

AN INFORMATICS APPROACH TO CHRONIC DISEASE MANAGEMENT
IN PRIMARY CARE: BLENDING BUSINESS INTELLIGENCE
AND CARE PROCESS MODELS

by

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ABSTRACT

Asthma, diabetes, and depression are chronic diseases managed through the Primary Care Clinical Program at Intermountain Healthcare. Primary Care Providers (PCPs) receive monthly reports on their patients with these conditions. The reporting paradigm focuses on individual diseases. PCPs have asked for a consolidated view of chronic disease, one that is patient-centric rather than disease-centric.

A clinical decision support tool was developed using data from Intermountain's enterprise data warehouse. A cube was built to report on asthma, diabetes, and depression patients simultaneously. 183,000 patients were included in the study. The tool measures PCP's adherence to best practices for chronic disease management. It also allows ad-hoc analysis of large data sets as well as actionable reports for PCPs to identify gaps in adherence to best practices.

Primary care providers can view their patient populations with asthma, diabetes and depression in a consolidated report. The decision support tool was successfully built as a prototype for chronic disease management. The tool has the potential to scale and include many chronic conditions for reporting. It was demonstrated to executives, directors, and PCPs at Intermountain.

Chronic disease management should be done with a patient focus rather than a disease focus. Information technology has an important role to play in the support of

primary care and the medical home. Clinical decision support tools can be built to improve population-level and patient-level chronic disease management.

*This thesis is dedicated to my wife, Kristine Barnett Wadsworth,
for believing in my dream.*

Yes, I believe in blue suns.

To my children, Samuel, Benjamin, Cora, and Rachel, you're my inspiration.

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LIST OF ABBREVIATIONS

AAP	American Academy of Pediatrics
ACO	Accountable Care Organization
BI	Business Intelligence
BIDS	Business Intelligence Development Studio
BO	Business Objects
CPM	Care Process Model
DSS	Decision Support System
EDW	Enterprise Data Warehouse
ETL	Extract Transform Load
IT	Information Technology
PCCP	Primary Care Clinical Program
PCMH	Patient Centered Medical Home
PCP	Primary Care Provider or Primary Care Physician
QI	Quality Improvement
SQL	Structured Query Language
SSAS	SQL Server Analysis Services
SSRS	SQL Server Reporting Services
WHO	World Health Organization

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INTRODUCTION

The Problem

Chronic disease affects a significant percentage of the world and US populations (1,2). Some chronic conditions may be difficult for Primary Care Providers (PCP) to manage, such as asthma, diabetes, and depression. When a patient presents in a clinic, PCPs tend to focus on the chief complaint of the visit. As patients with chronic disease present at the clinic, providers should certainly address the chief complaint, but they should also be aware of any chronic conditions the patient may have. With the patient in the clinic, care providers have the opportunity to better manage chronic conditions by checking progression and status of the conditions. For decades, chronic disease management has had a disease focus rather than a patient focus. Time constraints, financial incentives, and incomplete patient data are contributing factors that emphasize disease focus, rather than a holistic patient focus.

At Intermountain Healthcare (“Intermountain”), an integrated health care delivery system based in Utah, PCPs receive monthly reports on their patients with the chronic conditions asthma, diabetes, and depression. Each month, they receive an asthma report with all their patients who have asthma. They also receive diabetes and depression reports for their respective diabetic and depressed populations. This model of chronic disease reporting has been in use for over a decade. Patients who have multiple chronic conditions appear on multiple reports sent out to providers. The PCP is left to determine

which patients have multiple conditions and how to assimilate pertinent clinical information across the reports. The reporting paradigm is flawed. Each report is disease-centric, rather than patient-centric. PCPs have asked for one report that combines these chronic conditions.

Reporting on chronic disease management at a population level across an enterprise is a challenge. The complexity of the data architecture with multiple data sources available to analysts tasked with building reports often leads to inconsistencies in reporting. What one analyst from a particular department reports may not be congruent with findings from another analyst. The resulting discrepancies may leave clinicians and executive management skeptical of reports and unsure of an appropriate course of action. In this case, a consistent representation of clinical data is needed so clinicians, administrators, and executives can rely on trusted information to help them consistently make correct decisions.

Another challenge in chronic disease management is adherence to Care Process Models (CPM) for given chronic conditions. A care process model is a high-level mapping of the patient care continuum for a given disease. The mapping will include best practices for preventive, ambulatory, acute and invasive care on along the disease continuum. Some PCPs may do quite well in managing their diabetic patients. They may follow the diabetic CPM to the letter. However, those same PCPs may struggle to some degree with the asthma CPM and/or with the depression CPM. At Intermountain, the advent of data transparency and public reporting on PCPs has led to heated debate among PCPs who complain that their patient populations are sicker and less compliant than other PCPs whose patients may appear to have better outcomes. To date, PCP-to-

PCP population comparisons are difficult, awkward, and nonstandard. However, quality improvement theory allows us to examine unnecessary variation in order to identify opportunities for improved quality and efficiency. Intermountain has a vested interest in identifying PCPs and clinics that excel in managing their patients with chronic disease (i.e., improved clinical outcomes) so that best practices may be identified, understood, and disseminated across the enterprise. Historically, the outcomes focus has been on individual disease silos. Clearly, there is value in tracking patient outcomes, but these are not the only outcomes of value. What drives these outcomes? Is it patient compliance to care and medical advice? Is there not also a PCP component of adherence to prescribed best practices which have been captured in CPMs for chronic disease? The answer is yes. Pathman et al. (65) proposed an awareness-to-adherence model that suggests both providers and patients have responsibilities for compliance. In this study, it was recognized that the patient has responsibility for some levels of compliance; however, measuring and enhancing provider adherence to CPMs is the focus of this study. At Intermountain, no framework exists that could be used to measure PCP adherence to chronic disease CPMs simultaneously across multiple chronic conditions.

A Proposed Solution

Over the last two decades, tremendous advances have been made in the field of health care information technology. A few examples include electronic medical records, data warehouses, reporting tools, data modeling techniques, and business intelligence. Today, many of these technologies are employed to support health care delivery and disease management.

I propose a unique approach to support chronic disease management. PCPs within the Primary Care Clinical Program at Intermountain Healthcare requested a consolidated report that included asthma, diabetes, and depression while maintaining a patient focus. To date, no such report exists. As I considered building the consolidated report for my MS project, I felt that the development of such a report alone was insufficient for an MS project. While a consolidated report could add value to the Primary Care Clinical Program, there was no novel informatics contribution inherent in building a complex disease report. The idea then came to me to architect a framework. I wanted to build a chronic disease management tool, a veritable amalgamation of information technology and clinical care process models. I call it the *chronic conditions management tool (CCMT)*. The CCMT would be a clinical decision support tool. The CCMT would certainly meet the PCPs' request for a consolidated, actionable patient report, though reporting would be just one component of the model.

The model would leverage an enterprise data warehouse, necessary for data capture and consolidation. It would include dimensional modeling techniques to optimize reporting. It would also include cube technology, needed to aggregate and slice through millions of rows of data. Finally, a reporting solution would be connected to the cube to allow the end users (PCPs, clinical staff, managers, executives, and analysts) novel, self-service views of chronic disease management across the enterprise and across PCP patient populations.

The Thesis Layout

This project evolved into a data journey of chronic disease management. There are many moving parts and pieces. To help the reader understand the necessary components of the CCMT, I have outlined each component in the Background chapter of the thesis. The Background provides details on CPMs. Information technology components of the model are also outlined and explained in the Background chapter. The Methods chapter walks through the ways the individual components were employed in the CCMT. The Results chapter follows the Methods. The Discussion chapter delves into the value of each component and the contributions each makes in the model. Where possible, limitations of the components are discussed.

The purpose of the project was to architect and build the CCMT, not to implement it. I set out to build a novel approach to chronic disease reporting by blending information technology and care process models. The real result of the MS project is the resultant, working prototype. The paper ends with the Conclusion chapter, along with future recommendations for logical next steps with the model and other possible research that could come out of the CCMT.

BACKGROUND

General Concepts

The background chapter is broken down into sections. Each section will cover a topic relevant to the overall master's project. First, I cover general concepts such as chronic disease management and a data warehouse. Later in the Background chapter, I cover more in depth the Intermountain Healthcare adoption of the general concepts to establish a contextual framework for the reader.

Chronic Disease Management

Chronic disease affects a significant percentage of the US population. Among the most pervasive diseases are congestive heart failure, diabetes, asthma, and depression. Over 24 million Americans have diabetes (1). Nearly one in five Americans over 60 has diabetes and it is estimated that one in three Americans born in 2000 will develop diabetes over their lifespan (2). The financial burden of chronic disease is staggering. One in five health care dollars is spent on caring for someone with diabetes and one in ten dollars spent on health care can be attributed to diabetes and its complications (3). Americans spent \$18 billion treating asthma in 2008 (4), though cost to society through lost productivity estimates true cost at \$56 billion (5). As sobering as these statistics may be, the effects of depression are almost overwhelming. In 2009, depression was considered to be the largest cause of disability on a global scale by 2010 (6). Long-term

costs of those with psychological problems during childhood include diminished educational opportunities, reduced incomes, and reduced likelihood of marriage along with an overall estimated cost of \$300,000 in lost family income over a lifetime. Total lifetime economic cost for those affected is \$2.1 trillion (7). Treatment of chronic disease within the Primary Care setting continues to rise, currently accounting for 35% of all Primary Care Physician (PCP) visits (8). By 2051, 50% of people over 50 will have a chronic condition (9). Managing patients with multiple chronic conditions is possibly the greatest challenge for today's PCP (10-14).

Wagner Chronic Care Model

Chronic disease is no respecter of persons. It affects young and old, rich and poor. It affects people from all races and all walks of life. The varied nature of chronic disease requires a multifaceted approach to manage disease progression. As a result, models of chronic disease management address several components of disease management, including organizational factors (15-21), the medical home concept (22-23), payment models and reform (24-26,27), Care Process Model (CPM) development (28-29), decision support systems (DSS) (30-32), and information technology (IT) (33-37).

One model of chronic disease management has been adopted more than any other. It is the Wagner Chronic Care Model. See Figure 1. The model provides a framework of core elements to guide tools or programs designed to address chronic disease management. There are six core elements. First, the health care system is responsible for promoting safe, quality care. This initiative must be driven at all levels within an

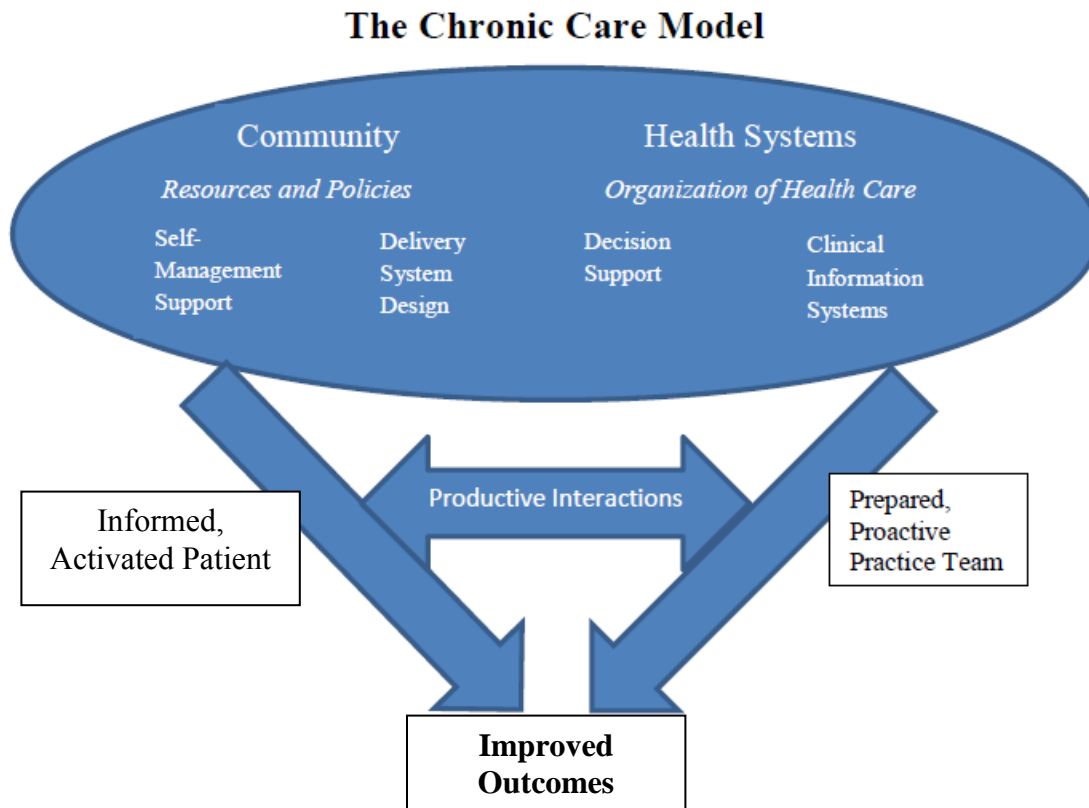


Figure 1. The Wagner Chronic Care Model.

organization, from executives, to clinical staff, to support services with the end goal of improving and coordinating care. Second, delivery system design seeks to promote effective and efficient clinical care. Appropriate interventions, reminders, and systematic follow-up are built into care delivery. Third, decision support is delivering the best care according to best protocols. Evidence-based guidelines are understood and consistently applied across the health care system. All members of clinical staff have access to and are continually trained in best practices. Fourth, clinical information systems are

designed to support individual patient interactions as well as create an aggregate view of patient populations to coordinate care. Tools give providers the ability to share data with one another and with the patient for improved care coordination. Reminders, alerting, and outcomes are used to improve care. Fifth, self-management support is designed to engage patients and help them to have accountability in managing their health care. Tools are provided to patients to help educate them about their health conditions as well as care options available to them. Sixth, the community supports not only individual patients but groups as well. Policies and community resources are utilized to promote self-management and care of patients with chronic disease (64). A visual representation of the Wagner Care Process Model can be seen in Figure 1.

The Wagner Care Process Model became a loose framework for the CCMT. Several of the Wagner components were evidenced in the CCMT. From the community, resources and policies dictated what the clinical guidelines were for PCPs to follow as they treated their patients with chronic diseases. The CCMT was designed within the context of the Intermountain Healthcare system utilizing data extracts from clinical systems. The CCMT was a decision support tool for PCPs at Intermountain. The information delivery provided by the CCMT helps PCPs be more prepared and proactive in chronic condition management for patients they treat.

Enterprise Data Warehouse

An Enterprise Data Warehouse (EDW) is a massive collection of data copied from many sources and consolidated into a single representation (one or more databases). An EDW is generally used for data reporting, data mining, population-based queries, and

research (47). An EDW does not generally create data; rather, it copies existing data from one or more transaction systems (sources) and stores a local copy that permits longitudinal and relational views of the data, transforming data to information.

Figure 2 shows components found in a typical health care EDW. On the left of the diagram are examples of source systems that may feed into an EDW. The center of the diagram shows the EDW proper. Before any data are ready for use in the EDW, they need to go through a preparatory process. First, the data are pulled into a staging area in raw form. Next, data are cleansed and finally, if deemed appropriate (by the business), data are summarized into logical groupings. The purpose of cleansing data is to ensure that data in the EDW consistently represent the source systems, and equally important, that EDW data consistently represent business rules. One of the natural consequences of data cleansing in the EDW is that it surfaces bad data captured in source systems. Generally, rules or constraints exist on source systems that dictate the method of data capture. When rules are ambiguous or not enforced, data entry on source systems may allow the capture of incomplete or erroneous information. For example, a laboratory system may require each of the following fields to have a value entered before the program will complete a transaction: the patient account number, the lab test, the nurse ID, the location of the lab draw, and the date and time the lab result was completed. However, suppose the data collection/storage program only required that some value, any value, be entered into each field. The person entering data in theory could enter gibberish into each field and the system would accept the transaction. This type of erroneous data is exposed when reporting against the EDW is instituted. As erroneous data are surfaced through the EDW, the business needs to come up with rules for how to deal with bad or

Enterprise Data Warehouse Model

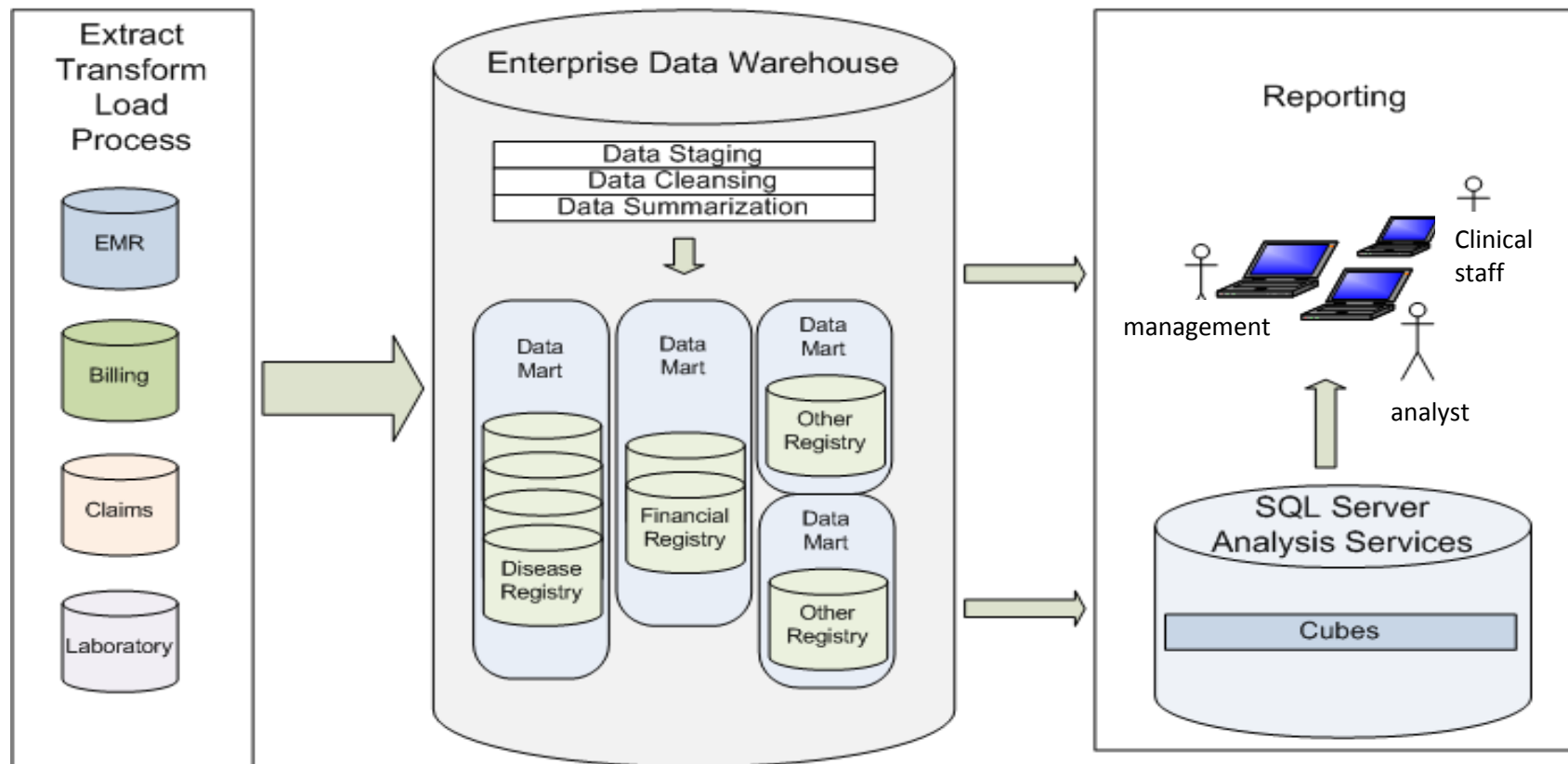


Figure 2. An example of enterprise data warehousing components. Related data are grouped into data marts. Reporting is built off the EDW.

incomplete data (e.g., do they include it or not?). These issues of data quality are often addressed in the process of data staging, data cleansing, and data summarization. It should be noted that data staging and cleansing could also be done as part of the extract, transform, load (ETL) process. Vended ETL tools typically offer these features.

Reporting against the EDW is represented in the far right portion of Figure 2. Reporting is a crucial part of data warehousing. It is the public-facing component for most users who consume data from the EDW. The concept of reporting against the EDW is explored in detail in the background section, *Reporting Against an EDW*.

The advent of data warehouses was driven by a need to do analysis over extremely large data sets and got its start at IBM with Barry Devlin and Paul Murphy (48). They coined the term ‘information warehouse’. The practicality of data warehousing took hold in 1991 when W.H. “Bill” Inmon published his book, *“Building a Data Warehouse”* (John Wiley and Sons). Today data warehousing is present in many industries, including banking, airlines, retail, manufacturing, and health care. Sources that feed into an EDW are usually transaction systems designed to process individual transactions and focused queries. Examples of transactions within transaction systems may include a pharmacy order for a patient, a withdrawal from a bank account, or perhaps a retail purchase. These systems are referred to as Online Transaction Processing (OLTP) systems. They are optimized to quickly perform many individual transactions almost simultaneously. However, OLTP systems are generally poor at performing large population queries that may include multiple transactions in aggregate. In fact, running large queries against a transaction system can bring performance to a halt; hence the need for an EDW.

In a data warehouse, data are organized and often tuned to allow large reports (queries) to run. By making copies of data and moving the data to a separate, physical environment, queries run against the copied data in the EDW will have no effect on the original source system(s).

The process of extracting, transforming, and loading (ETL) data into an EDW takes place at periodic intervals. This process requires a connection between the EDW and the source system(s) of interest. Once the connection is established, data are pulled from the source system into the data warehouse. The connections can be manually built with computer programming languages or they can be automated and scheduled using tools available to IT professionals. IBM and Microsoft are two mainstream vendors of ETL tools: DataStage and SQL Server Integration Services, respectively. After the data pull is complete, the connection between the EDW and the data source is severed. The ETL process is repeated at intervals set by the business requirements. Many source systems have stringent uptime requirements. For ETL processes to be effective, they need to minimize the impact they may have on the source systems. Consequently, the time of day for ETL is important. If the source system is busy during normal business hours (9-5), then the load needs to take place outside of these hours. Ideally, the load would take place as close as possible to the start of business hours. That way, even though data are loaded daily, the visible data in the EDW are not actually 24 hours old. If the ETL process ran at 6:00 AM and finished by 6:30, then the EDW data used for analysis that same day would never be more than 10.5 hours old, assuming the work day ends at 5:00 PM. This may seem a trivial detail but is actually quite important to users consuming data from the EDW.

Another consideration for loading the data is the method of loading. How much data need to be pulled from the source system each night? The answer to this question lies in the business needs for data analysis from the EDW, the size of the source system data source, and the tax of the ETL process on the source system when loading. If the need for the most up-to-date data is paramount to all other business requirements, then the load needs to be sure to capture the most recent data changes with row-level (transaction-level) precision. This is the most complex type of data load. The reason for the complexity is the potential transient nature of the data on the source system. It is not uncommon for some records to change, particularly within a high-volume system. When a record is copied from a source system and written into the EDW, the EDW record represents a set of values on that record that were present at the time of the ETL process. However, a record can, and sometimes does, change on the source system after the ETL process has already taken place. Changes made to source records that were previously pulled into the EDW lead to inconsistencies between the EDW and the source system. If not reconciled, the EDW data will not be trusted and users will revert to pulling their reports from source systems, defeating the purpose of the EDW, and consequently, putting an undue reporting burden on the transaction system. The EDW needs to have a robust, proven method for identifying changes on copied rows and ensure high data integrity through automation and auditing.

Considering the size of the source systems is important. Many tables that are copied to the EDW are reference or look-up tables. That is, they contain key values that are referenced by activity tables to record events. An example of a reference table may be a list of all laboratory tests a laboratory is able to perform. The table may contain the

full medical name, an acronym for the test, and the type of test (blood draw, saliva, swab, stool, etc.). Reference tables as a general rule do not contain many rows (thousands) when compared to activity tables (tens of millions). For this reason, reference tables are good candidates for a full refresh method, meaning the copied data in the EDW version of the table are deleted each night and then completely reloaded from the source system, guaranteeing the EDW and source system stay synchronized. Activity tables, on the other hand, are quite large and cannot practically be copied in their entirety each night. ETL processes against these tables are usually done in an incremental method, identifying only those rows which do not already exist in the EDW and pulling them into the EDW. An additional step in the ETL process may look for rows that were copied already but have since been changed on the source system, and the changes are pulled into the EDW and updated on the existing rows. The Data Architect responsible for the incremental ETL process needs to understand how far back changes could be made on source system rows. Otherwise, changes will be missed. Some source systems could have changes on rows which are months old, a common practice in the adjudication process on claims systems.

One final consideration for ETL is the tax imposed on the source system by the data pull. If the burden is heavy and the source system cannot support the weight, an EDW solution may require an intermediate step called an operational data store (ODS) that is nothing more than a scaled-down copy of the source database. In an ODS, transaction records are posted twice for each record with one row writing to the transaction system and another row being written to the ODS. This way, reporting can be done against real or near real-time data in the ODS without affecting the source system.

Data can then be pulled from the ODS to the EDW without any imposition. Within an ODS, copied data are generally stored for a period of up to the one year before being purged. Advancements in database systems commonly found in data warehousing today usually operate with such efficiency that the ETL burden is quite manageable. Data in the EDW may be stored for years.

EDWs are used to support chronic disease management using disease registries or data marts (16) with aggregate and individual patient data and Continuous Quality Improvement initiatives (12,35). Reporting from EDWs has been used to study payment reform and cost-savings of chronic disease management (25). Furthermore, the effectiveness of the medical home (see the *Patient Centered Medical Home* background section) is often analyzed and measured using EDW source data (11,44). EDWs are central to the study of the aforementioned topics, none of which could effectively be done against transaction systems. More virtues of an EDW are explored in the following background sections, *Disease Registries*, *Data Sources*, and *Reporting Against an EDW*.

An EDW is a tremendous asset for an organization if implemented properly. Copying the data into the EDW is an essential first step in adding value. With data copied and consolidated into a massive, central data store, previously unrelated data can now be grouped together. This grouping makes it possible to view events, transactions, or even patient care with a more holistic view. One such application of data warehousing technology is evident in health care, particularly in chronic disease management by building disease registries.

Disease Registries

Health care organizations that use EDWs to support chronic disease management often develop disease registries within their EDWs (15,27,67). A disease registry is used to identify patients with a given disease, track clinical indicators, and follow disease progression over time. Reports against these registries provide decision support to alert clinicians when patients are due for care according to Clinical Practice Guidelines (CPGs) (67) for a given disease. Generally, disease registries focus on one particular disease, though an EDW may house many disease registries (see Figure 2).

Diabetes is a chronic condition which affects the body's ability to manage blood glucose levels. If not managed, diabetes can lead to blindness, amputation of extremities, and even death (1-3). Three types of diabetes exist. Type I is the body's inability to produce insulin. This is often referred to as juvenile diabetes as it is generally discovered in young children. With Type II diabetes, the body does not produce enough insulin or cells ignore insulin. This is generally a later onset than Type I. Gestational diabetes occurs in some women around 28 weeks of pregnancy where blood sugar levels may deviate from the mother's normal range (high/low). These definitions are simple enough to understand when described verbally, using natural language such as English. It is also possible to represent or describe diabetes as a disease using the language of information technology.

Instead of combining words to represent diabetes, medical informaticists use combinations of medical coding values for specific doctor visits, laboratory data, and other codes to identify features which are characteristic of diabetes. For example, with Type II diabetes, blood sugar levels tend to be elevated. Therefore, laboratory tests

indicative of blood sugar levels and related factors could be used to identify patients with diabetes. Furthermore, the values of the tests could be used as indicators of the disease progression. Hemoglobin A1C, Microalbumin, high-density lipoprotein (HDL), and low-density lipoprotein (LDL) tests are lab values used by health care institutions to track diabetes progression in their diabetic population, though some variation may exist.

The diabetes laboratory tests described above provide a means of clinical data abstraction to logically represent the presence (or absence) of diabetes in a patient. For example, if a patient had an HBA1C > 9 , that could be an indicator that the patient has diabetes. This lab result, along with other clinical indicators (HDL, Microalbumin) could lead a clinician to diagnose the patient with diabetes.

Laboratory Information Systems (LIS) track lab orders and results for patients. An LIS is a good example of a source system that can be used to feed into an EDW. Using clinical data captured by an LIS coupled with knowledge of CPGs for a given disease, such as diabetes, may be logically grouped together to represent a disease in what is known as a disease registry (see Figure 2).

This logical representation of disease may reside within an EDW. It makes sense for registries to live in a data warehouse. Data from disparate data systems, (e.g., an LIS, an EMR, and a medical insurance claims system) can be logically and physically grouped together to identify patients who meet the health care organization's definition of a disease. Once patients are identified in a given disease registry, clinically relevant data are captured and analyzed over time. The data may also be used to track disease progression on patients, thus providing clinicians the potential for a more complete view of the disease than is available by tracking patients on the individual source systems. The

clinical data (or lack thereof) can also be used to measure care delivered by providers. Data can also be used to track providers' compliance with established protocols for best practices of disease management.

The process of logically grouping data within an EDW is called a data mart. Referring back to Figure 2, note that data marts surround the registries found in the EDW. A data mart can hold any number of registries, though the intent is generally to group like data together so it would be odd to have registries not related to one another to reside in the same data mart. From these logical groupings emerge disease registries.

Data Sources

Many data sources can and often do feed into a data warehouse (43). Figure 2 showed data sources as the foundation of the ETL process. Data sources can come in a variety of forms. They can be spreadsheets, delimited file structures, or databases. Typically, a data source is the database behind a transaction system. Within a source (database), there may be many tables required to support the front-end application. Not all tables in a source database need to be copied into the data warehouse. Ideally, if a source system is well documented, a vendor may include a data model, making the ETL process much easier. The data model helps to clarify which tables contain data of interest to pull into the EDW. Reference tables are easier to identify as well. Unfortunately, few vendors provide support or documentation on their underlying data model. This makes the ETL process a serious chore to make sense of undocumented and often poorly named tables.

Source systems are built for a specific purpose. For example, a billing system will document everything needed to generate a complete bill for a client. A hospital scheduling system will capture all that is needed to set up an appointment, to register a patient upon arrival, to transfer, and to discharge a patient. An electronic medical record system will have the ability to capture clinical information about a patient. Each of these source system examples could contribute data to create an EDW rich with information. In the health care industry OLTP, sources of data regularly include financial data (billing), insurance claims (Medicare, Medicaid, private insurance, etc.), as well as electronic medical records (EMR).

Two challenges arise in the process of building accurate and dependable disease registries. The first challenge lies in identifying which data elements are representative of the disease in question. Data architects need to work closely with those who understand well the process of clinical flow with its accompanying documentation in the source systems. This cooperative approach will greatly improve the odds of accurately capturing relevant coding and will ensure that the disease registry accurately identifies those patients with the chronic disease in question. The second challenge that surfaces when trying to build a disease registry lies in rich, overlapping data sets. The risk here is to not over-represent data elements on a patient by combining all feeding sources into one source of truth while not omitting key elements which could preclude patients from being included in a registry.

Reporting Against an EDW

With source systems identified, connected to, and feeding into a data warehouse and with data logically grouped into data marts and registries, an EDW is well prepared to support reporting needs. A data warehouse may hold tremendous value for an organization (43), but the value is not in simply having stored terabytes of data. The real value of the EDW is getting information out of data. This is best evidenced via the process of reporting.

Figure 1 showed that the final stage of an EDW is the reporting process. The reporting aspect of an EDW is how most people will interact with an EDW. Reports can be created, scheduled, automated, and delivered to thousands of information consumers internal or external to an organization. Vended systems support a host of reporting needs, from simple, one-time reports to incredibly complex enterprise dashboards. Some of the biggest reporting vendors today are Cognos (IBM), Business Objects (BO), Oracle, and Microsoft (SQL Server Reporting Services (SSRS) and their BI stack). Daily business and operations thrive on timely data and reports and many of these reports stem from a data warehouse.

Reporting Challenges

Reporting against an EDW is difficult. The burden of report development typically falls within a data analyst role. A successful data analyst tasked with report development must acquire a suite of technical skills (52). S/he must have the ability to directly query a database, most often using a computer language called Structured Query Language (SQL). S/he must be able to relate data from different tables to one another in

meaningful ways. S/he must understand how data are structured within a database and how to interpret data models and database documentation. S/he must be able to create reports using some form of reporting tool (Excel, Cognos, BO, Oracle, or SSRS) and deliver the data to those who need the data in a timely, secure manner. Developing this skill set can take years to become truly proficient. The learning curve in each of these areas is steep. Consequently, relatively few people actually have direct interaction with an EDW. Generally, a data warehousing team composed of data architects and data analysts (or IT equivalent) along with some departmental analysts have security clearance to directly query the EDW. The overwhelming majority of people within an organization know their EDW only through reports they receive from a vended product (Excel, BO, Cognos, SSRS, etc.) or from a report portal on an internal website.

Consistently reporting information across an enterprise is a desirable asset for any organization (43). Consistent representation of data is a second challenge which arises when reporting against an EDW. The challenge is magnified when attempting to aggregate and report on data to all levels of management within the organization. Developing a consistent version of the truth is a tremendous undertaking (43). The availability of multiple, overlapping data sources within an EDW can lead to inconsistencies in reporting (43,35). It is not uncommon for personnel to spend as much as 70 percent of their time searching for and reconciling information (45). This is both frustrating and terribly inefficient. Furthermore, managers and executives are frustrated by inconsistencies in reporting. What one analyst reports may not necessarily agree with what another analyst reports. This issue is not unique to Intermountain. Executive

mistrust in data is an unfortunate commonality among many organizations and industries (45).

Clinical Practice Guidelines

Most diseases have specific guidelines of care. To aid physicians in the management and treatment of disease, clinical guidelines and protocols have been developed. These are known as Clinical Practice Guidelines (CPGs). They are based on clinical evidence and leading experts in the field to establish recommendations for diagnosis, treatment, and management of diseases (46). The guidelines help to establish standards of care (47). When followed, they can improve the quality of care delivered to the patient (47,49). Traditionally, CPGs typically focus on one disease (50). When patients have multiple comorbidities, it is difficult for PCPs to follow CPGs because at times, different CPGs may contradict one another or collectively become too burdensome and/or complex for the patient to follow (51).

In this study, primary care physicians are held accountable for their level of adherence to CPGs for three chronic conditions.

Patient-Centered Medical Home

Over the last few years, the Primary Care Clinical Program at Intermountain Healthcare has engaged in considerable dialogue around the concept of the patient centered medical home (PCMH). A medical home is a physician-directed, patient-centered team approach to health care delivery with the purpose of improving and coordinating referrals and medical services (23,53). The American Academy of

Pediatrics (AAP) first introduced the idea of the “medical home” in 1967 as a means of improving the care of children who had special health care needs (54). In 1978, the World Health Organization (WHO) recognized the pivotal role of primary care stating it “is the first level of contact of individuals, the family and community within the national health system bringing health care as close as possible to where people live and work, and constitutes the first element of a continuing care process” (55). The PCMH is viewed as a key element of health reform, specifically to improve patient outcomes and to lower costs in primary care (56-62). States with greater reliance on primary care services tend to have lower Medicare spending, lower resource use, lower utilization rates, and higher quality of care (57).

The chronic conditions management tool (CCMT) developed in this study is intended to be used by PCMH staff (and other audiences). PCPs, nurses, and office staff may find that the CCMT supports coordination of care by alerting clinical staff to gaps in CPG adherence on patients with chronic disease.

Dimensional Modeling

Key to the CCMT is a method of data modeling called dimensional modeling. A dimensional model gets its name from the central table (fact table) that identifies the subject to be measured. Surrounding the fact table(s) are additional tables called dimensions (such as patient, provider, and reporting period). The primary key on the fact table includes the foreign keys from the surrounding dimensions. This enables quick look-ups when querying the cube. A cube is aggregated view of data that may be

analyzed along multiple dimensions. The dimensional data model underlying the CCMT can be seen in Figure 3.

When viewing the data stored in a cube, browsing takes place along the fact via one or more dimensions. For example, you may want to see compliance rates for asthma CPMs such as PFT and controller, and view these measures by reporting period and by provider. The ‘by provider’ and ‘by reporting period’ are dimensions and they allow you to slice through the fact table data/measures in meaningful ways. Data that can be aggregated into natural hierarchies are ideal for cube technologies. Measures can be categorized into groups and rolled up or aggregated into hierarchies, such as by product, by store, by city, by state, by country, etc. Financial data lends itself well to hierarchical organization. Time components are well suited to cubes as well (e.g., hour, day, month, quarter, and year). Clinical data may also be represented via cube technology, though not without some element of transformation to categorize and/or establish hierarchical organization conducive to cubes.

Cubes

Microsoft acquired its cube technology from Isreali-based Panorama Software in 1996. A couple years later, Microsoft released OLAP services as part of SQL Server 7. Since then, major advancements have been made in cube technology. A cube is roughly analogous to an Excel pivot table, though far more powerful. Today’s cube technology is housed within a robust database engine that allows people to sort, arrange, filter, and aggregate tens of millions of rows of data with subsecond response time. Furthermore, browsing the cube can be done by someone who is not technically adept. Data can be

Chronic Conditions Dimensional Model

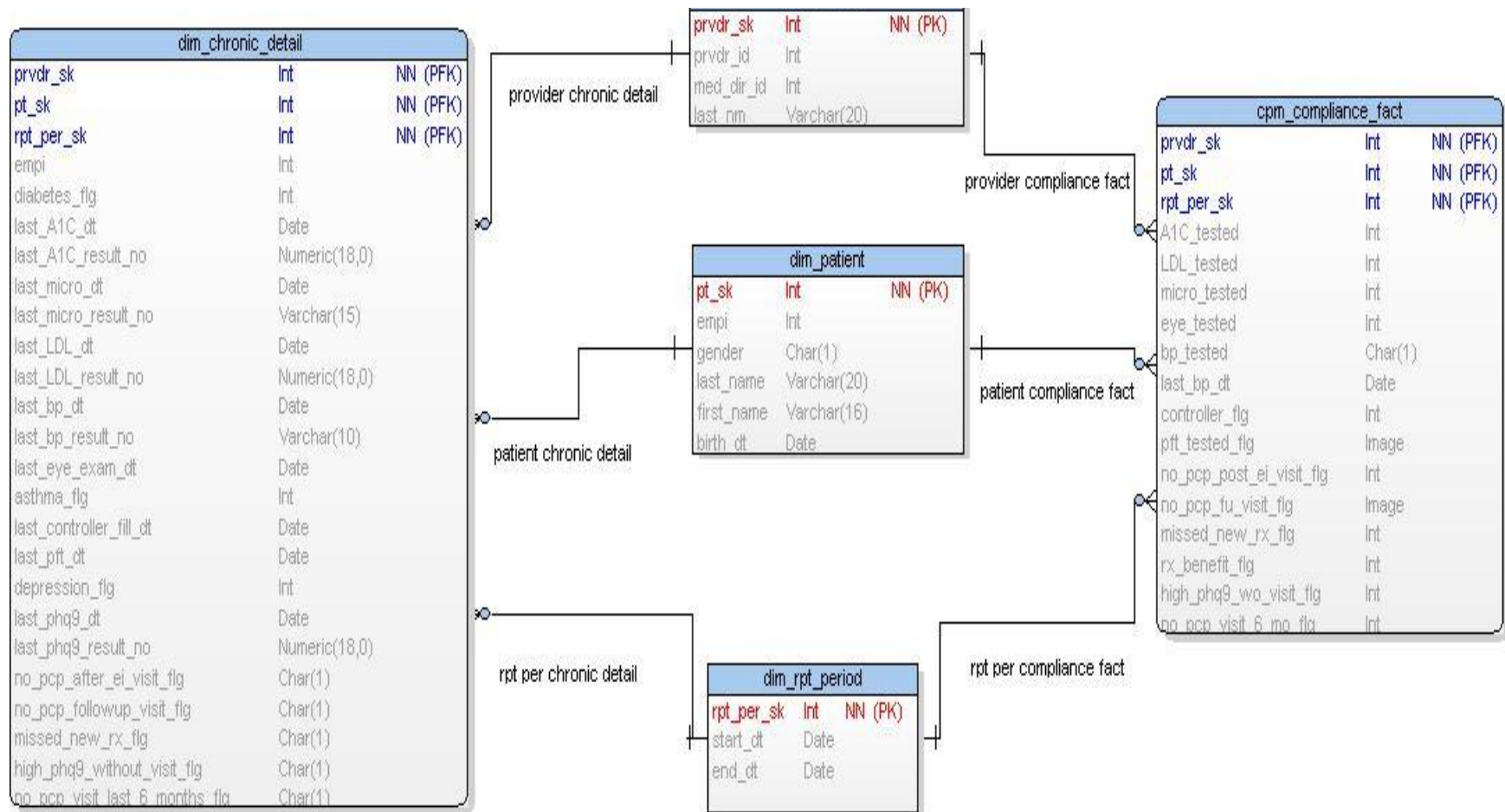


Figure 3. An example of dimensionally modeled data. Dimensions can relate to more than one fact table, as is the case in this example.

viewed across multiple dimensions simultaneously. Cubes allow nontechnical people to do much of their own analysis on data from an EDW without having to rely on an analyst to extract data from the data warehouse. Using the data tab in Excel 2007, a direct (OLAP) connection is made to the cube. In this manner, Excel acts as a viewer for the back-end data. Other tools such as ProClarity, Tableau, and PowerPivot can also be used to connect to and browse cubes.

The tool used to design and build a cube is a Microsoft product called the Business Intelligence Developer Studio (BIDS). It is a Visual Studio application. The cube design is managed at the desktop level through BIDS. SQL Server Analysis Services (SSAS) is the name of the Microsoft technology used to process data within cubes. When the cube is ready to be processed, it is deployed to the server hosting the SQL Server Analysis Services engine. After deployment, the cube must be processed by the SSAS engine. That means, it creates every possible, valid relationship for all dimensions and fact in the model. In this way, the cube knows exactly what data to render for viewing when a user using Excel (or some other cube-browsing tool) chooses specific dimensions and measures for data analysis.

SSAS requires the underlying data model of a cube to be dimensionally modeled. SSAS cannot process a relational model. SSAS will evaluate and pull in the dimensional model to create relationships across all (requested) dimensions through the fact table. Any hierarchies within the dimensions of the dimensional model can also be pulled in to the cube.

Intermountain Healthcare Context

The context for this study was the Intermountain Healthcare system.

Intermountain Enterprise Data Warehouse

At Intermountain Healthcare, data are pulled into the EDW on a daily basis with the bulk of ETL jobs running between midnight and 5:00 AM. All data used in CCMT came from Intermountain's EDW. The EDW is built on an Oracle platform, version 10g. There are roughly 10 terabytes of data in the Intermountain EDW.

Intermountain Disease Registries

At Intermountain Healthcare, much focus and effort has been put into chronic disease management. Congestive heart failure, coronary obstructive pulmonary disorder, asthma, diabetes, and depression are a few diseases actively managed at Intermountain. For this study, only three diseases were included in the CCMT: asthma, diabetes, and depression. Management of these three diseases falls predominately to the Primary Care Clinical Program (PCCP). The PCCP is explained in the Primary Care Clinical Program background section.

Similar to other health care organizations, Intermountain relies on its EDW to support chronic disease management. Clinical data elements are drawn from representative data sources to effectively represent diseases. For example, within the diabetes registry at Intermountain, Hemoglobin A1C, Microalbumin, HDL, and LDL lab test values are used to track diabetes progression in their diabetic population. At Intermountain, the most common method of using data to classify someone as diabetic is

found in the type of office visit billed. For a provider to be reimbursed for work done during a patient visit, the provider fills out specific forms with detailed billing codes and these are used as proof of work done to reimburse the clinical staff. Examples of a diabetic office visit type could be a 15-minute diabetes wellness check-up or an emergency room visit for diabetes complications. Using data captured in electronic medical records, electronic billing systems, and electronic claims systems, patients with diabetes and other chronic conditions can be identified. At Intermountain Healthcare, many data-rich sources exist from which disease definitions may be extrapolated (32).

At Intermountain Healthcare, clinical programs have been developed around business lines. Women and Newborn, Pediatrics, and Primary Care are a few examples. These clinical programs rely heavily on the EDW to help them better understand processes of care, efficiencies, quality improvement, and outcomes. Intermountain uses the EDW for research purposes as well.

It is worth noting some unique features of Intermountain's diabetes, asthma, and depression registries. The diabetes registry is biased toward patients covered by SelectHealth (the insurance division of Intermountain Healthcare) and focuses primarily on outpatient treatment with little emphasis on inpatient and/or emergency room visits. The bias from SelectHealth is significant because it illustrates how disease registries vary from one institution to another. Intermountain's definition of diabetes, as represented in the diabetic registry, excludes patients who are only identified and treated for diabetes while in an inpatient setting. Oddly, the registry does not distinguish between type I and type II diabetes. The reason behind these peculiarities reflects the fact that the diabetes

registry was initially designed as a HEDIS (insurance accreditation) reporting system rather than a decision support tool.

There are financial incentives for providers in the Medical Group to manage their diabetic populations. Only PCPs are eligible for the SelectHealth-driven financial incentive. SelectHealth wants to reward its PCPs who manage well their covered diabetic population. The philosophy is that if the patient with diabetes is not being treated within the Intermountain primary care network, then they are not the responsibility of the Primary Care Clinical Program for ongoing diabetes management.

The asthma registry has an even greater SelectHealth bias. Only patients covered by SelectHealth are included. This is in consequence of the way Intermountain has chosen to manage its asthmatic patients, namely tracking use of medications of its patients with asthma. Furthermore, this measure of filled prescriptions is required for HEDIS reporting. The only patients on whom Intermountain has a nearly complete view of pharmacy orders and fills is on those patients Intermountain both treats and insures. The consequence here is that many patients who are treated for asthma and who could be easily included in the asthma registry are excluded because Intermountain does not yet have a good way to track pharmacy fills for non-SelectHealth patients.

The depression registry is the most inclusive of these three registries. It is also the least influenced by SelectHealth initiatives. Some of the disease definitions for identifying patients with depression were influenced by SelectHealth. However, all patients regardless of insurance coverage are identified and included in the depression registry. Included are patients who were identified with depression in an outpatient

environment as well as those identified with diagnosed depression in an inpatient/ER setting.

Intermountain Data Sources

Although source systems support specific and varied business needs, sometimes the data from source systems may overlap in content. For example, a patient treated within Intermountain's integrated health care system may be treated for diabetes at one of the Intermountain clinics. A bill will be processed and generated for care provided. Medical coding standards have developed over the years to identify what was done to the patient, by whom, and when it was performed. These coding standards exist in most health care systems. Clinicians are paid based on what was documented in the billing for the visit. They have a vested interest to code appropriately to ensure proper payment. Two common medical coding standards are CPT and ICD-9/10 standards. Current Procedure Terminology (CPT) codes are used for physician billing by documenting exactly what was done on the patient and by whom. International Classification of Disease, Version 9 (ICD-9) and Version 10 (ICD-10) codes are standard codes classifying diseases and these are also used for billing purposes.

If the diabetic patient from the preceding example happened to be insured by SelectHealth (Intermountain's wholly owned payer), records would exist in the claims system documenting what was done to the patient during the visit. The same CPT and ICD-9/10 codes would likely exist in the claims and billing systems to document the diabetic visit. Within the EDW, the billing and claims systems overlap in their documentation for this patient visit even though claims and billing serve two very

different purposes. At Intermountain, the diabetes visit would have also been recorded in detail within the EMR, thus creating an additional source of record for the diabetes care received by the patient. Independently, the source systems which captured pertinent information to document the diabetic visit would have no overlap. Within the data warehouse, the combination of multiple data sets presents this unique and overlapping perspective on the patient care.

As stated earlier, one of the challenges of disease representation within an EDW is to not over-represent combined data elements coming from multiple source systems. An example of over-counting could happen as follows. Within Intermountain's EDW, the definition of depression is represented through a number of rules. One of these rules states that if a patient has two or more outpatient visits with a diagnosis of depression during a one-year period, then a patient would qualify to be in the depression registry. Suppose that a patient is covered by SelectHealth and this patient goes to her PCP for depression-related treatment. Her PCP treats the patients for mild depression. Three weeks later, the depression appears to have gone into remission. Assume the patient had no other depression-related visits for the rest of the year. The PCP will bill SelectHealth to reimburse the provider for care given. SelectHealth will generate a claim on the patient visit.

In the example given above, if the patient had only one documented visit for depression and no other depression rule was met during that year, then the depression registry rules mandate the patient should not be included in the depression registry. This scenario becomes interesting within the EDW. Data from billing and from claims are brought into the data warehouse. Copies of the depression visit from both sources would

be included in the primary care data mart. If the data architect did not recognize that the documented depression visit was represented in both claims and billing, and s/he used both billing and claims as sources to feed the depression registry, s/he could erroneously count the visit twice and consequently put the patient into the depression registry. The ETL process requires that data architects understand how data from different source systems can be related and how they may not be related. The risk here is to not over-represent data elements (false positive) on a patient by combining all feeding sources into one source of truth while at the same time not omitting key data elements (false negative) which could preclude qualified patients from being included in a registry.

Reporting Against Intermountain's EDW

In 1999, the first version of the diabetes registry was built at Intermountain Healthcare. The asthma registry was built a year later. In 2005, the first depression registry was built. Much of the value from the registries surfaced through reports built on data found in the registries. For the first time, PCPs could get a population view of their patients suffering from chronic disease. From 2000 – 2008, PCPs received a quarterly report for the diabetes and asthma registries. A robust algorithm was developed to map patients to a PCP each reporting period. All patients mapped to a provider would show up on his/her diabetes or asthma report (or both) at the end of each quarter.

Included in the reports were patient demographics such as name, age, and hospital account numbers plus a host of clinical indicators. Over the years, the reports became more sophisticated to help providers better manage their patients. For example, patients were tiered into low, medium, and high-risk groupings. High-risk patients appeared at

the top of the report. Medium-risk patients were in the middle and low-risk patients appeared at the bottom. The most recent lab values for some labs were displayed at the patient level, allowing providers to get a feel for disease progression. For nearly a decade, this model of disease reporting was refined and met many of the reporting needs within Intermountain's Primary Care Clinical Program. Nearly a thousand providers received this quarterly report on their patients. In late 2009, reporting moved from a quarterly basis to a monthly basis for asthma and diabetes. In 2009, the depression registry was completely overhauled and the first depression report went out to PCPs with their respective depressed patients. Since 2009, diabetes, asthma, and depression are reported to PCPs on a monthly basis.

Ironically, the advent of the new depression registry presented new challenges for PCPs. Adding one more disease-focused report seemed unsupportable to PCPs in the Primary Care Clinical Program. PCPs became frustrated with the disease-reporting paradigm. The common co-existence of diabetes and depression in patients was surfaced through reporting on patients who had multiple comorbidities. PCPs had to manually compare conditions of individual patients across multiple reports. These providers were faced with the challenge of assimilating information on the same patient across two, sometimes three, reports and the process of report comparison was disruptive to clinical work flow.

Intermountain's EDW has thousands of scheduled reports which run on a daily basis, not to mention the thousands of ad-hoc daily queries run against the warehouse as well.

Reporting Challenges at Intermountain

Intermountain's approach to EDW accessibility has been to give appropriate access to those (generally analysts) who need to use data to perform their core job function. Database roles are created and given read-only rights on tables within the EDW. People who are approved to access Intermountain's EDW are added to these database roles to access the data they need. Analysts at Intermountain write reports against the EDW. Additionally, they have the ability to do ad-hoc queries against the EDW. Quality improvement and research efforts at Intermountain drive analysts to spend significant time writing ad-hoc queries against the EDW. Hundreds of employees have access to query thousands of tables within the EDW. The rich data sources feeding the EDW are a blessing and a curse. Analysts who do not understand overlapping systems of record within the EDW run the risk of building reports which are incomplete or inaccurate.

Operationalizing Clinical Practice Guidelines

Intermountain has adopted CPGs for chronic disease management. At Intermountain, the process of operationalizing CPGs is referred to as a Care Process Model (CPM). This nomenclature is a peculiar adaptation because outside of Intermountain, a CPM refers to a framework or model of care, such as Wagner's Chronic Care Model (65). For the purposes of this study, any reference to a CPM will be within the Intermountain context. Intermountain has developed CPMs around asthma, diabetes, depression, and many other diseases. Several CPMs exist within the Primary Care Clinical Program at Intermountain Healthcare. For example, the diabetes CPM

recommends that each year, the patient receives the following care: eye exam, foot exam, blood pressure testing, Hemoglobin A1C, Microalbumin urine test, and HDL/LDL testing. For asthma, the CPM mandates that the patient have a pulmonary function test and that the patient be on a prescribed controller.

Primary Care Clinical Program

The Primary Care Clinical Program (PCCP) is one of several clinical lines developed at Intermountain Healthcare . Others clinical programs include Pediatrics and Women and Newborn. Clinical support services also exist, such as laboratory and radiology. The purpose of clinical programs at Intermountain is to strategically align business and clinical practices and to develop and disseminate best practices of care along each clinical line. The PCCP holds a monthly meeting for regional directors and their staff to attend. During this meeting, issues related to primary care are discussed and resolved. CPMs are evaluated and refined within workgroups. Clinical outcomes are often evaluated as well. This is a collaborative forum of collective discovery and knowledge dissemination.

The PCCP is geographically diverse as Intermountain Healthcare provides care across the entire state of Utah and some portions of Idaho. For practical purposes, the PCCP is broken down into regions. PCPs within a given region report to a PCP acting as a regional director. The regional director is responsible for ensuring that information shared at the monthly PCCP meeting is made available to all who practice within the region. It should also be noted that not all PCPs within the PCCP are employed by Intermountain Healthcare. Some PCPs and clinics have business agreements with

Intermountain to align themselves with Intermountain in order to gain access to the many resources available from an integrated system (such as an EMR, billing, labs, Rx orders, etc.). These nonemployed PCPs are referred to as affiliated physicians. Regional directors are responsible to ensure that affiliated PCPs and clinics also have access to the information coming out of the PCCP.

METHODS

Tools and Technologies

All data used in this research came from Intermountain Healthcare's EDW. The EDW is built on an Oracle database platform, version 10g. Connections to the EDW for querying purposes were done using Oracle's freeware SQLDeveloper. The process of extracting, transforming, and loading (ETL) data into the model was done completely through hand-written, SQL scripts using SQLDeveloper. Scripting for table creation, staging data, and ETL can be found in the scripting appendix. After data had been staged and loaded into the final dimensional model, Microsoft's Business Intelligence Developer Studio (BIDS) was used to design the structure of the cube. SQL Server Analysis Services (SSAS) was used to process the chronic-conditions cube. Microsoft SQL Server 2005 was the database platform for the back-end database where the cube was hosted. Excel 2007 was used as the cube-viewing tool for this research.

Cohort Identification

All patients for this research were identified from the three chronic disease registries within the Primary Care Clinical Program, namely asthma, diabetes, and depression. Not all patients from the registries were included. Only patients that

appeared in at least one of the disease registries between 01-Jul-2009 and 28-Feb-2011 were included in this research.

Patients identified in the diabetes registry are 18 or older. Patients with any payor type are included in the diabetes registry. A patient diagnosed with diabetes stays in the diabetes registry until the patient moves away or dies. The asthma registry includes only patients ≥ 18 years of age. Furthermore, only patients covered through SelectHealth (Intermountain's insurance arm) are included in the asthma registry. Asthma patients must meet clinical definitions for asthma each reporting period or they fall out of the registry and must qualify in a future reporting period. Patients from the depression registry include all ages and payor types. A patient in the depression registry stays active within the registry for one year at a time. If one or more rules qualify the patient to stay in the registry, the most recent rule qualifies the patient to stay in the registry for another year.

No attempt was made to challenge any of the rules of registry qualification for any of the diseases. The model simply accepted the definitions of disease adopted by Intermountain Healthcare. Mapping algorithms for the three disease registries differ in their approaches to assigning patients to a PCP. The differences were acknowledged though not challenged in this research.

The patient_classified table is the pivotal table for the diabetes registry. It contains unique identifiers for each diabetic patient. Additional patient demographic information is also captured. The tables surrounding patient_classified are supplemental tables providing needed information, such as medications, results from laboratory and/or clinical tests, and which PCP the patient belongs to for a given reporting period.

Figure 4 gives a visual representation of the organizational structure of the data for the diabetes registry. It does not show logic or data elements behind the tables.

Payer information is captured in the `pt_enrlmnt_hstry` table. The table on the far right of the diagram is the `pt_dbts_test_smry` table. It is the outward facing, visible diabetes table that drives the monthly PCP diabetes report. One row in the `pt_dbts_test_smry` table represents one patient for a given report period. The `pt_dbts_test_smry` table is loaded monthly. Consequently, if a patient had diabetes for the entire year of 2010, there would be 12 rows of data for the patient.

Appendix A shows the coding and logic used to identify patients with diabetes. It also shows codes for clinical values of interest to help providers better manage their diabetic patient populations respectively. Asthma and depression follow the same pattern though similar registry diagrams and patient identification code examples are not included in this paper.

Referring to Appendix A, the first page begins with documentation of the `primcare.patient_classified` table. On the left of the model are source systems (transaction OLTP) of record. Four primary sources are used to identify patients with diabetes. They are Health Plans claims data, outpatient billing (IDX), CDR (Clinical Data Repository, the database behind the electronic medical record) database, and Sunquest Lab data. Additionally, pharmacy data are used as a source of exclusion criteria to keep patients who have polycystic ovarian disease out of the diabetes registry.

Appendix A lists codes used to identify diabetic events. The combinations of these data elements qualify patients for inclusion in the diabetes registry. Standardized

Intermountain Diabetes Registry

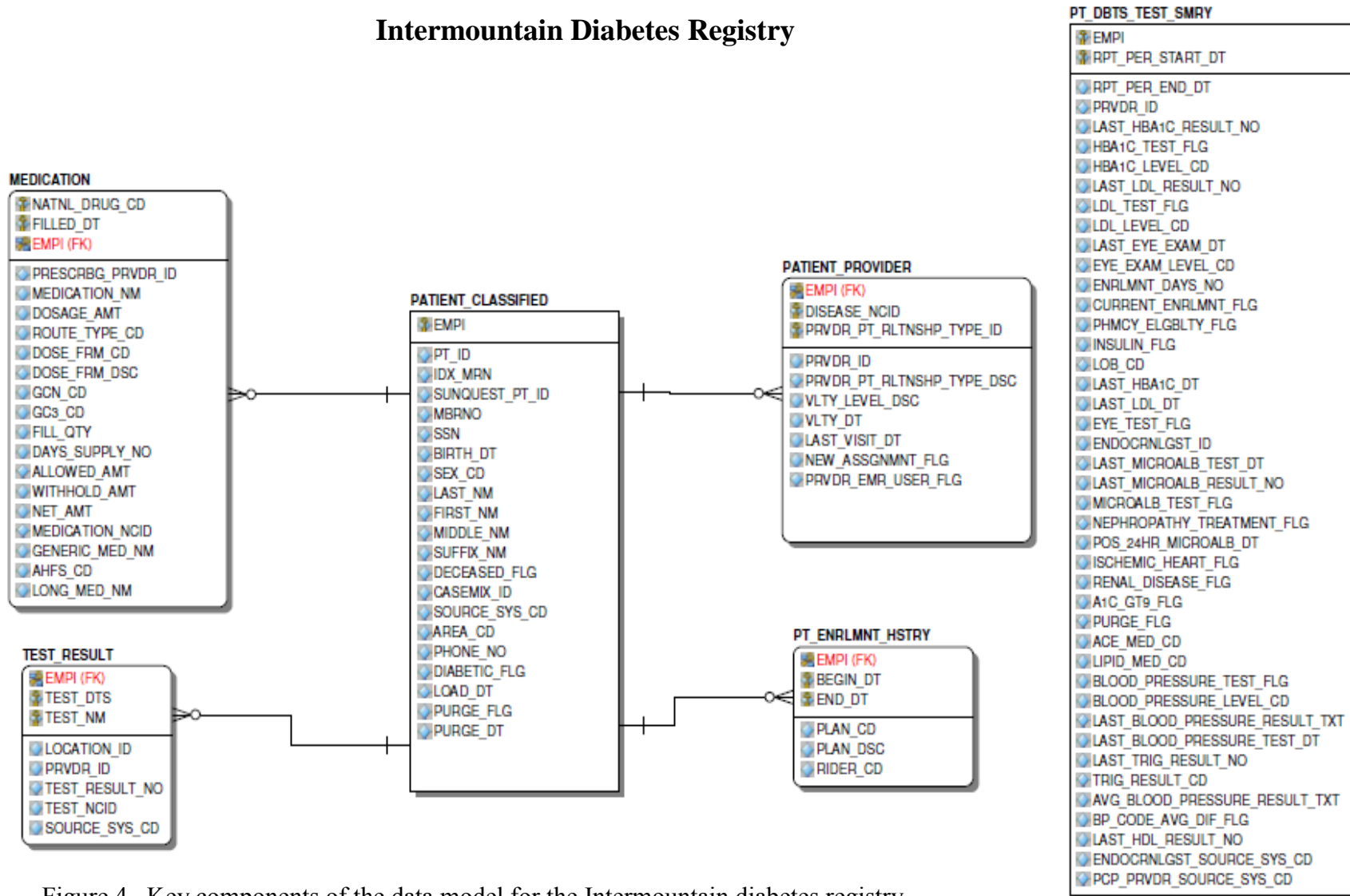


Figure 4. Key components of the data model for the Intermountain diabetes registry.

coding such as CPT, ICD-9, DRG, UB92, and NCID were used to identify diabetic events from source systems. English definitions for each rule used to identify a diabetic patient are documented as metadata in Appendix A. The rules for inclusion in the registry were determined by the Primary Care Clinical Program (PCCP) leadership.

Appendix A lays the foundation for the diabetic registry by first identifying the cohort of interest for a given time period. The remainder of Appendix A documents additional attributes of interest for diabetic patients, such as blood pressure values and dates, HBA1C values and dates, etc. All elements in the diabetic registry were defined by the PCCP composed of clinical leadership.

The asthma and depression registries in the EDW follow a similar pattern as that of diabetes. Each registry first identifies the cohort of interest for the current reporting period, then captures supplemental attributes for the newly identified cohort. As asthma and depression follow similar patterns to diabetes, they are not documented in Appendix A.

Care Process Model Definitions

The Care Process Models (CPMs) used in this research were taken from those adopted by the PCCP at Intermountain Healthcare for asthma, diabetes, and depression. The asthma CPM is outlined in Table 1. For the diabetes CPM, see Table 2. For the depression CPM, see Table 3.

Table 1. Identifies CPM components within the asthma data

Disease	CPM Component
Asthma	Pulmonary Function Test < 12 months
Asthma	Fill controller Rx < 12 months

Table 2. Identifies CPM components within the diabetes data

Disease	CPM Component
Diabetes	Hemoglobin A1C tested < 12 months
Diabetes	LDL tested < 12 months
Diabetes	Microalbumin urine test < 12 months
Diabetes	Blood pressure tested < 12 months
Diabetes	Eye exam < 24 months
Diabetes	Foot exam < 12 months

Table 3. Identifies CPM components within the depression data

Disease	CPM Component
Depression	PHQ9 tested <12 months
Depression	F/U visit with PCP < 31 days after Inpt/ER visit
Depression	F/U visit with PCP < 46 days after PHQ9 >14

The tables above document the written English definition of CPM components for asthma, diabetes, and depression. The data used to identify the CPMs come from supplemental tables surrounding the aforementioned cohort table (patient_classified). Using diabetes once more as an example, refer to Appendix A. The section labeled primcare.test_result captures all laboratory tests/results relevant to diabetic management. Specifically, the PCCP leadership tracks HBA1C, microalbumin, HDL/LDL, foot exam, and eye exam data.

Within Appendix A in the `primcare.test_result` section, all source systems used in the ETL process are identified. They are IDX, CDR, LabCorp, Sunquest, and HealthPlans claims systems. Metadata for each value of interest within the `primcare.test_result` section is documented. The metadata definitions were determined by PCCP leadership.

No attempt was made to challenge the validity of CPMs adopted by Intermountain to manage their patients with diabetes, asthma, or depression. Existing metadata from the asthma, diabetes, and depression registries, along with supplemental attributes, were accepted and included in this work.

Patient Provider Mapping

At the time of this study, the Intermountain asthma, diabetes, and depression registries are loaded on a monthly basis. For each reporting period, patients' clinical information is run through algorithms in an attempt to determine which PCP is most likely responsible for a patient's care. If a PCP can be identified, then the patient is mapped to a provider. For this study, patients were mapped to PCPs using algorithms already in place on each of the registries. Diabetes is the oldest, most trusted registry for mapping patients to a provider. The priority of mapping for the CCMT went as follows:

- 1) if the patient has diabetes, use the provider to whom the patient was mapped for the given reporting period;
- 2) If no mapping exists (these patients are referred to as orphaned), check to see if the patient also has asthma for the same reporting period and use that provider mapping;
- 3) If no mapping exists at the asthma level, move to the depression registry and search for a patient/provider mapping during that reporting

period; 4) If no prior mapping exists, the patient is assigned to the orphaned group and still counted in the study. For this study, an attempt was made to map patients to PCPs for each reporting period.

Extract Transform Load Process (ETL)

Data elements used to represent the Care Process Model (CPM) logic for each disease are embedded within the ETL process of each disease registry. CPMs are not used for cohort identification. A CPM has applicability only after the disease cohort has been identified. In other words, CPMs have a dependency on an already established patient cohort.

For example, one component of the diabetes CPM requires that an HBA1C lab test be run at least annually. A number of data sources in the EDW supply the data needed to determine whether a component of the diabetes CPM was met or not. In the claims data, there may be a specific CPT code indicating that an HBA1C test was performed. Billing data may also contain that information using the same, standard CPT code to identify the lab test. The EMR could also serve as source of the data. In this case, it would not be represented using a CPT code. Rather, a unique code, called a numeric concept identifier (NCID) specific to the health data dictionary and the CDR (back-end database behind Intermountain's EMR) could represent the HBA1C event. For a complete listing of all coding, data elements, and sources for the diabetes registry, see Appendix A.

To consolidate the potentially overlapping data sources needed to capture data elements representing each of the CPM components, intermediate staging tables were

created. In Appendix A, referring to HBA1C identification in the `primcare.test_result` section, the table `test_result` is one example of a staging table. Logic in the ETL process consolidates overlapping copies of the same clinical event so that the complete event is represented faithfully in the downstream, `pt_dbts_test_smry` table. A consistent, single representation of the CPM elements emerges from the staging tables to the summary or reference tables.

The ETL process above described the data flow from source systems into the EDW and into the disease registries. Similarly, for this research, I created an ETL process except that instead of pulling data from the original systems (claims, billing, CDR, etc.), I used the existing asthma, diabetes, and depression registries as my sources to feed the chronic conditions management model. No new data were brought into the EDW for the CCMT. Additional tables within the EDW were included to support the CCMT. Master reference tables were used to supplement characteristics for patients, provider, clinics, and regions. The data flow for the CCMT is shown in Figure 5.

With all staging and reference tables loaded, the ETL process ran once for each reporting period starting with 01-Jul-2009. Included in the loading of the dimensional model is a patient-provider mapping for each reporting period.

The CCMT model required the ability to query large databases, extract data, and write it out to staging and summarized tables. The EDW team granted me access to build the CCMT within the EDW-DEV environment. I ran the ETL in EDW-DEV and was able to populate the dimensional model in EDW-DEV as well.

Dimensionally Modeling Chronic Disease Management

The aforementioned Figure 3 shows the chronic conditions dimensional model. It is made up of two fact tables, namely `cpm_compliance_fact` and `dim_chronic_detail`. They are surrounded by three dimensions, namely `dim_provider`, `dim_patient` and `dim_rpt_period`. The primary keys on the dimension tables are foreign keys in the two fact tables to enable quick lookups. In the `cpm_compliance_fact` table, all components of the asthma, diabetes, and depression CPM are captured as facts. The facts are tied to providers and reporting periods to facilitate trending over time when the model is consumed by a cube. Figure 5 shows the logical flow of data captured in the chronic conditions dimensional model.

Chronic Conditions ETL Flow Diagram

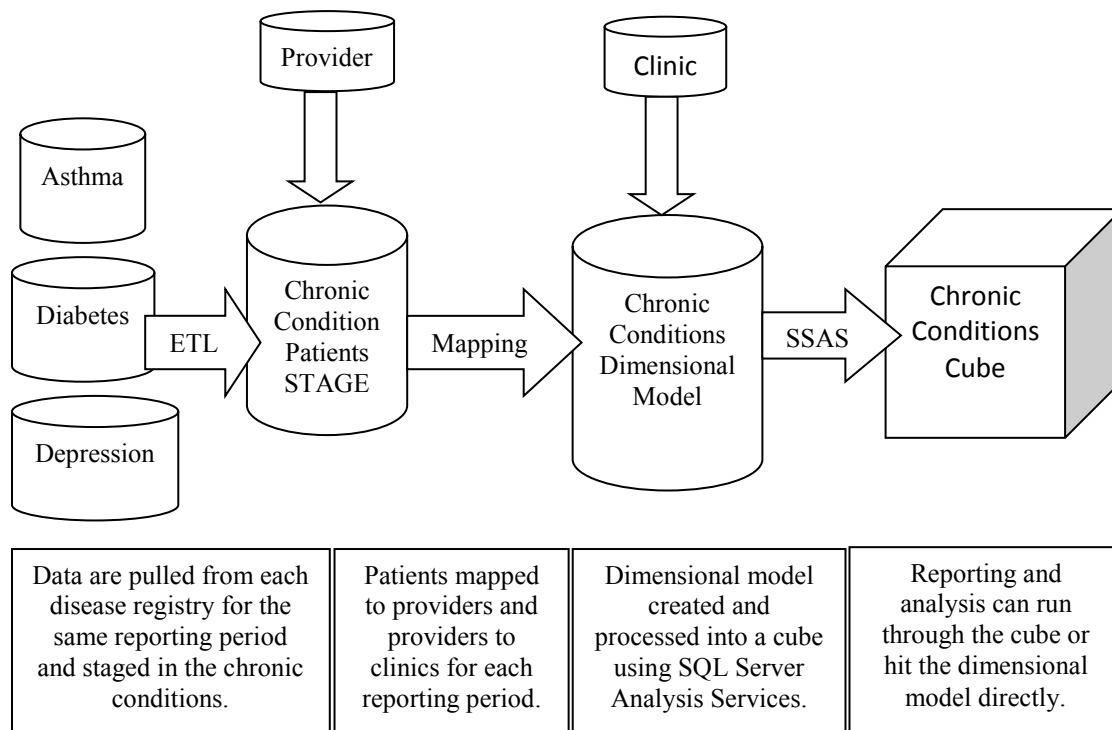


Figure 5. Highlights key components within the chronic conditions data mart.

The dim_chronic_detail fact table captures data at the most detailed level. It includes supporting attributes for related metrics. For example, in the cpm_compliance_fact table, we could see whether or not a patient had an A1C test done during a given reporting period. The dim_chronic_detail table includes more granular data by including the A1C test date along with the resultant A1C value.

Cubes

The chronic conditions cube was built on top of the chronic conditions dimensional model. It was hosted within the Intermountain EDW on an instance of SQL Server 2005. The cube was processed using Microsoft's SQL Server Analysis Services (SSAS).

Cube Calculations

Within the CCMT, PCPs' adherence to CPMs is captured and measured for their respective patient populations. Rates of compliance to the CPMs were calculated within the cube structure using Microsoft's SQL Server Analysis Services (SSAS). The rates were calculated at the individual PCP level for each CPM component (LDL tested, A1C tested, etc.). To be included in the denominator for each CPM measurement, a patient was required to have the disease pertaining to the CPM. To calculate compliance to the diabetes CPM for eye exam testing, the calculation would be:

(Sum the number of eye exams for patients mapped to provider for given report period)/

(Sum the number of patients with diabetes mapped to provider for given report period)

The same calculation format was done for each component of each CPM (asthma, diabetes, and depression). Rates were expressed as percentages within the cube. Excel 2007 was the tool chosen to view the chronic conditions cube. It is not uncommon for patients to see more than one PCP during a reporting period so it is possible that credit for CPM compliance may be given to a PCP when in reality, the measure was met by another provider. This was acknowledged but not changed across the population.

Accessing the Chronic Conditions Cube

Excel 2007 was the cube viewing tool. Microsoft enhanced Excel 2007 to seamlessly integrate with SSAS. Connecting to the cube requires a few simple steps. After a connection was made, I saved and re-used the connection with future connections/cube viewing. The chronic conditions cube did not attempt to tie in AD security permissions.

RESULTS

CCMT

The Chronic Conditions Management Tool is the resultant product for this project. 183,665 patients were included in the model between 01-Jul-2009 and 28-Feb-2011. Four components constitute the CCMT. They are ETL, the chronic conditions dimensional model, the chronic conditions management cube, and reporting against the chronic conditions management cube.

ETL Scripting

All ETL coding may be found in Appendix A, including scripts for table creation, data staging, and data loading into the dimension and fact tables.

Chronic Conditions Dimensional Model

The CCMT dimensional model contains a chronic conditions fact table, a patient detail fact table, a patient dimension, a reporting-period dimension, and a provider dimension. A diagram of the chronic conditions dimensional model is shown in Figure 6. The CPM for each disease was logically represented within the dimensional model and captured as non-key attributes (columns) on the fact tables. Two fact tables exist within the dimensional model, namely dim_chronic_detail and cpm_compliance_fact.

Chronic Conditions Dimensional Model

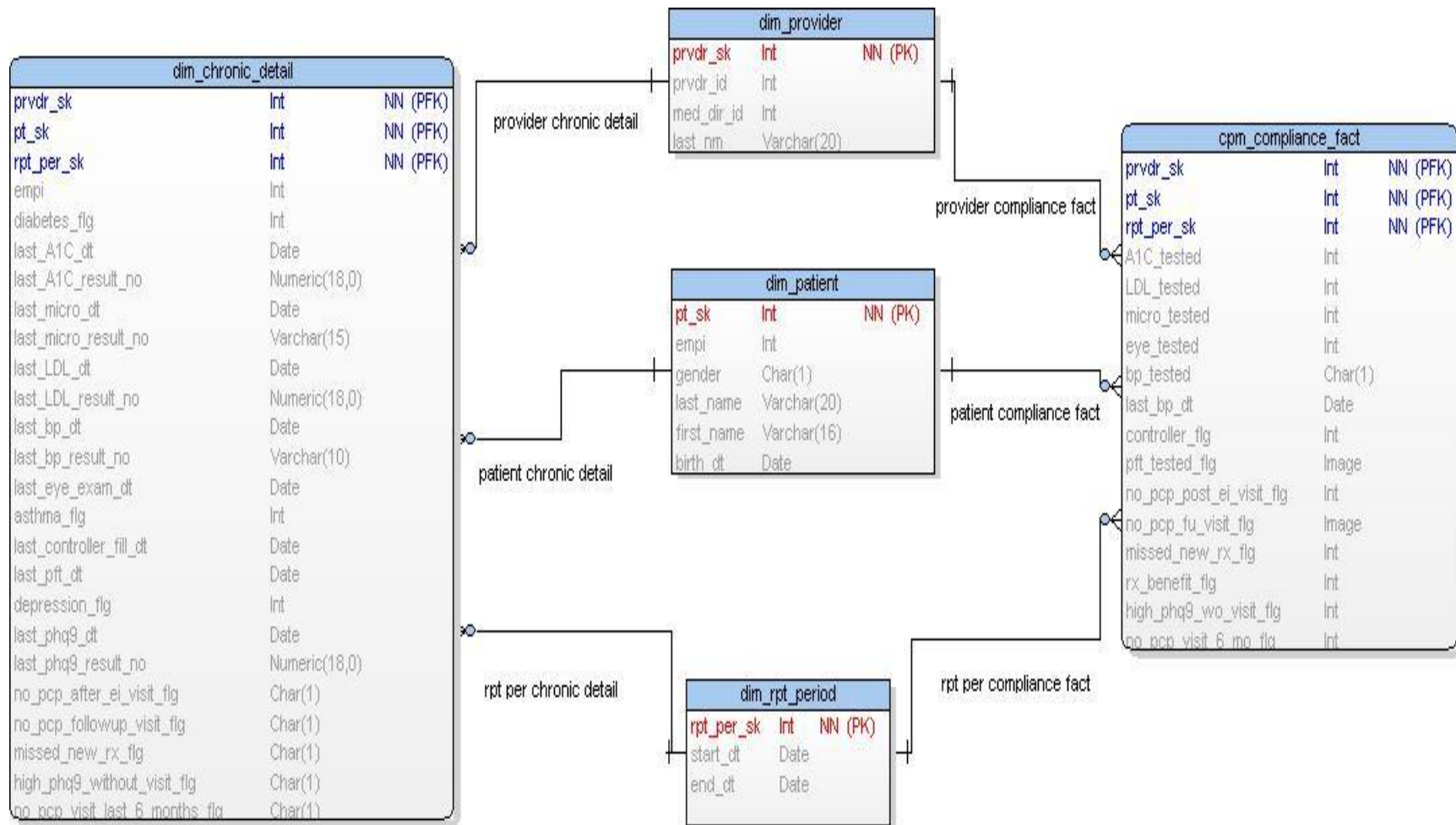


Figure 6. Three dimensions and two fact tables are included in the chronic conditions dimensional model. All three dimensions relate to each fact table.

The grain (a row) of the `pt_detail` fact table uniquely identifies a patient mapped to a provider for a given report period and includes the resultant lab values and dates for care delivered over a given disease. The `dim_chronic_detail` fact table is the basis for actionable, patient-detail reporting requested by PCPs. It captures data at the most granular level of the reporting, that is, by patient and by reporting period. Every aspect of each CPM is represented in the `dim_chronic_detail` table. Non-key attributes include such data elements as, a diabetes flag (indicating whether or not a patient has diabetes), an asthma flag, a depression flag, the last hemoglobin A1C result and date, along with all other data elements captured to represent each disease CPM.

The grain of the `cpm_compliance_fact` table uniquely identifies a patient mapped to a provider for a given report period columns representing all components of each CPM for asthma, diabetes, and depression. No clinical values or dates were included in the `cpm_compliance_fact` table. To represent compliance to the CPM for a given disease, each component of the CPM was expressed as follows. If the CPM was met for a given measure, a 1 was entered on the column; otherwise, a 0 was entered. For example, if a patient had asthma during the 01-Jan-2010 report period, the asthma CPM requires that the patient receive a pulmonary function test (PFT). If the patient had a PFT done during the reporting period, a 1 would be entered on the PFT column. Otherwise, a 0 would be entered. Nulls were not allowed on any measure field for any of the CPMs.

The model required that a patient have at least one chronic condition during a given report period to have a row in either fact table. Sometimes, patients had multiple comorbidities during a report period. Each fact table had a column to represent each disease that a patient may have. For example, if a patient had diabetes and depression but

not asthma during the 01-Jan-2010 report period, then there would be a 1 in the diabetes and depression columns on each fact table for that patient. However, there would be a 0 in the asthma columns for the same patient.

Three dimensions surround the two fact tables. They are dim_provider, dim_patient, and dim_rpt_period. Dimensions are related to fact tables through foreign-key relationships. The primary keys from the dimension tables constitute the primary keys on the fact tables. The primary key on the dim_provider table is a surrogate, identity key generated by the Oracle database. The dim_patient and dim_rpt_period tables each have surrogate primary keys generated by Oracle, following the same pattern as the dim_provider table. These surrogate keys comprise the primary keys on the dim_chronic_detail and cpm_compliance fact tables. See Figure 5 to see the primary key columns on the fact tables and their relationships to the dimensional tables.

The dim_provider table contains information about each clinician. It contains the provider_id, to whom the provider reports (Medical Director), the provider's last name, and the primary clinic where the provider practices medicine.

The dim_patient table contains several demographic attributes on patients. Gender, birth date, and age bracket were included to allow grouping of patients according to gender and age. City, state, and other attributes were included as well.

The dim_rpt_period captured all the valid reporting periods for the course of this study. This captured the start and end dates for each reporting period. These date attributes allow all fact table measures to be viewed over time.

Chronic Conditions Management Cube

The chronic conditions cube was built within Microsoft's BIDS environment. The cube structure is based on the chronic conditions dimensional model. Using SQL Server 2005, the dimensional model was pulled into the BIDS environment. Relationships were identified or created within BIDS for each of the tables in the model.

Within the chronic conditions cube, two hierarchies were created. They were built on the provider dimension and the patient dimension. The provider hierarchy is a geographic grouping of providers. It rolls up as follows: provider → clinic → region. One or more providers work in a clinic. One or more clinics are in each region. Within the PCCP, there are six regions covering all of Utah and parts of Idaho and Wyoming. Included in the PCCP are providers who are affiliated with Intermountain Healthcare though not employed by Intermountain. Some of the affiliated PCPs did not map in the hierarchy, so an 'unknown' value was inserted into the region field to allow all PCPs to map to either a region or the unknown grouping. The patient hierarchy was also geographic in nature and was represented as follows. Patient → postal code → city → state. A patient lives within one postal-code. One or more postal codes are in a city. Many cities are within a state.

The reporting period dimension was a proxy for a true date dimension within the dimensional model. A time dimension is almost always included in a cube. Time hierarchies are common in cubes, though creating a time hierarchy was not possible with this cube due to limitations within the existing diabetes, asthma, and depression registries. This peculiarity is explained in detail in the discussion section.

Reporting Against the Chronic Conditions Cube

Reporting against the chronic conditions management cube was done using Excel 2007. An Excel file was emailed or directly installed on a PCP's desktop to allow him/her to connect to the cube. Five tabs were included in the Excel file. They were named as follows: Asthma CPM, Diabetes CPM, Depression CPM, Patient Detail, and Ad-hoc. The first four tabs included prepopulated tables and graphs. For a PCP to view his/her compliance rates for the most recent reporting period on each tab, s/he would select his/her PCP user-id from a drop-list and the table and graphs would be updated. An example of the first tab for provider 29788 is shown Figure 7.

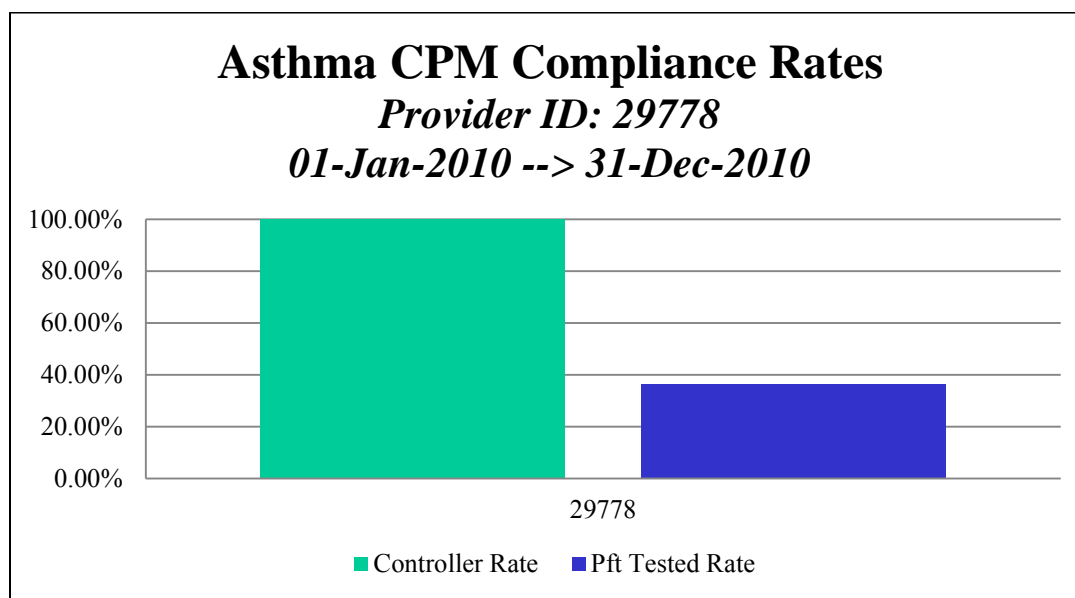


Figure 7. Provider example shows 100% compliance on controller rates and <40% compliance on pulmonary function tests.

The graph in Figure 7 indicates that provider 29778 was 100% compliant with the asthma CPM for his/her asthmatics being on a controller medication during between 01-Jan-2010 and 31-Dec-2010. The graph also shows that provider 29778 provided < 40% of his/her asthmatic patients with the pulmonary function test. The diabetes and depression tabs had similar graphs included as well, each showing levels of compliance for each CPM component.

The Patient Detail tab within the Excel file gave providers actionable information on their patient population only for the most recent reporting period. An example of the Patient Detail tab is given in Figure 8. Blue columns highlight the three diseases represented in the model. A red box indicates a component of the CPM that was missed by the provider. A yellow-highlighted field indicates that a patient is within one month of falling out of compliance for a given component of the CPM.

Figure 9 is an example of the ad-hoc analysis tab. This tab in the Excel file allowed PCPs to explore the cube and do their own analysis. Highlighted are three key sections. The section highlighted in red is where the measures are displayed. The values rendered are a function of the other two highlighted areas. In the green highlighted section, measures and dimension values are chosen to filter the selection. In this example, both fact tables from the model are visible, namely `cpm_compliance_fact` and `dim_chronic_detail`. The patient, provider, and report period dimensions are also visible. The [+] sign next to each of the facts and dimensions indicate that each can be expanded to reveal measures within the fact tables and attributes of the dimensions. The yellow highlighted section shows the current selections from the facts and dimensions in the green highlighted section.

Chronic Conditions Patient Detail Report

Provider: Steve Cannon (2214)				Reporting Period: 01-Mar-2010 --> 28-Feb-2011												
Patient Name (fake)	Sex	Age	Diabetes	A1C	LDL	Micro	Eye Exam	FootExam	BP	Asthma	Controller	PFT	Depression	PHQ9	Outpt Visit	ER F/U
Abby Barnett	F	29	Y	29-Mar-10	21-May-10	21-May-10	21-May-10		27-Jun-10	N			Y	27-Mar-10		8-Nov-10
Jacob Turner	M	44	Y	17-Jun-10		17-Jun-10		17-Aug-10	17-Aug-10	N			N			
Joseph Watts	M	33	N							Y			Y		30-Sep-10	N/A
Mary Thomasan	F	54	Y		26-Oct-10	19-Jan-10	29-Dec-10	29-Dec-10	13-Mar-10	N			Y	1-Nov-10	19-Mar-10	N/A
Mel Diffens	M	61	Y	17-May-10	17-May-10	17-May-10	17-May-10	17-May-10	17-May-10	N			N			
Nancy Griffs	F	40	N							N			Y		13-Oct-10	3-Nov-10
Nenny Wiggins	F	39	Y	21-Jul-10	21-Jul-10	21-Jul-10		21-Jul-10	13-Nov-10	N			Y	11-Mar-10	11-Mar-10	N/A
Oscar Wilde	M	61	N							Y	21-Aug-10	21-Aug-10	N			
Peter Broom	M	19	Y	3-Mar-10	3-Mar-10	3-Mar-10	1-Jun-10	3-Mar-10	14-Jul-10	Y	13-Dec-10	22-Feb-10	N			
Samuel Childs	M	23	Y	30-Sep-10	30-Sep-10	30-Nov-10	2-Mar-11	16-Mar-10	17-Aug-10	N			N			
Zachary Tuft	M	49	N							N			Y		3-Sep-10	N/A

Figure 8. Sample chronic conditions report for a provider at Intermountain. Diseases in the model are highlighted in blue with corresponding CPM elements in the columns that immediately follow each disease.

Chronic Conditions Pivot Table

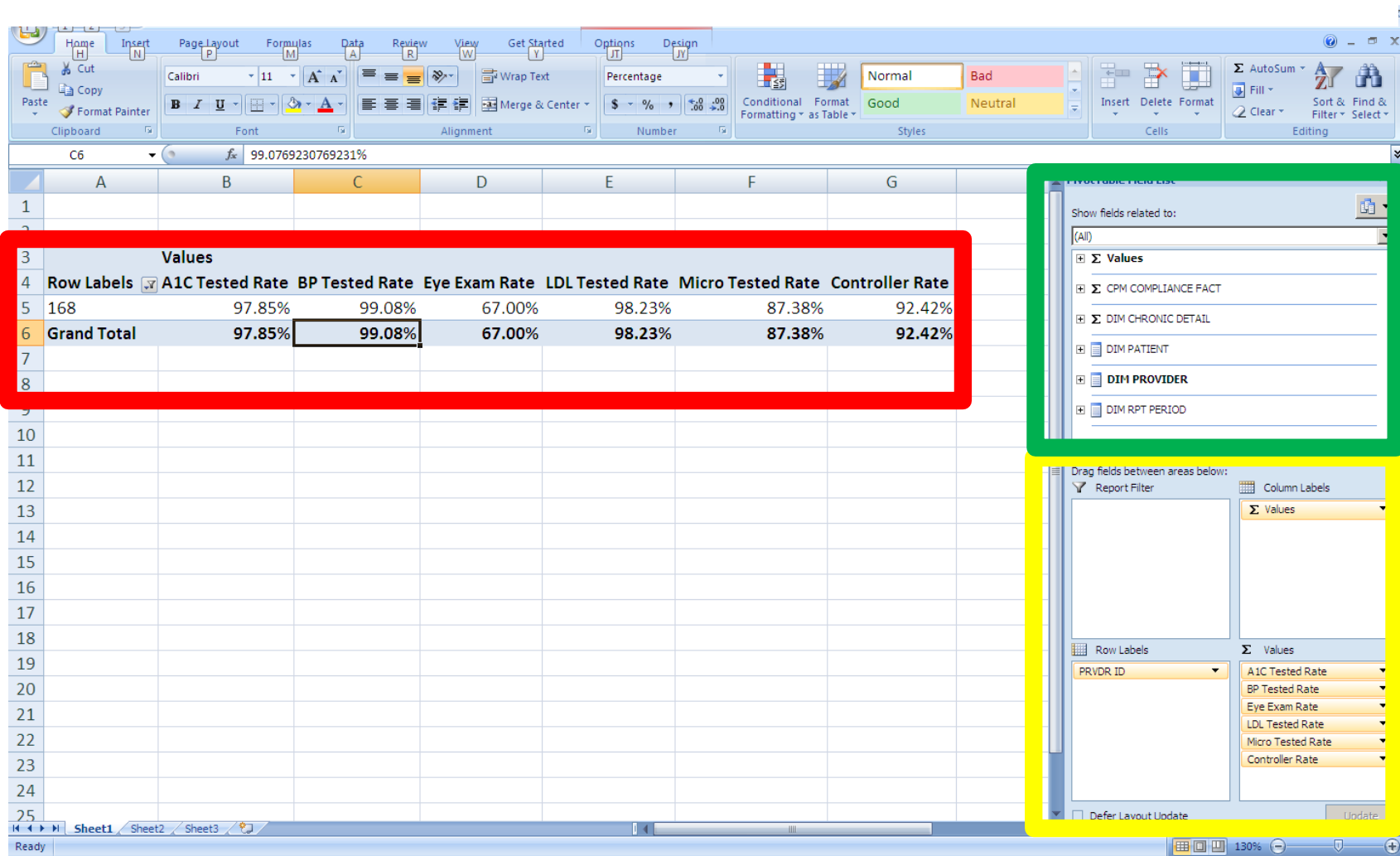


Figure 9. Sample pivot table from the chronic conditions cube focused on provider ID 168.

The example in Figure 9 shows the column values for the analysis will be rendered as A1C Tested Rate, BP Tested Rate, Eye Exam Rate, LDL Tested Rate, Micro Tested Rate, and Controller Tested Rate. The row-level granularity is at the `prvdr_id` (provider ID) level. The only row that shows up in this analysis is for provider 168 because the provider dimension is filtered to only render for provider 168. The filter can be removed to show all providers in a clinic.

Figure 10 shows the filter on the provider dimension is set to only show provider 168. The filter could be set to include any or all providers. Also visible in Figure 10, beneath the provider dimension (green section) is the provider hierarchy option. If selected, the values in the red highlighted section change to show the same columns, but now the rates are calculated and aggregated at the region level.

Figure 11 illustrates some of the hierarchical capabilities of dimensions. In this example, the red section shows rate calculations at three different levels. The highest level is the region level, rolled up to the Medical Director over each region. The [+] next to the provider ID of each Medical Director indicates that the values can be expanded to drill into the clinics within the region. Likewise, each clinic has a [+] to expand and show each provider at the clinic. The rate calculations render on the fly within the SSAS cube engine. To clarify, Medical Director 4711 has 88.41% compliance for his/her region on A1C Tested Rate. There are clinics which roll up to the Medical Director and their collective rates determine the overall region rate. Within the Sevier Valley Family Practice clinic, there are three PCPs who practice. Their individual compliance rates for A1C Tested are shown in Figure 11.

Chronic Conditions Provider Report

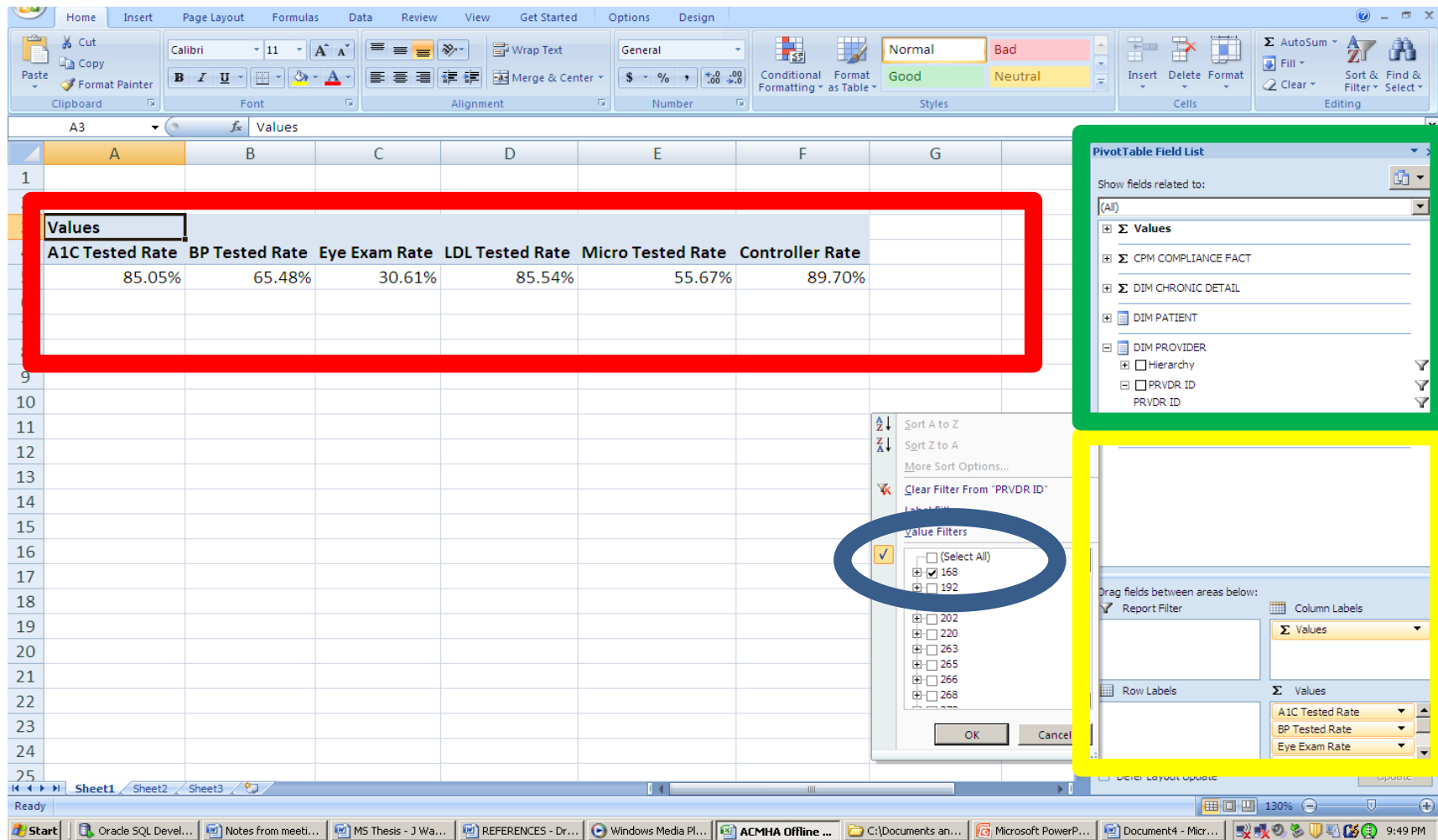


Figure 10. Sample page from chronic conditions cube pivot table highlighting ability to analyze by any provider.

Chronic Conditions Region Report

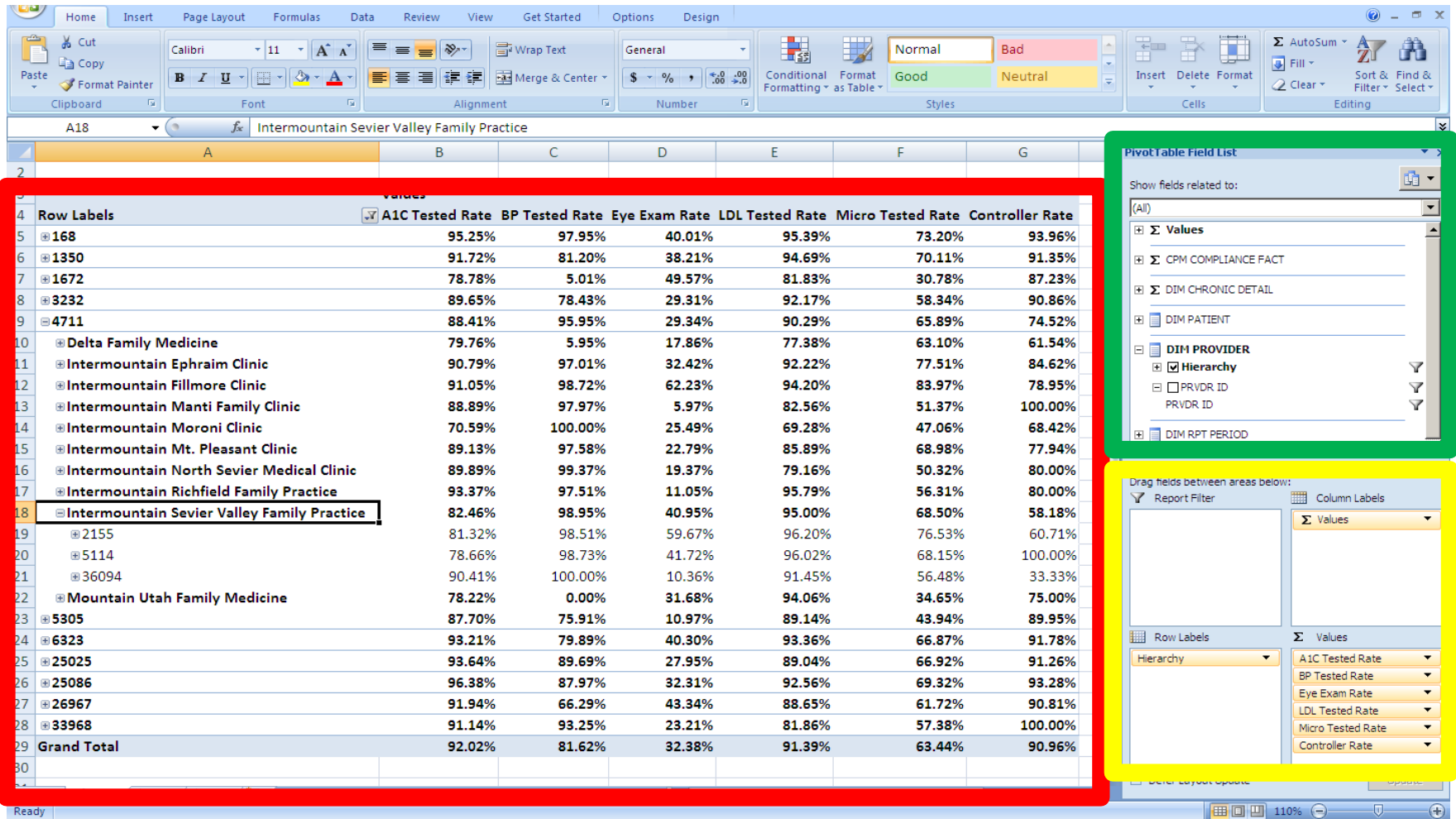


Figure 11. Sample report from chronic conditions cube. Results are aggregated at provider, facility, and region levels.

DISCUSSION

Tools and Technologies

Intermountain has consistently chosen 'best of breed' tools for Business Intelligence according to Gartner's quadrants for BI tools (63). Cognos is used for reporting. IBM's DataStage is used for ETL. Oracle is used for the EDW database platform. Other tools exist which could have met the requirements of this study. For example, Microsoft has an entire BI stack which is gaining traction in the health care IT market (63). The Microsoft stack would have allowed some seamless integration from ETL to modeling and cube processing that was not available using the tools at my disposal.

I did not have access to Intermountain's license for Datastage; consequently, I built all ETL for the CCMT using SQLDeveloper. It is freeware and was readily available. Additionally, many of the EDW data architects use SQLDeveloper as a tool to quickly script out SQL queries and/or ETL. For this reason, when I showed my queries to EDW architects during design reviews, they were familiar with the environment.

Querying EDW-PROD and writing ETL to EDW-DEV worked fine. I ran into problems when I attempted to process the dimensional model into the SSAS environment. At that point, Intermountain's security model prevented me from being able to process the chronic conditions cube. The security model prevented data on EDW DEV from being processed within their production SSAS environment. There was no

SSAS DEV environment in which to build. It became clear to EDW team management that unless I had access to write data out to EDW-PROD, the EDW's implementation of SSAS would not allow my model to be processed and the study would halt.

After some deliberation, EDW management agreed to give me a 'sandbox' area within EDW-PROD to allow me to build my model. All staging and summary tables were rebuilt on EDW-PROD, including the dimensional model. The ETL processes were modified to run against EDW-PROD. This required a significant amount of rework.

The CCMT is a novel assembly of existing technologies at Intermountain. Each component provides a vital function within the overall model. The components needed for the model to work are an EDW, chronic disease registries, CPMs around the chronic diseases, dimensional modeling, cube technology (SSAS), and a cube viewer (Excel or other). I did not have an approved budget to purchase additional tools for the study, so I used what was available and free. Excel 2007 was used as the cube viewing tool due to the wide-spread adoption of Excel on personal computers within Intermountain Healthcare and because it did not cost anything to implement for this research. Furthermore, I wanted to make use of tools that would be largely available to others outside of Intermountain doing similar work.

Cohort Identification

All patients for this study came from the asthma, diabetes, and depression registries, though not all patients in the registries were included. Inclusion criteria for patients within the CCMT went as follows. Prior to 01-Sep-2009, these registries were loaded on different reporting periods. Asthma and diabetes ran quarterly each year and

depression ran monthly. The first time all three registries ran on a consistent reporting timeframe was 01-Sep-2009. The lack of consistent reporting periods on the registries particularly influenced CCMT design at the dimensional modeling stage. Within a dimensional model intended to be consumed by a cube, all rows in the fact table must be at the same ‘grain.’ That means that every row represents the same consistent level of whatever is being measured. If two of the registries were represented with rows aggregated at a quarterly level and one registry was represented by rows aggregated at a monthly level, we would be representing data at different levels of aggregation (grains).

The lowest common grain among the three registries was not introduced until all registries ran on a monthly basis. That alignment did not happen until 01-Sep-2009, so all patients in the registries prior to that time who were not still in the registries after 01-Sep-2009 were not included in the model. The registry most affected by this limitation was the depression registry. Depression as a disease is still debated within the behavioral health care community as to the nature of the disease being chronic or transient or somewhere in between. Additionally, the number of patients in the disease registry is nearly five times the size of the diabetes registry and nearly fifteen times the size of the asthma registry by patient population.

Disease definitions for this model were adopted from Intermountain’s definitions of asthma, diabetes, and depression captured in the logical rules of existing registry qualification. There were some semantic drawbacks uncovered by digging into the disease definitions. Asthma and diabetes reflect a business bias rather than a true disease focus. This is evidenced by the fact that only SelectHealth patients appear within the asthma registry, though many patients with asthma are treated at Intermountain facilities

that are not covered by SelectHealth. Those patients (non-SelectHealth) are not represented within the asthma registry. The diabetes registry is limited in its definition of the disease because within, there is no distinction made between Type I and Type II diabetes. There would be clinical value in making the distinction, though to date, no such distinction exists.

In doing the study, I was well aware of these types of semantic limitations within the data, and no attempt was made to change/challenge the disease definitions. Doing so was outside the scope of this project. Recognizing these limitations ironically surfaces one of the virtues of the chronic disease model. It does not matter how Intermountain has chosen to represent disease definitions. A key tenet of the CCMT lies in the CPMs surrounding the diseases within the model. As long as CPMs within an organization can be defined, can be measured, and can be logically expressed with data, the tool works. The implication here is important to note. Other systems of care that have chosen to represent diabetes, asthma, and other chronic conditions with definitions that may differ from Intermountain's definitions can still adopt this chronic conditions model using their own versions of CPMs surrounding chronic disease. Theoretically, the model is *portable*; that is of course, as long as the adopting institution has all of the other needed components of the CCMT in place.

Despite the cohort limitations, the decision support tool captured enough of a representative sampling to build a functioning prototype. 183,665 patients were included in the model between 01-Jul-2009 and 28-Feb-2011.

Care Process Model Definitions

Definitions for each CPM were listed in Tables 1, 2, and 3. The CPMs for asthma and diabetes and depression vary in the manner of representation. For asthma and diabetes, the CPMs included in the CCMT are expressed in positive terms or measures. For example, part of the diabetes CPM mandates that every patient with diabetes should have A1C, LDL, and Microalbumin tests done annually. The model expresses what should be done on each and every patient within the registry. At every level of the asthma and diabetes CPMs, it is desirable to get the highest possible rates of adherence reflected with a high percentage for each and every measure (meaning most if not all patients received the CPM component).

Within the depression registry, there exists a different representation of a CPM measure. Not all patients with depression will receive all components of the depression CPM. For example, for depression patients who end up in the ER, a PCP follow-up visit should take place within 30 days of discharge. A significant though small percentage of patients with depression end up in the ER, though most do not. It is interesting to observe how the Primary Care Guidance Council and the EDW team chose to model this data element in the depression registry. The rule is represented through *negative* logic. Patients who end up in the ER and who did not receive a follow-up visit with their PCP are flagged with a binary field (0,1). Aggregating over this column will identify the number of times a provider should have followed-up with a patient yet failed to do so. I am not sure of the reason behind this kind of representation. By only identifying those who should have received care but did not receive it, the ability to measure those who needed care and received it cannot be measured. With this implementation, the CCMT

cannot show PCPs how well they are doing in managing that aspect of the depression CPM. Instead, it can only render the percentage of patients who should have received care and did not get it. Therefore, in the CCMT, a low rate for this component of the depression CPM is desirable rather than a high rate. A high rate would indicate the PCP is missing many follow-up visits. The CCMT made visible the inconsistency of logical representation of the depression CPM.

Within the logical representation of the depression CPM, positive rules of implementation also exist. One such rule is that every patient with depression should have a PHQ9 annually. For this CPM component, a PCP would want to have a high rate, indicating a consistent level of compliance with the depression CPM.

The CCMT has no problem making use of both methods of CPM logical representation (positive or negative logic). However, having both types of logical representation does present a challenge at the data presentation layer. This is evident in the cube where for some components, low rates are desirable while for other CPM components, high rates are desirable. Representing both of these paradigms in the same graph and/or table is potentially confusing. Consistently representing all CPM definitions as positives rates of compliance would remove some confusion that now exists when reporting over the depression CPM. Consideration should be given to changing the CPMs in the depression registry to be consistently represented using positive logic. It would take a fair amount of rework to make this change within the existing depression registry. This suggestion was shared with the current data architect responsible for the depression registry at Intermountain.

Patient Provider Mapping

The mapping of patients to providers followed the methods of assignment which exist in the current registries as previously outlined. Patients who had no assignment to a PCP for a given chronic condition were still included in the model. In the disease registries, these patients are referred to as orphaned patients. I chose to include these patients for two reasons. First, by including the orphaned population, the CCMT provides a more complete perspective on how well Intermountain is doing with CPM adherence for chronic disease management. Second, comparative analysis can be done on these patients and those who are assigned to compare outcomes in future studies.

The patient provider mapping allows a natural hierarchy to develop within the model. It goes as follows: Patients → Providers → Clinics → Regions. By mapping patients to providers, structures can be built into the cube (called hierarchies) to accommodate levels of aggregation at the provider level, the clinic level, the region level, and the enterprise level (all patients). The hierarchy affords a powerful view into the study population to identify which regions are performing better than others with CPM adherence or which clinics are outperforming other clinics (at the region level, etc.). Comparisons can also be done at the provider level. The cube makes it easy to identify those PCPs, clinics, or regions that are outpacing the rest in terms of adherence to CPMs. This identification provides opportunities to identify processes and/or methods of implementation that may differ from the majority of providers. These can be studied and shared across Intermountain to more quickly disseminate knowledge and best practices across the enterprise.

Within the study population, the majority of patients are assigned PCPs employed by Intermountain Healthcare. There are also dozens of PCPs who are not employed by Intermountain and consequently, these affiliated PCPs are not assigned to a region. The hierarchy of patients → providers → clinics → regions still works for patients of affiliated PCPs by mapping affiliated PCPs to an ‘unknown’ region and grouping them all together in the model.

One potential enhancement for mapping patients to providers who are not employed by Intermountain could be to use zip codes for clinic locations to create a proxy for the region level for affiliated providers.

Extract Transform Load Process

The scalability of the chronic conditions model to support the addition of future chronic diseases is manifest in the ETL process to stage all conditions for every patient. Using Oracle’s MERGE function, all chronic conditions for each patient and reporting period are flattened into one row of the chronic conditions fact table. The MERGE option allows a simple and elegant solution to updating columns where a patient has the given condition and does nothing to update columns if the condition is not present on the patient. See Appendix A to see code logic for creating tables, loading dimension, and fact tables included in the CCMT. Appendix A also includes ETL logic for the staging tables used in the model.

One limitation of the study is the assumption of scalability which has not been stress-tested. I make the assertion that the CCMT can scale because of my experience as a data architect for the last 8 years. I have created and maintained dimensional models

with multiple fact tables, many dimensions (>10), and tens of millions of rows to be processed by the cube. These have scaled well using partitioning methods available within the SSMS environment.

The CCMT only contains three chronic conditions. Dimensional models that I have built over the years are much larger and difficult to maintain. The CCMT could include many chronic conditions. However, I do not know how the cube would respond if the CCMT had 20 chronic diseases and hundreds of CPMs. I suspect that considerable work would need to go into maintenance of partitions for cube performance to be acceptable. Future work could be done to improve the ETL process by inserting scripts into a robust ETL tool. Indexing would also need to be addressed at the database level for such a large dimensional model.

Dimensionally Modeling Chronic Conditions

The CCMT makes use of existing chronic disease registries (asthma, diabetes, depression). Each of these registries was modeled previously as relational models. Within Intermountain's Primary Care Clinical Program, historical and current disease reporting is driven off of summary tables, almost exclusively in the context of a relational model. Upstream from the summary tables, components of the summary tables are staged into many tables (labs, visits, pharmacy data, etc.) then coalesced into one summary table for a given reporting period. This approach of relational modeling has served the PCCP for over a decade. However, relational data model will not work with the chronic conditions care model.

For this study, I represented the summarized data through a dimensional model (see Figure 6) for the chronic conditions cube to work as previously outlined. The two fact tables and their related dimensions allow aggregate and detailed reporting to happen across dimensions. The reason two fact tables can work within the same dimensional model is made possible by using shared dimensions across both fact tables (see Figure 6).

The `chronic_conditions_fact` table contains many more rows than the `patient_detail_fact` table. It contains history of CPM compliance and mapping to PCPs going back to 01-Jul-2009. The `patient_detail_fact` table only contains rows from the latest reporting period. This is intentional. Data in the `patient_detail_fact` table need to be actionable. It makes sense then that only the most current reporting period would be needed if PCPs are to take action. Consequently, this fact table is truncated and repopulated every time the ETL load runs with only data from the latest reporting period.

Nearly all dimensional models have a date dimension. A date dimension allows you to slice fact table data in aggregate time levels, depending on the grain of the fact table. In this study, the grain level was at a month level so I could not get any more granular than a month within the fact table. As a consequence, I could not create meaningful date hierarchies using a time dimension. In fact the only time component in the model is found in the reporting period dimension. A reporting period in the CCMT covers an entire year period. The ETL process runs monthly and it always looks back over one year. For example, the January 2010 (start date) load would cover everything between 01-Jan-2010 and 31-Dec-2010. The next month, the reporting period (start date) would cover everything between 01-Feb-2010 and 31-Jan-2011. It was not possible to have a date dimension in this model because of the data representation within the

registries. A row in any of the registries depicts one patient for a given reporting period (covering 12 months).

The lack of a date dimension did not prevent the model from being represented nor deployed. In fact, slicing by reporting period is something Intermountain PCPs are familiar with, so the lacking date dimension was not a deterrent for PCPs who have seen the model. The lack of a true date dimension is a natural consequence of the data granularity found in the existing disease registries. The missing date dimension surfaced yet another virtue of the chronic conditions model. That is, to some extent, it is flexible, even to accommodate nonstandard, date-dimension representation.

Cube Calculations

Rate calculations in the cube may be viewed using Excel 2007. In this model, under the measure pick-list, there are counts and rates. There are two ways that these could be captured within the chronic conditions model. The first option would be to add a column to the fact table for each calculation or measure. The second option would be to build the calculations within the cube itself.

Option one is a simplistic approach but could become unwieldy if the model is to include many future chronic diseases and CPMs. That would mean many columns would continue to grow, making the table wide. Furthermore, adding columns for each calculation would unfortunately have many rows with null values on many columns as not all patients are going to have every disease added to the model. At some point, the cost of maintaining such a large table needs to be considered for indexing and partitioning schemes to improve query performance.

The second option, that is, building calculations in the cube, seemed the more sustainable approach for this study. It lends itself to scalability. To build the calculations, no changes would need to be made on the fact tables. Furthermore, calculations built within the cube do not actually store data. The cube stores the pointers needed for each legitimate calculation and the calculated data are rendered at run time. This could become a cost which needs to be considered after many chronic diseases are added to the model, but was not an issue for this model. Query performance within the cube could suffer if partitioning within the cube is not well managed. Partition management for the cube takes place within the Microsoft Business Intelligence Development Studio (BIDS) environment. Doing this properly required some study and some trial and error. Cubes require a good deal of work to be designed and implemented properly.

A potential drawback with option two is that in order to build calculations, I had to learn some basic Multi-Dimensional Expression (MDX) coding, which is cube language. The learning curve becomes quite steep for any calculations beyond those that are quite basic. I had to verify results in the cube were consistent with the same calculations I got using disease registries and the dimensional model by using Structured Query Language (SQL). MDX presents quite a challenge for IT professionals.

Given the amount of effort it took me to learn sufficient MDX to build the calculations, it was worth the investment. It allowed me to create a clean data model on the fact tables by not having multiple columns with many potential nulls. Doing so would have been poor data modeling and would certainly affect cube performance as the cube would be creating many unnecessary relationships across many columns that were

sparsely populated. Additionally, if I had created the calculations within the fact table, the ETL used to populate the fact tables would have, of necessity, become much more complicated. I recommend building all cube calculations within the cube.

Access and Reporting

For this study, I chose to use Excel 2007 as the cube viewing tool. Some compelling reasons drove that decision. First, every Intermountain employee who has a need for Microsoft Office to be installed on their computer has a copy of Excel 2007. Intermountain's Computer Support office confirmed this fact. Therefore, no additional expense would need to be incurred to purchase a tool for cube rendering of the data. Second, Microsoft has built their BI stack with seamless integration. Excel 2005 had some cube viewing capabilities, though not nearly as seamless as Excel 2007. Connecting to the cube requires a few simple steps. Once a connection is made, it can be saved and re-used in future connections/cube viewing. Third, Excel is a simpler alternative than other reporting tools such as Crystal Reports or Cognos, though it still requires some learning to become comfortable with the tool. For the chronic conditions model to add value to Intermountain PCPS, clinics, and mid/senior management, the viewing tool needs to be as simple and user-friendly as possible. Excel seemed a reasonable entry point for the majority of users who simply want reports to render for them when they open it. Fourth, the chronic conditions model was built with intended (future) portability to be able to share with other health care organizations. Excel is a tool which is quite familiar to analysts at Intermountain and it seems plausible that this

would be a tool familiar to analysts at other institutions for health care delivery. Using Excel seems to support the notion of portability.

Data security can be handled at the cube level. Groups may be created with varying levels of access to the cubes to secure the data. I recognized the need for cube security to be addressed; however, creating and implementing a security model was outside the scope of this project. I implemented no such security model.

Making reports available to PCPs, staff, and management within Intermountain is another area which deserves real scrutiny and planning prior to implementation. For this study, I was able to demonstrate that an Excel file could be created and emailed to a provider, who then could save the attachment to a desktop. The provider could open the attached Excel file, enter appropriate login credentials, and connect to the cube. An appealing feature of the Excel 2007 viewer is the ability to save a copy of the ad-hoc analysis, close the file, and re-open it later to continue working on a model. I demonstrated this functionality to each of the PCPs to whom CCMT was shown. Saving analysis and re-opening the file at a later date appealed to each provider who saw the tool.

As a future recommendation for security within cubes, I recommend using Active Directory (AD) authentication. Using AD authentication, each user would only have access to browse data granted under the security policy. Furthermore, with AD as the form of authentication used against the cube, when the user connects to the cube, Active Directory could pass along credentials of the person logged on to the terminal as a parameter and reporting template could render data-based AD credentials. Yet another option would be for central computer support to push out a standard Excel file to each

desktop on a scheduled basis. This option holds appeal because it could be a way to push out new cube versions with updated features as enhancements are made and released.

Cube viewing and ad-hoc analysis of cubes would require some training for most users. Herein lays a limitation of the study. Each of the PCPs who saw the CCMT commented on the process of accessing the information. Unanimously, the stated preferred method for report delivery at Intermountain would be via the intranet. Links could be sent out to PCPs to take them to a cube link on the intranet, but that was beyond the scope of this project.

Ad-hoc Analysis Within Cubes

The notion of PCPs being able to do ad-hoc analysis on their patient populations via the cube was an intriguing concept. The idea was consistent with Intermountain's push to create self-service reporting tools to make data more accessible to nontechnical audiences. However, it was clear that simply having access to the data did not mean that all PCPs would take advantage of the ad-hoc capability. The director of quality improvement for SelectHealth along with the director of the Primary Care Clinical Program each told me that the majority of PCPs at Intermountain are content to receive a canned report tailored to their practice and their patient population to let them know how well they are managing their chronic disease populations. Both believed that very few providers would actually take time to learn the tool and do their own analysis.

PCPs are financially incentivized to maximize their patient workflow. Taking time to do their own analysis on their patient populations would mean cutting into potential time with patients or doing analysis outside of normal business hours. I asked

each PCP who saw the tool if they saw themselves using a tool like the CCMT to study their population. Only one answered yes without hesitation. All others said they were intrigued by the possibility but did not realistically see themselves taking time to learn the tool to study their populations.

The majority of PCPs within the Primary Care Clinical Program will likely not do ad-hoc analysis on their patient populations. I suspect that existing resource constraints on providers would keep most from learning to browse cubes. For the few providers who will want to do some ad-hoc analysis, the last tab in the Excel file allows them to explore the cube. Examples of ad-hoc analysis are found in Figure 9, Figure 10, and Figure 11.

CCMT Data Validation

My decision support tool is a prototype. Nevertheless, there was a significant amount of quality assurance processing done to validate data. I spent roughly 20 hours doing comparative analysis between results from the CCMT reporting both in aggregate and individual patients against the existing traditional clinical reports for diabetes, asthma, and depression. I researched reports from a dozen Primary Care Providers. The results from CCMT reporting aligned perfectly with the existing, stand-alone reports.

Two seasoned analysts from the Institute for Healthcare Delivery and Research spent some several hours validating the tool by doing their own comparative analysis against the CCMT and the existing reporting. Their findings were consistent with my own quality assurance findings.

CCMT Face Validity

Face validity for the CCMT was accomplished by demonstrating the tool to key Intermountain employees, hand-picked by me. I chose the employees based on existing relationships that I had from my former employment with Intermountain as well as my experience supporting the Primary Care Clinical Program. These key users are described in detail below.

This chronic conditions management tool and cube was demonstrated to people in the following positions within Intermountain Healthcare: two Clinical Program Directors, namely the Primary Care Clinical Program and the Medical Home division; the Director of Quality Improvement for SelectHealth; two Consultant Analysts within the Institute for Healthcare Delivery and Research; and three Primary Care Providers. Additionally, a working prototype was demonstrated at the American College of Mental Health Administration 2011 Summit in New Orleans.

I sat down with the Directors of Primary Care and the Medical Home and members of their staff to demonstrate the prototyped CCMT. We met for one hour. During that time, I walked them through the CCMT framework. Then, I spent a significant portion of the hour getting them familiar with the cube and doing ad-hoc analysis. I showed them how analysis could be done through multiple dimensions simultaneously. I demonstrated the hierarchical groupings in the provider and patient dimensions. I demonstrated how canned reports with template reports could be opened from a desktop icon and how PCPs could see their CPM compliance by simply selecting their provider IDs from a drop menu. Last of all, they were shown how gaps in adherence were reported by the provider through an actionable, detailed work list. Prior

to our meeting, none in the room had ever heard of cubes and few had seen pivot tables. Only one person (an analyst) had experience with pivot tables.

There was genuine interest and enthusiasm from the Primary Care Clinical Program and the Medical Home division. When asked what potential value the model could hold for their respective programs, they responded with three areas of potential value. First, nontechnical people could do ad-hoc analysis within Excel. Managers and nontechnical staff often had dependencies on analysts to pull data sets for analysis. Analysts are extremely busy at Intermountain. This makes turnaround time for report requests a long process. It is not uncommon for a report to take weeks if not months to produce a first draft. Diminishing the dependency on analysts where appropriate and where possible appealed to leadership for the Primary Care Clinical Program as well as the Medical Home Division. Each of the directors expressed interest in learning how to use the cubes to do their own analysis. In my four years as a data architect supporting the PCCP for Intermountain Healthcare, I had never before heard a director ask for direct access to data for the purpose of doing his/her own analysis.

Second, the CCMT allowed actionable reporting for PCPs on their respective patients in one consolidated view. PCPs could quickly identify gaps in CPM adherence without having to look across multiple reports as is the current process for diabetes, asthma, and depression. They liked the whole-patient focus of the CCMT rather than emphasis on individual disease management. Each of the three PCPs naturally gravitated to gaps in CPM adherence as reported in the cube. One of them opened the EMR to verify a missed gap and was disappointed to discover the finding was confirmed. However, the confirmation bolstered confidence in the cube data and the PCP

commented that it would be great to have a trusted, consolidated view of CPM compliance for his patients with chronic disease. He then commented that the CCMT fell short in not showing actual clinical values for current outcomes, such as the last A1C value, last HDL value, and/or last blood pressure value. I agree that there would be clinical utility in seeing the clinical indicators for disease progression, but made the contention that including the individual clinical values was outside the scope of my project.

Third, the CCMT supported the missions of both the Primary Care Clinical Program and the Medical Home programs by making available aggregate views of chronic disease management at multiple levels of reporting. These directors seem to have a population focus on chronic disease management. The ability to drill-up and drill-down multiple hierarchies was an attractive feature of the model. The aggregate reported values from the CCMT addressed the directors' needs to report to executives on how well the enterprise was doing in managing chronic disease via adherence to best practices. Furthermore, the directors could drill into the hierarchies based on those regions, clinics, or providers who consistently had the higher/lower rates to identify outliers. The good outliers could be further scrutinized to potentially understand best practices of chronic disease management that could possibly be shared more quickly across the enterprise. Both directors agreed that the CCMT was a tool that showed potential in supporting the missions of their clinical programs.

Potential for Improved Business Intelligence
and Reporting at Intermountain

Analysts at the Institute for Healthcare Delivery and Research expressed interest in the CCMT model. I asked them to describe how this model could add value to better management of chronic disease at Intermountain. They gave me three areas in which the CCMT could add value. First, both analysts agreed that enabling nontechnical managers and executives to do ad-hoc analysis was quite valuable. This was a step toward self-service Business Intelligence and could potentially remove some of the burden of reporting from the analysts. They felt they were often asked the same question by different people and had to repeatedly create the same report with different parameters to meet the needs of the business. By introducing the means of self-service analysis into the hands of managers and executives, analysts could make better use of their time by leveraging their technical expertise on more complex reporting and analysis. Of course, this assumes that managers and executives could learn to be self-sufficient in browsing the cube within the Excel environment.

The second area in which the CCMT could add value may be found in putting real data into the hands of management. They felt this could improve the overall reporting process. The analysts explained that the process of report development is iterative in nature, sometimes unnecessarily so. In the current reporting paradigm, management tasks an analyst to write a report to address a specific question. Weeks may pass before the analyst returned with the first draft of the report. Together, they review the report and often management refines the criteria and the reporting cycle repeats itself. The cycle can go on for months before the report is truly addressing what management

set out to understand. The analysts felt that this model could refine the requirement gathering process by allowing managers and executive to view real-world data prior to making requests. Additionally, the iterative lifecycle of report development may be shortened because managers may be able to better articulate their reporting needs by doing some of the analysis themselves.

One of the analysts pointed out a third area of potential value in the model. He felt there was benefit in letting clinic managers take more accountability by doing a portion of their own reporting and analysis. Not all clinics within Intermountain are the same. Clinics vary by patients they serve, by location (rural vs. urban setting), and by staffing. These differences make a one-size-fits-all approach to reporting difficult to support. He explained that clinics will have varying results in CPM adherence and patient outcomes which are influenced by variations in clinics throughout Intermountain. The idea of collective knowledge discovery and dissemination across the enterprise could have merit by letting clinics scrutinize outcomes at the patient, provider, and clinic levels. Self-service BI could help each clinic discover better what works to improve clinic, provider, and patient outcomes. Some of this knowledge discovery could be generalizable to similar clinics throughout Intermountain. Rather than trying to force a one-size-fits-all solution from many dissimilar clinics, multiple models could emerge depending on clinic type, clinic staffing, patient demographics and the clinic setting.

Potential for Usability at Intermountain

I met for an hour with the Director of Quality Improvement for SelectHealth. His interest in the CCMT focused on the consolidated, centralized view of disease management. SelectHealth offers financial incentives to PCPs on their panel for adherence to best practices. The CCMT made PCP CPM compliance more transparent, thus aligning itself well with existing SelectHealth needs and incentives. The Director was quite familiar with pivot table functionality within Excel and it appeared that this familiarity made it easy for him to grasp the visualization of the data. He said the model was limited by its lack of clinical outcomes data on patients. He suggested this as logical next step for future research in chronic disease management.

I met with three practicing Primary Care Providers to walk them through the model. Each one expressed interest in the actionable component of the model (Figure 5). The consolidated view of CPM compliance across multiple chronic diseases held their interest. Each of them commented that the detailed, actionable list could become a patient work-list for them and their office staff to get patients compliant with care. A patient work-list is a report for a PCP which shows some level of action that needs to be done for patients. Providing a PCP with a consolidated view of multiple chronic conditions could make his/her work-list more meaningful and efficient by possibly catching more of the actions that need to be done.

Despite the appeal of the model, each PCP expressed frustration in having to leave the HELP2 (Electronic Medical Record) application to connect to the chronic conditions cube using a separate, stand-alone application. All of them wanted the chronic conditions model functionality embedded within HELP2. Switching among applications

was disruptive to clinical work-flow. Consequently, none of the PCPs would likely use the application during a patient visit; rather, they, or their staff, would use the actionable components of the model (Figure 5) to identify which patients were lacking care but would rely solely on HELP2 for clinical documentation once the patient was in the exam room with the provider.

When asked whether they would do ad-hoc analysis on their patient populations using the model, one of the three PCPs said yes. Each provider said s/he is pressed for time and that s/he would not have the time needed to do their own population analysis. The canned reports tailored to their practice would meet their basic reporting needs. There also seemed to be an aversion to learning pivot tables within Excel.

Potential Portability to Other Health Care Organizations

On March 17th, I presented the Chronic Conditions Management Model at the American College of Mental Health Administration 2011 Summit, held at the Royal Sonesta Hotel in New Orleans, Louisiana. ACMHA was founded in 1979. It is a behavioral health leadership member organization with representation from “public and private administrators of services; national, state, and county government; mental health and addiction recovery professional organizations; consumer and family advocacy organizations; the provider treatment community; managed behavioral health care organizations; research and academia; insurers; and other stakeholders” (64). The ACMHA 2011 Summit provided me with a good opportunity to demonstrate the model to a broad representation of health care organizations and affiliates from around the country, particularly for low-income and Federally Qualified Health Centers.

One night of the conference was a dedicated poster session. For nearly three hours, I presented the logical design of the CCMT to people in attendance. More than forty people stopped at my poster where they had the CCMT explained to them and they also watched a working prototype of the model. One of the virtues of SSAS (cube) technology is the ability to save a portable version of a cube to a local computer. I pulled down a copy of the chronic conditions cube onto my laptop in order that I might show a functioning prototype to people attending the poster session. Next to my poster I set up a small table with my laptop opened on top. Prior to the poster session, I used Excel to establish a connection to the local copy of the cube on my laptop and I created canned reports (Figure 4 and Figure 5) to run against the local cube copy. As groups listened to my poster presentation, I drew their attention to the laptop and then demonstrated for them how the graphs on each tab would dynamically change as I selected different provider IDs. Next, I would do ad-hoc analysis against the cube.

Those attending the Summit were typically director-level or executive-level medical professionals. Feedback from this group echoed that of the directors at Intermountain, specifically, that there was real value in looking at patients holistically rather than focusing on individual disease models. The aggregate views of CPM adherence rates at the enterprise, regional, clinic, and PCP level was also well received. This national audience seemed encouraged by the potential flexibility of the model being able to accommodate varying definitions of disease as well as CPMs in other systems of care. The portability of the CCMT to other health care organizations was an attractive feature.

SIGNIFICANCE

Three aspects of this study are significant. First, in my literature review, I have not come across a tool which gives providers the ability to view more than two chronic diseases simultaneously. Some have included two conditions, such as diabetes and depression (13), though none have included capabilities for viewing three or more conditions all at once. The traditional method of reporting for clinical programs at Intermountain has been to build rich data registries around a specific condition or disease. This has been helpful in understanding a great deal about each disease population. However, this approach to disease-focused care has evolved to the point that Intermountain is looking for a way to put the patient as the point of focus and somehow tie together all chronic disease registries to better inform providers about all conditions that a patient may have. To date, no tool or data model within the EDW has been built to support this PCCP need. The CCMT architecture successfully put the patient at the center of chronic disease management. The CCMT is scalable to include more chronic diseases. While the magnitude of scaling has not yet been explored, three conditions are included and I expect 3-4 others could be included without performance degradation in the cube.

Second, the CCMT supports population views of chronic disease management as well as actionable, patient-level reporting to aid providers in managing individual patients with chronic diseases. In my experience as a data architect assigned to support the

Primary Care Clinical Program, these two types of reporting were not often connected. Operational, or day-to-day, reporting for clinicians to manage their respective diabetic, asthmatic, and depressed populations were based off of summarized data tables intended for that specific purpose. On the other hand, dashboard-type reporting, intended for the executive team, were based off of SQL query logic embedded into the dashboard. These queries were not usually based on the summary tables as the summary tables were not designed to support dashboard reporting. Although both types of reporting addressed the Intermountain diabetic population, dashboard metrics could not be effectively compared with operational reports based off the summary tables because the logic for both types of reports addressed different needs of the organization. The danger lays in metrics from both report types that address related, though different, metrics. These often gave significantly different results. This scenario proved challenging for the clinical leadership team charged with guiding the Primary Care Clinical Program. The PCCP wanted one consistent representation of data that would support all their reporting needs. The CCMT supports both types of reporting with the same underlying data model.

Third, the CCMT supports canned reporting as well as ad-hoc cube analysis. The underlying dimensional model coupled with the cube structure allows various types of reporting and analytics to provide a more consistent reporting paradigm. This is significant because of the self-service BI component as demonstrated using Excel 2007. In my experience with the Intermountain PCCP, PCPs were not expected to generate their own reports and/or do their own analysis on their patient populations. Analysts and BI developers shouldered that responsibility. These analysts often worked directly with clinicians to identify reporting needs. Each month, the PCCP Guidance Council met to

review new or enhanced reporting outcomes. During these meetings, PCPs representing each region within Intermountain would discuss the data and how the findings related to current care delivery. They would often look for areas that could be improved and with consensus, established targets for board goals to improve outcomes based on data found in the operational reporting. I often heard providers ask BI developers if it would be possible to do ‘what if’ scenarios and capture that capability in a reporting tool that could support data exploration by nontechnical clinicians who had an interest in doing some of their own analysis. No such tool was ever built while I was the data architect for the PCCP. It was not that the project could not be done; it was due to a lack of available technical resources (analysts/BI developers) compounded by other competing projects with higher priority. The CCMT demonstrates in a small but significant manner that clinical data can be modeled in a way that supports both traditional and self-service reporting needs for a clinical program such as the Intermountain PCCP.

FUTURE RECOMMENDATIONS

This study paves the way for future informatics work in chronic disease management at Intermountain. For example, with the potential of the CCMT being adopted by Intermountain, implementation of a population-level decision support tool could be studied to identify challenges in workflow adoption. Additionally, work could be done to explore outcomes on patients who receive care from PCPs who are consistent in CPM delivery but then focus on the accountability of the patient for their role in following through on prescribed care, such as Rx fill-rate on asthma and/or depression medication.

I have three recommendations for future use of the chronic conditions management tool. First, pilot the CCMT within the Primary Care Clinical Program or the Medical Home division at Intermountain. This could be done with a clinical champion at one clinic, an outcomes analyst, and a data architect. I would estimate that I spent 160 hours developing technical content for the CCMT. Hundreds of hours went into researching the project need and documenting the problem. These considerations should be taken into account to help manage expectations around how long it may take to build the CCMT into a pilot clinic.

My second recommendation would be to map patients to clinics in addition to PCPs. At Intermountain, there has been considerable dialogue around primary care integration and providing a medical home for a patient to receive the majority of clinical

care. Inherent in the definition of a medical home is a clinical care team working together to deliver care. Patients often receive care from a team of providers rather than just one PCP. A patient in the PCCP may visit the same clinic 3-4 times a year, or more, to receive care. Not every visit will be with the same PCP. This is understood and recognized by Intermountain and mapping algorithms have been developed to make an educated guess as to which PCP is reasonably accountable for the patient over the course of a reporting period. The mapping to providers is an incomplete reporting paradigm. A more complete approach would be to map patients to teams of clinicians and staff and then hold the team accountable for care delivery consistent with best practices. The chronic conditions cube could support a hierarchical reporting structure that mapped patients to a clinic. Comparative analysis could be done across clinics and regions to study team-based care.

My third recommendation would be to include CPM components that track patient adherence to prescribed care. In its current state, the CCMT holds PCPs accountable for adherence to CPMs in chronic disease management. However, PCP CPM adherence is one part of the solution needed to improve chronic disease management. The patient also has a responsibility to comply with care prescribed by the PCP. For example, the patient is responsible to show up for an ordered eye exam. If the PCP orders the exam and refers the patient to an ophthalmologist, but the patient never follows through on the referral, the fault lies with the patient, not the PCP. The same holds true for medications ordered by the PCP but never filled by the patient. The CCMT needs to grow its capacity to track patient adherence to prescribed care.

CONCLUSION

In the near future, medical home reporting capabilities will be mandated by the federal government. Aligning the chronic conditions model with the medical home model reporting needs is important. A strategic alignment such as this would maximize work efforts of a technical staff tasked with supporting clinical lines at Intermountain. A population-based decision support tool like the CCMT could support a health care organization in their quest to demonstrate meaningful use as mandated by the Affordable Care Act. A pilot study of implementation for usability testing could shed light on the challenges of implementing such a decision support tool. If the model can sufficiently address public reporting measures required by the government, there may be components within the tool which could be generalized to other health care organizations that may have similar reporting needs.

This project had two main objectives. The first was to create a Business Intelligence solution to support a more comprehensive approach to chronic disease management. The tool needed to be flexible to accommodate multiple disease definitions, scalable to support additional chronic diseases, and portable to allow adoption by other health care systems. The second objective was to create a tool that could satisfy Intermountain PCP requests to consolidate asthma, diabetes, and depression reporting into one view.

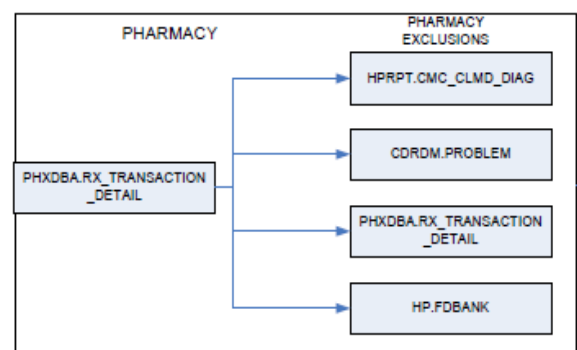
To satisfy the first objective, the following steps were taken: 1) CPMs for asthma, diabetes, and depression as adopted by Intermountain Healthcare's Primary Care Clinical Program were researched, defined, and logically captured in SQL: 2) A supporting infrastructure complete with ETL, staging, and summary tables along with a dimensional model was developed within Intermountain's EDW: 3) Clinical data extracts from asthma, diabetes, and depression registries as well as other supporting tables were loaded into the chronic conditions dimensional model: 4) A chronic conditions cube was built over the chronic conditions dimensional model to capture measures around PCP CPM adherence for asthma, diabetes, and depression.

To meet the second objective, a reporting solution was built using Excel 2007 as a way to visualize data captured within the chronic conditions cube. The reporting component of the CCMT had the ability to view data in aggregate, population views as well as the ability to drill to a granular, patient-provider level of detail to identify gaps in adherence to CPMs for asthma, diabetes, and depression patients.

Feedback from key stakeholders at Intermountain Healthcare indicate that the CCMT 1) takes steps towards establishing a consistent version of truth with respect to chronic disease management in Primary Care at all levels of management, 2) may add value to PCPs managing patients with chronic disease by identifying gaps in adherence to CPMs across multiple chronic conditions simultaneously, 3) could allow nontechnical managers and executives to do some self-service analysis over large data sets, 4) has the ability to scale to include additional chronic conditions, and 5) has potential to be generalized to other health systems of care, assuming technical dependencies could also be supported.

APPENDIX A

DATA MODELS



PRIMCARE.PATIENT_CLASSIFIED

Pharmacy Exclusions

- Polycystic ovarian disease who were identified through diabetes related pharmacy claims.
- Hprpt.cmc_clmd_diag ICD9 256.4
- Cdrdm.problem with comment/problem PCOS or problem NCID 83260 or 1002531, dx_flg = 1 and status_ncid = 1024
- Check previous list against rx claims for 2 fills metformin and 2 fills rosiglitazone/pioglitazone
- Gc3 from fdbank='C4N' and BN from fdbank != avandament or rezulin.

HP Inpatient Inclusion Criteria

- ≥ 2 service dates w/in 2 yrs on [(ICD9 Dx: 250%, 357.2, 362.0, 366.41, 648.0)] or [(DRG: 294, 295) and UB92: 0100-0169, 0200-0229, 0450-0452, 0459, 0720-0729, 0800-0809, 0981, 0987) or (CPT: 99221-99223, 99238-99239, 99251-99255, 99261-99263, 99281-99188, 99291-99292, 99356-99357)]

HP Outpatient Inclusion Criteria

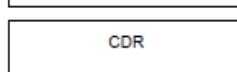
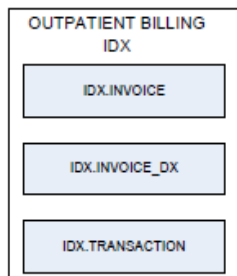
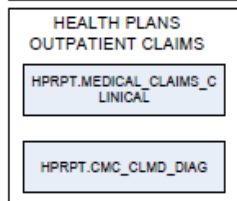
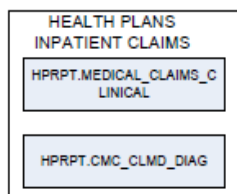
- ≥ 2 service dates w/in last 2 yrs on [(ICD9 Dx: 250%, 357.2, 362.0, 366.41, 648.0) or (DRG: 462)] and [(UB92: 0490-0539, 0550-0599, 0456, 0650-0669, 0760-0769, 0770-0779, 0820-0859, 0880-0889, 0920-0929, 0940-0949, 0960-0969, 0972-0979, 0982-0986, 0988-0989) or (CPT: 92002-92014, 99201-99205, 99211-99215, 99217-99220, 99241-99245, 99341-99345, 99347-99350, 99384-99387, 99394-99397, 99401-99404, 99411-99412, 99420, 99429, 99455-99456, 99499)]

IDX Outpatient Inclusion Criteria

- ≥ 2 service dates w/in last 2 yrs on [(ICD9 Dx: 250%, 357.2, 362.0x, 648.0) and (billing provider specialty IM, IMP, PD or FP)] or (CPT: 92002-92014, 99201-99205, 99211-99215, 99217-99220, 99241-99245, 99341-99345, 99347-99350, 99384-99387, 99394-99397, 99401-99404, 99411-99412, 99420, 99429, 99455-99456, 99499)]

HP Claims Exclusion Criteria

- Exclude if claim or bill with ICD9 Dx 962.0, 648.8, 251.8 or 256.4



CDR Inclusion Criteria

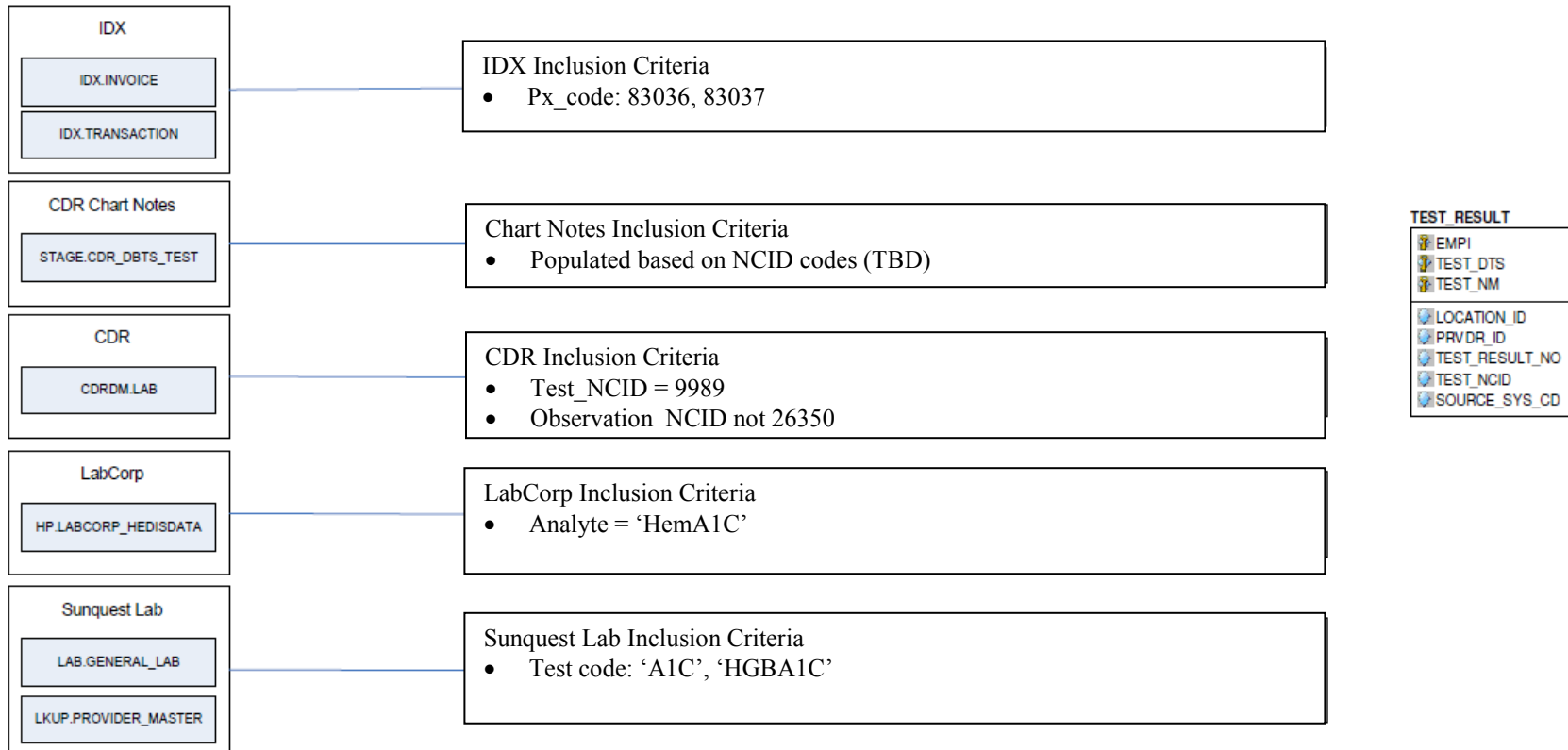
- Include diabetes listed on problem list. Exclude notes with 'rule out' and /or 'question of'.

PATIENT_CLASSIFIED

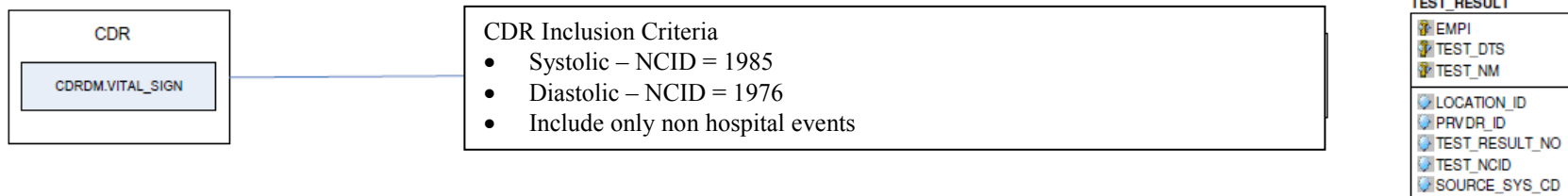
EMPI
PT_ID
IDX_MRN
SUNQUEST_PT_ID
MRNO
SSN
BIRTH_DT
SEX_CD
LAST_NM
FIRST_NM
MIDDLE_NM
SUFFIX_NM
DECEASED_FLG
CASEMX_ID
SOURCE_SYS_CD
AREA_CD
PHONE_NO
DIABETIC_FLG
LOAD_DT
PURGE_FLG
PURGE_DT

Hemoglobin A1C

PRIMCARE.TEST_RESULT

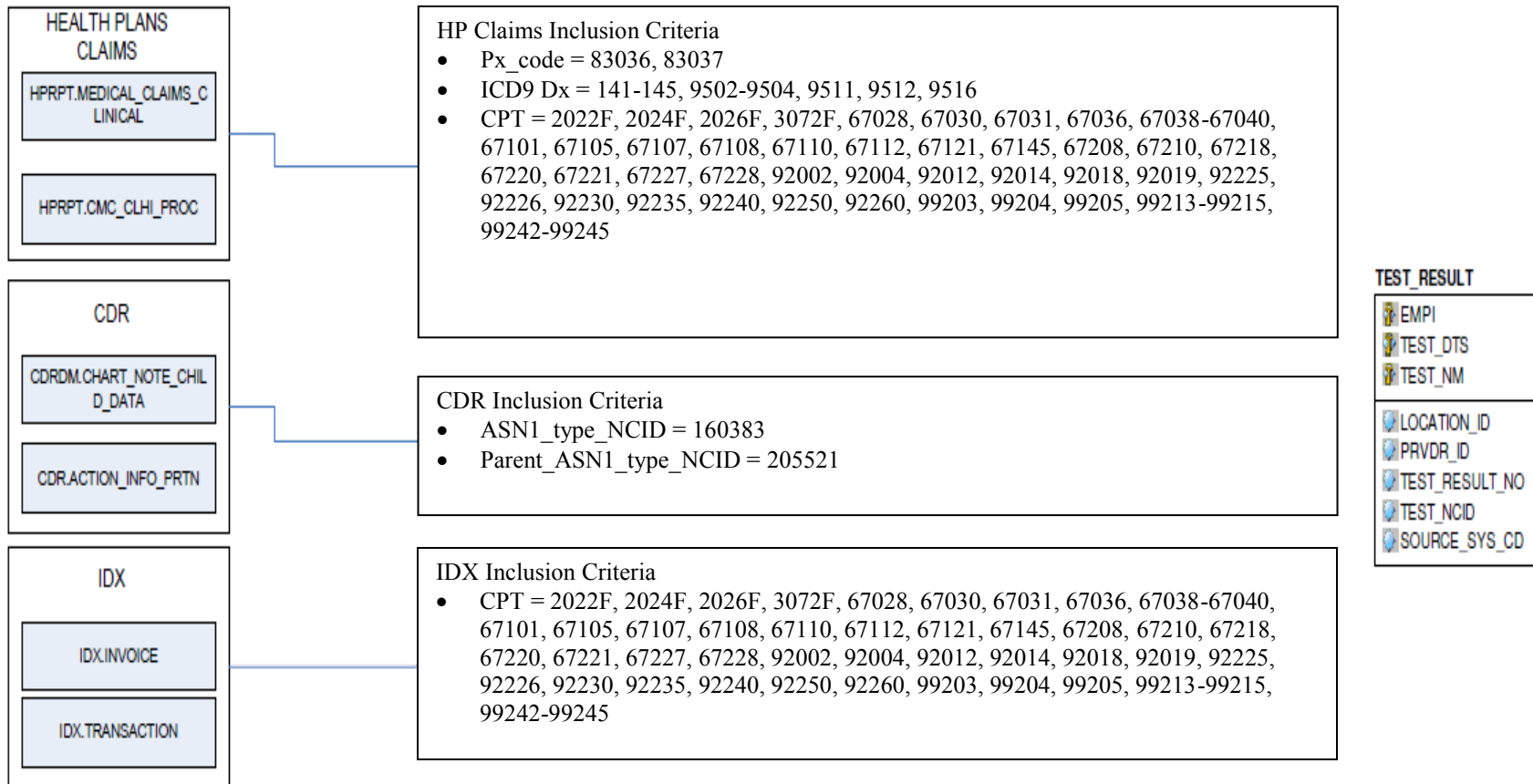


Blood Pressure



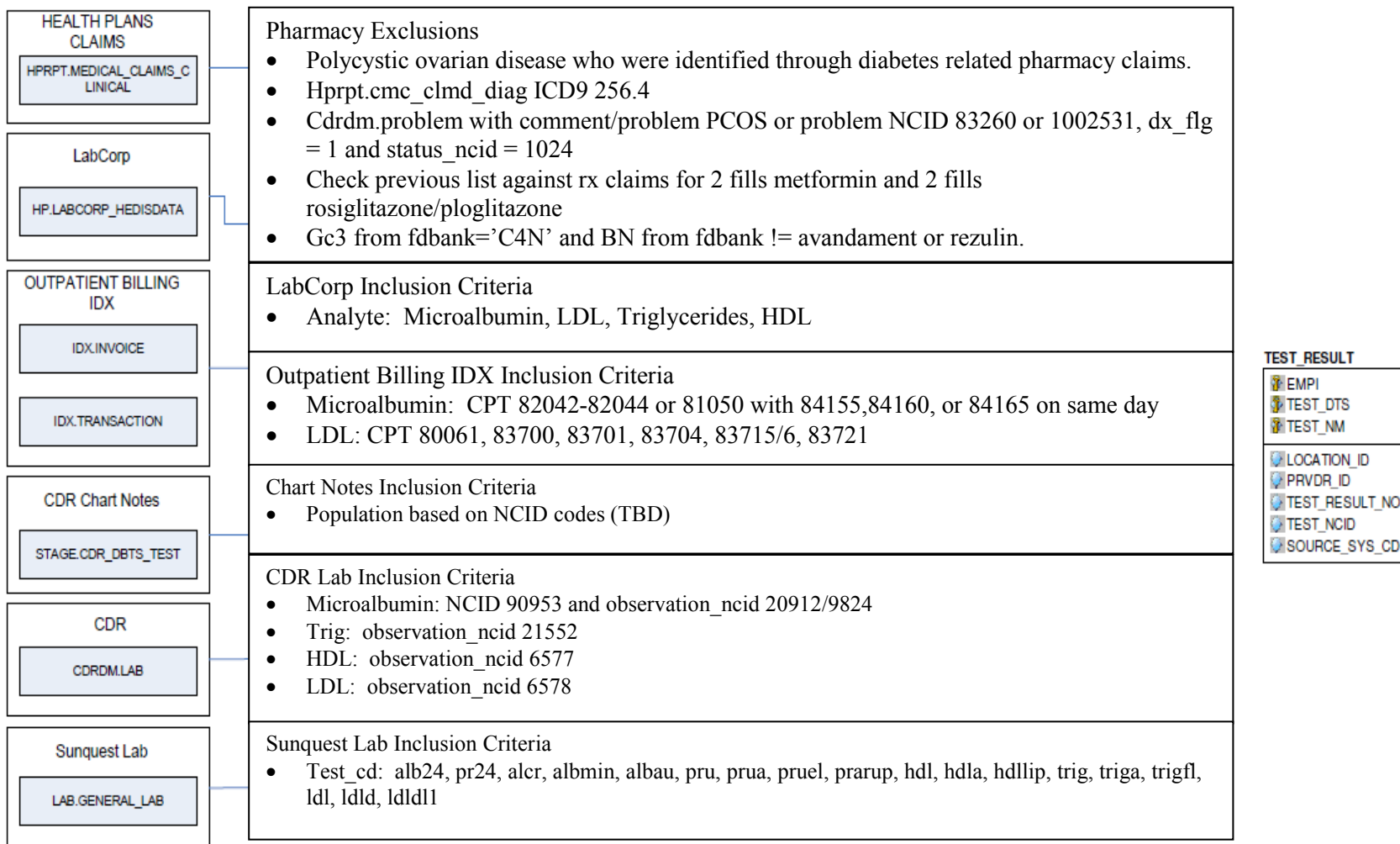
Eye Exams

PRIMCARE.TEST RESULT

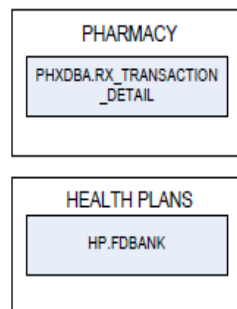


LDL (Microalbumin, LDL, TRIG)

PRIMCARE.TEST RESULT



PRIMCARE.MEDICATION

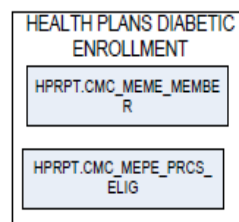


Contains all the medications for diabetes patients. Data comes from pharmacy commercial and Medicaid claims from the Health Plan data mart in the EDW.

MEDICATION

NATNL_DRUG_CD
FILLED_DT
EMPI
PRESCRBG_PRIVDR_ID
MEDICATION_NM
DOSAGE_AMT
ROUTE_TYPE_CD
DOSE_FRM_CD
DOSE_FRM_DSC
GCN_CD
GC3_CD
FILL_QTY
DAYS_SUPPLY_NO
ALLOWED_AMT
WITHHOLD_AMT
NET_AMT
MEDICATION_NCID
GENERIC_MED_NM
AHFS_CD
LONG_MED_NM

PRIMCARE.PT ENRLMENT HISTORY



Contains a history of health plan diabetic member enrollment and eligibility.

PT_ENRLMNT_HSTRY

EMPI
BEGIN_DT
END_DT
PLAN_CD
PLAN_DSC
RIDER_CD

APPENDIX B

SCRIPTING

+++++

Table Creation - DDL

+++++

DIM_CHRONIC_DETAIL

create table sandbox.dim_chronic_detail

```
(
    dim_detail_sk int not null
,   empi int not null
,   prvdr_id int not null
,   rpt_per_start_dt date not null
,   diabetes_flg int null
,   last_A1C_dt date
,   last_A1C_result_no number null
,   last_micro_dt date null
,   last_micro_result_no varchar2(15) null
,   last_LDL_dt date null
,   last_LDL_result_no number null
,   last_bp_dt date null
,   last_bp_result_no varchar2(10)
,   last_eye_exam_dt date null
,   asthma_flg int null
,   last_controller_fill_dt date
,   last_pft_dt date
,   depression_flg int null
,   last_phq9_dt date null
,   last_phq9_result_no number null
,   NO_PCP_AFTER_EI_VISIT_FLG char(1) null
,   NO_PCP_FOLLOWUP_VISIT_FLG char(1) null
,   MISSED_NEW_RX_FLG char(1) null
```

```

, HIGH_PHQ9_WITHOUT_VISIT_FLG char(1) null
, NO_PCP_VISIT_LAST_6_MONTHS_FLG char(1) null
, constraint dim_chronic_detail_pk primary key (dim_detail_sk)
, unique (empi, prvdr_id, rpt_per_start_dt)
);

grant select, insert, update, delete, alter on sandbox.cpm_compliance_fact to lpjwadsw ;
commit;

```

```
create sequence dim_chronic_detail_seq2;
```

```

create or replace trigger dim_chronic_detail_trigger
before insert on sandbox.dim_chronic_detail
for each row
when (new.dim_detail_sk is NULL)
begin
  select dim_chronic_detail_seq2.nextval
  into :new.dim_detail_sk
  from dual;
end;

```

CPM_COMPLIANCE_FACT

```
create table primcare.cpm_compliance_fact
(
```

```
-----
/*Primary Key on table
```

```
-----
  pt_sk int not null
, rpt_per_sk int not null
, prvdr_sk int not null
, dim_detail_sk int not null
-----
```

```
/*Measures on the fact table
```

```
-----
, A1C_tested int
, LDL_tested int
, Micro_tested int
, eye_tested int
, bp_tested int
, last_bp_dt int
, controller_flg int
, pft_tested_flg int
, no_pcp_post_ei_visit_flg int
, no_pcp_fu_visit_flg int

```

```

    , missed_new_rx_flg int
    , rx_benefit_flg int
    , high_phq9_wo_visit_flg int
    , no_pcp_visit_6_mo_flg int
    , constraint cpm_compliance_pk
PRIMARY KEY (pt_sk, rpt_per_start_dt_sk, prvdr_sk, dim_detail_sk)
);

```

```

grant select, insert, update, delete on primcare.cpm_compliance_fact to lpjwads ;
commit;

```

DIM_PATIENT

```

create table dim_patient
(
    pt_sk int not null
    , empi int not null
    , gender char(1) null
    , last_name varchar2(20) null
    , first_name varchar2(16) null
    , birth_dt date null
    , constraint dim_patient_pk primary key (pt_sk)
    , unique (empi)
);

```

```

commit;

```

```

grant select, insert, update, delete on primcare.cpm_compliance_fact to lpjwads ;
commit;
create sequence dim_pt_seq;

```

```

create or replace trigger primcare.dim_pt_trigger
before insert on primcare.dim_patient
for each row
when (new.pt_sk is NULL)
begin
    select dim_pt_seq.nextval
    into :new.pt_sk
    from dual;
end;

```

DIM_PROVIDER

```

create table primcare.dim_provider_stage
(

```



```

        prvdr_id int null
    , med_dir_id int null
    , last_nm varchar2(20) null
    , clinic_nm varchar2(60) null
);

```

```

grant select, insert, update, delete on primcare.cpm_compliance_fact to lpjwadsw ;
commit;

```

```

create sequence dim_provider_seq1;

```

```

create or replace trigger primcare.dim_provider_trigger1
before insert on primcare.dim_provider
for each row
when (new.prvdr_sk is NULL)
begin
    select dim_provider_seq1.nextval
    into :new.prvdr_sk
    from dual;
end;

```

DIM_RPT_PERIOD

```

create table primcare.dim_rpt_period
(
    rpt_per_sk int not null,
    start_dt date not null,
    end_dt date not null,
    constraint rpt_per_pk primary key (rpt_per_sk)
    , unique (start_dt, end_dt)
);

```

```

grant select, insert, update, delete on primcare.cpm_compliance_fact to lpjwadsw ;
commit;

```

```

create sequence dim_rpt_period;

```

```

CREATE OR REPLACE TRIGGER sandbox.DIM_RPT_PER_TRIGGER
before insert on sandbox.dim_rpt_period
for each row
WHEN (new.rpt_per_sk is NULL) begin
    select dim_rpt_per_seq.nextval
    into :new.rpt_per_sk
    from dual;

```

end;

+++++

Data Staging

+++++

DIM_PATIENT_STAGE

```

/*Gathers all patients from asthma, diabetes and depression registries
Starting with rpt_per_start_dt = 01-Jul-2009
--inserted 203,819 rows 07-Apr-2011
*/
insert into sandbox.dim_patient_stage (empi)
with dbts as
(
select distinct p.empi as empi
from primcare.pt_dbts_test_smry p
--left join primcare.prvdr_dir_assoc@edw dir on dir.prvdr_id = p.prvdr_id
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
),
asthma as
(
select distinct a.empi as empi
from primcare.pt_asthma_smry a
--left join primcare.prvdr_dir_assoc@edw dir on dir.prvdr_id = a.pcp_prvdr_id
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
),
dprs as
(
select distinct d.empi as empi
from mhi.depression_summary d
--left join primcare.prvdr_dir_assoc@edw dir on dir.prvdr_id = d.pcp_prvdr_id
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
)
select dbts.empi
from dbts
union all
select asthma.empi

```

```

from asthma
union all
select dprs.empi
from dprs;

```

```

commit;

```

DIM_PROVIDER_STAGE

```

/*

```

This loads all PCP providers for the chronic conditions model into a staging table.
The driving registries are the asthma, diabetes and depression registries.

NOTE: Do NOT load prior to 01-Jul-2009. This is the first time all three registries were loaded on a monthly basis rather than a quarterly basis.

```

*/

```

--3,364 rows inserted 07-Apr-2011

```

insert into sandbox.dim_provider_stage (prvdr_id, med_dir_id, med_dir_region, last_nm,
clinic_nm, prmry_spclty_cd)

```

```

with dbts as

```

```

(

```

```

select distinct nvl(p.prvdr_id, -1) as prvdr_id
, nvl(dir.med_dir_id, -1) as med_dir_id
, nvl(med_dir_region, 'Unknown') as med_dir_region
, nvl(dir.prvdr_lst_nm, 'Unknown') as last_nm
, nvl(dir.clinic_nm, 'Unknown') as clinic_nm
, nvl(prmry_spclty_cd, 'Unk') as prmry_spclty_cd

```

```

from primcare.pt_dbts_test_smry p

```

```

left join primcare.prvdr_dir_assoc dir on dir.prvdr_id = p.prvdr_id

```

```

left join lkup.provider_master pm on pm.prvdr_id = p.prvdr_id

```

```

where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')

```

```

),

```

```

asthma as

```

```

(

```

```

select distinct nvl(a.pcp_prvdr_id,-1) as prvdr_id
, nvl(dir.med_dir_id, -1) as med_dir_id
, nvl(med_dir_region, 'Unknown') as med_dir_region
, nvl(dir.prvdr_lst_nm, 'Unknown') as last_nm
, nvl(dir.clinic_nm, 'Unknown') as clinic_nm
, nvl(prmry_spclty_cd, 'Unk') as prmry_spclty_cd

```

```

from primcare.pt_asthma_smry a

```

```

left join primcare.prvdr_dir_assoc dir on dir.prvdr_id = a.pcp_prvdr_id

```

```

left join lkup.provider_master pm on pm.prvdr_id = a.pcp_prvdr_id

```

```

where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')

```

```

),
dprs as
(
select distinct nvl(d.pcp_prvdr_id, -1) as prvdr_id
      , nvl(dir.med_dir_id, -1) as med_dir_id
      , nvl(med_dir_region, 'Unknown') as med_dir_region
      , nvl(dir.prvdr_lst_nm, 'Unknown') as last_nm
      , nvl(dir.clinic_nm, 'Unknown') as clinic_nm
      , nvl(prmry_spclty_cd, 'Unk') as prmry_spclty_cd
from mhi.depression_summary d
left join primcare.prvdr_dir_assoc dir on dir.prvdr_id = d.pcp_prvdr_id
left join lkup.provider_master pm on pm.prvdr_id = d.pcp_prvdr_id
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
)
select dbts.prvdr_id
      , dbts.med_dir_id
      , dbts.med_dir_region
      , dbts.last_nm
      , dbts.clinic_nm
      , dbts.prmry_spclty_cd
from dbts
union all
select asthma.prvdr_id
      , asthma.med_dir_id
      , asthma.med_dir_region
      , asthma.last_nm
      , asthma.clinic_nm
      , asthma.prmry_spclty_cd
from asthma
union all
select dprs.prvdr_id
      , dprs.med_dir_id
      , dprs.med_dir_region
      , dprs.last_nm
      , dprs.clinic_nm
      , dprs.prmry_spclty_cd
from dprs;

commit;

```

DIM_PT_RPT_CC_STAGE

--1,538,471 rows inserted 07-Apr-2011

```

insert into sandbox.dim_pt_rpt_cc_stage
with dbts as
(
    select empi
        , rpt_per_start_dt as start_dt
        , nvl(prvdr_id, -1) as prvdr_id -- -1 is the default for an unknown PCP
        , 1 as dbts_flg
    from primcare.pt_dbts_test_smry
    where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
),
asthma as
(
    select empi
        , rpt_per_start_dt as start_dt
        , nvl(pcp_prvdr_id, -1) as prvdr_id -- -1 is the default for an unknown PCP
        , 1 as asthma_flg
    from primcare.pt_asthma_smry
    where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
),
dprs as
(
    select empi
        , rpt_per_start_dt as start_dt
        , nvl(pcp_prvdr_id, -1) as prvdr_id -- -1 is the default for an unknown PCP
        , 1 as dprs_flg
    from mhi.depression_summary
    where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
)
select dbts.empi
    , dbts.start_dt
    , dbts.dbts_flg
    , dbts.prvdr_id as dbts_prvdr_id
    , null as asthma_flg
    , null as asthma_prvdr_id
    , null as dprs_flg
    , null as dprs_prvdr_id
from dbts
union all
select asthma.empi
    , asthma.start_dt
    , null as dbts_flg
    , null as dbts_prvdr_id
    , asthma.asthma_flg
    , asthma.prvdr_id
    , null as dprs_flg

```

```

    , null as dprs_prvdr_id
from asthma
union all
select dprs.empi
    , dprs.start_dt
    , null as dbts_flg
    , null as dbts_prvdr_id
    , null as asthma_flg
    , null as asthma_prvdr_id
    , dprs.dprs_flg
    , dprs.prvdr_id as dprs_prvdr_id
from dprs ;

commit;

```

DIM_RPT_PERIOD_STAGE

--26 rows inserted 23-Feb-2011

```

insert into sandbox.dim_rpt_period_stage (start_dt, end_dt)
with dbts as
(
select distinct p.rpt_per_start_dt as start_dt
    , p.rpt_per_end_dt as end_dt
from primcare.pt_dbts_test_smry p
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
order by 1
),
asthma as
(
select distinct a.rpt_per_start_dt as start_dt
    , a.rpt_per_end_dt as end_dt
from primcare.pt_asthma_smry a
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
order by 1
),
dprs as
(
select distinct d.rpt_per_start_dt as start_dt
    , d.rpt_per_end_dt as end_dt
from mhi.depression_summary d
where rpt_per_start_dt >= to_date('2009-07-01','YYYY-MM-DD')
order by 1
)
select dbts.start_dt
    , dbts.end_dt

```

```

from dbts
union all
select asthma.start_dt
      , asthma.end_dt
from asthma
union all
select dprs.start_dt
      , dprs.end_dt
from dprs;

commit;

```

+++++

Extract Transform Load

+++++

DIM_RPT_PERIOD

```

insert into sandbox.dim_chronic_detail
  ( pt_sk, rpt_per_sk, prvdr_sk, EMPI, PRVDR_ID, RPT_PER_START_DT,
    DIABETES_FLG,
    LAST_A1C_Days, LAST_A1C_RESULT_NO, LAST_MICRO_Days,
    LAST_MICRO_RESULT_NO, LAST_LDL_Days, LAST_LDL_RESULT_NO,
    LAST_BP_Days, /*LAST_BP_RESULT_NO*/ LAST_EYE_EXAM_Days,
    ASTHMA_FLG, LAST_CONTROLLER_FILL_Days,
    LAST_PFT_Days, DEPRESSION_FLG, LAST_PHQ9_Days,
    LAST_PHQ9_RESULT_NO, NO_PCP_AFTER_EI_VISIT_FLG,
    NO_PCP_FOLLOWUP_VISIT_FLG, MISSED_NEW_RX_FLG,
    HIGH_PHQ9_WITHOUT_VISIT_FLG, NO_PCP_VISIT_LAST_6_MONTHS_FLG
  )
with pt_rpt as
(
  select pt_sk
        , emp_i
        , rpt_per_start_dt
        , case when asthma_flg is null then 0
              else asthma_flg
              end as asthma_flg
        , case when dbts_flg is null then 0

```

```

        else dbts_flg
      end as dbts_flg
    , case when dprs_flg is null then 0
      else dprs_flg
    end as dprs_flg
    , coalesce(asthma_prvdr_id, dbts_prvdr_id, dprs_prvdr_id, 99999) as prvdr_id
  from sandbox.dim_pt_rpt_cc
  where rpt_per_start_dt = to_date('2010-01-01','YYYY-MM-DD')
),
rpt as
(
  select rpt_per_sk
    , start_dt
    , end_dt
  from sandbox.dim_rpt_period
  where start_dt = to_date('2010-01-01','YYYY-MM-DD')
),
prvdr as
(
  select prvdr_sk
    , prvdr_id
    , med_dir_id
    , last_nm
    , clinic_nm
  from sandbox.dim_provider
),
pt as
(
  select pt_sk
    , empi
  from sandbox.dim_patient
),
dbts as
(
  select empi
    , rpt_per_start_dt
    , case
      when last_hba1c_dt is null then -1
      else trunc((86400*(last_hba1c_dt-rpt_per_start_dt))/60/60/24)
    end as LAST_A1C_Days
    , last_hba1c_result_no as LAST_A1C_RESULT_NO
    , case
      when last_microalb_test_dt is null then -1
      else trunc((86400*(last_microalb_test_dt-rpt_per_start_dt))/60/60/24)
    end as LAST_MICRO_Days
    , last_microalb_result_no as LAST_MICRO_RESULT_NO

```



```

, case
    when last_ldl_dt is null then -1
    else trunc((86400*(LAST_LDL_DT-rpt_per_start_dt))/60/60/24)
end as LAST_LDL_Days
, LAST_LDL_RESULT_NO
, case
    when last_blood_pressure_test_dt is null then -1
    else trunc((86400*(last_blood_pressure_test_dt-rpt_per_start_dt))/60/60/24)
end as LAST_BP_Days
--, last_blood_pressure_result_txt as LAST_BP_RESULT_NO
, case
    when last_eye_exam_dt is null then -1
    else trunc((86400*(LAST_EYE_EXAM_DT-rpt_per_start_dt))/60/60/24)
end as LAST_EYE_EXAM_Days
from primcare.pt_dbts_test_smry
where rpt_per_start_dt = to_date('2010-01-01','YYYY-MM-DD')
),
asthma as
(
    select empi
    , rpt_per_start_dt
    , case
        when LAST_CONTROLLER_FILL_DT is null then -1
        else trunc((86400*(LAST_CONTROLLER_FILL_DT-
rpt_per_start_dt))/60/60/24)
    end as last_controller_fill_days
    , case
        when LAST_PFT_DT is null then -1
        else trunc((86400*(last_pft_dt-rpt_per_start_dt))/60/60/24)
    end as last_pft_days
    from primcare.pt_asthma_smry
    where rpt_per_start_dt = to_date('2010-01-01','YYYY-MM-DD')
),
dprs as
(
    select empi
    , rpt_per_start_dt
    , case
        when LAST_PHQ9_DT is null then -1
        else trunc((86400*(LAST_PHQ9_DT-rpt_per_start_dt))/60/60/24)
    end as LAST_PHQ9_Days
    , last_phq9_sev_no as LAST_PHQ9_RESULT_NO
    , NO_PCP_AFTER_EI_VISIT_FLG
    , NO_PCP_FOLLOWUP_VISIT_FLG
    , MISSED_NEW_RX_FLG
    , HIGH_PHQ9_WITHOUT_VISIT_FLG

```

```

        , NO_PCP_VISIT_LAST_6_MONTHS_FLG
    from mhi.depression_summary
    where rpt_per_start_dt = to_date('2010-01-01','YYYY-MM-DD')
)
select pt.pt_sk
    , rpt.rpt_per_sk
    , prvdr.prvdr_sk
    , pt_rpt.EMPI
    , pt_rpt.PRVD_R_ID
    , cast(to_char(rpt.start_dt,'YYYYMMDD') as int) rpt_per_start_dt
    , pt_rpt.dbts_flg as DIABETES_FLG
    , dbts.LAST_A1C_Days
    , dbts.LAST_A1C_RESULT_NO
    , dbts.LAST_MICRO_Days
    , case when dbts.last_micro_result_no is null then -1
        when dbts.last_micro_result_no = 'NEG' then 0
        when dbts.last_micro_result_no = 'POS' then 1
    end last_micro_result_no
    , dbts.LAST_LDL_Days
    , dbts.LAST_LDL_RESULT_NO
    , dbts.LAST_BP_Days
    --, dbts.last_bp_result_no --hard-coded for now to get the regex working then break
out systolic/diastolic values
    , dbts.LAST_EYE_EXAM_Days
    , pt_rpt.ASTHMA_FLG
    , asthma.LAST_CONTROLLER_FILL_Days
    , asthma.LAST_PFT_Days
    , pt_rpt.dprs_flg as DEPRESSION_FLG
    , dprs.LAST_PHQ9_Days
    , dprs.LAST_PHQ9_RESULT_NO
    , dprs.NO_PCP_AFTER_EI_VISIT_FLG
    , dprs.NO_PCP_FOLLOWUP_VISIT_FLG
    , dprs.MISSED_NEW_RX_FLG
    , dprs.HIGH_PHQ9_WITHOUT_VISIT_FLG
    , dprs.NO_PCP_VISIT_LAST_6_MONTHS_FLG
from pt_rpt
inner join pt on pt.empi = pt_rpt.empi
inner join rpt on rpt.start_dt = pt_rpt.rpt_per_start_dt
inner join prvdr on prvdr.prvdr_id = pt_rpt.prvdr_id
left join dbts on (dbts.empi = pt_rpt.empi and dbts.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
left join asthma on (asthma.empi = pt_rpt.empi and asthma.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
left join dprs on (dprs.empi = pt_rpt.empi and dprs.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
;

```

commit;

CPM_COMPLIANCE_FACT

```

insert into sandbox.cpm_compliance_fact (pt_sk, rpt_per_sk, prvdr_sk, dim_detail_sk,
asthma_flg, dbts_flg, dprs_flg
                                , alc_tested, ldl_tested, micro_tested, eye_tested, bp_tested,
controller_flg
                                , pft_tested_flg, no_pcp_post_ei_visit_flg, no_pcp_fu_visit_flg
                                , missed_new_rx_flg, high_phq9_wo_visit_flg,
no_pcp_visit_6_mo_flg)
with pt_rpt as
(
/*
  This is the DRIVING table for the whole fact.  However, I don't use any
  key off the table to ultimately land in the fact.  There's no need.
  The natural key on the table is empi and rpt_per_start_dt.
*/
  select pt_sk
        , empi
        , rpt_per_start_dt
        , asthma_flg
        , dbts_flg
        , dprs_flg
        , dbts_prvdr_id
        , dprs_prvdr_id
        , coalesce(asthma_prvdr_id, dbts_prvdr_id, dprs_prvdr_id, -1) as prvdr_id
  from sandbox.dim_pt_rpt_cc
  where rpt_per_start_dt = to_date('2009-07-01','YYYY-MM-DD')
),
rpt as
(
  select rpt_per_sk
        , start_dt
        , end_dt
  from sandbox.dim_rpt_period
),
dbts as
(
  select empi
        , rpt_per_start_dt
        , nvl(hb1c_test_flg,0) as alc_tested
        , nvl(ldl_test_flg,0) as ldl_tested

```

```

        , nvl(microalb_test_flg,0) as micro_tested
        , nvl(eye_test_flg,0) as eye_tested
        , nvl(blood_pressure_test_flg,0) as bp_tested
    from primcare.pt_dbts_test_smry
    where rpt_per_start_dt = to_date('2009-07-01','YYYY-MM-DD')

),
asthma as
(
    select empi
        , rpt_per_start_dt
        , pft_test_flg as pft_tested
        , decode(controller_flg, 'Y', 1, 'N', 0) on_controller
    from primcare.pt_asthma_smry
    where rpt_per_start_dt = to_date('2009-07-01','YYYY-MM-DD')
),
dprs as
(
    select empi
        , rpt_per_start_dt
        , no_pcp_after_ei_visit_flg
        , no_pcp_followup_visit_flg
        , missed_new_rx_flg
        , high_phq9_without_visit_flg
        , no_pcp_visit_last_6_months_flg
    from mhi.depression_summary
    where rpt_per_start_dt = to_date('2009-07-01','YYYY-MM-DD')
),
prvdr as
(
    select prvdr_sk
        , prvdr_id
        , med_dir_id
        , last_nm
        , clinic_nm
    from sandbox.dim_provider
),
pt as
(
    select pt_sk
        , empi
    from sandbox.dim_patient
),
dtl as
(
    select dim_detail_sk

```

```

    , empi
    , prvdr_id
    , rpt_per_start_dt
  from sandbox.dim_chronic_detail
)
select pt.pt_sk --Let the dim_patient give the pt_sk. Join on the natural key to pt_rpt!
    , rpt.rpt_per_sk
    , prvdr.prvdr_sk
    , nvl(dim_detail_sk, 1) as dim_detail_sk --this is only valid for the most recent
reporting period.
    , pt_rpt.asthma_flg
    , pt_rpt.dbts_flg
    , pt_rpt.dprs_flg
    , dbts.a1c_tested
    , dbts.ldl_tested
    , dbts.micro_tested
    , dbts.eye_tested
    , dbts.bp_tested
    , asthma.on_controller as controller_flg
    , asthma.pft_tested as pft_tested_flg
    , no_pcp_after_ei_visit_flg as no_pcp_post_ei_visit_flg
    , no_pcp_followup_visit_flg as no_pcp_fu_visit_flg
    , missed_new_rx_flg
    , high_phq9_without_visit_flg as high_phq9_wo_visit_flg
    , no_pcp_visit_last_6_months_flg as no_pcp_visit_6_mo_flg
    -- Add in asthma_flg, dbts_flg, dprs_flg. Drive off the pt_rpt_cc table
  from pt_rpt
  inner join prvdr on prvdr.prvdr_id = pt_rpt.prvdr_id
  inner join rpt on rpt.start_dt = pt_rpt.rpt_per_start_dt
  inner join pt on pt.empi = pt_rpt.empi
  --left join dtl on (dtl.empi = pt_rpt.empi and dtl.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
  left join dbts on (dbts.empi = pt_rpt.empi and dbts.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
  left join asthma on (asthma.empi = pt_rpt.empi and asthma.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
  left join dprs on (dprs.empi = pt_rpt.empi and dprs.rpt_per_start_dt =
pt_rpt.rpt_per_start_dt)
;

commit;

DIM_PATIENT

--inserted 189,885 rows 07-Apr-2011

```

```

insert into sandbox.dim_patient (empi, sex_cd, last_nm, first_nm, birth_dt, death_dt, age,
age_bracket, city_nm, state_cd, postal_cd)
with s as
(
select distinct empi
from sandbox.dim_patient_stage
where empi is not null
),
l as
(
select empi
      , sex_cd
      , last_nm
      , first_nm
      , birth_dt
      , death_dt
      , TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) as age
      , case when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12))
<= 18 then '1-18'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
24 then '19-24'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
34 then '25-34'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
44 then '35-44'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
54 then '45-54'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
64 then '55-64'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) <=
74 then '65-74'
      when TO_CHAR(FLOOR(MONTHS_BETWEEN(SYSDATE, birth_dt)/12)) >
75 then '75+'
      end as age_bracket
      , nvl(city_nm, 'Unknown') as city_nm
      , nvl(state_cd, 'Unknown') as state_cd
      , nvl(postal_cd, -1) as postal_cd
from lkup.patient_master
where test_patient_flg = 0
)
select s.empi
      , l.sex_cd
      , l.last_nm
      , l.first_nm
      , l.birth_dt
      , l.death_dt

```

```

    , l.age
    , l.age_bracket
    , l.city_nm
    , l.state_cd
    , l.postal_cd
from s
left join l on l.empi = s.empi;

commit;

```

DIM_PROVIDER

```

/*
Loads the sandbox.dim_provider table from sandbox.dim_provider_stage
--loaded 1,467 rows on 07-Apr-2011
*/
insert into sandbox.dim_provider (prvdr_id, med_dir_id, med_dir_region, last_nm,
clinic_nm, prmry_spclty_cd)
with s as
(
select prvdr_id
    , max(med_dir_id) med_dir_id
    , max(med_dir_region) med_dir_region
    , max(last_nm) last_nm
    , max(clinic_nm) clinic_nm
    , max(prmry_spclty_cd) prmry_spclty_cd
from sandbox.dim_provider_stage
--where prvdr_id is not null
group by prvdr_id
) /* -- I changed the staging script to handle nulls so I don't need the dummy script
anymore
dummy as
(
    select -1 as prvdr_id
        , -1 as med_dir_id
        , 'Unknown' as med_dir_region
        , 'Unknown' as last_nm
        , 'Unknown' as clinic_nm
        , 'Unk' as prmry_spclty_cd
    from dual
) */
select distinct s.prvdr_id as prvdr_id
    , s.med_dir_id as med_dir_id
    , s.med_dir_region as med_dir_region

```

```

        , s.last_nm as last_nm
        , s.clinic_nm as clinic_nm
        , s.prmry_spclty_cd as prmr_y_spclty_cd
from s /*
union all
select dummy.prvdr_id
       , dummy.med_dir_id
       , dummy.med_dir_region
       , dummy.last_nm
       , dummy.clinic_nm
       , dummy.prmry_spclty_cd
from dummy */
;

commit;

```

DIM_PT_RPT_CC

```

/*      Purpose of Load
Do an upload of all depression rows first. This is the largest patient cohort.
Follow up with two additional merge scripts to pull in the diabetes patients
(next largest cohort) followed by the asthma patients (smallest cohort).
*/

```

```

-----
/* Part One: Insert Depression rows from stage to dim_pt_rpt_cc */
-----

```

```

/*      NOTE!
Be sure to NOT go back prior to 01-July-2009 as this is the
first time that all three chronic conditions have a monthly
load time. Prior to that, diabetes is on a quarterly basis.
Asthma goes back a bit earlier than July.
*/

```

```

insert into sandbox.dim_pt_rpt_cc
(
    empi
    , rpt_per_start_dt
    , asthma_flg
    , asthma_prvdr_id
    , dbts_flg

```



```

        , dbts_prvdr_id
        , dprs_flg
        , dprs_prvdr_id
    )
select empi
    , rpt_per_start_dt
    , asthma_flg
    , asthma_prvdr_id
    , dbts_flg
    , dbts_prvdr_id
    , dprs_flg
    , dprs_prvdr_id
from sandbox.dim_pt_rpt_cc_stage
where rpt_per_start_dt = to_date('2010-03-01','YYYY-MM-DD')
and dprs_flg = 1;

```

```
commit;
```

```
-----
/*  Part Two: Merge in the diabetes rows for the same reporting period  */
-----
```

```

/*      NOTE!
Be sure to not go back prior to 01-July-2009 as this is the
first time that all three chronic conditions have a monthly
load time. Prior to that, diabetes is on a quarterly basis.
Asthma goes back a bit earlier than July.
*/

```

```

merge into sandbox.dim_pt_rpt_cc target
using (
    select distinct
        src.empi
        , src.rpt_per_start_dt
        , src.asthma_flg
        , src.asthma_prvdr_id
        , src.dbts_flg
        , src.dbts_prvdr_id
        , src.dprs_flg
        , src.dprs_prvdr_id
    from sandbox.dim_pt_rpt_cc_stage src
    where rpt_per_start_dt = to_date('2010-03-01','YYYY-MM-DD')
    and dbts_flg = 1
) source
on (target.empi = source.empi and target.rpt_per_start_dt = source.rpt_per_start_dt)
when matched then

```

```

update set dbts_flg = source.dbts_flg
      , dbts_prvdr_id = source.dbts_prvdr_id
when not matched then
insert
(
    target.empi
  , target.rpt_per_start_dt
  , target.asthma_flg
  , target.asthma_prvdr_id
  , target.dbts_flg
  , target.dbts_prvdr_id
  , target.dprs_flg
  , target.dprs_prvdr_id
)
values
(
    source.empi
  , source.rpt_per_start_dt
  , source.asthma_flg
  , source.asthma_prvdr_id
  , source.dbts_flg
  , source.dbts_prvdr_id
  , source.dprs_flg
  , source.dprs_prvdr_id
);

commit;

```

```

-----
/*  Part Three: Merge in the asthma rows for the same reporting period  */
-----

```

```

/*      NOTE!
    Be sure to not go back prior to 01-July-2009 as this is the
    first time that all three chronic conditions have a monthly
    load time.  Prior to that, diabetes is on a quarterly basis.
    Asthma goes back a bit earlier than July.
*/

```

```

merge into sandbox.dim_pt_rpt_cc target
using (
    select distinct
        src.empi
      , src.rpt_per_start_dt
      , src.asthma_flg

```

```

        , src.asthma_prvdr_id
        , src.dbts_flg
        , src.dbts_prvdr_id
        , src.dprs_flg
        , src.dprs_prvdr_id
    from sandbox.dim_pt_rpt_cc_stage src
    where rpt_per_start_dt = to_date('2010-03-01','YYYY-MM-DD')
    and asthma_flg = 1
) source
on (target.empi = source.empi and target.rpt_per_start_dt = source.rpt_per_start_dt)
when matched then
update set asthma_flg = source.asthma_flg
        , asthma_prvdr_id = source.asthma_prvdr_id
when not matched then
insert
(
    target.empi
    , target.rpt_per_start_dt
    , target.asthma_flg
    , target.asthma_prvdr_id
    , target.dbts_flg
    , target.dbts_prvdr_id
    , target.dprs_flg
    , target.dprs_prvdr_id
)
values
(
    source.empi
    , source.rpt_per_start_dt
    , source.asthma_flg
    , source.asthma_prvdr_id
    , source.dbts_flg
    , source.dbts_prvdr_id
    , source.dprs_flg
    , source.dprs_prvdr_id
)
;

commit;

```

DIM_RPT_PERIOD

```

--6 rows inserted 23-Feb-2011
insert into sandbox.dim_rpt_period (start_dt, end_dt)

```

```
with dbts as
(
select distinct p.start_dt
      , p.end_dt
from sandbox.dim_rpt_period_stage p
where p.start_dt >= to_date('2009-07-01','YYYY-MM-DD')
)
select start_dt
      , end_dt
from dbts

commit;
```

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