of financial risk a healthcare institution faces when agreeing to implement an APM. Studies like this may improve and accelerate the development of sensible APMs that are acceptable to both clinicians and payers.

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