DISSERTATION

INTEGRATING MBSAP WITH CONTINUOUS IMPROVEMENT FOR DEVELOPING RESILIENT HEALTHCARE SYSTEMS

Submitted by

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ABSTRACT

INTEGRATING MBSAP WITH CONTINUOUS IMPROVEMENT FOR DEVELOPING RESILIENT HEALTHCARE SYSTEMS

The high cost of healthcare is a well-known topic. Utilizing systems engineering methods to address the problem is less well-known in the healthcare industry. There are many variables that impact the cost of healthcare, and this dissertation proposes a solution for the systemic problem of same day missed appointments. Healthcare systems have had success using Continuous Improvement (CI) tools and methods to change and improve processes, but the use of CI tools alone has not yet produced a sustained solution for same day missed appointments. Robust healthcare systems are driven by the architecture. Through utilization of the Model-Based Systems Architecture Process (MBSAP), an architecture was developed to automate utilization management and ultimately reduce the impact of same day missed appointments.

During the needs analysis phase of system development, the history of the problem at an outpatient imaging center was studied and initial experiments for system feasibility were performed. It was found that elements of the architecture are feasible but needed to be more fully developed before implementation. Benchmarking against other service-oriented industries provided additional context for the problem and a set of alternatives for subsystems within the architecture. These two efforts also resulted in the overarching system objective to create a solution that does not rely on changing patient behavior. Since the outpatient imaging center is a sociotechnical system, four social dimensions – the customer dimension, the planning dimension, the operations dimension, and the technical dimension – were defined and analyzed to find the right balance between alternative architectures for the diverse

set of stakeholders needs. A subdomain that included the creation of a master dataset, a visual dashboard, and a predictive model was fully developed by integrating CI methodologies with MBSAP.

The proposed architecture includes automating the integration of the results of the predictive model with existing systems, but this piece of the architecture is still under development. In manually simulating how the results would change internal workflows to provide proactive targeted interventions, a 17% improvement ($260k) in the annual cost (~$1.5M) of same day missed appointments for the outpatient imaging center was realized. MBSAP has been invaluable in adding systemic and systematic rigor to the complex real-world problem of same day missed appointments in an outpatient imaging center. The resulting systems architecture ensures that the needs of all stakeholders are met while anticipating potential unintended consequences.

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The need for this work was identified by Radiology Associates and the methodologies used to address the problem were learned through the Systems Engineering program at Colorado State. Learned might be an understatement, inspired is more accurate. My advisor, Dr. Kamran Eftekhari Shahroudi, has been a constant and reliable source for challenging me to look deeper and better connect the thread between my research veins. I am grateful for his time over the last five years and wish I could keep meeting with him weekly to discuss all my future work. He has been such a wise, kind, and honest advisor. When I first took a class with Dr. Mike Borky and learned MBSAP, one of the missing puzzle pieces for my research appeared. The way I work has now been forever improved by learning this methodology and I am grateful to Dr. Borky for all the time he took to patiently explain some of the concepts that were new to me at the time. In the same vein, Dr. Dan Herber guided me through the modeling process all the way to creating a physical instance of part of the system and has been a constant in reminding me to tie the improvements back to the architecture. The class I took with Dr. Leo Vijayasarathy provided the second missing puzzle piece. My mind was blown when I took that class. That class combined my love of statistics with a process for generating future predictions. Dr. Vijayasarathy provided key insights and support in developing the predictive model that was invaluable to making the system a reality. Finally, Professor Ann Batchelor taught me more about how to generate and write requirements than I even knew was possible. She was also instrumental in connecting me initially (before I was accepted into the program) with my advisor and for that I am forever grateful.

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CHAPTER 1: INTRODUCTION

Engineering a System in Healthcare

Healthcare systems are constantly faced with a barrage of challenges in their quest to improve overall patient outcomes. One of these challenges is the cost of healthcare. Same day missed appointments are a contributor to the cost of healthcare and known systemic problem in the industry. The healthcare industry recognizes this but efforts to improve or manage the impact are mostly reactive or focused on changing patient behavior. Same day missed appointments at an outpatient imaging center in California were studied for this application (see Figure 1).

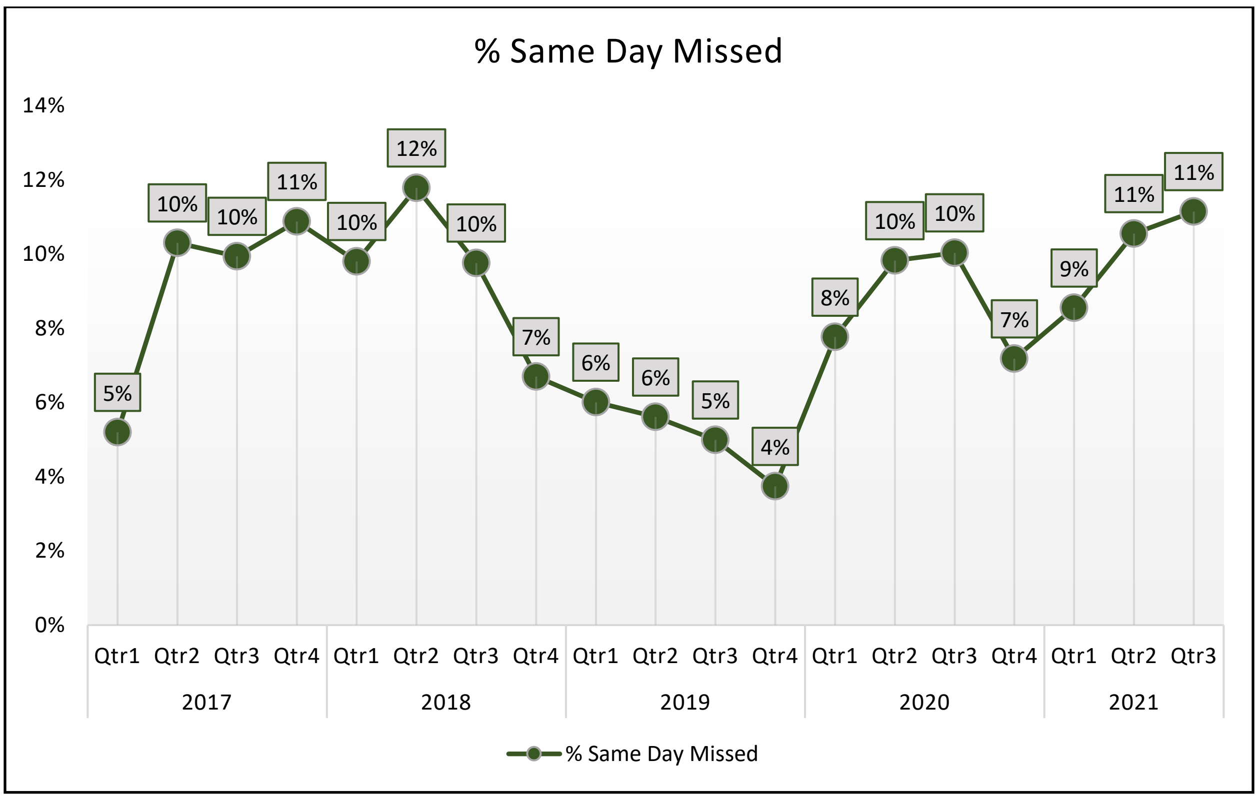

Figure 1: % Same Day Missed Appointments - Outpatient Imaging Center

Lost revenue by year for this outpatient imaging center is shown in Table 1.

Table 1: Lost Revenue by Year Due to Same Day Missed Appointments

Year	Total Revenue	Lost Revenue Due to Same Day Missed Appointments	% Total Possible Revenue
2017	$19M	$1.5M	7.3%
2018	$21M	$1.8M	7.9%
2019	$22.5M	$1.2M	5.1%
2020	$15.5M	$1.3M	7.7%

Multiple initiatives have been undertaken over the last 9 years under the umbrella of continuous improvement with varied results. See Figure 2 for a timeline summary of initiatives.

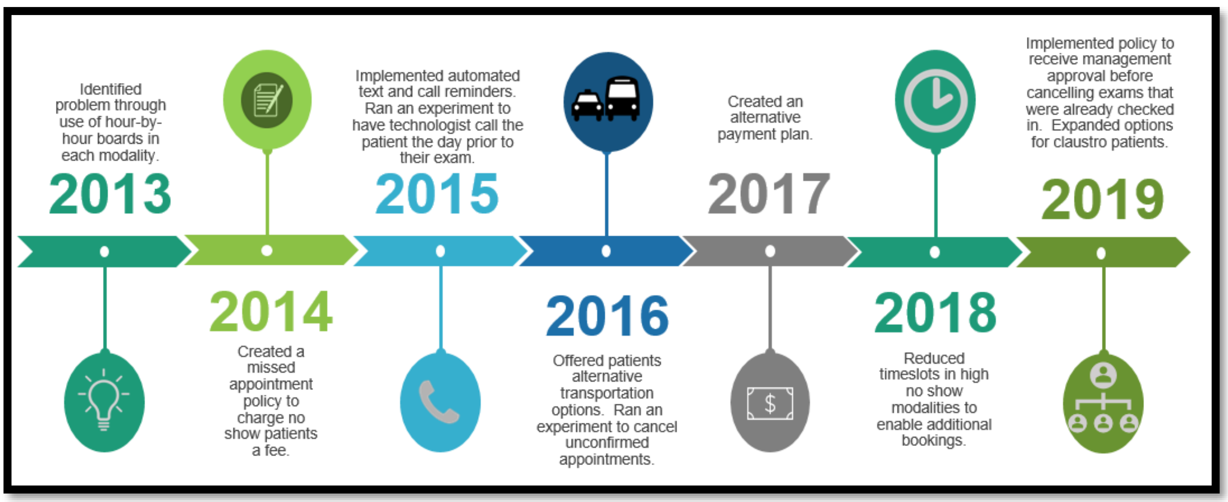

Figure 2: Timeline of same day missed appointment initiatives

Eventually it became clear that a different approach to the problem is required. Recognition that this complex problem requires a systems approach opened the door to a new set of methodologies. The integration of engineering, management, and social science approaches is accomplished using advanced modeling methodologies (Kossiakoff, Sweet, Seymour, & Biemer, 2011). Continuous Improvement (CI) methodologies had already been well-established at the outpatient imaging center and process flow maps were quickly accepted as the standard for communicating complex processes. It is much easier to assimilate the visual communication of a process map than written instructions.

Therefore, the Model-Based Systems Architecture Process (MBSAP) seemed to be the most intuitive choice for engineering a new system in healthcare to sustainably minimize the impact of same day missed appointments. The objective of the research presented is to show that integrating MBSAP with CI is an effective methodology for developing resilient healthcare systems. To determine if MBSAP can produce an effective solution for a persistent problem in healthcare, a system architecture for managing the impact of same day missed appointments is presented. To expand upon the CI methodology already adopted, a model for combining a technical approach with continuous improvement in a clinical context is presented. See Figure 3 for a summary of the research objective, questions, and approach.

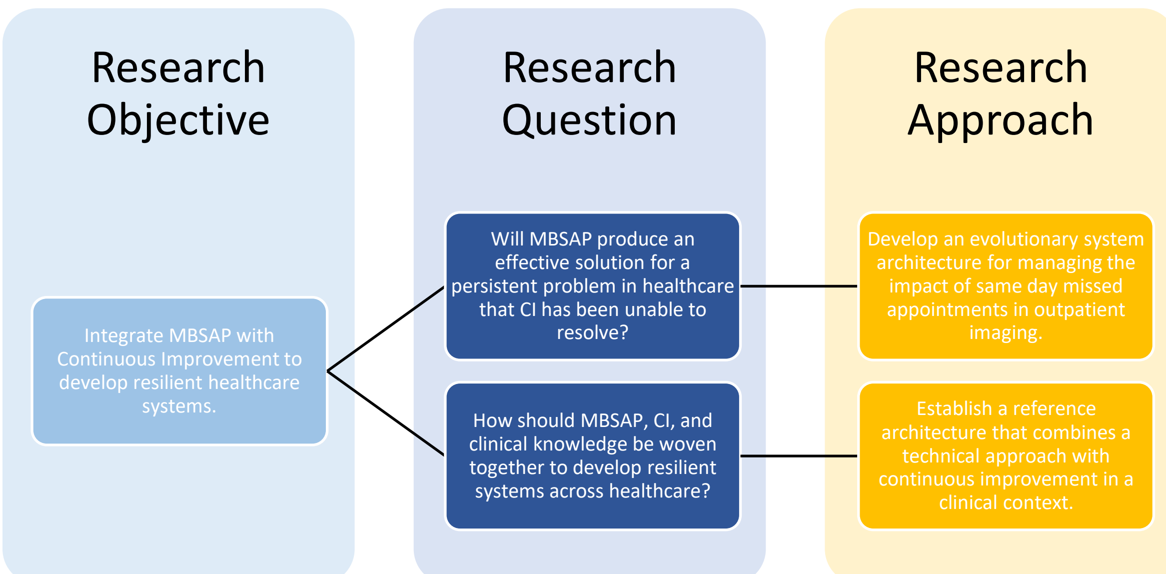

Figure 3: Summary of Research Objective, Questions, and Approach

Dissertation Organization

This dissertation presents a proposed architecture for proactively managing the impact of same day missed appointments and the development of critical domains within the architecture. To show the need for this system and the application in an outpatient imaging context, the content of this paper is organized as follows:

- Chapter 1 presents a summary of the context for this dissertation and the research questions the following chapters address.
- Chapter 2 presents the history of the same day missed appointment problem in healthcare and issues with previous initiatives. An approach for proactively managing the impact of same day missed appointment is presented through initial use of rudimentary predictive modeling. While predictive modeling proved to be beneficial, as a standalone system it was not practical. This chapter concludes with the need to integrate the benefits of predictive modeling into existing systems.
- Chapter 3 presents benchmarking performed against other service-oriented industries to develop a set of system level requirements and alternatives appropriate for healthcare. A summary of the methods used and potential applications for the same day missed appointment problem in healthcare are provided.
- Chapter 4 shows how outpatient imaging centers are sociotechnical systems with multiple dimensions that needed to be analyzed to develop a balanced architecture. The social dimensions in outpatient imaging and how they influenced the proposed architecture are presented in this chapter.
- Chapter 5 provides additional system artifacts and a case study to show how integrating MBSAP with CI produced a sustained instance for one subsystem within the proposed architecture. Manual data analysis has long been an obstacle in understanding the causes of same day missed appointments in a timely manner. The development of an automated dashboard that is visible to all stakeholders is presented in this chapter.
- Chapter 6 presents the development of a model that is used to predict the probability of a patient becoming a same day missed appointment and its use in operations. The technology required to realize this subsystem was a significant unknown in the early development of the

architecture. The ability to develop a working prototype of the predictive model is a significant step in validating the overall proposed architecture.

- Chapter 7 reviews the status of the proposed system in operation at the outpatient imaging center. A summary of how certain requirements were verified and validated along with recommended future research is presented in this chapter.

CHAPTER 2: REDUCING THE IMPACT OF SAME-DAY MISSED APPOINTMENTS

The Need

The process for patients to be seen at an outpatient imaging facility starts with an order from a referring physician. Referring physicians of all specialties send patients for specific imaging for a variety of clinical reasons. The two primary choices for imaging are inpatient which refers to imaging performed within the hospital and outpatient. Outpatient centers have the benefit of being able to offer patients more affordable exams. However, reimbursement cuts over the last few years have led to significant reductions in payments received by radiologists (Levin, Parker, & Rao, 2017). These reimbursement cuts motivated outpatient imaging centers to find innovative ways to cut costs, improve efficiency and remain competitive.

One outpatient imaging center in California started a lean journey in 2013 to address the need. Learning the lean methodology awakened management and staff to the benefits of collecting real-time performance data and using tools to manage daily improvement. Through use of hour-by-hour boards in each modality, this outpatient imaging center could begin identifying recurring obstacles that prevented them from meeting their daily target of efficiently seeing all scheduled patients. Hour-by-hour boards are a visual management tool that display real-time output versus target output and allow technologists to communicate problems (Simpler Consulting, 2014).

A significant source of waste revealed through use of the hour-by-hour boards was same-day patient cancellations and no-shows. These events left the imaging center in a position where they were often unable to fill the time slot. Patients that cancel waste resource time spent scheduling, financial counseling, and vetting the examination. Vetting includes following up on laboratory orders, obtaining necessary authorizations, and ensuring patients pick up any preparation materials for the examination. Same-day cancellations and no-shows (both fall under the category of same-day missed appointments) cause accessibility issues for other patients and increase costs if the imaging center is unable to fill the time slot.

This problem is not a new one for the healthcare industry. England's National Health System (NHS) found that appointment no-shows cost the health service £1 billion in 2017 (Matthews-King, 2018). A recent MGMA survey found that about 44% of respondents said patient no-shows are the biggest challenge in their medical practice, followed by appointment availability (38%), unfilled slots (7%) and cancellations (6%) (Harrop, 2017).

Ongoing Experimentation

For 4 years, this California-based outpatient imaging center has been actively working to close the gap between the total number of scheduled appointments and the appointments kept (see Figure 4) by running experiments designed to reduce the occurrences of these same-day missed appointments.

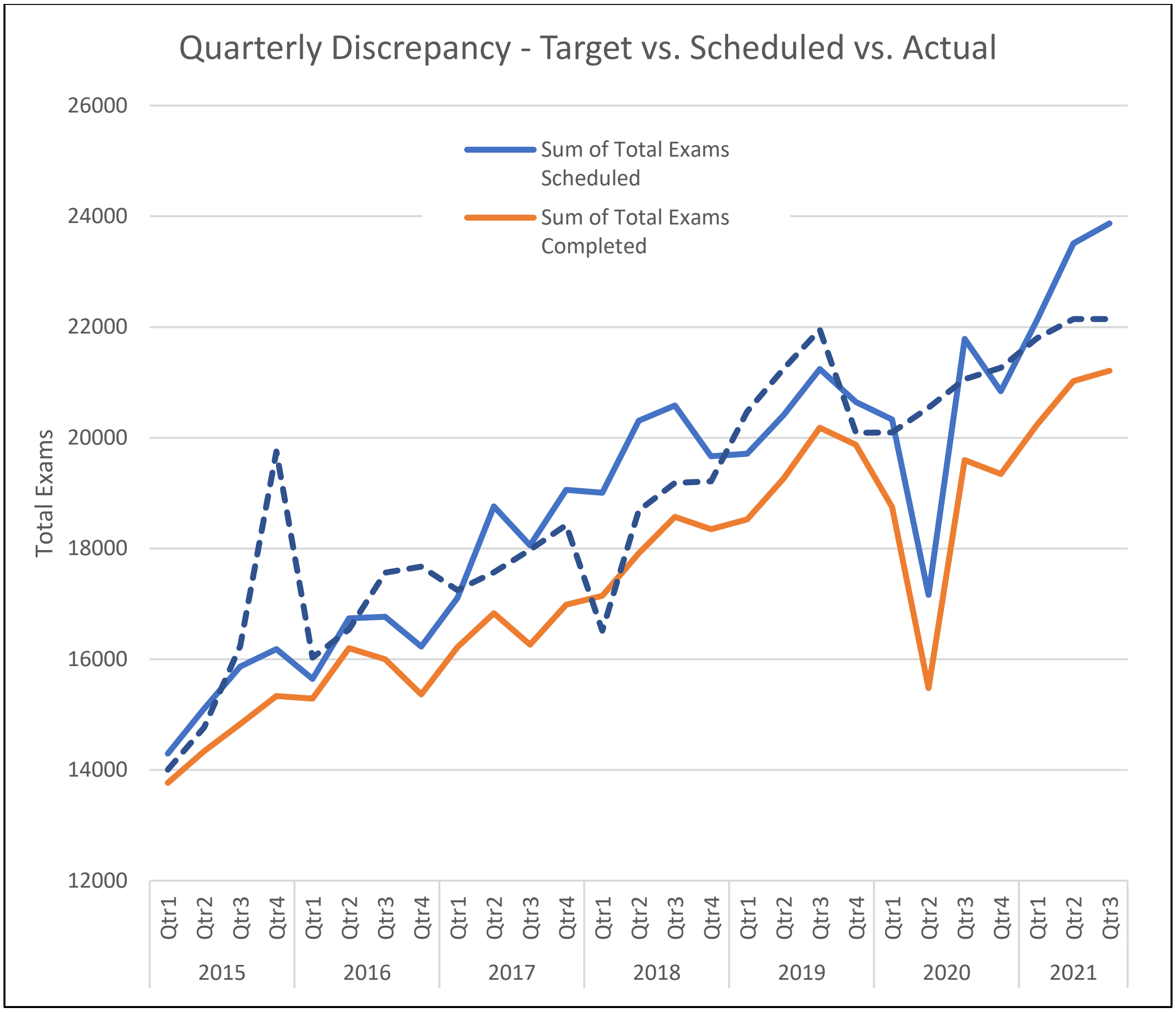

Figure 4: Total Scheduled Versus Target Versus Actual by Quarter

The front office staff is required to call no-show patients at the time of the scheduled examination to obtain a reason for not showing up for their appointment. For patients who answered the phone, the biggest reason for being a no-show was simply that they forgot, followed by various personal reasons. Therefore, by following the Pareto principle (Krajewski & Ritzman, 2005), a series of experiments were conducted over the years designed to help remind patients of their scheduled examination and alleviate personal obstacles to showing up for their appointment.

In 2014, the organization briefly attempted to charge no-show patients for missed appointments, but this was quickly rescinded when patients refused to pay, stating they would just start using competitors.

In 2015, a sanctioned improvement team conducted an experiment to have MRI and CT technologists personally call to confirm the patients scheduled for the next day. The goal was to establish a rapport with the patient and perhaps create a feeling of obligation to show up for the appointment. This experiment failed. The average percentage of same day missed appointments stayed the same. The outpatient imaging center also implemented an automated text and call reminder system.

In 2016, a grassroots effort was undertaken to cancel unconfirmed appointments to open the time slots up for scheduling. This experiment failed because of the high percentage of patients who still showed up for their appointment and were highly dissatisfied to find that it had been cancelled. Transportation options were also added to the website to help patients who cancel for the personal reason of having no means of transportation. In early 2017, an alternative payment plan was developed for patients who indicate during scheduling that they will have to cancel their examination because they are unable to pay the full estimated out-of-pocket amount due all at once.

All the experiments conducted were tracked for 90 days to see if a significant change in the same day missed rate occurred. Unfortunately, none of the experiments produced a significant difference to the organization, and the same day missed issue was set aside for a year and a half to focus on other continuous improvement efforts. However, in early 2018, the same day missed appointment issue grew to unacceptable proportions, and the organization needed to take another stab at the problem. This time, a different tactic was introduced. The consensus among all staff members was that trying to prevent same day missed appointments is important; however, the time had arrived to finally accept that this phenomenon would continue to occur. The decision was to accept the reality and move forward. This shift in mindset allowed the outpatient imaging center to begin considering innovative ways to schedule more examinations every day, knowing same day missed appointments would occur. Instead of analyzing just same day missed appointment data, the outpatient imaging center pulled all cancellation data and created a Pareto chart for cancelled examination reasons (see Figure 5). The data on cancelled examinations provided additional information that the same day missed data were lacking due to the ability to collect a cancellation reason from the patient while on the phone. The biggest controllable issue was that patients cancelled their examinations because they could schedule elsewhere sooner. This eye-opening data led to a further analysis of overall capacity and availability.

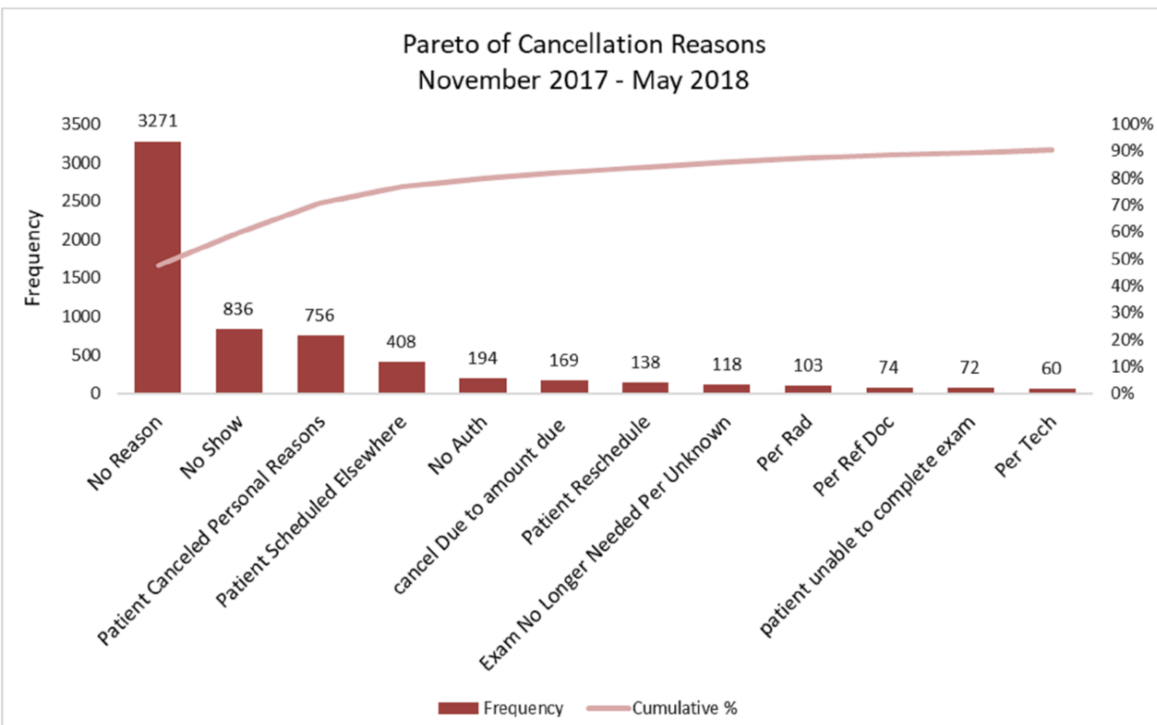

Figure 5: Pareto of Cancellation Reasons

Scheduling More to Cover the Deficit

The most cancelled examinations were screening mammograms, so the first experiment was double-booking screening mammograms at the top of the hour only. This conservative experiment resulted in an average increase of two more screening mammograms performed every day (see Figure 6). The success of this experiment led to an in-depth cluster analysis to identify specific types of patients who cancel their examinations.

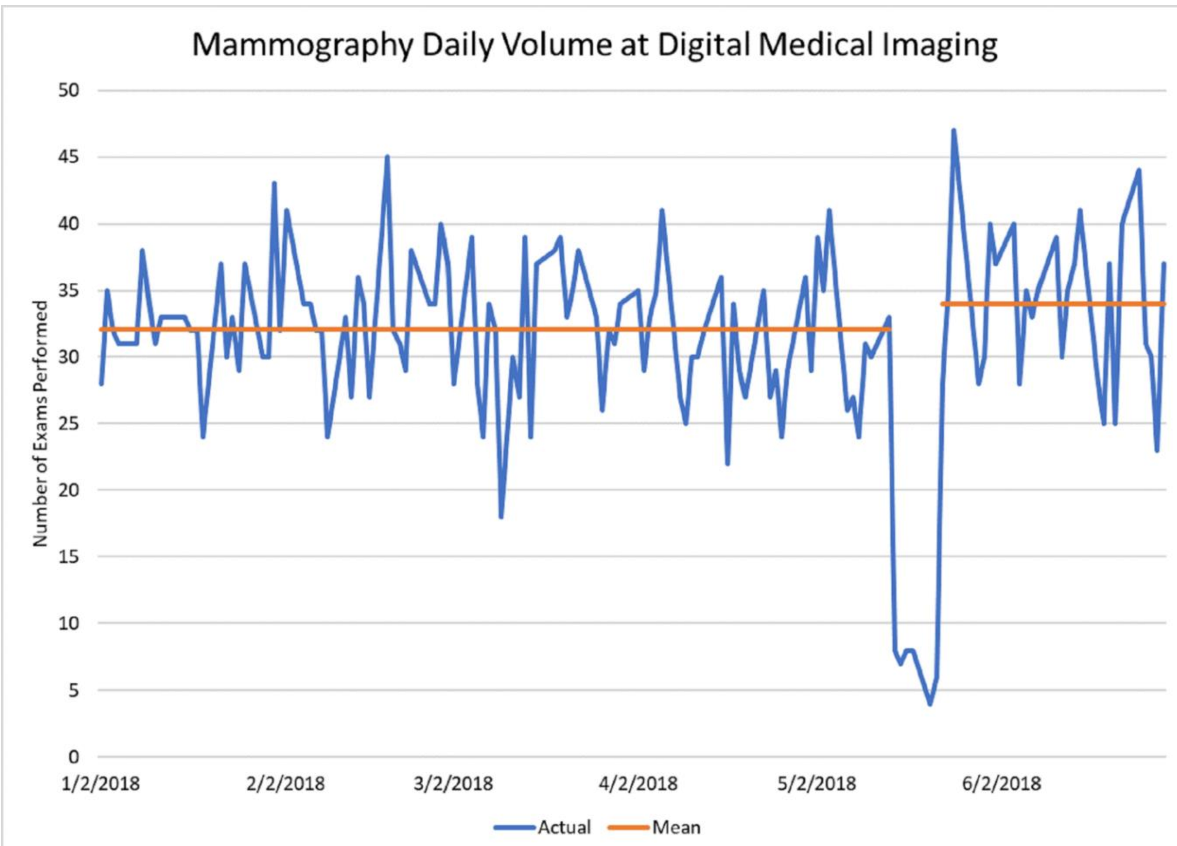

Figure 6: Mammography Daily Volume

The cluster analysis for this chapter was generated using SAS Enterprise Miner^{TM} software. Copyright © 2013 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, North Carolina. Experimentation with the maximum number of clusters produced the most valuable results when set at 10. The model found three useful, distinct clusters (see Figure 7).

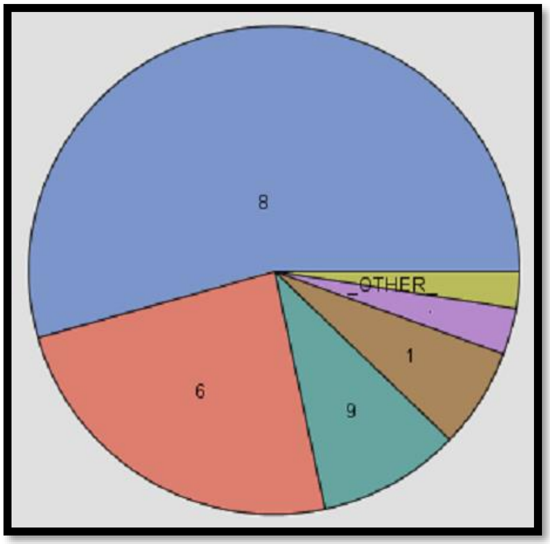

Figure 7: SAS cluster analysis results segment size

Cluster 8 was the largest segment with 3,442 patients. Patients in this cluster fall under the "I just didn't want to, and I don't have to" category by exhibiting the following characteristics (see Figure 8):

- A total of 3,442 (100%) did not reschedule.
- A total of 2,822 (82%) were never reached by the front office.
- A total of 2,444 (71%) were scheduled at a single center.
- A total of 1,446 (42%) had government-funded insurance.

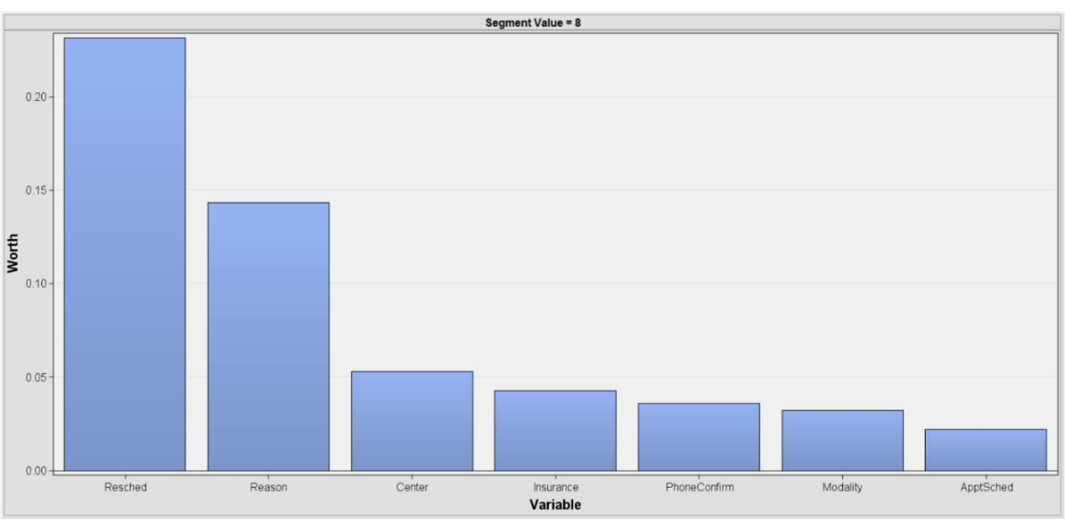

Figure 8: Cluster 8 variables

Cluster 6 was the next largest segment with 1,517 patients. These “Whoops, I did it again” patients cancelled by exhibiting the following characteristics:

- A total of 1,502 (99%) rescheduled their appointments.
- A total of 667 (44%) stated that they forgot about their appointment and another 152 (10%) thought their appointment was on a different day or at a different time.

Cluster 9 was the third largest segment with 601 patients. Patients in this segment differed from patients in cluster 8 because the majority never bothered to confirm their appointment through any of the means presented. This cluster’s data are the most interesting because it contains the strongest leading indicator of a same day missed patient. The indifference of these patients causes them to fall under the frustrating “Whatever . . .” category by exhibiting the following characteristics:

- A total of 469 (78%) were scheduled at a different center than the patients in cluster 8.
- A total of 445 (74%) never confirmed their appointment.
- A total of 264 (44%) were scheduled for a mammogram, 138 (23%) were scheduled for an MRI, and 132 (22%) were scheduled for an ultrasound.

The results of the cluster analysis were helpful for starting to better understand the distinct types of patients who cancel their examination and move toward a method for predicting every patient’s likelihood to cancel.

An Interim Solution and Proposed Path Forward

Although the benefit of utilizing the cluster analysis and more sophisticated predictive models to double-book high-probability patients is obvious, the current system of scheduling does not allow the scheduling staff to easily execute this. With a high volume of incoming orders and limited amount of time to schedule and financially counsel a patient, schedulers are unable to investigate the details of every scheduled examination and decide whether the appointment can be double-booked or not. When a patient's order is sent, it first shows up in a fax queue in Perceptive Content, the document imaging and management system used to consolidate patient paperwork. Upon scheduling a patient examination, relevant information is transferred into the digital radiography (DR) system. When staff schedules an examination, the scheduling system only provides the staff with the next available time slot and a high-level view of the schedule for the day. Schedulers are unable to quickly see the necessary details like phone confirm status, insurance, and so on to efficiently double-book. Being unable to double-book specific examinations without sacrificing scheduler throughput, a cross-functional team chose to shorten time slots in certain modalities with high cancellation rates as an interim solution. By analyzing high-frequency examinations and comparing current standard time to actual times, standard times in DR could be reduced to schedule approximately 3 more MRIs, 14 more ultrasounds, and 3 more CT scans every day. It is good patient care to both schedule patients for the time and day they request or need and provide technologists with the ability to spend the necessary time with the patients to provide the radiologists with clear and useful images. Considering these changes, the reinforced message to technologists was "*The intent of the shortened time slots is not to rush through examinations at the expense of quality and patient care. We have shortened some time slots (and increased others) after seeing what the current average time to complete the examination is and factoring in the quantity of same day missed appointments. We want you to spend the same amount of time with your patients that you are currently, with the understanding that if you get behind in your day, there will be same-day missed appointments that will give you the opportunity to catch up*" (Radiology Associates, 2018). The journey of continuous improvement goes on for this innovative outpatient imaging center. The next steps are to work toward creating a dynamic system that can predict each patient's likelihood of cancelling his or her examination, allowing schedulers to optimize the schedule without sacrificing scheduling throughput. The long-term plan is to develop a predictive model that seamlessly integrates with the DR system, instantly providing the probability of a patient cancelling an examination at the time of scheduling. This information would enable the outpatient imaging center to make proactive decisions to improve examination appointment availability and reduce the overall cost of health care.

CHAPTER 3: WHAT WE CAN LEARN FROM HOW SERVICE-ORIENTED INDUSTRIES MANAGE NO-SHOWS

Introduction

A significant source of waste in healthcare is unutilized time slots due to patients that never show up for their scheduled examination. The total lost revenue for a medium-sized outpatient imaging center that attempted to proactively prevent same-day missed appointments (no-shows and patients who call to cancel the same day) came to approximately $1.5 million in 2017 and $1.8 million in 2018. After 4 years of running experiments to try and change patient behavior to reduce the occurrences of same day missed appointments, it became obvious that a different solution is required. The need for an automated system to proactively manage utilization in outpatient imaging centers was established in Chapter 2. The primary objective is to build a system that optimizes utilization without a dependency on patient behavior modification.

However, because the health care industry is not the only one suffering from this problem, it is necessary to look at how other industries are handling this issue and adopt their best practices in developing this new system. Same day missed appointments are an issue for all reservation-based service industries. Each of these industries—airline, restaurant, hotel, and car rental—have developed methods to either change customer behavior or change internal processes to proactively manage utilization.

How Service-oriented Industries Manage the Impact

Airlines require customers to pay in advance. Depending on the ticket level, customers who do not show for their flight may be eligible to retain the full value and book another flight or may be out of luck altogether. Airlines also review previous passenger no-show trends to determine the amount they will overbook an airline. Because this is not an exact science, and sometimes more people than calculated show up for their scheduled flight, airlines have resorted to incentivizing passengers off the flight by offering significant compensation. Airlines rely on the additional revenue that double-booking provides, and if they are unable to recoup their lost revenue, then passengers' tickets prices may go up. Although it is not an option in the health care industry to raise insurance reimbursements to cover the deficit same day missed appointments cause, it would be an option to offer incentives to double-booked patients if both arrive and the second patient to arrive is unwilling to wait.

OpenTable, the online restaurant reservation system, has created a policy in which a customer's OpenTable account is terminated after four no-shows in a year (OpenTable, n.d.). This practice changes customers' behavior because they are being punished for careless behavior. This practice highlights the need to notify no-show customers that they failed to show for their scheduled appointment and track individual no-show frequency. However, in health care it is not responsible to ban a patient from utilizing services or identifying them as a walk-in patient only because it will detract them further from receiving necessary care.

Another interesting tactic that some restaurants have resorted to is publicly shaming no-show diners on social media (Bernot, 2018). However, this is not a method that an outpatient imaging center should or could consider because it would be a HIPAA violation as well as inappropriate by most decency standards. Chef Ron Eyester, of Rosebud in Atlanta, will jot down a note if a diner seems to be wavering on the phone, so that the staff knows not to hold the empty table too long (Reddy, 2012). Schedulers often state that they can tell just by the patient's tone of voice or sense of noncommittal that a patient will eventually cancel the appointment. An automated utilization management system should provide the option for the scheduler to indicate cancellation probability in the system.

Many car rental companies offer two payment options—pay now or pay later. The pay now option is less expensive than the pay later option but comes with strings attached. Enterprise has a policy that reads as follows:

- If you did not prepay for your reservation, there will not be a cancellation fee.
- If you prepaid for your vehicle, the following conditions will apply (applicable in US and Canada only):
    - If you cancel your booking more than 1 day (24 Hours) before your specified pick-up time, you will receive a full refund minus a cancellation fee of USD $50 / CAD $65.
    - If you cancel your booking less than 1 day (24 Hours) before your specified pick-up time, you will receive a full refund minus a cancellation fee of USD $100 / CAD $135 (Enterprise).

For the automated utilization management system, if a patient's cancellation reason is due to excessive out-of-pocket amount, then the system could modify the scheduler's workflow to offer a less expensive pay now option.

Hotels have varying cancellation policies for customers with consequences for failure to comply that range from a nominal fee to full loss of out-of-pocket costs. The hotel industry has the flexibility to employ revenue management and dynamic pricing strategies to optimize utilization. So does the airline industry. These strategies allow hotels to maximize the room price when demand exceeds supply and maximize hotel capacity when supply exceeds demand (Bandalouski, Kovalyov, Pesch, & Tarim, 2018).

Focusing on customer service by effectively managing in-facility wait time may help reduce no-shows. Solution Reach, a company that provides automated reminders, believes that "asking a patient to wait 20 to 40 minutes or more for an appointment will increase the likelihood of them opting out of future appointments. If patients don't feel you value their time, they are less likely to value yours. This is how a no show turns into a lost patient" (Solutionreach, 2018). The system will need to notify patients who have checked in of their approximate wait time and keep them updated with any changes. See Figure 9 for a summary of methods covered.

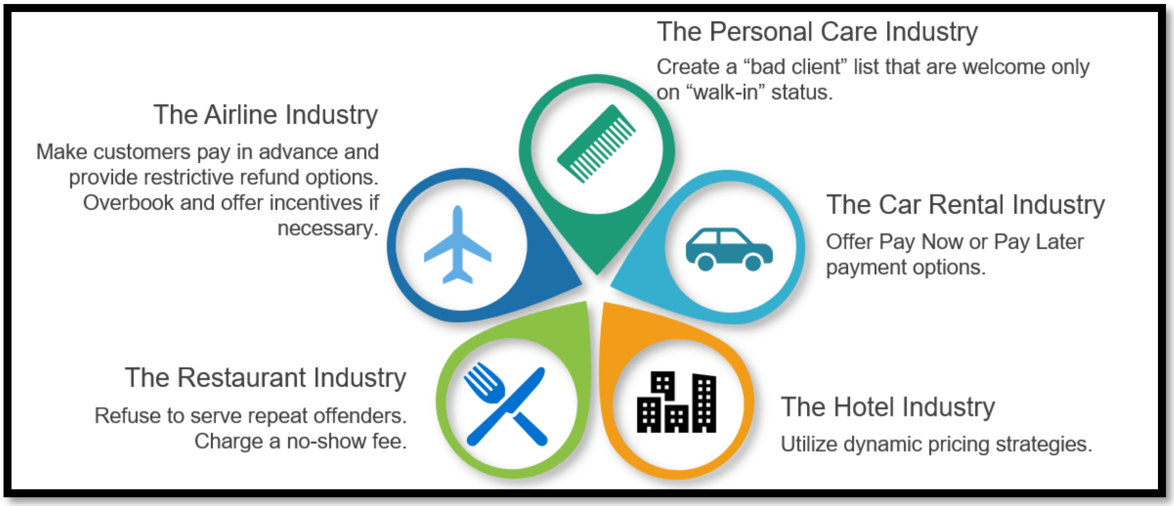

Figure 9: Summary of Methods Used by Optional Service Industries

Conclusion

In an optional-service industry, if the service is being withheld because of past careless behavior, then customers will adapt their behavior going forward if it is truly something they want. However, in healthcare, we want to change patient behavior because of the negative impact to the entire system, and that is a hard sell for people who do not necessarily care that they prevented another individual from getting a needed appointment or affected the profitability of the provider. It would be wrong to withhold a basic need from "bad patients." In health care, efforts to change the system are a better and more reliable option than trying to change patient behavior. See Table 2 for a summary of possible application in healthcare, specifically for outpatient imaging centers.

Table 2: Summary of Benchmarking Methods and Possible Application in Outpatient Imaging Centers

	Benchmarking Method	Applicable for Healthcare?	Currently Used in Outpatient Imaging?
Change Patient Behavior	Require customers to pay in advance	Limited Applications	Only at check-in, not during scheduling
	Text reminders	Yes	Yes
	Refuse service if repeat offender	No	
	Notify customer that it is known that they were a no-show	Yes	Yes
	Charge a no-show fee	No	
	Public shaming on social media	No	
	Bad-client list	No	
	Pay Now or Pay Later Options	Limited Applications	No
	Overbook and incentivize	Limited Applications	No
Change the System	Raise rates to cover deficit	No	
	Make it easy to cancel a scheduled appointment	Yes	No
	Allow schedulers to indicate cancellation probability based on conversation	Yes	No
	Reduce schedule to appointment wait time	Yes	Yes

CHAPTER 4: APPLICATION OF MBSAP TO A COMPLEX PROBLEM WITH SOCIAL DIMENSIONS: UTILIZATION IN OUTPATIENT IMAGING CENTERS

The Need

Outpatient imaging centers, like most service-based organizations, struggle daily to manage the negative impact of same-day missed appointments. Engineering a solution for this problem is complex due to the "diverse, clashing interests and goals" (Garcia-Diaz & Olaya, 2018) of the stakeholders that make up this sociotechnical system. The technical component of outpatient imaging centers includes complex IT infrastructure and advanced medical imaging equipment. The social component of outpatient imaging centers includes stakeholders that regularly interact with these technologies and one another all to help physicians diagnose their patients. The effectiveness of the technology used in outpatient imaging is dependent on operator ability and stakeholder collaboration. Problems in this type of system require intentional systems thinking to completely understand the needs of each stakeholder. In Systems Thinking for Social Change, the author argues that systems thinking in practice covers the spiritual, emotional, physical, and mental dimensions of a social system (Stroh, 2015). A way that systems thinking can be intentionally practiced in a sociotechnical system is through use of the Model-Based System Architecture Process (MBSAP) (Borky, 2009-2018). MBSAP provides a comprehensive and visually understandable framework for system development in an industry unfamiliar with Systems Engineering methods. Using systems thinking and Model-Based Systems Engineering (MBSE) to solve this type of problem in healthcare is new. In fact, a search for the terms "MBSE" and "Radiology" or "Outpatient Imaging" yielded zero results in both the Engineering Village and the ABI/INFORM Complete databases. The MBSAP methodology includes three viewpoints – Operational Viewpoint, Logical/Functional Viewpoint and Physical Viewpoint – that are each organized into Behavioral, Structural, Data, Service and Contextual Perspectives.

Outpatient imaging centers are not alone in their need to proactively manage utilization. Most service-based organizations are actively employing various methods to modify customer behavior to reduce the impact of no shows. However, for outpatient imaging centers, methods to change patient behavior to reduce same day appointments have had minimal impact. In healthcare, efforts to change the system are a better and more reliable option than trying to change patient behavior. This chapter presents an architecture for a system that utilizes all available exam time slots without a dependency on modifying patient behavior to prevent same day missed appointments. The data and information presented is primarily pulled from an outpatient imaging center in California that lost $1.5M in 2017 and $1.8M in 2018 to same day missed appointments (Radiology Associates, 2015-2019). This problem spans the healthcare industry with the national impact to the total United States healthcare system estimated to be $150 billion (Gier, 2017).

The primary social dimensions in outpatient imaging are the Customer Dimension, Planning Dimension, Operations Dimension, and Technical Dimension. Each of these dimensions have stakeholders with a diverse set of needs that must be well-understood and incorporated into the requirements. Empathy for all stakeholder needs in requirements development in the healthcare world is key to the success of the system. The goal is to develop a system that works alongside and supports each of the stakeholder groups without requiring manual interventions in their workflows. The role human users will play in the system will be minimized to current job requirements with adjustments being made primarily to the systems they are using. Users will be trained to understand how the dynamic adjustments will affect their workflow but should not be expected to remember the nuances of the system to perform their job. The system itself should be invisible to the staff members. To design an "invisible" system architecture, the needs of each social dimension must be understood. Artifacts from the Operational Viewpoint for a system that minimizes the impact of same day missed appointments in an outpatient imaging center are presented in this chapter.

Structural Perspective of the Operational Viewpoint

The proposed system is envisioned to have two domains – Center Exam Status and Cancellation Prediction. The Center Exam Status domain breaks down further into the Patient Status and Wait Room Notification subdomains. The Patient Status subdomain will track patient status - early, on time, late or exam not completed - and automatically feed the data to a dashboard and predictive model. Patients who have not arrived by their table time will be assigned a status of “exam not completed.” This will trigger front office receptionists to contact the patient and determine a reason. The Wait Room Notification subdomain is the system that automatically notifies patients who have arrived of their approximate wait time and place in the queue. In an outpatient imaging setting, there are multiple queues for the different modalities however patients usually do not understand that, and multiple complaints have been received about wait time. The Waiting Room Notification system will use check-in time information pulled from the Patient Status subdomain or Radiology Information System (RIS) as well as exam cycle time data. This system is necessary to reduce the unnecessary burden of asking front office staff to track everyone in the waiting room and notify them continuously of their approximate wait time.

The Cancellation Prediction domain will be an independent model that predicts the probability of a patient cancelling their exam and either triggers an alternative workflow or enables double-booking for patients with a high cancellation probability. This domain will receive scheduled patient data from RIS and calculate cancellation probability and cancellation reason regardless of whether the patient has been seen before or not. The model will need to self-update by regularly incorporating data received from the Center Exam Status System. After each patient analysis, the model will send a signal to RIS to either trigger a change to the scheduler’s workflow, enable double-booking or do nothing. See Figure 10 for a concept of operations that shows the system domains and how they interact with the different social dimensions in outpatient imaging. See Figure 11 for a use case objectives diagram that shows the needs of each major stakeholder group.

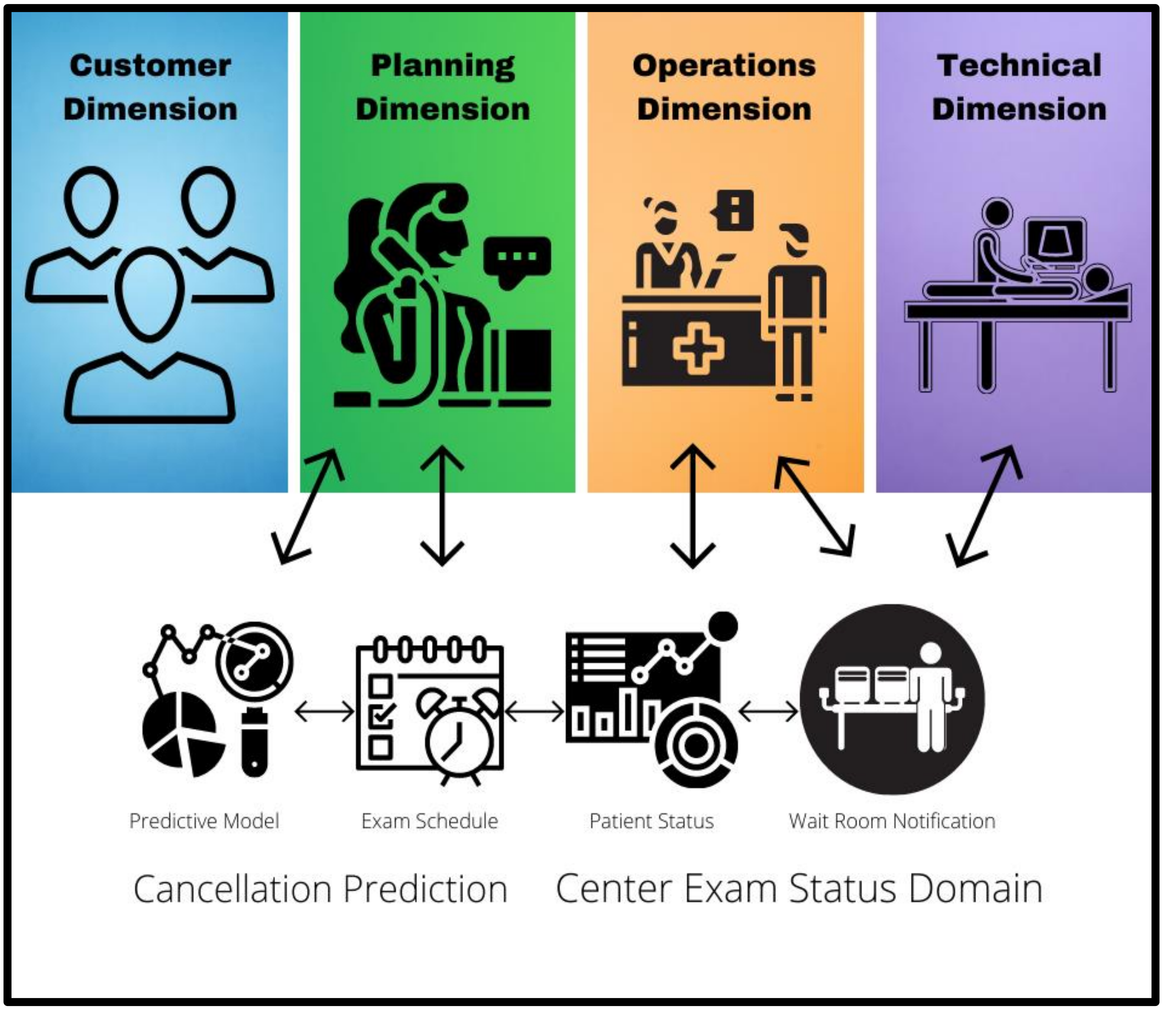

Figure 10: Concept of Operations for Automated Utilization Management (AUM) System with Stakeholder Social Dimensions

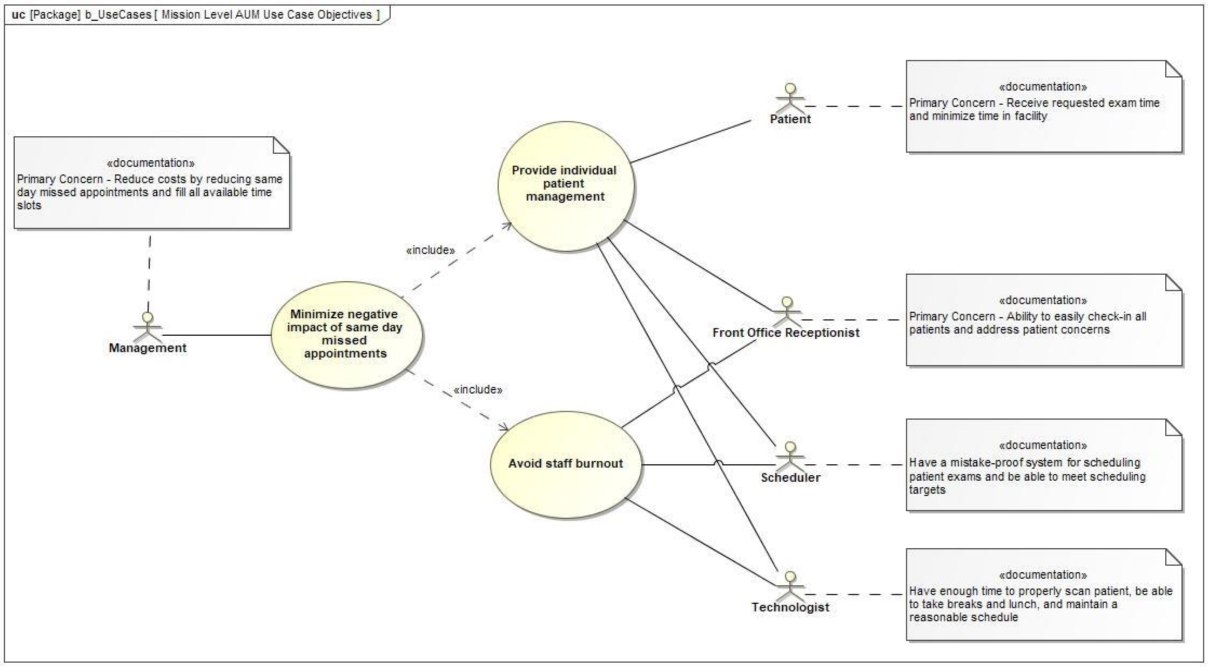

Figure 11: Mission Level Use Case Objectives

The Customer Dimension

Patients and referring physicians need a quick turnaround on imaging orders. In outpatient imaging, an actionable item on the Pareto for cancellation reasons is “scheduled elsewhere.” Often this means they were able to schedule at another facility sooner and forgot to call and cancel the appointment they scheduled first. This is the justification for requirement 1.1 (see Figure 12) that the system shall minimize the number of unused exam time slots.

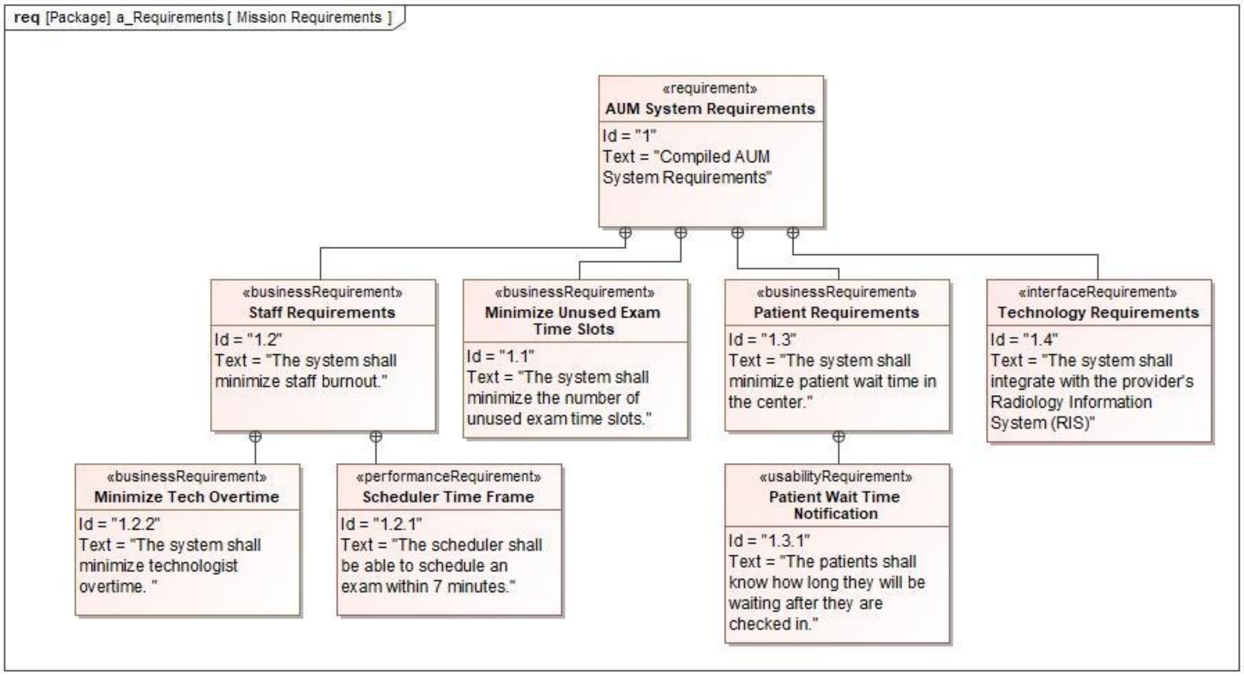

Figure 12: Mission Level Requirements for AUM

Minimizing unused exam time slots can be accomplished by either proactively preventing the same day missed appointment before it occurs or overbooking. Part of the concept for the automated utilization management (AUM) system came first from realizing that the healthcare industry is not the only service-oriented industry suffering from the impact of same day missed appointments. Benchmarking other service-oriented industries to understand their best practices on how they manage this issue helped further evolve the system-level requirements. An automated utilization management system with individualized workflows to prevent same-day cancellations and optimize modality utilization is a patient-friendly and industry-friendly option. See Figure 13 for a sequence diagram of automatically modifying scheduler workflows based on the potential cancellation reason.

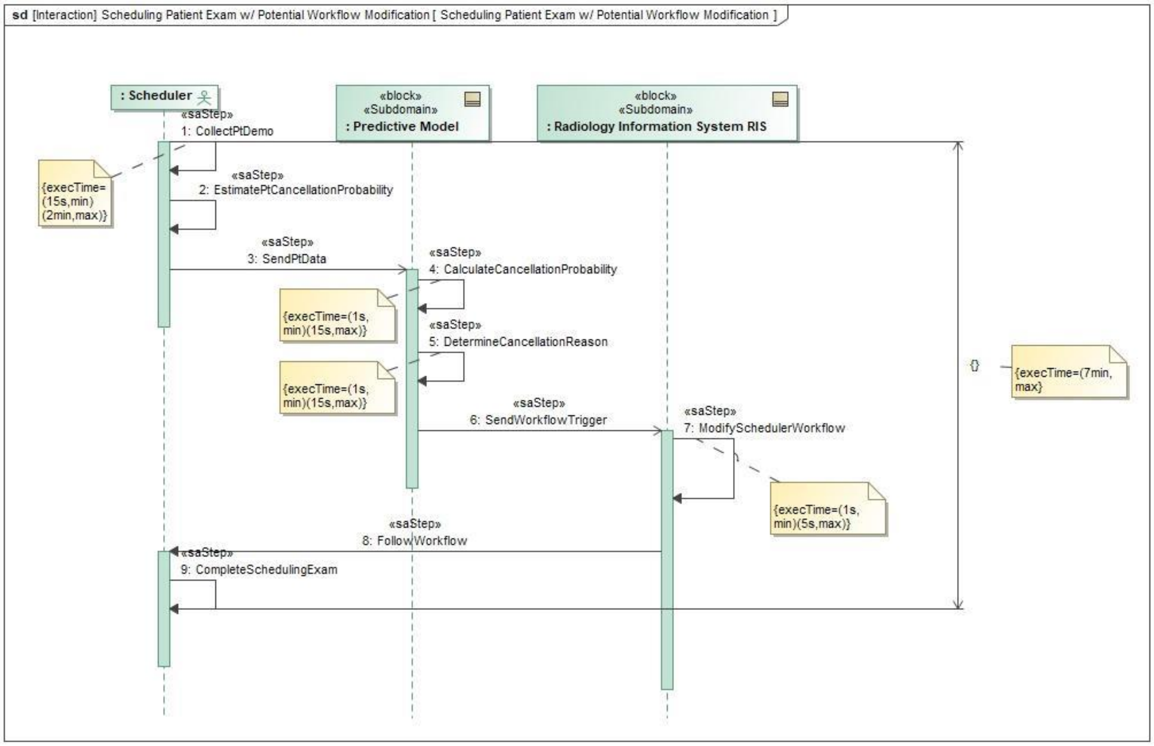

Figure 13: Sequence Diagram of Scheduling Patient Exams w/ Potential Workflow Modification

The Planning Dimension

Schedulers need a solution that does not increase their current scheduling cycle time. Upon scheduling a patient exam, relevant information is transferred into the Digital Radiography (DR) system. When staff members schedule an exam, the system only provides them with the next available time slot and a high-level view of the schedule for the day. Schedulers are unable to quickly see the necessary details like phone confirm status, insurance, and more, to efficiently double book. This is the justification for the requirement 1.4 that the system needs to integrate with the provider's Radiology Information System (RIS).

Schedulers are required to follow the RIS workflow that is presented while scheduling a patient's exam. If the patient's cancellation probability is high and an actionable cancellation reason has been identified, then the predictive model will send the RIS system a trigger to modify the scheduler workflow to fit the patient's needs. This process will be invisible to the scheduler as they will simply need to follow the system prompts. If the patient's cancellation probability is high and an actionable cancellation reason cannot be identified, then the predictive model will send the RIS system a trigger to allow the exam time to be double-booked, but the scheduler's workflow will not change.

The Operations Dimension

Front office receptionists need a solution that allows them to provide the best possible customer service. The risk to this type of system is that it may create a less rigid and more fluid schedule, making staff members that deal directly with potentially angry patients uncomfortable. To alleviate this stress for the front office, the system itself needs to provide up-to-date status reports to the patient (requirement 1.3.1).

Front office receptionists are responsible for checking patients into the system. This is currently the only way the RIS knows if a patient has physically arrived for their exam. The check-in process involves confirming that the patient has arrived in the system, collecting any out-of-pocket amount due and ensuring the patient fills out necessary paperwork. If a patient has not checked in by their scheduled time, then the front office receptionist needs to be alerted to attempt to contact the patient and obtain a reason for the same day missed appointment. For each patient scheduled, the front office receptionists will either check them in or obtain a reason for the missed appointment. The system needs to provide the alert to reach out to no-show patients because the front office receptionists are too busy checking in current patients to keep constant tabs on the schedule. These needs are incorporated into the development of the Patient Status domain.

The Technical Dimension

Technologists need a solution that does not put them at risk for burnout (requirement 1.2). There is a risk that a packed schedule will create required overtime for the technologists and staff. Overtime is one cause of burnout in healthcare (Genly, 2016) and the system must ensure that required overtime is minimized or not even required. To mitigate the risk of staff burnout and increasing turnover, the frequency of overtime will be tracked, and causes will be analyzed closely. If overtime exceeds a certain threshold, then modifications to the algorithm for determining when to double book will be made.

Unintended Consequences

Unintended consequences may arise from the implementation of this system. To detect these unknowns as they occur, the qualitative and quantitative feedback from both the patient and staff surveys will be monitored regularly. Patient surveys can be sent automatically post-scheduling and post-exam so feedback can be collected and analyzed daily. Staff surveys are currently conducted quarterly at Radiology Associates but would be recommended to send monthly after the implementation of the new system.

Conclusion

MBSAP has been invaluable in adding systemic and systematic rigor to the complex real-world problem of same day missed appointments in an outpatient imaging center. The resulting systems architecture ensures that the needs of all stakeholders are met while anticipating potential unintended consequences of the new architecture that might appear in separate identified social dimensions. This system architecture is intended to minimize the impact of same day missed appointments on operations and improve exam availability for all patients without increasing workflow complexity for schedulers, front office receptionists, or technologists. The MBSAP artifacts are the starting point for making the system a reality with stakeholders and finding the right balance between separate social dimensional measures. While the utilization management process is not identical for all healthcare providers, the high degree of similarities makes it possible to create a verified and validated system architecture that could blaze the path towards making a dent in the $150 billion dollar problem in healthcare.

CHAPTER 5: INTEGRATING MBSE WITH CONTINUOUS IMPROVEMENT TO DESIGN A ROBUST SYSTEM FOR MANAGING SAME DAY MISSED APPOINTMENTS

MBSE and CI in Healthcare

Healthcare systems have had success using Continuous Improvement (CI) tools and methods to change and improve processes, but the success of using CI methods to facilitate significant changes to the overall system architecture is user dependent. Robust healthcare systems are driven by the architecture. Robust systems can withstand or overcome adverse conditions. In healthcare, robust systems are insensitive to the following adverse conditions:

- Operational changes
- Operator adoptability rate
- Variabilities in patient behavior

Same day missed appointments have long plagued the efficiency of healthcare operations (Speece, Reducing the Impact of Same-Day Missed Appointments, 2019). Fixes to systemic problems require changes to the system architecture. A case study to show how model-based systems engineering (MBSE) combined with CI to produce a robust architecture for one aspect of this problem is presented in this chapter. The key to sustainability is to align the improvement with the organization's strategy and culture. Alignment with strategy can be achieved by deriving system requirements from high-level organizational targets. Alignment with culture can be achieved through understanding stakeholder use cases and system context. The MBSE process enforces both activities. A merger between MBSE and CI provides a framework for successfully addressing systemic problems in healthcare through significant changes to the architecture.

Successful changes to the architecture require the rigor of explicitly tying the change to a system need and capturing all stakeholder requirements and use cases. Systems Engineering and MBSE provide the rigor through dynamic modeling while CI provides the exploratory process for how to realize the stakeholder requirements. MBSE is defined by INCOSE as “the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases.” Continuous Improvement (CI) is an umbrella term for Lean Six Sigma. The Lean methodology seeks to reduce waste and create predictable processes and the Six Sigma methodology seeks to reduce process variation and create capable processes. There is a lot of overlap between the two methodologies, and they share the common goal of differentiating the abnormal from the normal and making it visible so it can be addressed immediately. Foundational CI strategies that are effective in improving processes are:

- Define, measure, analyze, improve, and control (DMAIC)
- Plan-do-check-act (PDCA)

During the Define phase of DMAIC, the voice of the customer should be collected. Per the American Society for Quality (ASQ), the voice of the customer is a process “to understand feedback from current and future customers indicating offerings that satisfy, delight, and dissatisfy them.” (American Society for Quality, n.d.) During the Plan phase of PDCA, an opportunity is recognized (American Society of Quality, n.d.). The methods used to recognize the opportunity are plenty and a benefit of the PDCA strategy is that it is broad enough to cover a wide variety of opportunities. While both strategies are effective in implementing changes to processes, neither explicitly directs linking the effort with the system architecture and ensuring system updates. MBSE strengthens CI by establishing a link between the effort and system-level requirements and by creating visualizations of all stakeholders use cases.

Drotz and Poksinska found in a study of Lean from the healthcare employee's perspective that the physical presence of the patient causes staff members to bury operational problems to focus on the current patient's safety and comfort. This common practice leads to a system where problems are hidden instead of addressed. The inability to understand the need to fix systemic problems is a known problem. Lean has long been touted as the method to address this known issue but Lean in healthcare is primarily implemented as a process improvement approach and tends to focus just on tools and techniques that fail to align improvements with culture and strategy (Drotz & Poksinska, 2017).

MBSE Applications in Healthcare

Khayal et al. argue that the ability to transform a system is predicated on the ability to understand a system. They utilized SysML activity diagrams for a behavioral health program to help higher level management comprehend the big picture and help standardize processes for clinical personnel (Khayal, McGovern, Bruce, & Bartels, 2017). The only diagrams utilized were activity diagrams and while those are not an exclusive feature of MBSE they are a good first step for introducing healthcare to MBSE because they are easy to understand. Visual models help healthcare stakeholders gain a better understanding of the full context of the system. However, this process would have been strengthened with the MBSE artefacts of a block definition diagram and stakeholder use case diagram. In a white paper for InterCAX LLC, Dr. Dirk Zwemer demonstrated the use of Model-Based Engineering (MBE) in four different healthcare applications using SysML that linked with other modeling tools. In his drug delivery example, he shows how requirements can be verified by creating a simulation that links the system architecture with patient databases and a math solver (Zwemer, 2016). Howard Lykins is leading an effort to help hospitals create a reference model using MBSE to enable them to plan for enduring through a prolonged power outage. The goal is to "enable hospitals to successfully integrate their operational references into broader health care coalition catastrophic event planning, execution, and evaluation frameworks, as well as national emergency healthcare response systems." (Lykins) MBSE has also been used by GE Healthcare in various applications. Notably, they used MBSE techniques to perform a behavioral analysis of their computed tomography (CT) system (Unger, 2014).

Linking CI and MBSE Together

While there are parallels between the two methodologies, CI and MBSE are missing explicit ties to show how they can leverage one another's strengths for the benefit of the system. Figure 14 shows the MBSE methodology with the different viewpoints of the mission level, operational level, logical/functional level, and physical level highlighted on the right. The CI methodology in A3 Process format is highlighted on the left and a link between the two loosely exists today in the definition of True North Metrics. CI projects are more successful when they have a proper understanding of context and can clearly translate stakeholder needs into verifiable system requirements. Neither DMAIC, PDCA, nor the A3 Process enforce completion of the activities.

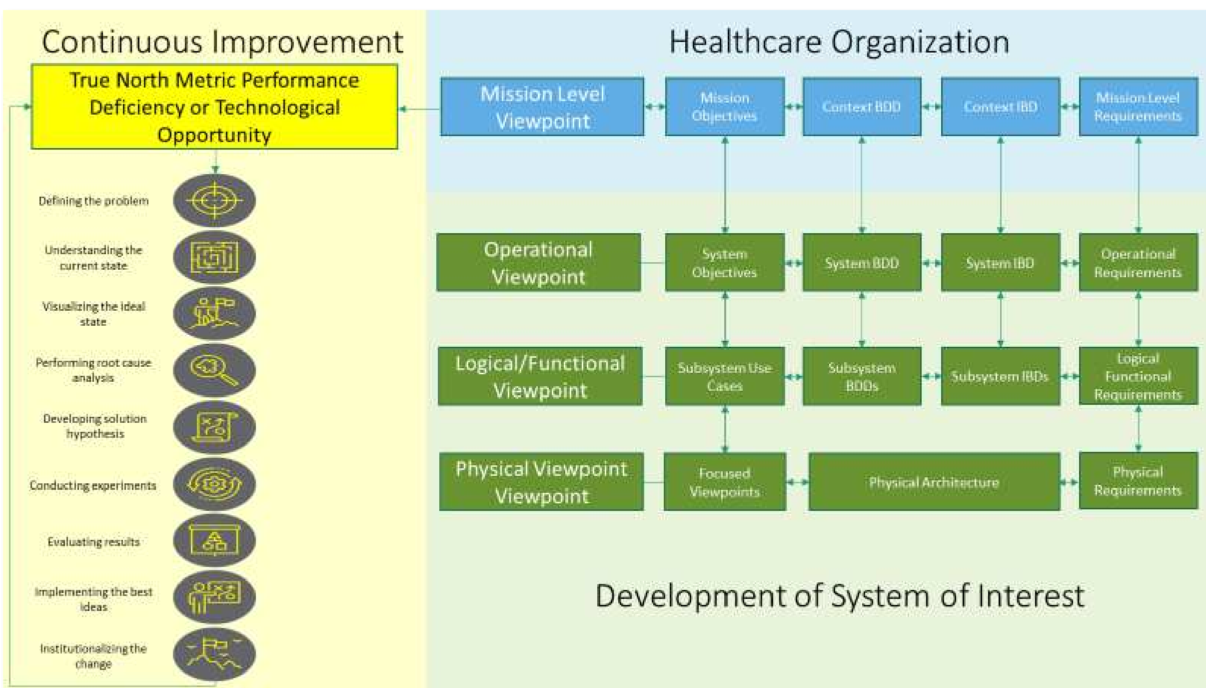

Figure 14: Current Relationship Between CI and MBSE in Healthcare

A proposed model, shown in Figure 15, adds explicit links between the CI A3 Process and MBSE and shows the following:

- Two-way flow of information between CI and the mission level viewpoint.
- How context analysis through stakeholder use cases should be incorporated in understanding the current state.
- A roadmap for utilizing MBSE for system development and improvement and how to use CI for realizing the physical viewpoint for non-point solutions.

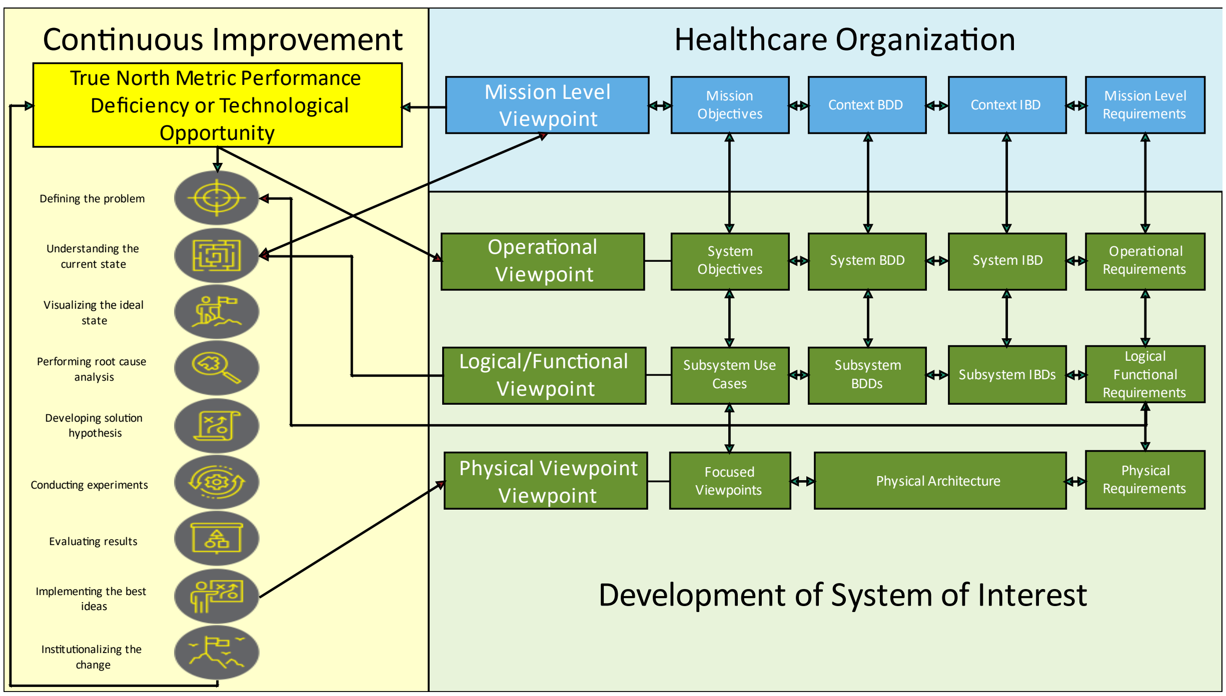

Figure 15: Proposed model linking CI with MBSE in Healthcare

For requirements that do not easily break down into physical point solutions and require an analysis of options, the A3 Process commonly used for process improvement projects is effective. The A3 Process is a problem-solving methodology with nine steps that are an "elaboration of the PDCA process" (Ghosh & Sobek, 2015) . The A3 Process links well with the MBSE model when transitioning requirements from the logical/functional viewpoint to the physical viewpoint. When integrated with

MBSE it helps ensure that proper rigor is followed in defining the choices for each component. The A3 Process output flows back to the MBSE model to realize the physical viewpoint.

Development of the Operational Viewpoint from TNM Performance

True North Metrics (TNM) are the system level requirements in a healthcare organization. True North Metrics typically fall into five main categories – human development, quality, safety, flow, and financial. The specific metrics and their TNM category are shown in Table 3. Metrics that fall short of the target indicate need for a focused improvement initiative. It is important to meet these metric targets to keep serving as the standard for patient care in the community, provide generously for the staff, and sustain a resilient outpatient imaging business.

Table 3: True North Metrics and Operational Definition

TNM	Operational Definition
Human Develop	Quarterly Staff Satisfaction
Safety	Safety Incidents
Quality	Customer Service
Flow	Turnaround Time Check-in to Report Approved
Flow	% Same day Missed
Financial	Productivity per Employee revenue/ salary $
Financial	Net Income Quarter (EBITDA)

A culture of continuous improvement will only happen through intentional implementation of a new business system. Wishing and hoping or talking endlessly about creating a culture of continuous improvement without any concrete actions, is a waste of everyone's time. A culture of continuous improvement is evident when a workforce is collectively working together to achieve the organization's

TNM targets. Organizational metrics may be called True North Metrics because they are a constant to measure yourself against. For any continuous improvement effort, it is a best practice to understand which TNM target(s) the effort aims to improve. In establishing new architectures or changing the architecture in place, it is necessary to align the effort with the organization's True North metrics and develop a full understanding of system context in the beginning of each effort.

Greg Baxter wrote an article for the Irish Medical Times which argued that in business, people are primarily driven by money, whereas this is not true in medicine (Baxter, 2007). Providers and healthcare staff members care equally about patient care and financial performance. Therefore, high-level organizational metrics must address multiple aspects of the business in the context of healthcare. TNMs are not the only way to achieve robust holistic business objectives but they are effective and easily translate into system level requirements that drive system improvement down throughout the organization.

Gastaldi et al. present a business intelligence (BI) maturity model for healthcare that has the key objective of detecting the gap between current and desired states. Business Intelligence is defined as a set of technologies and processes that use data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management, which drive decisions and actions, enabling an accurate understanding of business performance (Gastaldi, et al., 2018). The BI maturity model presents an algorithm for determining which dimension of the business to focus on. Performance to True North Metrics is a component of BI maturity model and both will show users where to focus; however, how to trace resulting efforts is still a fuzzy area. MBSE as a holistic model for system improvement that ties the higher-level organizational gap with the lower-level physical solution.

A new system architecture that is being developed to reduce the impact of same day missed appointments has been coined as the Automated Utilization Management (AUM) system (Speece, Using the Model-Based System Architecture Process (MBSAP) for Automated Utilization Management in Outpatient Imaging, 2019). The current state internal block diagram in Figure 16 shows how the system of interest, the AUM, would fit within the existing outpatient imaging technology context.

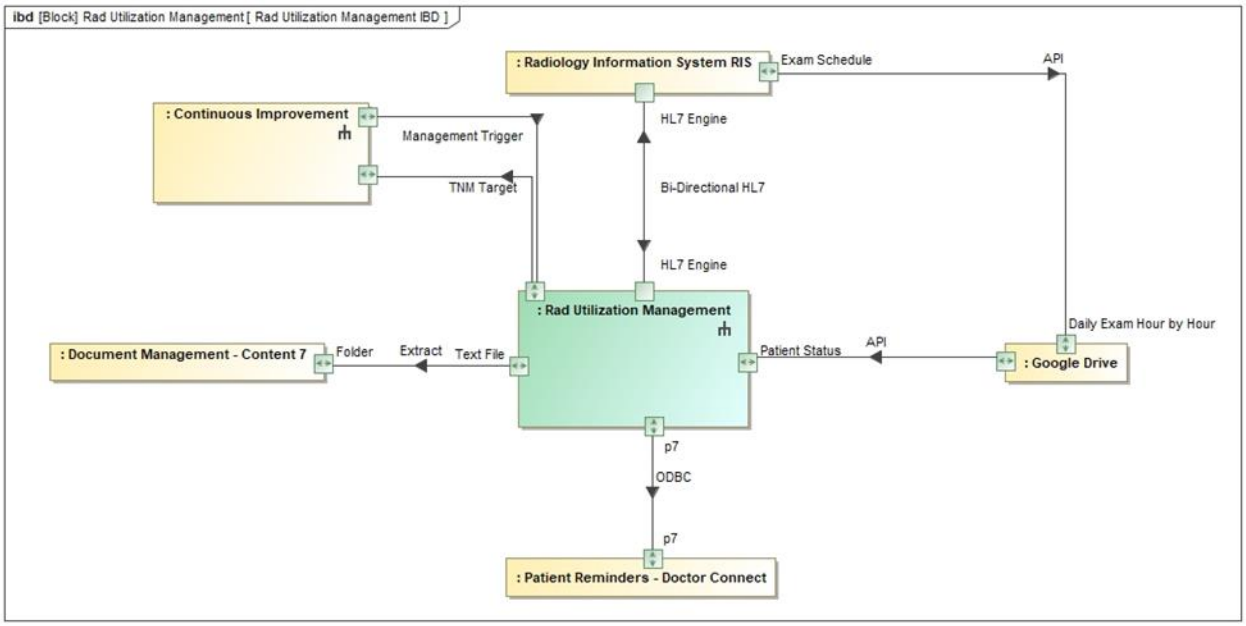

Figure 16: AUM IBD

The AUM is stereotyped as the system of interest and the other domains are stereotyped as existing systems. It is important to understand where the AUM fits within the overall technology framework. The AUM breaks down into two subdomains – the Center Exam Status and the Cancellation Prediction. See Figure 17. The Center Exam Status domain breaks down to two subdomains (shown as parts) – Patient Status and Wait Room Notification. This case study will specifically focus on the development of the Patient Status subdomain within the Center Exam Status subdomain.

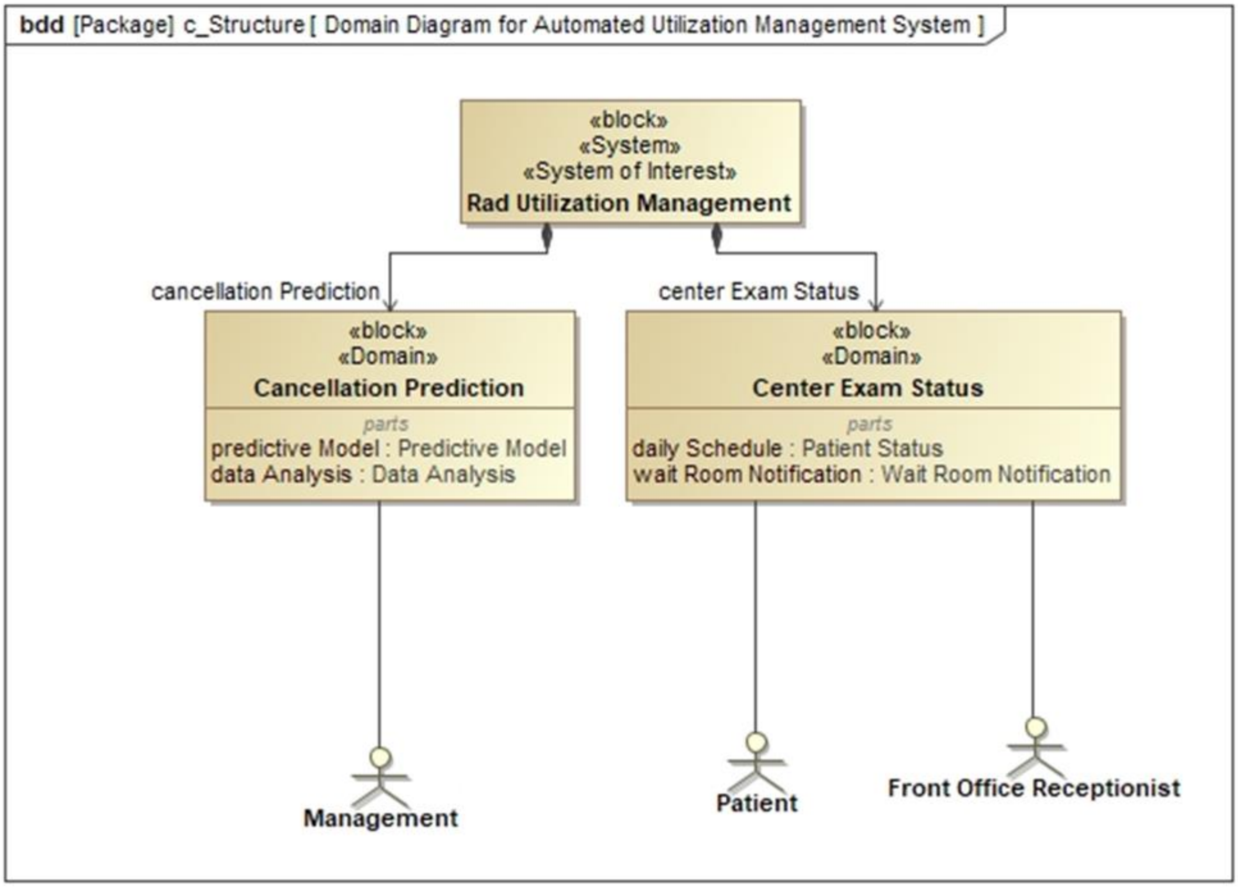

Figure 17: AUM Domain Diagram Operational Viewpoint

Understanding the Current State to Establish Logical/Functional Viewpoint

The current process for tracking patient status and determining a reason for all same day missed appointments has evolved over the last seven years. The process starts with copying the exam schedule for the day from the scheduled tab in the radiology information system (RIS) onto a tab in a Google Sheets workbook every day at 6:00 AM by a scheduling staff member. Due to existing system constraints, this process is necessary in order for staff members to clearly see a list of who should be arriving for their exam. If a patient did not arrive by table time or if the exam was cancelled after the patient arrived, which happens for a variety of reasons, then front office receptionists use the Google Sheets workbook to document notes for the reasons these exams became same day missed appointments. Transferring data from the RIS to a Google Workbook is currently necessary because the cancellation reasons drop down box in the RIS system does not populate a report and the vendor has stated they have no intention of fixing what is broken in the existing management reports. The management reports subdomain of the current system is a “dead” system in that no further development is being performed. It would be possible to access the data within the system via an open database connectivity (ODBC) and that may be a further development down the line but it currently is not a value-added activity to categorize cancellations within the system. In addition, the reasons for the same day missed appointments are reviewed and categorized by management in the morning huddle to ensure due diligence has been performed in researching each issue. This process has created a Google Sheets workbook with a large volume of data that is split between multiple sheets. When capacity is reached on the hour-by-hour workbook then a whole new workbook is created. Multiple workbooks with multiple worksheets make manual aggregation of data difficult. In addition, the data contains patient information so it can only reside on a HIPAA compliant system.

There is little debate that understanding the needs of all stakeholders will lead to a better outcome. While the “why” is widely accepted, the “how” is less clear in healthcare. Context matters. Different decisions will be made by the system architects when they understand who will be using the system, how the users expect to be using the system, what current systems exist, and existing limitations with current systems if they are to be used going forward. Torma and Claudio found that creating a cross-functional course with both nurses and ISE professionals working together on a clinical problem helped both functions gain an appreciation for one another and put together proposals that demonstrated a better understanding of the context of the problem (Torma & Claudio, 2013). Hobbs and Rivera performed a literature review that argues for the inclusion of the patient and family on the healthcare team (Hobbs & Rivera, 2014). Patient outcomes are affected by family engagement in the healthcare delivery process. Both patients and their families, as an extension of the patients, are stakeholders whose needs should be understood to better understand the context of the system. The

Institute for Healthcare Improvement (IHI) has long advocated allowing patients and their families control over all aspects of their care (Berwick, 2009). In addition, the community that the provider serves should be considered a stakeholder. Providers with homogeneous leadership teams and physicians who do not reflect the communities they serve will find it difficult to address community specific social determinants and move the needle on racial and ethnic health disparities (Livingston, 2018). Identifying the needs of all stakeholders in the context of their experience with the system of interest will help leaders in healthcare, regardless of their personal demographics. The outcome would be the development of better solutions for the entire community. A study on the benefits of using phenomenological hermeneutics to design a better nebulizer for treating children with various breathing problems showed the benefits of fully understanding the stakeholder's lived experience in any human-centered design effort. The study emphasized the need to acknowledge that multiple realities exist (Høiseth & Keitsch, 2015). Arguably, all improvement efforts in healthcare should be considered a human-centered design effort and phenomenological hermeneutics can be realized through a robust stakeholder analysis. In 2010, hospitals realized that one of their primary stakeholders, independent physicians, had various levels of financial resources and may not be able to purchase an electronic medical record (EMR) that would facilitate information exchange with the hospital seeking their business (Lawrence, 2010). Hospitals who recognized that independent physicians and their offices play a critical role in choosing a new EMR for the hospital itself had smoother transitions than hospitals who remembered these key stakeholders after choosing a system.

"If a hospital chooses the EMR vendor, it may not be what the physicians really need. We need to understand that the physician's life and the physician's office are completely different from the hospital." (Lawrence, 2010)

In any process improvement project, you have multiple stakeholders who are essentially customers of the current process and customers of the future process. The terminology “Voice of the Stakeholder” is preferable over “Voice of the Customer” so that the needs of both internal and external customers are collected. By collecting the “Voice of the Stakeholder” you can figure out what your stakeholders’ frustrations are with the current process and what their desires are for a new and better process. These frustrations and desires can be translated into Stakeholder Requirements for the project.

MBSE can also help with “stakeholder recognition”. A study by Mohammad A. Ali out of Pennsylvania State University found that “stakeholder recognition is a socially constructed phenomenon in which societal context plays a crucial role” (Ali, 2018). Ali found that a robust process of stakeholder recognition will help managers prioritize time and resources in meeting the critical needs of the stakeholders without over-engineering the system to placate all of them. MBSE can guide the system architect in not only identifying all the stakeholders and understanding their needs, but it can also help prioritize stakeholder needs by visually showing the frequency of individual stakeholder interaction with the system.

The use case objective diagram in Figure 11 shows the objectives of each stakeholder in the development of the AUM system. The stakeholders’ objectives were translated into the system level requirements and the derived requirements for the patient status database are shown in Figure 18.

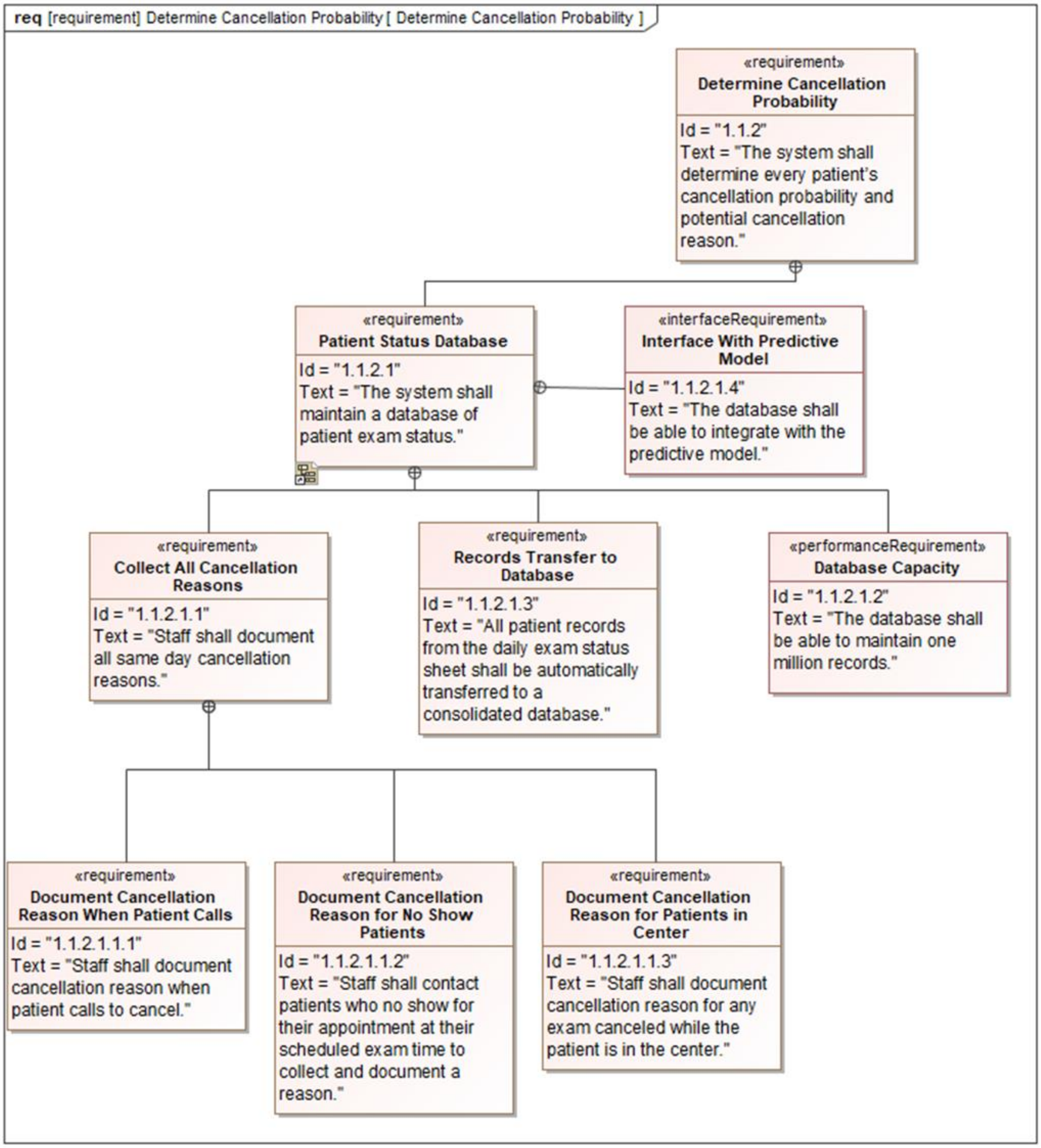

Figure 18: Breakdown of Requirements for Patient Status Database

Using CI to Determine Solutions for Logical/Functional Requirements

The ideal state is a process that automatically combines the data from each tab into a master spreadsheet that will feed a visual dashboard for management to be able to easily analyze same day missed appointment data. In addition, this same master dataset needs to feed a predictive model to fulfill requirement 1.1.2.1.4. The new process should also help the system achieve the objective of avoiding staff burnout by implementing a process that does not change the current process for the Front Office staff collecting information.

In performing root cause analysis, it is important to understand the context for using Google Sheets to manage the hour-by-hour data. In 2013, a Lean consulting company introduced the idea of using hour by hour boards to do the following:

- Visually monitor output vs. takt time goals
- Enable operators to easily communicate problems and issues
- Make supervisors responsible for resolutions
- Document problems and solutions
- Make the day's status visible

Existing systems did not provide this capability, so the information was collected in each modality manually using dry erase boards. Initially, the benefits of this time commitment outweighed the costs (the costs being the technologists time to fill out the hour-by-hour boards and management's time spent reviewing the hour-by-hour boards). Two of the most notable initial benefits of gathering this data were:

- The realization that a fair number of patients are no-show for their appointments.
- The realization of the negative impact of late patients on the rest of the day.

However, as each center's volume of patients grew, the technologists and management team found themselves unable to rigorously monitor each modality status board in-person. The chief complaint from technologists became "why am I filling this out and then erasing it at the end of the day when management does not even give it a passing glance?" Management agreed that this was an indisputable problem. Therefore, in April 2017, a cross-functional team was commissioned to reimagine the hour-by-hour boards. Almost immediately the team unanimously decided to work towards developing an electronic hour by hour board that would be easy to use, visual for all and automatically collect historical data. The outpatient imaging center is a small company with limited resources, so the goal was to attempt to develop a new system internally before buying an off-the-shelf product. After some trial and error, staff members agreed to a process where the Front Office staff would monitor a shared Google Sheets workbook.

The root cause of using Google Sheets to monitor patient status is the deficiency of existing systems to effectively track the data. However, the Google Sheets workbook has been effective for the front office to use because it is easy to access, easy to use, and collaborative for all front office staff across all three centers. Therefore, in developing the subsystem to combine the data into a master sheet and create a new dashboard, it became a requirement to utilize the existing design of the Google Sheets workbook to minimize disruption to Front Office processes.

In developing potential solutions, three components needed to be brainstormed – the method for combining the data from the different tabs in the Google Sheets workbook, the platform for storing the combined data, and the platform for analyzing the same day missed appointment data. A data analytics intern researched options for each that would meet the system level requirements and came up with following:

- Same day missed dashboard platform:
    - Tableau – Chosen as an option due to existing domain knowledge within the organization.
    - Google Sheets – Chosen as an option due to use in a comparable capacity for analyzing patient feedback from customer service surveys.

    - Power BI – Chosen as an option due to previous use as a platform for analyzing billing issues.
- Master data store options:
    - Excel
    - Google Sheets
    - MySQL
- Method for transferring data from master data store to same day missed dashboard:
    - Use Zapier to directly connect hour by hour data to Tableau
    - Download data from Google Sheets to and Excel workbook and then transfer to MySQL
    - Transfer data from Google Sheets hour by hour workbook to a new master document in Google Sheets and link to Tableau.

Implementing the Best Ideas to Determine the Physical Viewpoint

Different combinations of the options for each component were prototyped and a binary analysis of whether the option fulfilled the criteria that aligned with system level requirements was completed. See Figure 19 for an analysis of the alternatives and Figure 20 for a block diagram with chosen block instances that provide the physical viewpoint of the Patient Status Domain.

Same-Day Missed Dashboard	Connects with Google Sheets	Large Data Capacity
Tableau	Yes	Yes
Power BI	No	Yes
Google Sheets	Yes	No

Master Data Store	HIPAA Compliant	Connects with Google Sheets	Large Data Capacity	Connects with SAS
MySQL	Yes	No	Yes	TBD
Excel	Yes	Yes	Yes	TBD
Google Sheets	Yes	Yes	Ok	TBD

Method for Transferring Data	HIPAA Compliant	Connects with Google Sheets	Automated
Zapier to Tableau	Unknown	Yes	Yes
Google Sheets to Excel to MySQL	Yes	Yes	No
Google Sheets to New Google Sheet to Tableau	Yes	Yes	Yes

Figure 19: Analysis of Alternatives for Patient Status Domain

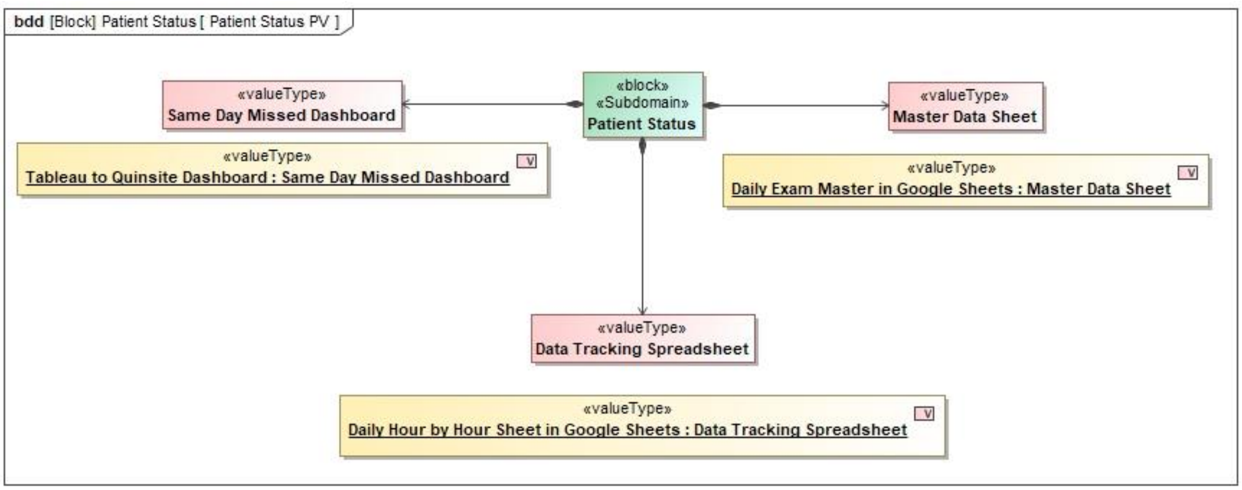

Figure 20: Physical Viewpoint for Patient Status Domain

Verification and Validation of Same Day Missed Dashboard

The same day missed dashboard that was built in Tableau was able to be published in an online platform that had published other dashboards utilized by managers across the organization. See Figure 21 for a screenshot of the main page of the dashboard.

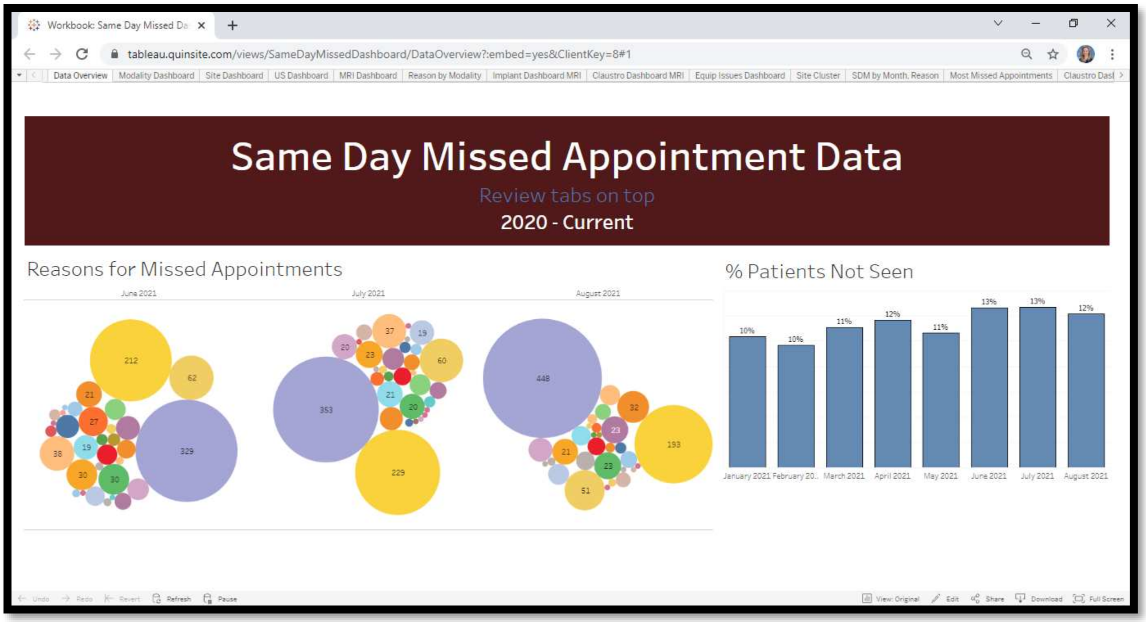

Figure 21: Screenshot of SDM Dashboard Front Page

Managers access the data to track trends in same day missed reasons and ensure their efforts are focused on the areas that will make the biggest impact. For example, in the Magnetic Resonance Imaging (MRI) modality, the same day missed reason of claustrophobia had been increasing in trend (see Figure 22) so the following solutions are being implemented:

- Update exam preparation instructions to include visuals for “what to expect” during the exam.
- Require patients who opted for sedation at the time of scheduling to come an hour early so that the medicine would be effective at table time.
- Utilize fast protocols on the MRI machine for patients with known claustrophobia.
- The variety of ways to visualize the data has provided greater understanding of where to focus resources in addressing the controllable causes of same day missed appointments.

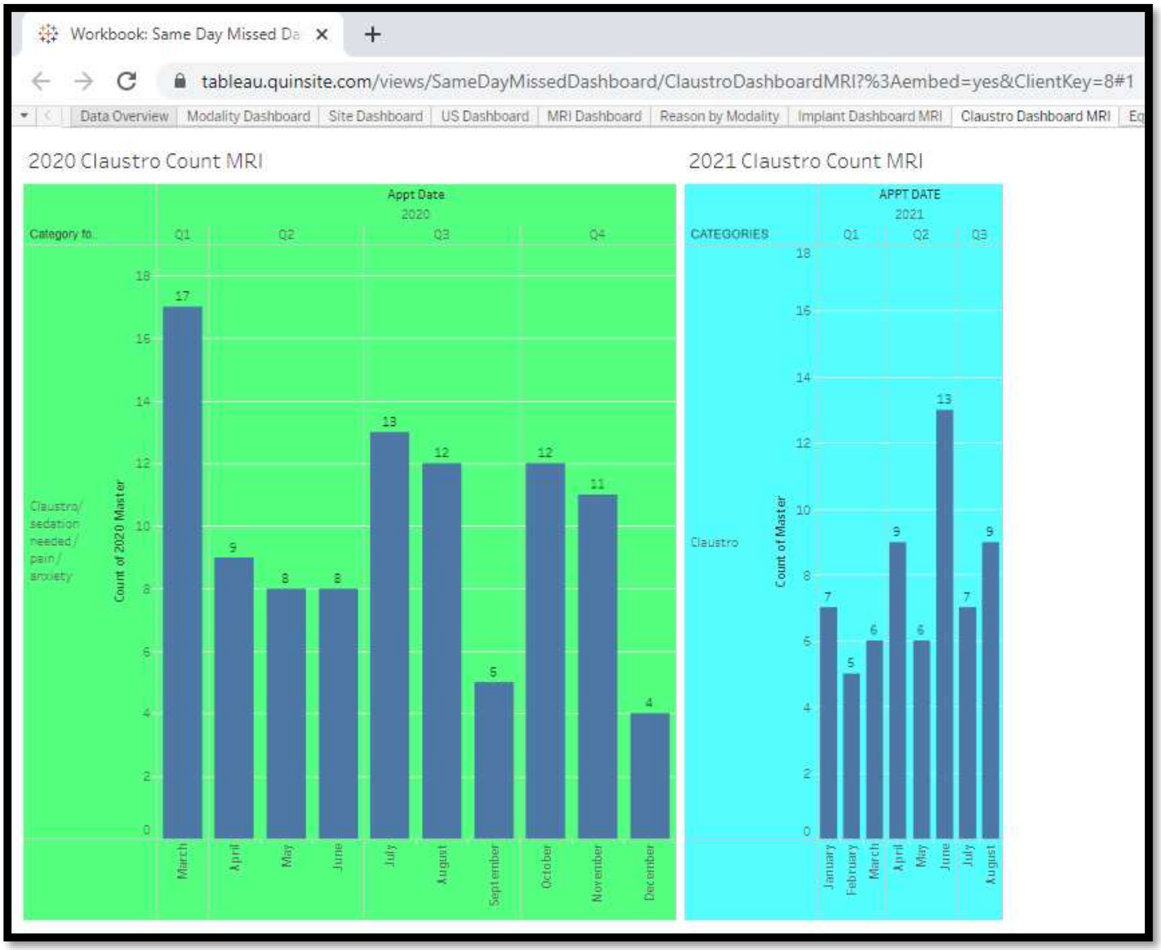

Figure 22: Screenshot of SDM Claustrophobic Patients in MRI

Lessons Learned

Determining a mutual beneficial solution that would be sustained for the Patient Status domain was challenging. It had been an ongoing effort for many years. MBSE provided the structure needed to work through the competing objectives in human factors and come to a solution that satisfied all stakeholders. The SysML diagrams were intuitive for the staff and provided a means for the stakeholders to better communicate and improve the system. With the upfront rigor of using MBSE to visualize operational scenarios and system requirements, using CI as the structured process to move between the functional and physical viewpoint was successful.

Conclusion

Integrating the CI A3 thinking process with MBSE in healthcare provided a robust solution for a piece of a system that is being designed to manage the negative impact of same day missed appointments. CI provided the mission level requirements of true north metrics, MBSE provided the system-level requirements, use cases, and context diagrams for a complex system design and then CI provided the continuous improvement process to ensure that the solutions chosen fulfilled the system-level requirements to start moving the needle on a key true north metric. CI without MBSE led to measurable improvements in data collection methods and accuracy in patient status classification but did not result in creating a sustainable and robust architectural solution. MBSE without CI provided a way to rapidly discover and map stakeholder needs to operational scenarios and requirements, but a gap emerged in making process decisions that affected the final architecture. The first key advantage of integrating these two methodologies was a sustainable solution to a key piece of an architecture being designed to reduce the impact of same day missed appointments. The second key advantage is proving that using MBSE to determine the subsystem architecture resulted in a more robust solution than CI alone has been able to produce. The physical architecture for the patient status domain is now robust in that it can be adapted for any operational changes, collects information independent of operator adoption, and accounts for variabilities in patient behavior with flexible data collection.

CHAPTER 6: DEVELOPMENT OF A PREDICTIVE MODEL FOR SAME DAY MISSED APPOINTMENTS IN OUTPATIENT IMAGING

Introduction and Purpose

The ability to estimate the probability of a patient becoming a same day missed appointment is an important component in enabling a system of proactive utilization management in an outpatient imaging center. Medical imaging services are an important domain in the overall healthcare system. Medical imaging helps physicians investigate a specific concern or detect disease before symptoms are present (Mayfair, 2018). For outpatient medical imaging services, the process starts with a physician writing a prescription for their patient to receive medical imaging. The patient then completes the appropriate exam and a radiologist reads their images and sends the referring physician a report with their findings. With this information, the physician can determine a treatment plan for their patient. A report may be delayed for many reasons with a primary example being waiting for prior images from other institutions (Morgan, Young, Harada, WInkler, & Riegert, 2017). However, if the patient never completes their prescribed imaging exam, then a report will never be created, and a provider will be missing the information needed to determine the best possible treatment plan. Patients who schedule an appointment for their imaging exam and neither cancel at least the day before nor complete their exam the day of are considered same day missed appointments. Same day missed appointments lead to delays in treatment management (AlRowaili, Ahmed, & Areabi, 2016) for both the scheduled patient and patients waiting to be scheduled. Same day missed appointments also create operational inefficiencies for the outpatient imaging center by creating abandoned appointment timeslots.

Proactive resource utilization planning is performed in a variety of industries to build robust schedules (Lambrechts, Demeulemeester, & Herroelen, 2008). A proposed system to automate proactive resource utilization planning for an outpatient imaging center is shown in Figure 17**.** A significant part of the proposed system is a predictive model that determines the probability of a patient becoming a same day missed appointment. Proactive in this context is synonymous with predictive. The resources that have been widely recognized as needing to be properly utilized for overall cost of healthcare management and efficient operations are the technologists and imaging equipment (Hu, 2011). A predictive model that can determine the probability of patient becoming a same day missed appointment produces an output that can be used as an input for determining actions to take to either prevent the same day missed or overbook strategically. This chapter covers the development of a predictive model for use in proactive resource utilization planning for an outpatient imaging center.

Known Challenges and Limitations

Historical Data Source

The historical data used to build the predictive model was pulled from an electronic hour by hour board managed by front office personnel. The electronic hour by hour board combines scheduled patient data pulled from the Merge Unity™ database with live monitoring and manual data inputs by the front office on patients who become same day missed appointments. The process for categorizing same day missed appointments is completed by the management team during the morning huddle. To build this model, hour by hour data accumulated from January 2, 2020, through April 26, 2021, was pulled and resulted in in approximately 95,000 records. The target variable for this set of data is SeenYN which is a binary input on whether the patient has been seen (1) or has not been seen (0). Patients that were seen made up 90% of the records and patients that were not seen (same day missed appointments) made up the remaining 10%. The variables as they stood in the compiled data were not in a plug and play format for executing the predictive model. Inputting the data as it stood resulted in an error for the Referring Physician and Exam Date variables exceeding the maximum target levels of 1,000. Too many overall levels are a data mining issue that can cause difficulties in model fitting (Wielenga, 2007). By rejecting these inputs, the remaining variables – Modality, Sex, Age, Exam Description, Site, and Suite – were used to evaluate different models. The model comparison produced acceptable average squared error rates (~0.077), but it also produced the Receiver Operating Characteristic (ROC) chart shown in Figure 23. The ROC chart for the model comparison that used raw variable inputs shows model overfitting with the curve of the different models flattening towards the diagonal (Chan).

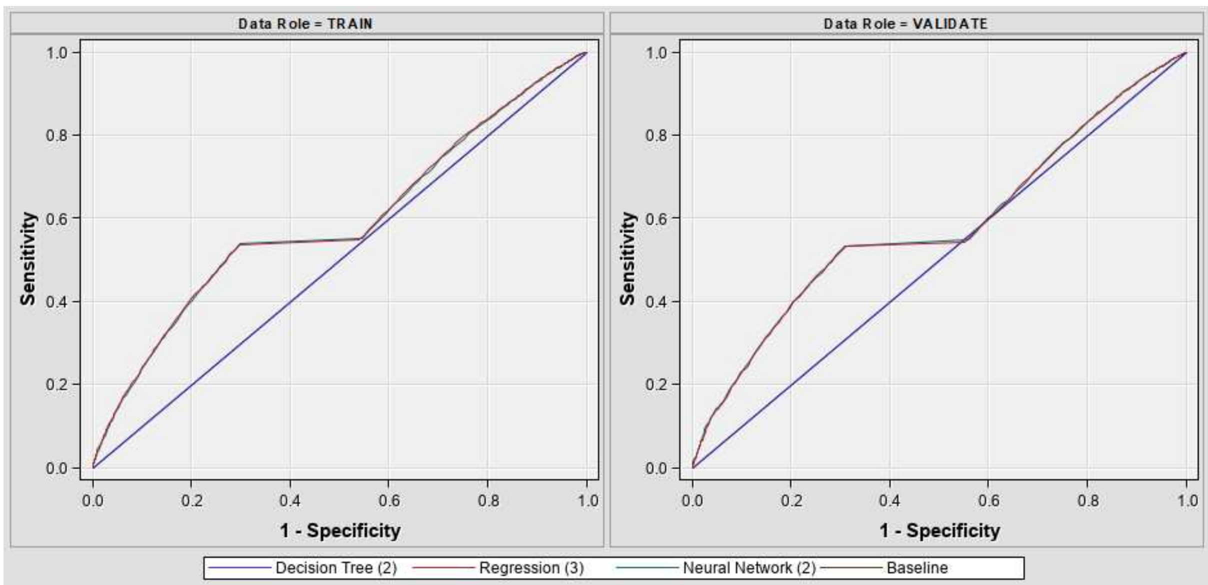

Figure 23: Receiver Operating Characteristic Chart for Non-Transformed Variables

Input Variable Levels

Many of the input variables had to be further stratified and categorized to produce useful results. An explanation of the process for transforming two of the variables with the most levels – exam description and referring physicians – follows, and the full list of all variable transformations is shown in Table 4.

Exam Description

A chi-square % defective test for the top 12 highest frequency exams was performed using Minitab to test the hypothesis that the % defective (seen divided by total) differed and was therefore a useful predictor. With an alpha value of 0.005, the p-value of less 0.001 shown in Figure 24 concludes that there are differences among the % defective by exam description. However, in its raw form there are over 400 levels which is too high to produce a useful predictive model with the historical data set provided. Therefore, exam description was stratified into three input variables – body part being scanned, prep required for the exam, and whether the exam was a screening exam or not. A chi-square % defective test for the top 12 highest frequency exams by body part, shown in Figure 25, still showed a significant difference between the % defective.

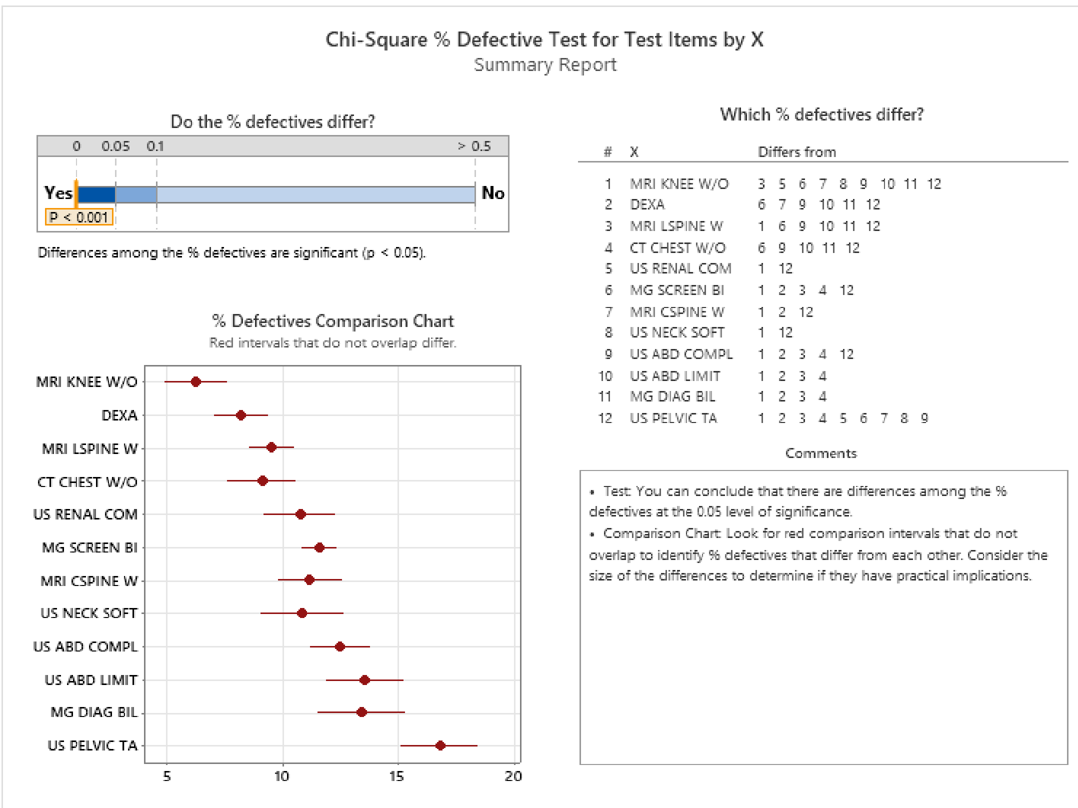

Figure 24: Chi-Square % Defective Test for % of Patients Not Seen by Exam Description

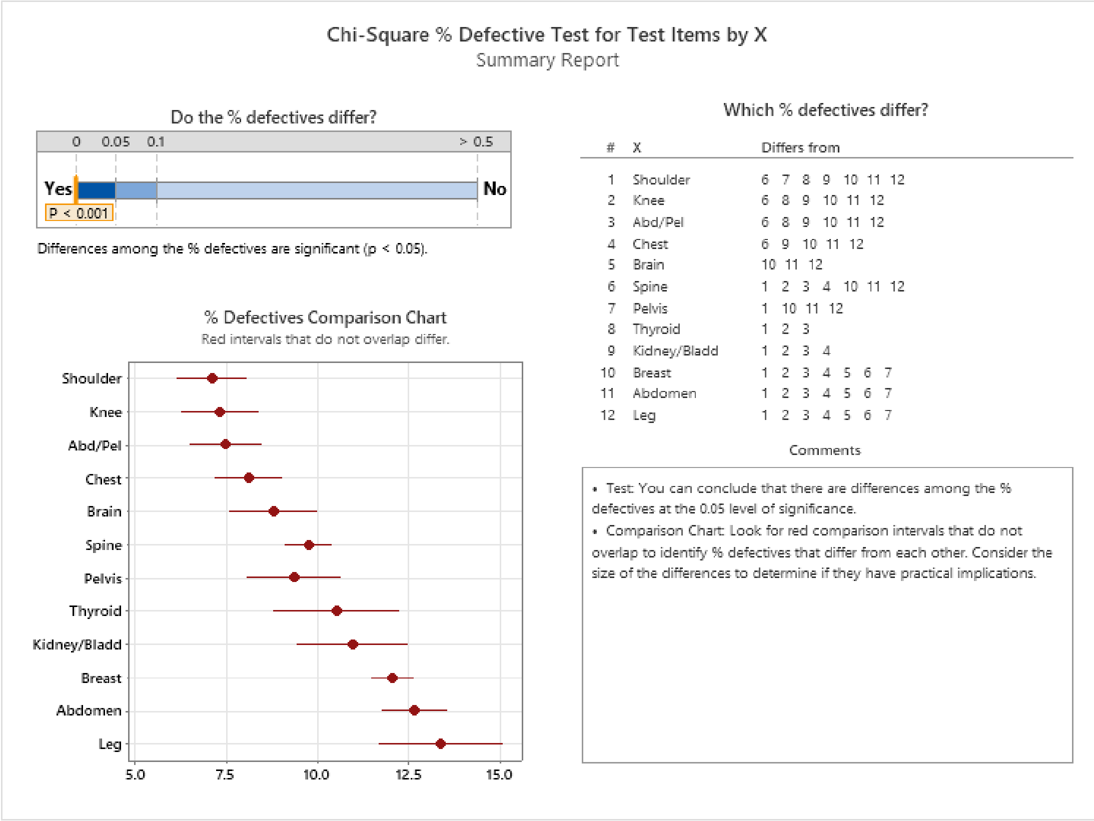

Figure 25: Chi-Square % Defective Test for % of Patients Not Seen by Body Part Being Scanned

Referring Physicians

The referring physician variable also showed a significant difference in historical same day missed appointment rates. This historical same day missed appointment rate for each referring physician replaced was categorized as high (35% - 100% not seen), medium (5% - 34%), and low (0% - 4%). The histogram in Figure 26 shows the distribution of the historical rates. This categorization replaced the specific name of the referring physician for this input variable.

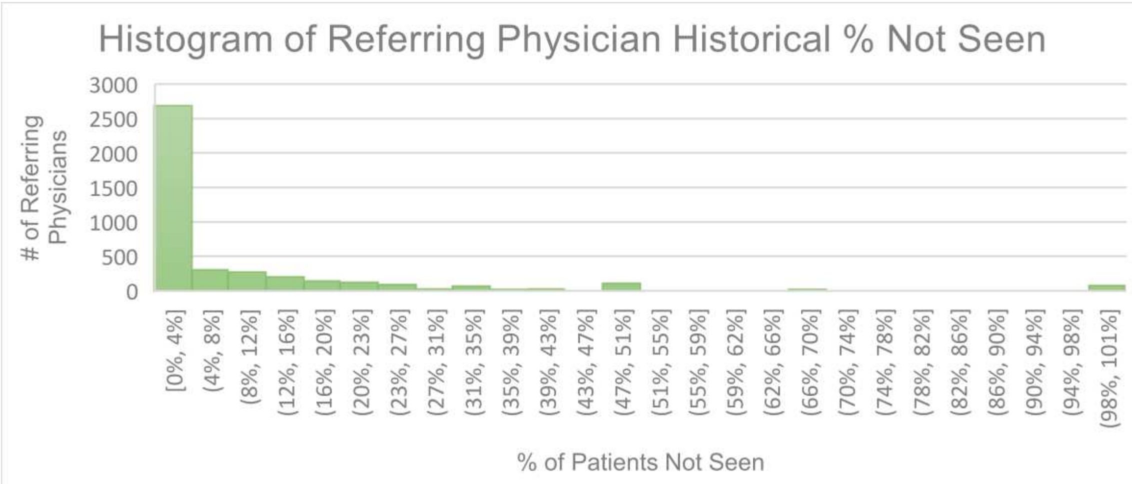

Figure 26: Histogram of Referring Physician Historical % Not Seen

Table 4: Variables for Predictive Model

Variable - Raw	Operational Definition	Raw # of Levels	Variable - Transformed	Transformed # of Levels	Role
SeenYN	Y = Yes the patient was seen N = No the patient was not seen	2	From Y/N to 1/0	2	Target
Appt Date	Date and time of scheduled appointment	Infinite	**DayOfWeek** – Day of the week **TimeOfDayM** – Morning, Afternoon, or Evening **MoY** – Month of year **DoM** – Day of month	DayOfWeek – 5 TimeOfDayM – 3 MoY – 12 DoM - 31	Inputs
Exam Description	Detailed description of exam scheduled	422	**BodyPart** – Body part being scanned **PrepYN** – Prep required for exam yes or no **ScreeningExamYN** – Screening exam yes or no	BodyPart – 43 PrepYN – 2 ScreeningExamYN - 2	Inputs
Age	Age of the patient	143	Patients less than 1 had age stated in	102	Input

Variable - Raw	Operational Definition	Raw # of Levels	Variable - Transformed	Transformed # of Levels	Role
			months or weeks – converted all to 0 years and AgeBracket was determined by pulling tenths place of their age		
Referring Phys	Referring physician	1800+	**NoShowRate** – pulled historical data and classified referring physician as high, medium, or low rate of patients who become a same day missed appointment	3	Input
Suite	Exam room scheduled	28	Simplified to combine non-unique suites	16	Input
Site	Location where the patient was seen	3			Input
Sex	Sex of the patient	2			Input
MOD	Modality	8			Input

Missing Variables

During the initial model generation, it became evident that other variables would be interesting to analyze, specifically copay due and patient insurance provider. These variables have since been added to the grid of data that is now pulled into the daily hour by hour board, but those fields do not exist in the historical data set. With the information known about the scheduled appointment, all the input variables, the goal of the model is to predict whether the patient will become a same day missed appointment or not.

Modeling Method – Predictive Model Verification Process

To efficiently determine the feasibility of creating a useful predictive model in an outpatient imaging environment, SAS Enterprise Miner software was used for data mining and the evaluation of different models. The historical data was uploaded, and each variable's role and level were identified.

The data was filtered to remove missing values and rare % values. Then the data was partitioned to designate 70% of the data for training and 30% for validation. Five models were created – a customized decision tree based on stakeholder input, a decision tree created from the data, a neural network model, a linear regression model, and a logistic regression model. The selection criteria for model goodness is average squared error. Average squared error is the selection criteria because it provides a metric to show how close the predictions were to the expected value. A perfect mean squared error value is 0.0, which means that all predictions matched the expected values exactly (Brownlee, 2021) . With the transformed variables, the average squared error for the chosen model of a decision tree is .072151 (see Figure 27) and the ROC chart is shown in Figure 28***.***

Fit Statistics
Model Selection based on Valid: Average Squared Error (_VASE_)

Selected Model	Model Node	Model Description	Valid: Average Squared Error	Train: Average Squared Error	Train: Misclassification Rate	Valid: Misclassification Rate
Y	Neural	Neural Network	0.071565	0.071808	0.082766	0.082288
	Tree	Decision Tree	0.072151	0.072785	0.082704	0.081886
	Tree4	Interactive Tree	0.072151	0.072785	0.082704	0.081886
	Reg2	logistic Regression	0.072848	0.073387	0.085227	0.084702
	Reg	linear Regression	0.073378	0.073850	0.085102	0.084592

Figure 27: Fit Statistics for SDM Predictive Model

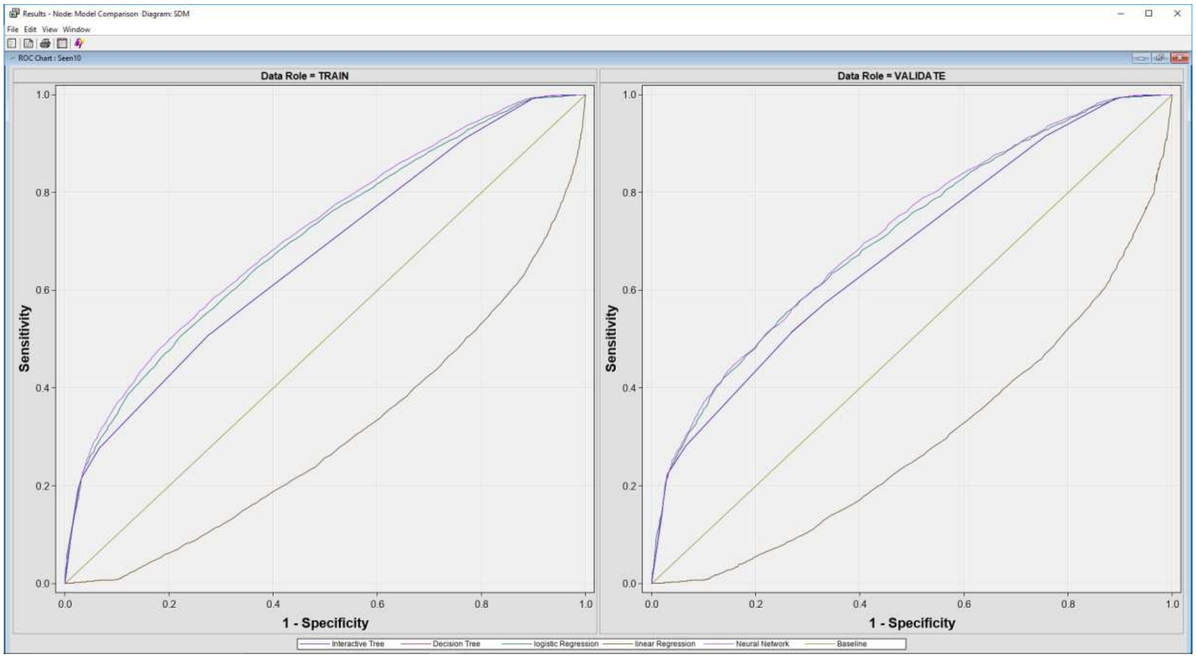

Figure 28: Receiver Operating Characteristic Chart for Transformed Variables

A neural network model was selected for the having the lowest average squared error. The process is set up to always evaluate historical data across multiple models and then score future scheduled appointments using the best fit model. This streamlines the process of incorporating data newly compiled from the hour-by-hour board with additional variables that may become significant predictors for future model improvements.

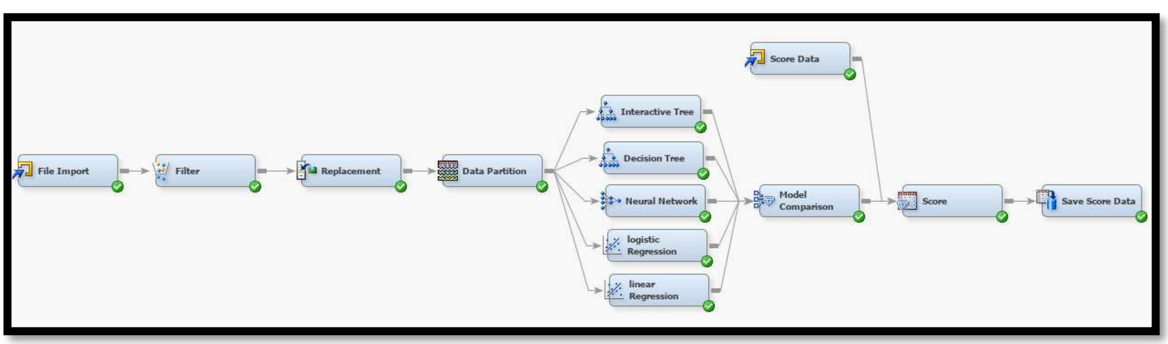

Figure 29: SDM Diagram in SAS Enterprise Miner

The model shown in Figure 29 uploads future scheduled appointments to the Score Data node and the node automatically uses the model selected from the historical data to generate a probability of the target event for the future appointments. In this model, the score node is being used to generate the probability of a patient being seen. Low seen probabilities are an indicator that intervention may be needed to ensure proper resource utilization planning.

Operational Use – Predictive Model Validation

Without having realized a fully integrated system between the predictive model and Merge Unity database, the data is manually extracted from the output of the Save Score Node and entered on to a separate sheet for targeted patient call confirmations. In April 2021, a team had been commissioned with the charter to solve the following problem statement:

> *In 2020, 18,586 exams were ordered by referring physicians, but the patients were never seen. In 2021, this number is already 4,779 for Q1. A patient's health can be negatively affected due to failure to be seen for a requested exam. In addition, the operational inefficiencies (hours utilized vs. hours available during normal working hours) realized during normal work hours have caused extended hours to meet the demand and capacity issues (Radiology Associates).*

A cross-functional team came up with several requirements for the ultimate solution set that are shown in Table 5.

Table 5: Requirements for Solution Set for DMAIC Optimize Exam Schedule

Requirement	Audience					Measurement Method *How will we know we have satisfied this?*
	Patient	Technologists	PSM Staff	Front Office Staff	Management	
The solution shall accommodate patients' needs. 1. Professional 2. Quick 3. Efficient	X					• Professional - Patient survey results • Quick - Turnaround time by modality • Efficient - Patient complaints, # of exams vetted and financial counseled prior to date of service
The solution shall balance staff and patient satisfaction.	X	X	X	X	X	Patient survey data and daily employee data
The solution shall fill the schedule.	X	X	X	X	X	Utilization or Volume
The solution shall be realistic.	X	X	X	X	X	Meet DMAIC project metrics,
The solution shall demonstrate respect for all patient-facing staff members.	X	X	X	X		Late and missed breaks/lunches. Overtime.

One of the planned experiments was to use the output of the predictive model to create a targeted call confirmation list. Approximately 350 patients are scheduled every day and while these patients receive automated text reminders, these reminders do not include patient or exam specific information that has been shown to be significant variables for the probability of becoming a same day missed appointment. The decision tree model shown in Figure 30 shows the importance of certain variables.

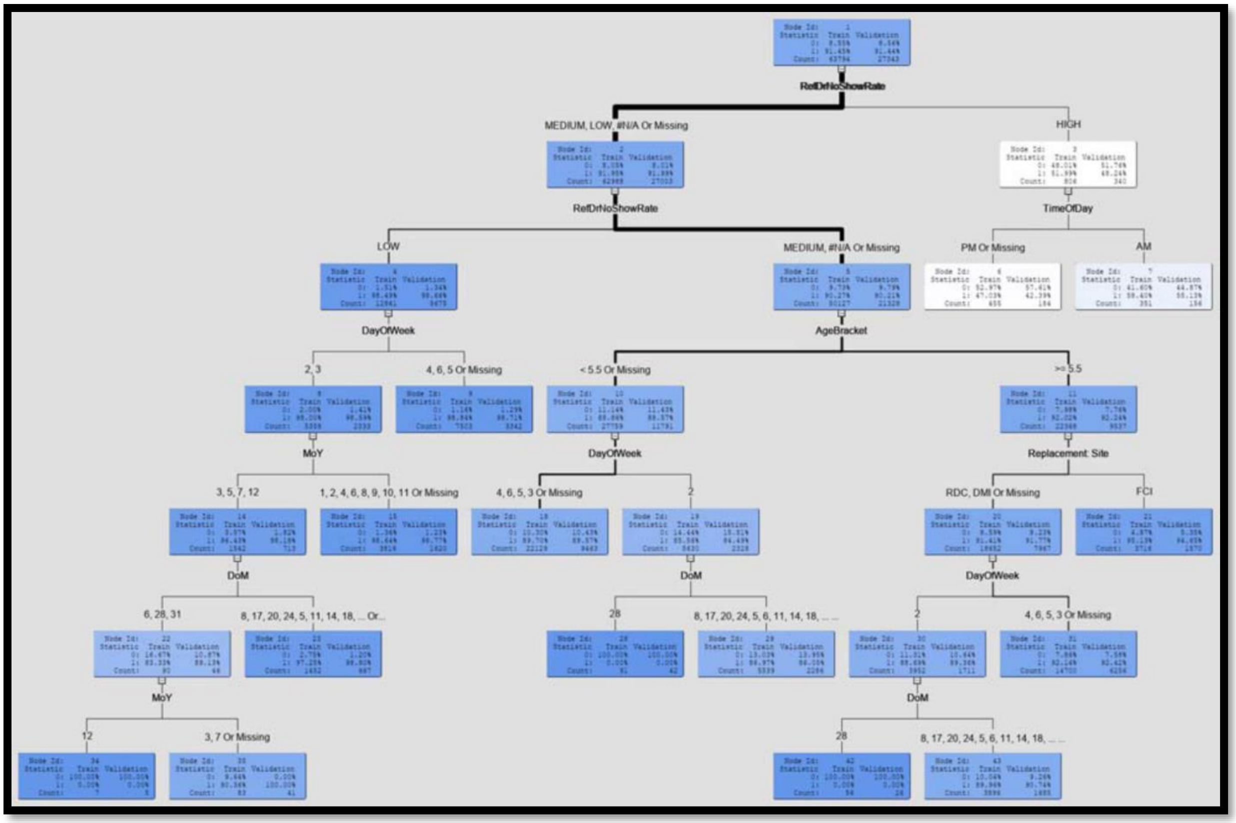

Figure 30: Decision Tree Model

The process for pulling the targeted call confirmation list is shown in Figure 31.

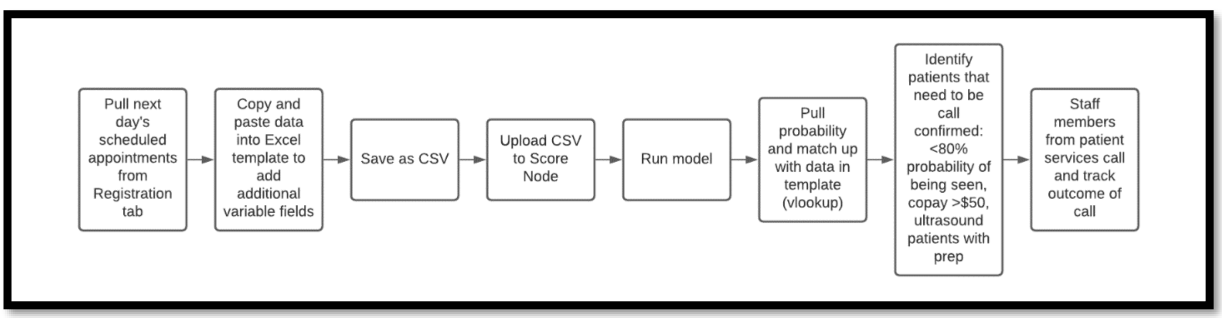

Figure 31: Process for pulling daily call confirm sheet

Since the targeted call confirm process is temporary pending positive results, an experiment was designed to identify the patients who should be called and then have each assigned staff member call as many as possible, knowing that they will never be able to call everyone. See Figure 32 for a breakdown of the different sample sets.

		Did Call Confirm	
		Yes	No
Should Have Been Call Confirmed	Yes	360 patients (YY)	1,170 patients (YN)
	No	N/A	4,683 patients (NN)

Figure 32: Design of Targeted Call Confirm Experiment

With an alpha value of 0.1, an ANOVA was run on the three sample sets with the results shown in Figure 33.

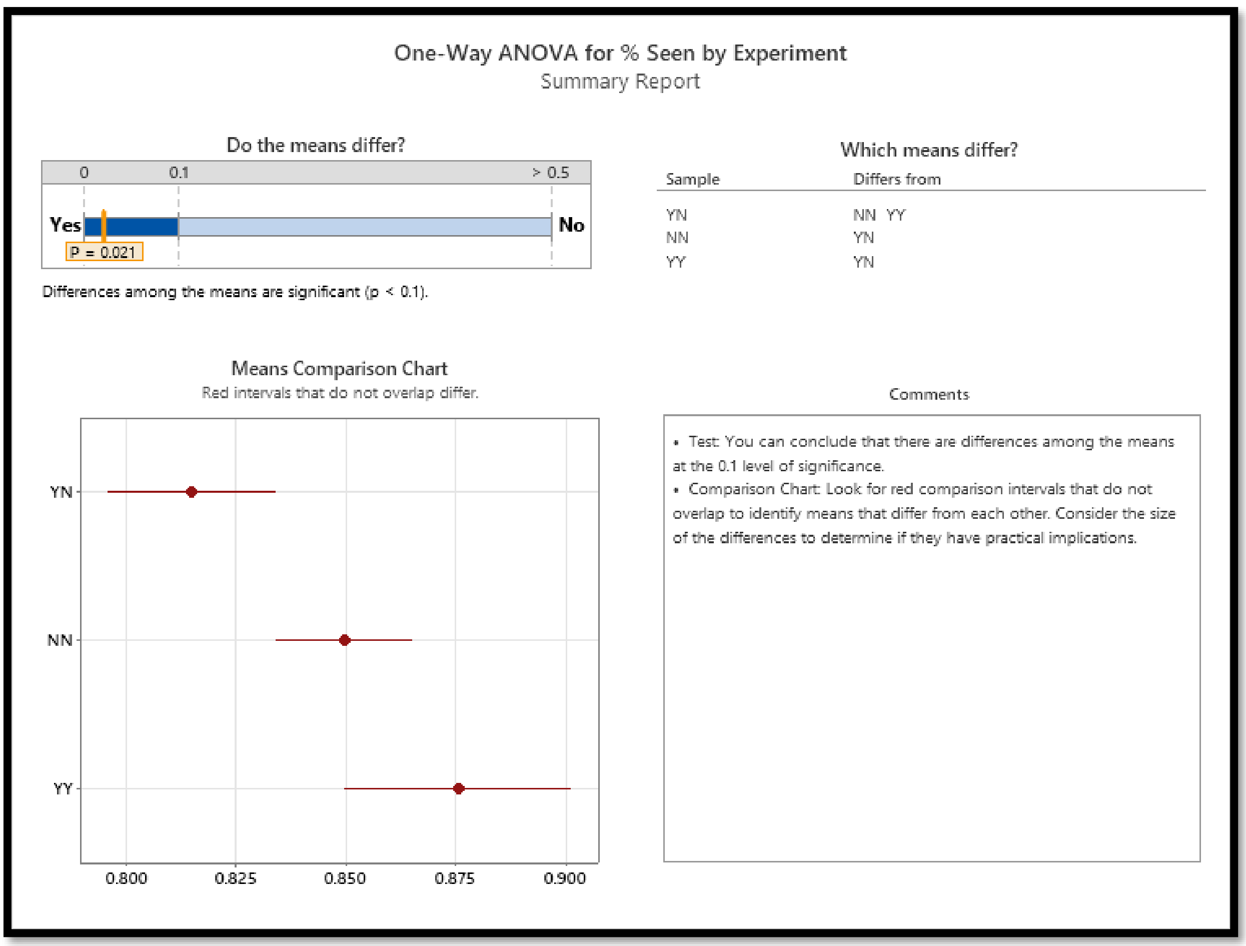

Figure 33: One-Way ANOVA for % Seen by Should/Did

The p-value of 0.021 shows that there are differences among the means at the 0.1 level of significance. The % seen for the patients who should have been called but were not is significantly less. The call confirm experiment was a success. See the boxplot in Figure 34.

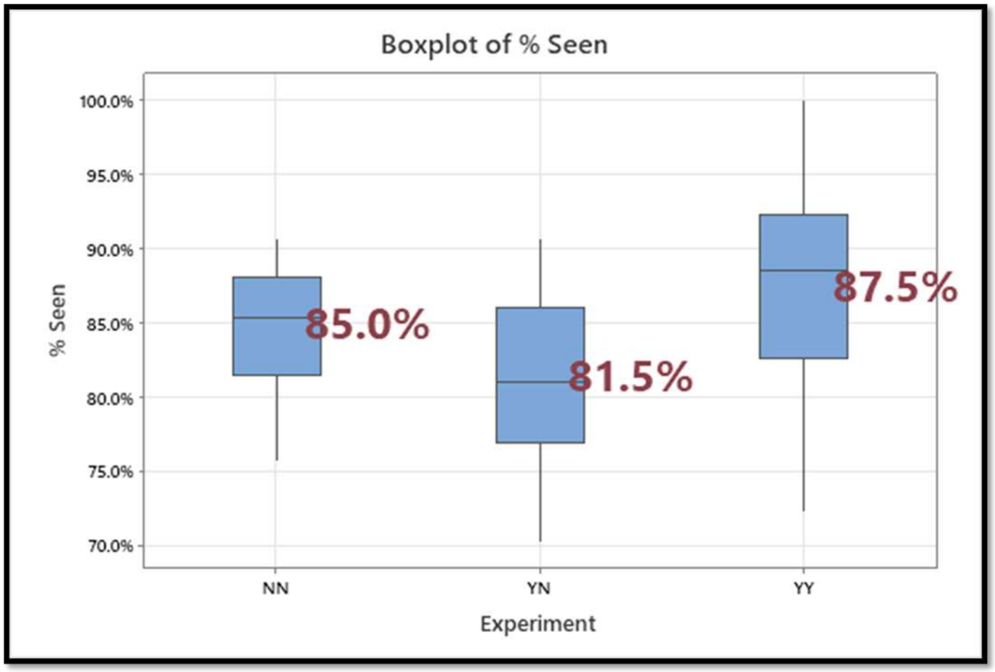

Figure 34: Boxplot of % Seen for Each Factor Level

The mean seen rate for the sample set of patients who should have been call confirmed and were call confirmed is better than the sample set of patients who did not get tagged as needing a call and did not receive a call. The mean seen rate for the sample set of patients who "should have been call confirmed and were not" is the smallest of the three.

A projected revenue improvement of $260k annually could be realized if all patients who were marked as needing to be call confirmed were call confirmed. See Table 6 for a summary of the revenue calculations. Overall, this feasibility study showed that a significant domain in the proposed system of automated utilization management can be realized and there is an operational and financial benefit to utilizing the output of the predictive model to perform targeted patient interventions.

Table 6: Projected Annual Revenue Improvement of Call Confirm Experiment

# of Days Experiment Conducted Properly	# of Patients Call Confirmed	# of Patients Who Should Have Been Call Confirmed	# of Patient Who Did Not Need Call Confirm
17	360	1170	4683
Average % Seen Rate	88%	82%	85%

Daily Average # of Patients for Call Confirm	90
# of Patients Who Show With Call Confirming	78.75
# of Patients Who Show Without Call Confirmation	73.35
Difference	5.40
Average Reimbursement for Mix of Exams Call Confirmed	$193
Daily Revenue	$1,043
Potential Annual Revenue	$262,869

Modality	CT	DX	FL	MG	MR	US
Total # of Exams	154	9	16	60	165	601
Average Reimbursement	$247	$56	$141	$225	$374	$130
Total Reimbursement	$38,038	$504	$2,256	$13,500	$61,710	$78,130
Weighted Average Reimbursement	$193.17					

Conclusions and Recommended Future Work

The probability of a scheduled patient becoming a same day missed appointment can be generated through use of predictive modeling. Key variables that contribute to this probability were identified and used to generate an internal experiment for the usefulness of the data. Resources are limited so improving ways to ensure staff are working on value-added tasks is appreciated. In addition, staff members who have been conducting the call confirming report that patients appreciate the opportunity to ask questions about their exam.

For future development efforts, the predictive model may be improved with addition of different variables found to be useful during other modeling efforts. Variables that other researchers have found to be significant include days between schedule date and appointment date (Dravenstott, Kirchner, Strömblad, Boris, & Leader, 2014), neighborhood characteristics (Mohnen, Schneider, & Droomers, 2019), and even employment status (Briggs, Ulses, VanEtten, Mansfield, & Ganim, 2021). For additional modeling techniques, machine learning methods have been shown to be valuable in predicting patient no show behavior in general outpatient settings (Daghistani, AlGhamdi, Alshammari, & AlHazme, 2020). In this initial modeling effort, decision trees were shown to be useful models so it would be worth it to also explore use the random forest technique which has been useful in studying Parkinson's, diabetes, and breast-cancer (Khaled & Gaber, 2020). These are relevant future research efforts in moving forward with the next steps of predicting actionable whys for a same day missed appointment patient.

CHAPTER 7: CONCLUSION

Research Overview

The objective of this research was to integrate MBSAP with CI to develop resilient healthcare systems. To realize this objective, the specific problem of same day missed appointments in healthcare was analyzed. Same day missed appointments are an accessibility and cost variable in the overall pursuit of resilience. A focused experiment was conducted on the usefulness of MBSAP in an outpatient imaging setting to address same day missed appointments. Integrating MBSAP with the existing CI framework helped the outpatient imaging center fully implement two domains of the proposed architecture that had either been unsuccessfully attempted in the past or only existed as a vision of the future.

MBSAP was used to explore the need and develop an architecture that balanced the stakeholder objectives. The benefits of integrating CI with MBSAP was shown through development of the Patient Status subdomain. Artifacts of the architecture are shown in chapters 4, 5, and 6 and can be used as a reference system architecture by other healthcare providers. The link between a CI system and the AUM is shown back in Figure 16 and the internal block diagram for the CI system is shown in Figure 35. The CI system itself can be modeled and the tie to system developments made explicit.

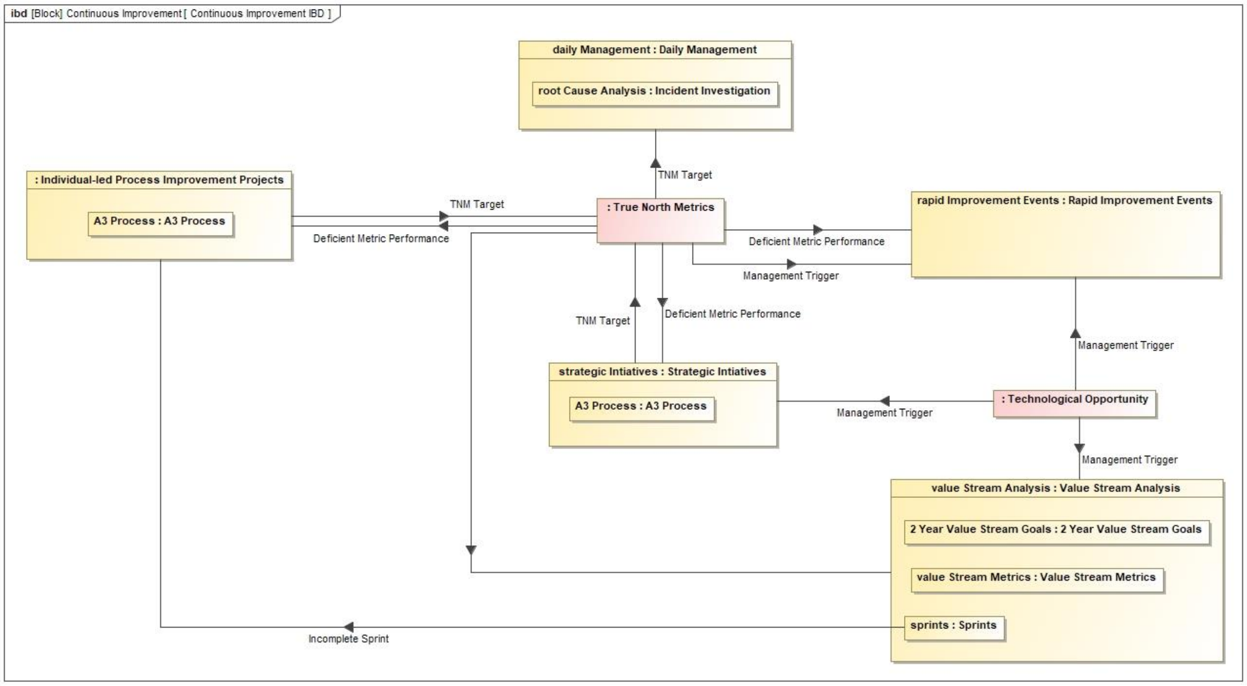

Figure 35: Continuous Improvement (CI) Internal Block Definition Diagram

AUM System Verification and Validation

A system architecture was developed to manage the impact of same day missed appointments and the requirements satisfied to date are summarized in Table 7. The Center Exam Status and Cancellation Prediction domains were partially implemented in the outpatient imaging center operations. The architecture for the remaining domains has been partially developed through the logical/functional domains and the remaining domains are ongoing research efforts.

Table 7: System Requirements Verification and Validation Summary

System Level Requirement	Origin	Verification	Validation	Status
1.1 The system shall minimize the number of unused exam timeslots.	*Figure 11: Mission Level Use Case Objectives*	------------------	An experiment conducted to understand the benefits of targeted call confirmations produced significant results.	Some parts of the system are developed but the full system has not yet been realized in the physical viewpoint.

1.1.1 The system shall have the ability to modify scheduler work flows in the provider's Radiology Information System. (See Figure 36)	Benchmarking service-oriented industries and understanding of social dimensions in outpatient imaging	------------------	-----------------------	The predictive model for determining the probable reason the patient will become a same day missed appointment is needed first. A prototype of this model is being built by a Cal Poly, SLO graduate student using KNIME.
1.1.2 The system shall determine every patient's cancellation probability and potential cancellation reason.	*Chapter 1: An Interim Solution and Proposed Path Forward*	------------------	-----------------------	The model to determine patient's probability of becoming a same day missed appointment was built and tested but the model for the reason is not complete.
1.1.2.1 The system shall maintain a database of patient exam status.	*Understanding the Current State to Establish Logical/Functional Viewpoint*	*Verification and Validation of Same Day Missed Dashboard*	*Verification and Validation of Same Day Missed Dashboard*	A multi-faceted dashboard of SDM appointment reasons and trends is available for all of management.
1.1.2.1.1 Staff shall document all same day cancellation reasons.	Collect timely data on same day missed appointments.	Staff enters notes in EMR system.	Notes reviewed and categorized during morning huddle. Any missing notes are researched by the management team.	
1.1.2.1.1.1 Staff shall document patient reasons when patient calls to cancel.	Collect timely data on same day missed appointments.	Customer Navigation staff members have standard work for documenting notes when	Notes reviewed and categorized during morning huddle. Any missing notes are researched by the management team.	

		patients call to cancel.		
1.1.2.1.1.2 Staff shall call patients who no show for their appointment at the scheduled exam to collect and document a reason.	Collect timely data on same day missed appointments.	Front Office staff members have standard work for calling no show patients at table time and documenting notes on the hour-by-hour board.	Notes reviewed and categorized during morning huddle. Any missing notes are researched by the management team.	
1.1.2.1.1.3 Staff shall document cancellation reason for any exam cancelled while the patient is in the center.	Collect timely data on same day missed appointments.	Front Office staff members have standard work for documenting notes on the hour-by-hour board.	Notes reviewed and categorized during morning huddle. Any missing notes are researched by the management team.	
1.1.2.1.2 The database shall be able to maintain one million records.	Maintain historical data.	The Google Sheets document can hold a million records.	Tableau has a capacity limit on the number of records that can be exported from a single Google Sheets workbook.	Incomplete – the Google Sheet can hold a million records but there is a capacity on the number of rows that can be exported to Tableau, so a single database still needs to be developed.
1.1.2.1.3 All patient records from the daily exam status sheet shall be automatically transferred to a consolidated database.	Automate a tedious and repetitive task.	By indicating that the sheet on the hour by hour is ready to be exported, the script pulls the sheet and combines the	The sheet still needs a manual indication that it is ready to be consolidated so it is not fully automated.	The sheet still needs a manual indication that it is ready to be consolidated so it is not fully automated.

		data on a master sheet.		
1.1.2.1.4 The database shall be able to integrate with the predictive model.	Ensure the predictive model is connected to up-to-date data.	------------------	-----------------------	The data that was used to build the predictive model was pulled from an Excel worksheet. All the data cleaning is performed in Excel. Data pulled out of the system is put into an Excel document that uses formulas and functions to clean the data.
1.1.2.2 A dynamic predictive model shall calculate the patient's probability of cancelling their scheduled appointment.	*Chapter 1: An Interim Solution and Proposed Path Forward*	*Modeling Method – Predictive Model Verification Process*	*Operational Use – Predictive Model Validation*	A verified and validated predictive model produces patient cancellation probabilities and the output is in use operationally.

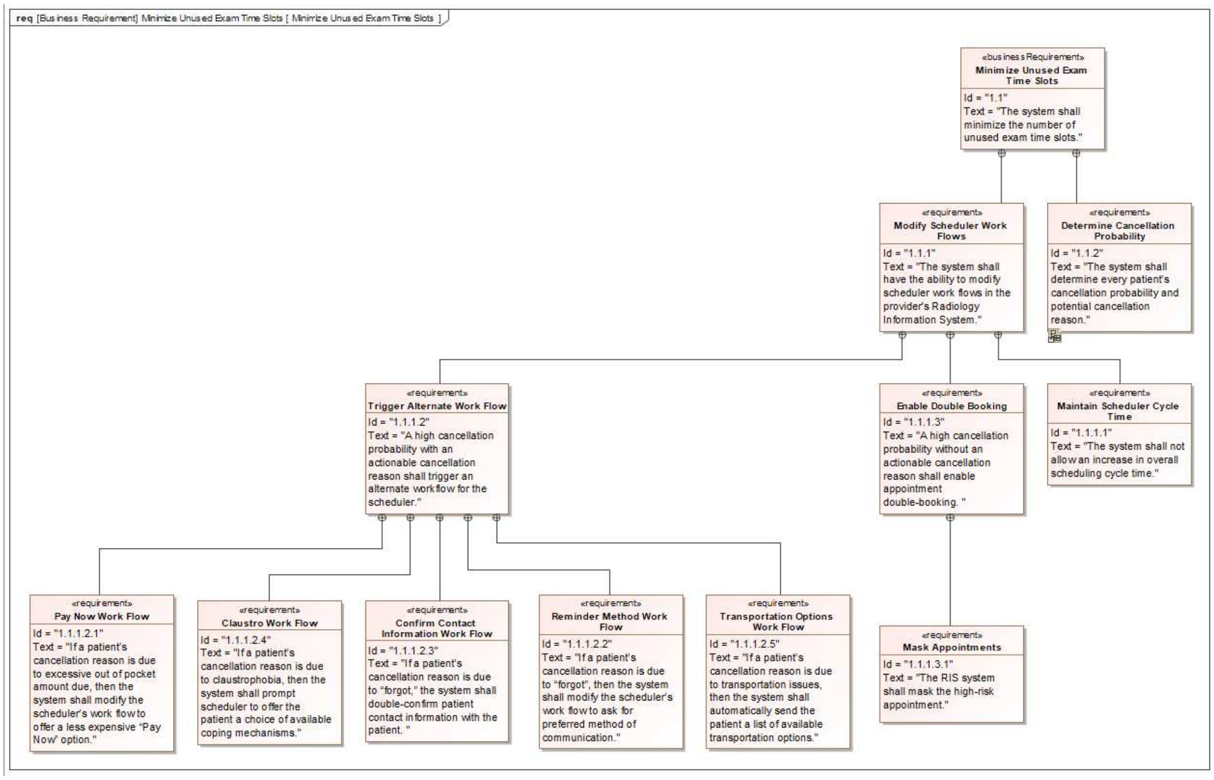

Figure 36: Requirements Breakdown for Minimize Unused Exam Time Slots

Automation, Industry Applications, and Conclusion

Requirements at the system level that still need to be satisfied include the following:

- 1.2 The system shall minimize staff burnout
- 1.3 The system shall minimize patient wait time in the center
- 1.4 The system shall integrate with the provider's Radiology Information System (RIS)

A future research opportunity is to develop an algorithm that defines an optimal exam schedule that can meet the demand using proactive measures like strategic double-booking, while ensuring staff receive their breaks and lunches and do not incur significant overtime. For minimizing patient wait time in the center, an experiment was conducted many years ago to develop a waitlist notification system using existing systems that failed by not taking all the social dimensions into consideration. A future subsystem research and development effort recommendation is using MBSAP to develop an automated waitlist notification system that integrates with existing systems. Finally, figuring out how all these systems integrate with the RIS system is a standalone research effort. Discussion with companies around creating a whole new system that incorporates this system architecture upfront to using artificial intelligence (AI) to train computer robots to perform the functions within existing systems were a first step in generating alternative solutions to satisfy this requirement, but more research is needed in this area.

The AUM architecture presented can be used as a reference architecture in other clinical healthcare settings. The structure and behaviors developed during the operational and logical/functional viewpoints are solution agnostic and can be physically realized differently depending on the context while still achieving the same goal. For example, the Center Exam Status domain breaks down into two subdomains (see Figure 37) for having a system for monitoring patient status and a system for automating wait room notifications. There are multiple ways to realize both systems and some were even presented in Chapter 5 through an analysis of alternatives.

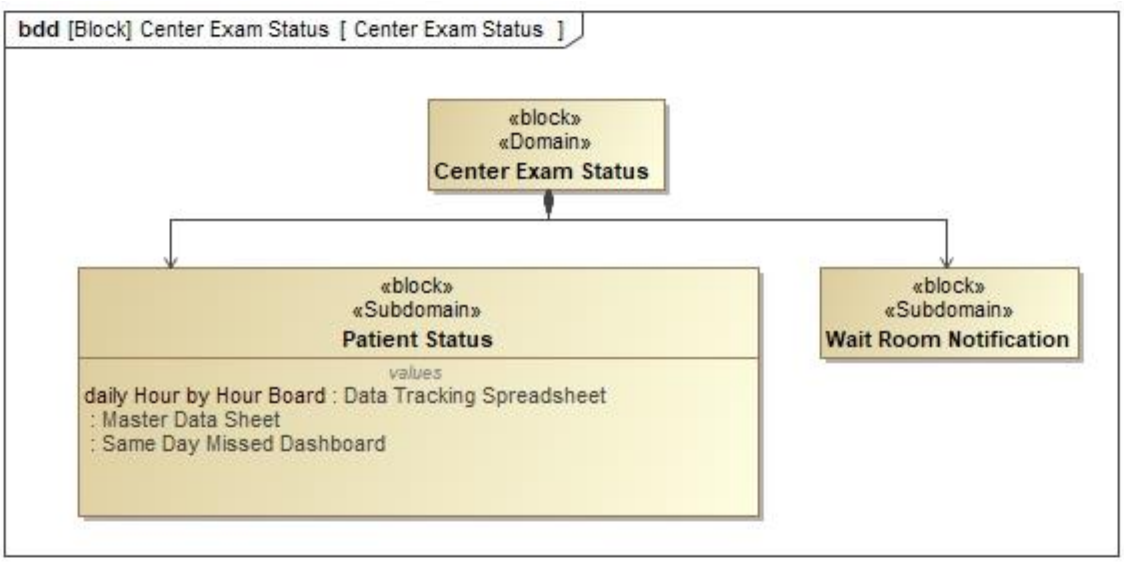

Figure 37: Center Exam Status BDD

Ultimately, the MBSAP process generated a feasible system architecture for better managing the impact of same day missed appointments in healthcare. Significant domains in the architecture were validated through prototype creation, experimentation, and implementation that realized a 17% impact (~$260k annual savings) against the outpatient imaging center's $1.5M annual problem. This experiment showed that targeted interventions can make an impact on the same day missed appointment problem and through repetitive cycles of using MBSAP and CI, realization of the full AUM architecture is feasible.

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