Application of Binary Integer Programming to Align Healthcare Facility Capital Renewal Models to Business Objectives

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Dedication

This work is dedicated to my dearest Lenis, my other half, and to my little lights, Lucia and Elena, who brighten my path.

Acknowledgments

I thank God for the opportunity to learn and contribute. I would like to acknowledge the family and friends who sacrificed and supported me through this effort—I am forever grateful.

I would like to thank The George Washington University for accepting me into the program. I thank all of the professors who taught my cohort, especially Dr. Etemadi and Dr. Widener, for taking the time to guide me on this journey.

Abstract of Praxis

Application of Binary Integer Programming to Align Healthcare Facility Capital Renewal Models to Business Objectives

This research explored decision modeling for facilities infrastructure projects in a hospital setting. Specifically, this research studied how to improve existing project selection through an integration of the financial goals of the hospital, the physical condition of hospital spaces, and patient risk. The lack of an integrated project selection model has led to a $243 billion underinvestment in facilities infrastructure. This underinvestment, or deferred maintenance, can compromise patient care by rendering physical space unusable. Also, if fewer patients can be treated due to unusable space, less money is available for facility infrastructure investments, which increases the deferred maintenance backlog. Statistical analysis was used to determine relevant project selection criteria and produce a decision model that produced more revenue and less patient risk than existing project selection methods. This study builds on previous research and represents a next step toward a system mindset that healthcare facility managers can use to bring immediate value to the healthcare management field.

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List of Acronyms

ASHE	American Society of Healthcare Engineers
BIP	Binary integer programming
CMS	Centers for Medicare and Medicaid Services
CPT	Current procedural terminology
FCA	Facilities condition assessment
FCI	Facility condition index
HCPCS	Healthcare common procedure coding system
HVAC	Heating, ventilating, and air-conditioning
ICRA	Infection control risk assessment
MFPS	Medicare physician fee schedule
MLR	Multiple linear regression
RVU	Relative value units
SCI	System condition index
VIF	Variance inflation factor

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Glossary

Accreditation: Government certification that a healthcare system meets government regulations and standards.

Bed utilization: Ratio of patient beds in use to total beds available.

Binary integer programming: A linear programming method in which equations are constructed to produce decision variables with a 0 or 1 value.

Capital renewal models: Mathematical models used to predict future facility infrastructure needs and requirements.

Deferred maintenance: Maintenance, repair, and capital requirements not performed due to lack of funding.

Facilities condition assessment: Building system analysis of building components, age, condition, and replacement cost.

Facilities condition index: Ratio of a building's accumulated deferred maintenance requirements to total replacement costs.

Fixed cost: Direct cost of an asset.

High-reliability organization: An organization that operates in a hazardous, fast-paced, and complex environment yet avoids catastrophic accidents.

Hospital physical environment: Combination of physical infrastructure, fire safety, and utility systems inside a hospital.

Indirect cost: Incidental cost required to enable the use of an asset.

Little's law: Mathematical equation expressing queue length as the product of arrival rate and service time.

Multiple linear regression: Statistical technique that uses at least two independent variables to predict one dependent variable.

Payer mix: The combined total of healthcare reimbursement payment methods. Components of the payer mix add up to 100%.

Preventative maintenance: Maintenance action taken before asset failure to prevent asset failure.

Reactive maintenance: Maintenance action taken after asset failure.

Variable direct costs: Variable costs directly attributable to the use of an asset.

CHAPTER 1: INTRODUCTION

1.1 Background

Generally, healthcare is an industry with heavy fixed cost requirements (Taheri & Butz, 2005). Facilities and equipment make up the bulk of those fixed costs. The expenses incurred by the hospital must be less than the revenue received from care for hospitals to maintain a positive operating margin. Hospitals recover costs by serving patients. The cost recovery consists of three components: variable direct costs, fixed direct costs, and indirect costs (Harkins et al., 2006). Variable direct costs are directly attributable to each patient, such as medication and medication delivery, while fixed direct costs are attributable to the service the patient receives, such as being in the intensive care unit (Harkins et al., 2006). A percentage of the costs of the salaries of the nurses in the intensive care unit and the laboratory equipment is charged to each patient (Taheri, 2020). The remaining component, indirect costs, comprises costs not attributable to any particular patient or service, such as the fire safety system (Harkins et al., 2006). Revenue related to indirect costs is the funding source for facilities infrastructure investments.

After patients receive services, hospitals typically receive payments from patient cost reimbursement (Taheri, 2020). Cost reimbursement for patient care comes in the form of private funding (personal or insurance) and government funding. Federal government funding supports cost reimbursement from the Centers for Medicare and Medicaid Services (CMS). Reimbursements for CMS account for approximately 35% of the hospital payer mix (Keisler-Starkey & Bunch, 2021). To qualify for CMS reimbursement, hospitals must be accredited. Several entities have been approved by

CMS as viable to perform hospital accreditation activities. The Joint Commission is one of the largest entities authorized by CMS. Without CMS reimbursements, the business model for a nonprofit hospital would not be viable. For example, an operating room in a hospital needs to push air out of the room to prevent airborne hazards from entering the space. On the other hand, a room containing a patient with an infectious disease in the hospital may need to bring air into the room to prevent airborne hazards from exiting the space. If a hospital cannot meet these standards, CMS could remove accreditation, which would make the hospital ineligible for CMS reimbursements. The function of moving air in and out of the space is the responsibility of the facility manager.

Construction for hospitals considers lifespans of over 40 years (Olsson & Hansen, 2010). Costs for construction and equipment are primarily debt financed. Those debts are repaid by amortizing the costs of the debts over patients who receive treatment at the hospital (Taheri, 2020). The number of patients served can be viewed as an application of Little's law (Harkins et al., 2006). Patients arrive at the hospital, receive some form of treatment or service, and then are discharged. Hospitals are therefore incentivized to treat the highest number of patients with the highest-cost treatments and services (Taheri, 2020). There are two ways facilities management critically impacts the business model in the context of Little's law. First, the capacity of the hospital is a limiting factor. Knowing how many patients can be served is a factor in determining, for example, how large to build a hospital, wayfinding in a hospital, or if a space should be leased. Second, the type of treatment is important in terms of cost recovery. Spaces such as operating rooms generate more revenue per square foot per unit of time than waiting rooms. The

utilization of square footage inside a hospital has a direct impact on the revenue a hospital can generate.

After construction is completed, the function of the facility manager from the business perspective is twofold. The first function is to maximize uptime for existing square footage. The second function is to ensure spaces perform at their highest and best use. The funds for these two functions in a nonprofit setting come primarily from the operating margin. An observation on cost recovery from the facility manager perspective is that maximizing uptime for spaces, and having those spaces perform at their highest and best use, means that more patients receive treatment, more revenue is received, and more dollars are available for the hospital bottom line and, in turn, facility investments.

After construction, facilities investments take the form of routine maintenance, which are tasks performed to maintain the function of a system, such as lighting or air-conditioning. Facilities investments also take the form of capital renewal, replacing items that are obsolete or no longer useful. Lastly, facilities investments can take the form of renovating or repurposing spaces for new uses. Over its lifespan, a hospital makes all three types of investments. This study examined how capital renewal investments are made.

Today, facility investments are governed primarily by the lifespan and condition of the facility. A heuristic called facility condition index (FCI) is the basis for investment decisions. The FCI is expressed as the ratio of deferred maintenance costs of a facility to the cost of replacing the facility (Cecconi et al., 2019). The FCI percentage is categorized in a range where the lowest percentages represent buildings in better conditions and the highest percentages represent buildings with worse conditions. Generally, the building with the higher FCI will receive higher priority for funding over a building with a lower

FCI. An additional consideration for hospitals is compliance with CMS standards. However, healthcare facility capital renewal models do not currently account for how capital renewal investments impact the financial bottom line of the medical system.

1.2 Research Motivation

The purpose of this research was to better integrate facility managers into the business of healthcare delivery. This integration would lead to more revenue for healthcare systems and, more importantly, increase patient safety. The foundational text for financial training for facility managers commissioned by the American Hospital Association does not mention healthcare infrastructure specifics when discussing financial modeling (American Society of Healthcare Engineers [ASHE], 2022). From the perspective of the facility manager, the job is to keep the infrastructure operational at the lowest cost.

In general, business investments are aimed at generating positive revenue and minimizing costs. Financial officers view facility infrastructure as an indirect cost burden and seek to minimize investments in facility infrastructure maintenance and operations. As a result, there is approximately $243 billion of facility infrastructure risk in the form of deferred maintenance (Morgan, 2021). From an accreditation perspective, from 2015 through 2018, at least eight of the top 10 Joint Commission citations against all U.S. hospital physical environments were related to deferred maintenance (Magliocchetti, 2018). Without intervention, the cost of deferred maintenance is expected to grow to $391 billion over the next 10 years (Morgan, 2021).

This research explored the possibility of overlap between these two perspectives. If a method of facility investment can be shown to improve the financial bottom line,

hospitals can use those funds to decrease patient risk and threats to accreditation through facility investments. Multiple linear regression was used to determine which factors in terms of facility investments were related to revenue generation. After factors were determined, binary integer programming was used to construct relative weights of factors to properly weight facility risk factors against profit generation.

1.3 Problem Statement

Facility capital renewal models are not designed to increase revenue, resulting in an underinvestment in infrastructure, which has led to $243 billion in deferred maintenance in healthcare institutions.

1.4 Thesis Statement

A decision model is required by facility managers to prioritize facility projects in a way that increases revenue.

1.5 Research Objectives

This research was conducted to discover if a medical facility capital investment model could meet the following objectives:

- Link facility capital renewal needs to the business objectives of a healthcare organization.
- Identify which facility capital investment parameters relate to cost, function of space, and operational risk to profit in a healthcare organization.
- Produce a model that can select, from a set of potential projects, a budget-based subset that increases revenue and decreases operational risk.

1.6 Research Questions and Hypotheses

The study addressed three research questions:

RQ1: What is the relationship between capital renewal investments and revenue goals?

RQ2: What are the factors that influence potential facility project investments?

RQ3: Can a decision model help facility managers select the best set of potential facility projects that will decrease operational risk while increasing revenue?

There were two hypotheses:

H1: Factors of system condition index, zone classification, and patient risk classification lead to the selection of projects that will yield the highest revenue.

H2: A decision model can provide a list of potential facility projects that will increase revenue while decreasing operational risk.

1.7 Scope of Research

This praxis explored the relationship between the various factors that constitute medical facility capital investments and the revenue objectives of the medical organization. The basic proposition is that if facility capital renewal is aligned with the business objectives of the medical system, the facility project portfolio will result in more dollars for facility requirements as well as decrease operational risk for the medical organization. After identifying factors relevant to profit and risk, a binary integer programming model was used to determine proposed weighting of significant factors in order to achieve the best trade-offs between factors. The goal of the research was to improve the current decision-making process for medical facility managers by modifying existing capital renewal models. Additionally, the goal was to offer a model aimed at

adding a different perspective, namely a financial perspective, to the medical facility managers who manage the highly capital-intensive, fixed-cost medical industry. The data for this praxis came from a combination of facility data from a medical facility and open-source federal government sources.

1.8 Research Limitations

This research provided only a high-level overview of healthcare business operations to serve as the foundation for facility managers' planning. As such, this study did not describe all the business processes of the medical industry. Also, this research was limited to the portion of the medical payer mix available via CMS. State systems, private insurance, and self-pay mechanisms have been excluded due to varying levels, types, and business rules. The CMS system is transparent, transferable across medical systems, and comprises approximately 35% of the payer mix. For-profit medical systems, medical education facilities, and medical research facilities were excluded from the research.

The analysis in this research was limited to Heating, Ventilation and Air Conditioning (HVAC) systems. HVAC systems were chosen to allow a clear exploration of building information necessary to address the research questions. Each HVAC system in a hospital can be linked to specific area of the facility, which allows for patient procedures, patient risks, and revenue associated with each HVAC system to be obtained. In contrast, building systems such as roofing support patient care but do not allow a direct link between the individual component, patient risk, and revenue.

1.9 Organization of Praxis

This chapter has provided a general overview of the reasons for the research, the current operating context, and the method for addressing the stated problems. The perspective is that of a hospital as a nonprofit entity, working in partnership with the federal government to provide healthcare to the population of the United States. In this context, facilities management is an integral part of the provision and business of healthcare. The gap between medical industry and facility manager incentives is a core reason for the large backlog of facility capital requirements—a gap addressed in the study's research questions.

Chapter 2 provides a detailed literature review. The literature is sourced from academic texts, research journals, and government sources. Selected literature is used to introduce the reader to the functions and complexities of the healthcare field; to describe the evolution of the facilities management field and its current limitations; and to highlight why the gap between healthcare and facility management provides an opportunity to deliver value to the medical system and improve patient care.

Chapter 3 begins by describing the data sets selected for this praxis. It also introduces the rationale and intent of the selected research methodologies. The techniques of multiple linear regression and binary integer programming analysis are described in terms of functionality and relevance to the research questions and hypotheses.

Chapter 4 presents the results of the methodologies outlined in Chapter 3. Data are presented for a sample project portfolio and validated to demonstrate the robustness of the binary integer programming model.

Finally, Chapter 5 discusses the research findings and offers conclusions. It reviews the usefulness of the binary integer programming model and proposed questions for future research. Conclusions demonstrate the results of the hypothesis testing and implications for the facilities management field. The novel contribution to the body of knowledge is a new perspective, reflected in a validated model rooted in improving the physical environment. The intent is for facility and financial managers to consider better prioritizing deferred capital requirements in excess of annual budgets.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This research explores the intersection between the business objectives of a healthcare system and the role of the facility manager. To understand this intersection, the literature review focuses on a high-level overview of the ways hospitals recognize revenue, the role of the facility manager in the operations of the healthcare system, and the current perspectives of facility managers around capital renewal. The literature is organized into four main sections:

- The healthcare operating environment
- Facilities management practices
- Healthcare facility performance
- Gaps between business decisions and facility decisions

2.2 Healthcare Operating Environment

In-person services in a healthcare system involve a patient arriving at a building, receiving some form of treatment, and being discharged. For these services to be provided, several prerequisites must be satisfied. There needs to be physical space capable of providing the services. There must be equipment capable of providing and supporting services. Finally, there must be people qualified to perform services. From an operational perspective, healthcare can be viewed largely as a fixed-cost industry (Taheri & Butz, 2005). The costs for brick and mortar, durable medical equipment, billing systems, and salaried professionals are largely fixed and do not vary with the number of patients (Taheri & Butz, 2005). In the case of a 24-hour-per-day, 7-day-per-week

hospital, these fixed costs are even higher since the hospital must be continuously operational.

Since fixed costs are inherently a part of the provision of care, healthcare providers must consider how to recover upfront fixed costs. The cost recovery consideration has implications for issues such as how large the hospital should be or where a hospital should be located. Size and location are important because, for a nonprofit institution, the primary mechanism for cost recovery of fixed costs is the cost charged to each patient. The total cost per patient is the sum of three components: variable direct costs, fixed direct costs, and indirect costs (Harkins et al., 2006). Variable direct costs cover things like medication or supplies, directly attributable to the patient; fixed direct costs are not directly attributable to the patient, but to the unit providing the service, such as the emergency room; and indirect costs comprise expenses such as general salaries, general services, and facilities (Harkins et al., 2006). Harkins et al. (2006) discussed these components and made a special note regarding overhead: "It is noteworthy to appreciate that hospital overhead is real and costs associated with infrastructure must be recouped in the revenue stream" (p. 128). This observation is important because it provides a rationale for how facilities infrastructure management is core to the business concern of a healthcare system.

The revenue stream for hospitals comes mainly in the form of reimbursement for care provided. There are several types of reimbursement, as shown in Table 2.1.

Table 2.1
Major Types of Hospital Reimbursement

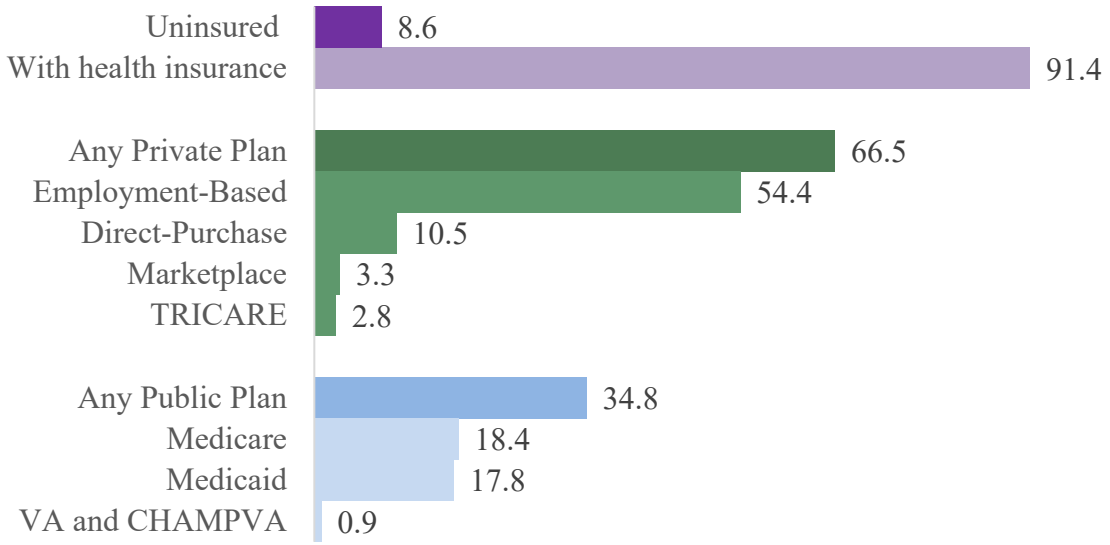
- Philanthropy and grants
- Global budgets
- Charges
- Per diem
- Cost reimbursement for DRGs (per admission)
- Capitation
- Managed care contracts

Note: Reprinted from Getzen (2012) with permission from Wiley. DRGs indicate diagnosis-related groups.

Reimbursements come from public and private sources. The combined sources of payment are collectively called the payer mix (Taheri, 2020). The private components of the payer mix come from self-payees and private insurance policies. Private policies may be employment-based, directly purchased, provided by a marketplace, or provided by government-sponsored entities such as Tricare. Tricare (n.d.) is the healthcare program for uniformed service members, retirees, and their families around the world. Public forms of insurance come from Medicare, Medicaid, Veterans Affairs, or the Civilian Health Medical Program of the Department of Veterans Affairs (Keisler-Starkey & Bunch, 2021). Medicare is defined by the Centers for Medicare and Medicaid Services (CMS) (2021b) as a "health insurance program for people 65 or older, people under 65 with certain disabilities, and people of all ages with end-stage renal disease (permanent kidney failure requiring dialysis or a kidney transplant)" (para. 1). According to CMS (n.d.), Medicaid "provides health coverage to over 72.5 million Americans, including children, pregnant women, parents, seniors, and individuals with disabilities. Medicaid is the single largest source of health coverage in the United States" (para. 1). The U.S. Department of Veterans Affairs oversees the Veterans Health Administration (2022), the

largest integrated healthcare system in the United States, providing care to over 9 million veterans. Figure 2.1 displays the elements of the payer mix as of 2020. Most of the reimbursement comes from the private sector, at approximately 65%. The remaining coverage, approximately 35%, comes from public sources.

Figure 2.1
Percentage of People by Type of Health Insurance in 2020



Note: Reprinted from Keisler-Starkey and Bunch (2021) from the U.S. Census; not protected by copyright.

2.2.1 Relative Value Units

When a patient receives services from a hospital, the hospital allocates charges for the patient to the patient's reimbursement mechanism. It is important to note that even though the hospital charges for patient services, the parties providing reimbursement do not pay 100% of the charges (Taheri, 2020). Reimbursement parties, such as private insurance providers, often work with healthcare systems to negotiate reimbursement rates lower than the charge rates. On the other hand, funds provided by the federal

government, such as CMS, provide Medicare reimbursement rates utilizing current procedural terminology (CPT) codes (Taheri, 2020). An important tool to utilize CPT codes is the Medicare Physician Fee Schedule (MFPS). The MFPS uses the Healthcare Common Procedure Coding System (HCPCS) to determine patient procedure reimbursement rates (CMS, 2021a). The HCPCS uses CPT codes to describe services and procedures provided by physicians (CMS, 2021c). Because Medicare is funded and administered by the federal government, the MFPS and all current HCPCS codes are publicly available via CMS.

An important use of HCPCS codes is the link to relative value units (RVUs). Using the MFPS, hospitals can input an HCPSC code and determine the reimbursement cost for a given procedure. Healthcare systems may use RVU information to learn, based on projected patient demand, revenue inflows from the Medicare component of its patient population. The reimbursement payment for RVUs has five components: work RVUs, physician expense RVUs, malpractice RVUs, geographical practice cost index, and a conversion factor (CMS, 2021a). As defined by CMS (2021a), work RVUs reflect the time and intensity associated with providing a service. Practice expense RVUs reflect the cost of maintaining the practice (rental, equipment, staff costs). Malpractice RVUs reflect the costs of malpractice insurance. Geographical practice cost indices account for the different locations in the United States where services are provided. The conversion factor is a federal statutory adjustment factor, which is updated annually (CMS, 2021a). Equation 2.1 shows the CMS (2021a) formula to calculate reimbursement payments.

$$\text{Payment} = [(\text{Work RVU} \times \text{Work GPCI}) + (\text{PE RVU} \times \text{PE GPCI}) + (\text{MP RVU} \times \text{MP GPCI})] \times \text{CF} \quad (2.1)$$

The calculation of RVUs is useful because it provides a proxy to understand both costs and reimbursement rates for care. Since hospitals must charge each patient to recover fixed costs, and hospitals eligible for federal funds are reimbursed using the MFPS, it is possible to review the costs and reimbursements for different types of procedures. For example, the cost and reimbursement rate for a routine physical exam is lower than for a heart surgery. The difference in reimbursement rates highlights the reality that from a financial perspective, it is in the hospital's interest to have sicker patients with higher reimbursement rates than less sick patients with lower reimbursement rates (Taheri, 2020). This financial concept highlights for the facility manager how the use of physical space is an important component of how hospital systems recognize revenue.

2.2.2 Hospital Throughput

Another factor in hospital revenue is how the system processes patients. Again, healthcare systems recover costs by servicing patients. Therefore, it is in the interest of the hospital to serve as many patients as possible, which lowers the unit costs of its fixed assets (Taheri, 2020). The reception, servicing, and discharging of patients can be viewed as an application of Little's law (Hopp & Lovejoy, 2012), where the patient inventory is the product of the arrival rate of admissions to the hospital and the average length of stay per patient. Practically, for an expected number of admissions, a reduction in length of stay would mean more capacity for the hospital to treat more patients. However, the number of admissions could vary with the capacity of the system. The term *bed utilization* is a useful way to understand system capacity (Takagi et al., 2017). If a room

is unable to perform its function due to staffing, then bed utilization is reduced, and the hospital is unable to service patients.

Another factor that impacts utilization is accreditation. Accreditation is a mechanism through which healthcare systems are evaluated and certified to provide different types of healthcare (Hussein et al., 2021). Health systems that seek CMS reimbursement must adhere to accreditation standards. These standards describe the acceptable use and function of systems such as heating, ventilating, and air-conditioning (HVAC), fire safety, and electrical power systems (Baretich, 2008). The operations and maintenance of these systems are the responsibility of the facility manager.

In conclusion, from a throughput perspective, the function of the facility manager is critical for the smooth flow of patients through the system. If a room cannot be utilized due to failure of a facility system, such as HVAC, hospital capacity is reduced. If a room cannot meet accreditation standards, hospital capacity is reduced. If there is underutilized space, such as a space that does not contribute to RVU generation, or a function not supporting RVU generation, hospital capacity is reduced. It is therefore in the interest of the medical system as well as the facility manager to ensure spaces operate at maximum uptime and operate at their highest and best use.

2.3 Facilities Management

Civil infrastructure consists of transportation, water and wastewater, waste management, energy production and distribution, buildings, recreation facilities, and communication networks (Hudson & Haas, 2013). As of 2013, the underinvestment in U.S. infrastructure was $1.1 trillion (Grigg, 2015). At a high level, infrastructure investment needs are important because the conditions of a nation's infrastructure are a

critical factor in determining a nation's prosperity (Lu & Jiang, 2011). With respect to facilities infrastructure, a 2020 study revealed that two of the most important criteria for infrastructure investments are code compliance and health/safety (Besiktepe et al., 2020). More than a simple funding problem, the lack of facilities infrastructure investment has particular safety implications for the healthcare industry, where the projected 10-year deferred maintenance backlog is estimated to be approximately $391 billion (Morgan, 2021).

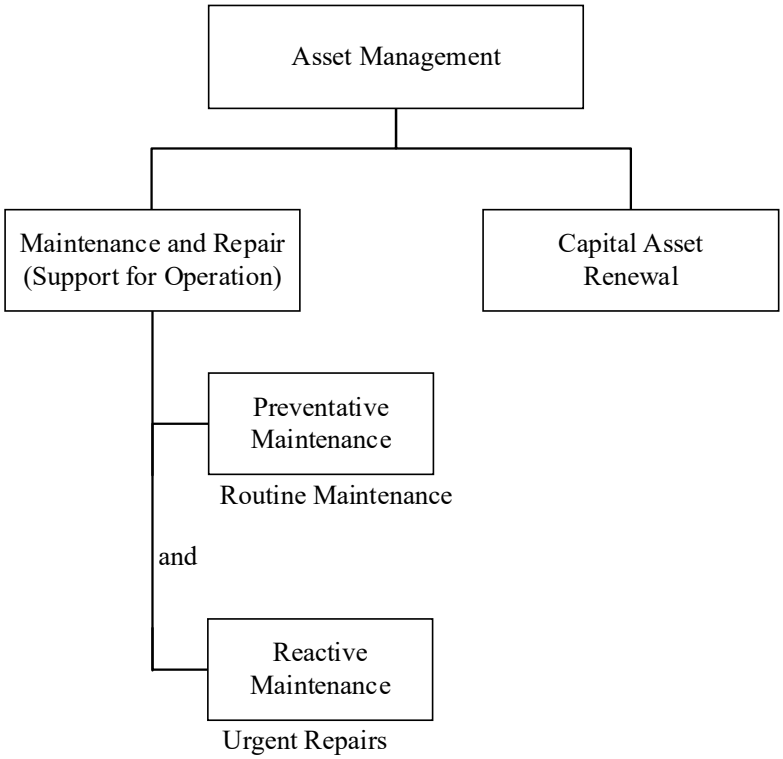
2.3.1 Asset Management

As a general matter, the physical infrastructure deteriorates over time, causing adverse effects on function (Grussing & Liu, 2014). If investments in infrastructure maintenance, repair, and renewal do not keep pace with deterioration, the risk of asset failure begins to accumulate. This risk can be considered deferred maintenance. There are several reasons the infrastructure is deteriorating faster than it is renewed (Vanier, 2001). Pagano and Perry (2008) argued that financial investment need arises from the fact that "infrastructure needs continue to outstrip infrastructure spending" (p. 33). According to Grigg (2015), lack of political alignment and lack of political trust are the main drivers for lack of investment. However, Grussing (2018) argued that even with adequate funding, it can be difficult to maintain building infrastructure because "one must have keen insight on what to fix, when to fix it, and the construction activities and techniques required to address those fixes" (p. 1).

The determination of what, when, and how to fix facility infrastructure is known as asset management. After construction, infrastructure takes two forms: preventive/ reactive maintenance and capital renewal (Elhakeem & Hegazy, 2012). Maintenance

functions support daily operations, and capital renewal upgrades or completely replaces an asset (Elhakeem & Hegazy, 2012) (Figure 2.2).

Figure 2.2
Asset Management Dimensions

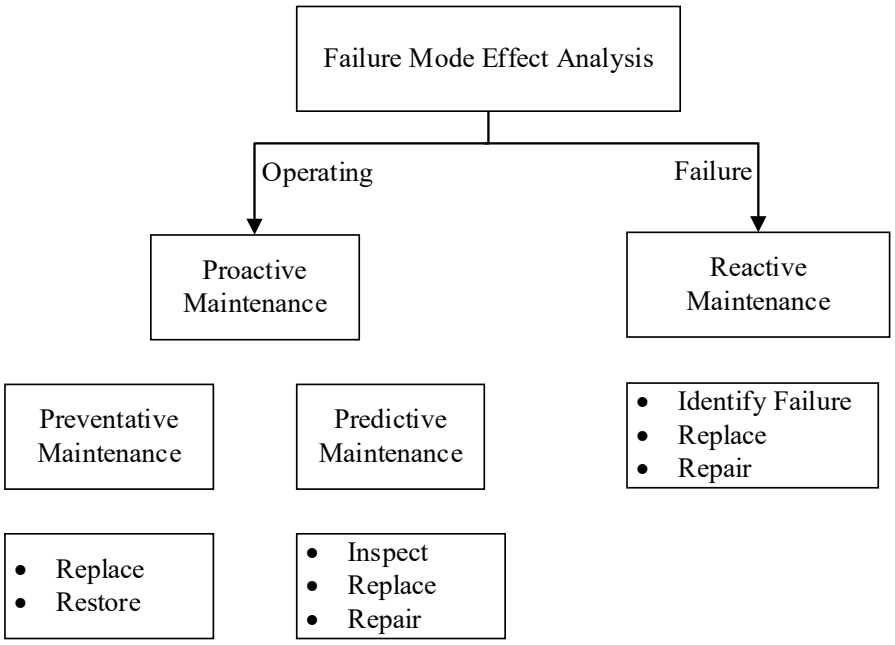


Note: Reprinted from Elhakeem and Hegazy (2012) with permission from Taylor & Francis.

The maintenance and repair of infrastructure was further explored by Salah et al. in 2018. Salah viewed maintenance and repair from the perspective of asset failure, using failure mode effect analysis. Preventative maintenance is a type of proactive maintenance, where action is taken prior to asset failure, while reactive maintenance is action taken after failure occurs (Salah et al., 2018). The breakdown of the components of predictive and reactive maintenance is shown in Figure 2.3. Capital renewal plans are designed to maintain the operations of infrastructure assets in a cost-effective manner

(Rashedi & Hegazy, 2015). These assets are managed by facilities management. While there are many definitions for facilities management, this research used the definition of Shohet and Lavy (2004): "The application of integrated techniques to improve the performance and cost effectiveness of facilities to support organisational development" (p. 211).

Figure 2.3
Failure Mode Effect Analysis



Note: Reprinted from Bellamy (2020) with permission of the author.

For operational and safety reasons, proactive maintenance is preferred to reactive maintenance. One of the primary tools used in facilities management is the facilities condition assessment (FCA). This assessment provides information necessary to determine conditions and work needs, as well as forecasting future conditions to identify long-range work planning requirements (Grussing, 2018). The primary output from a

FCA is a well-known and globally acceptable way to determine the building condition called the facility condition index (FCI) (Anuar et al., 2021). The FCI is a ratio of the estimated current costs of deferred maintenance to the estimated current replacement value of the facility. The equations for FCI and current replacement value are shown in Equations 2.2 and 2.3 (Anuar et al., 2021).

$$FCI = DM/CRV \times 100\% \quad (2.2)$$

$$CRV = GA \times RCSF \quad (2.3)$$

Where FCI = facility condition index; DM = deferred maintenance; CRV = current replacement value; GA = gross area; RCSF = replacement cost per square foot.

FCI scores are rated on a scale of 0 to 100, where 0 is the best condition and 100 is the worst condition (Anuar et al., 2021). The FCI scale is coded as follows: 0%–10%, excellent; 10%–20%, good; 20%–40%, fair; 40%–60%, poor; and >60%, deficient. While the FCI represents the sum of the building deficiencies relative to the building replacement costs, each deficiency in the building is classified at the system level. The system condition index (SCI) is calculated and classified in the same fashion as the FCI with two exceptions. First, the index represents the ratio of deferred maintenance of a component relative to the replacement cost of the component. Second, the current replacement value is the replacement cost of the individual component. For an FCA, building systems can be classified using the American Society for Testing and Materials Uniformat II System Classification (Table 2.2)

Table 2.2

American Society for Testing and Materials Uniformat II System Classifications

Level 1 Major Group Elements		Level 2 Group Elements		Level 3 Individual Elements	
A	SUBSTRUCTURE	A10	Foundations	A1010	Standard Foundations
				A1020	Special Foundations
				A1030	Slab on Grade
		A20	Basement Construction	A2010	Basement Excavation
				A2020	Basement Walls
B	SHELL	B10	Superstructure	B1010	Floor Construction
				B1020	Roof Construction
		B20	Exterior Enclosure	B2010	Exterior Walls
				B2020	Exterior Windows
				B2030	Exterior Doors
		B30	Roofing	B3010	Roof Coverings
				B3020	Roof Openings
C	INTERIORS	C10	Interior Construction	C1010	Partitions
				C1020	Interior Doors
				C1030	Fittings
		C20	Stairs	C2010	Stair Construction
				C2020	Stair Finishes
		C30	Interior Finishes	C3010	Wall Finishes
				C3020	Floor Finishes
				C3030	Ceiling Finishes
D	SERVICES	D10	Conveying	D1010	Elevators & Lifts
				D1020	Escalators & Moving Walks
				D1090	Other Conveying Systems
		D20	Plumbing	D2010	Plumbing Fixtures
				D2020	Domestic Water Distribution
				D2030	Sanitary Waste
				D2040	Rain Water Drainage
				D2090	Other Plumbing Systems
		D30	HVAC	D3010	Energy Supply
				D3020	Heat Generating Systems
				D3030	Cooling Generating Systems
				D3040	Distribution Systems
				D3050	Terminal & Package Units
				D3060	Controls & Instrumentation
				D3070	Systems Testing & Balancing
				D3090	Other HVAC Systems & Equipment
		D40	Fire Protection	D4010	Sprinklers
				D4020	Standpipes
				D4030	Fire Protection Specialties
				D4090	Other Fire Protection Systems

Level 1 Major Group Elements		Level 2 Group Elements		Level 3 Individual Elements	
		D50	Electrical	D5010	Electrical Service & Distribution
				D5020	Lighting and Branch Wiring
				D5030	Communications & Security
				D5090	Other Electrical Systems
E	EQUIPMENT & FURNISHINGS	E10	Equipment	E1010	Commercial Equipment
				E1020	Institutional Equipment
				E1030	Vehicular Equipment
				E1090	Other Equipment
		E20	Furnishings	E2010	Fixed Furnishings
				E2020	Movable Furnishings
F	SPECIAL CONSTRUCTION & DEMOLITION	F10	Special Construction	F1010	Special Structures
				F1020	Integrated Construction
				F1030	Special Construction Systems
				F1040	Special Facilities
				F1050	Special Controls and Instrumentation
		F20	Selective Building Demolition	F2010	Building Elements Demolition
				F2020	Hazardous Components Abatement

Note: Reprinted from Charette and Marshall (1999); not under copyright.

The SCI provides relative conditions of each system and system component. A higher SCI indicates a component in poorer condition than a component with a lower SCI.

2.4 Healthcare Facility Performance

Healthcare facilities are considered among the most complicated and difficult types of facilities to manage, maintain, and operate (Lavy & Shohet, 2009). In addition to the normal operational parameters for commercial buildings, facilities that treat patients must have a higher standard of care due to the nature of their operations. Recognizing the complexity of the healthcare operating environment, in 2008 The Joint

Commission partnered with hospitals to transform systems into high-reliability organizations (The Joint Commission Center on Transforming Healthcare, 2022). The complex, interconnected systems that define the healthcare industry meet the hazardous, fast-paced, continuous operation characteristics of a high-reliability organization (Tolk et al., 2015). For example, operating conditions related to HVAC, such as temperature, humidity, and pressure, directly relate to the ability of hospitals to utilize operating rooms. The facilities management team is responsible for the installation, operation, and maintenance of HVAC systems. Failure to maintain operating room parameters results in capacity reduction and may result in hospital-acquired infections. These infections are influenced by a number of operating room conditions, among which is HVAC performance. Hospital-acquired infections result in over 100,000 deaths per year (Balaras et al., 2007).

2.4.1 Performance Criteria

In healthcare, along with condition indices, other factors should be considered. The basic FCI calculation does not consider other aspects such as technical performance (Cecconi et al., 2019). Also, the FCI does not consider healthcare-specific issues such as indoor air quality, which have a profound impact on organizational performance, as they are responsible for the health, comfort, and safety of building occupants (Lavy et al., 2014b). Despite this, the American Society of Healthcare Engineers (ASHE) uses FCI as its primary metric for health care (Flannery et al., 2018). Performance metrics are important not only to ensure the proper functioning of equipment but also because the building infrastructure must perform at an acceptable level to provide patient care.

Many studies have been conducted to assess hospital facility performance. Performance measurement provides information for organizations to analyze courses of action to align facility investments to organizational goals (Lavy et al., 2014a). An extensive literature review by Lavy and Shohet in 2014 resulted in the grouping of over 34 performance metrics into four categories: financial, functional, physical, and user satisfaction. The following are examples of metrics in each category:

- Financial: Operating costs, capital costs, building maintenance, facility condition index
- Functional: Qualitative and quantitative building condition, resource consumption, health and safety, security
- Physical: Productivity, space adequacy, space utilization, parking
- User satisfaction: Satisfaction of customer/building occupants and community, appearance, learning environment

In 2020, Lai and Yuen conducted a literature review and analysis that found over 61 indicators applicable to hospital performance. Through a focus group study, 18 key performance indicators were shortlisted and grouped into four categories (Table 2.3).

Table 2.3
Key Performance Indicators I

Aspect	Facet	Performance indicator
Physical	Task related	[P1] Work request response rate [P2] Number of completed work orders per staff
	Equipment related	[P3] Availability of fire services system [P4] Availability of lift system [P5] Average age of major facilities (e.g. chiller and boiler)
	Physical condition	[P6] Facility condition index
Safety	Accident/injury	[S1] Number of accidents per year
	Fire incident	[S2] Number of unwanted (false) fire incident calls per year
	Statutory compliance	[S3] No. of statutory orders per year [S4] No. of statutory orders per 5 years
Environmental	Energy performance	[E1] Energy utilisation index [E2] Carbon emissions per building area
Financial	Operational cost	[F1] Actual costs within budgeted costs [F2] O&M cost per building area [F3] Energy cost per building area [F4] FM cost per building area
	Maintenance cost	[F5] Maintenance cost per building area
	Resource allocation	[F6] AME of total replacement value

Note. Reprinted from Lai and Yuen (2020) with permission from Emerald.

In 2020, Salem and Elwakil proposed condition assessment factors that combined 20 indicators into five main categories, as shown in Table 2.4.

Table 2.4
Key Performance Indicators II

Category	Variables	Description
Main Factors	Physical Assessment	An evaluation of the physical condition of the building that lists any deficiencies and assesses the useful life of the major facility components
	Environmental Assessment	An evaluation of the environmental performance of the building that includes an infection prevention assessment of water and air contaminations as well as environmental considerations such as lead, asbestos, and mould
	General Safety Assessment	An evaluation of the general safety and life safety of the equipment and the risk of physical harm to patients or staff (e.g. fire protection)
	Revenue Loss Factors	An evaluation of equipment importance to hospital revenue including extra (avoidable) corrective maintenance cost
Physical Assessment Factors	Age/Life Expectancy	A statistical measure of the average time equipment is expected to work effectively
	Condition Assessment	An evaluation of the overall functioning of equipment performance as well as equipment appearance
	Parts Availability	A measure of the availability of Original Equipment Manufacturer (OEM) spare parts
	Code Compliance	An evaluation of whether the equipment meets professional standards, codes, and regulations
	Energy Efficiency	Replacing this equipment could increase overall energy efficiency
Environmental Assessment Factors	Lead	An evaluation of equipment lead contamination
	Asbestos	An evaluation of equipment asbestos contamination
	Mould	An evaluation of equipment mould contamination
	Water Contamination	An evaluation of the equipment's risk of water contamination
	Indoor Air Quality	An evaluation of the equipment's risk of air contamination or poor indoor air quality
General Safety Assessment	Life Safety	An evaluation of the equipment's contribution to life safety systems
	Physical Safety	The equipment's potential to cause physical harm to patients or staff
Revenue Loss Assessment	Labor Hours	The extra (avoidable) number of labor hours needed for equipment repair (corrective maintenance)
	No. of Work Orders	The extra (avoidable) number of work orders placed for the repair process (corrective maintenance)
	Repair Cost	A calculation of the total extra (avoidable) cost of repairs incurred (corrective maintenance)
	Redundancy	An evaluation of the extra equipment and components that are necessary in the event of an equipment failure

Note. Reprinted from Salem and Elwakil (2020) with permission from Taylor & Francis.

2.5 Healthcare Facilities—Business Perspective

Although facility managers have provided several approaches to identify, weight, and formulate facilities, an extensive literature review performed by Salem and Elwakil (2020) found a significant gap between critical asset assessment and healthcare capital needs decision making. Specifically, healthcare facility investment models suffer from a lack of an integrated platform that accounts for criteria such as component condition, patient safety, revenue loss, and business value retained (Salem & Elwakil, 2020). One of the persistent problems with facilities management has been the use of operational, facilities-oriented measures of its contribution to business, which does not correspond to what business views as its main drivers or key performance indicators (Hinks, 2000). In 2004, Lavy and Shohet suggested that certain factors—the proportion of hospital revenue allocated to facility management expenditure; asset productivity with regards to capital replacement value; asset productivity with regards to net present value; and the ratio of income to floor area—relate to financial performance and are therefore not the principal concern of public hospitals (Lavy & Shohet, 2004). However, in today's public, nonprofit patient care environment, in which reimbursement is based on value-based care such as RVUs, there is increased focus on quality and cost savings (Jasuta, 2016). An alternative approach to that of Lavy and Shohet (2004) is to view facility investment as a driver of return on investment. The asset condition assessment model by Salem and Elwakil (2020) offered an initial approach for an integrated platform. In 2020, Galli proposed several methods for giving proper consideration to financial and economic impacts when evaluating projects. In the current phase of development of medical facility infrastructure investment planning, research would be enhanced by optimization functions for capital

renewal and allocation (Salem & Elwakil, 2020). Planning for facility capital investment portfolios should adopt a margin plus mission approach, where mission investments such as improvements to building systems avoid negative financial impacts and mission investments such as reconfiguring of spaces increase value (Jasuta, 2016).

2.6 Summary and Conclusion

Facilities management is a core component of the delivery of healthcare. This literature review aimed to provide a high-level overview of the ways facilities management specifically intersects with and impacts the delivery of healthcare. In the context of nonprofit, low-margin healthcare operations, the question is: How do investments in facility infrastructure improve the bottom line? To date, several approaches have been offered for cost avoidance, such as failure to invest in *x* risks asset failure of component *y*, which leads to a loss of *z* dollars. However, there are still gaps in the literature to address how, with a limited budget and many systems that require investment, the best set of projects can be chosen to deliver the highest revenue to the system without compromising patient care.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter focuses on the methodology for providing an integrated model for infrastructure maintenance from a revenue perspective. Currently, there is a gap between facility management models and the business objectives of nonprofit medical institutions. Facility condition assessments (FCAs) are basic building blocks of facility management models. One output of an FCA is the facility condition index (FCI) (Anuar et al., 2021). Section 2.3.1 described the modeling and use of the FCI. Scholars have recognized that the FCI alone is insufficient to accurately capture requirements for assets in a medical environment. Shohet, Lavy, Ali, Salem, and Elwakil have each added assessment factors that consider aspects such as building performance and asset criticality. Each of these contributions has moved the medical facilities management field forward. This research considered an additional factor: revenue. To remain viable over time, businesses must generate revenues that exceed expenses. The need for revenues to exceed expenses is especially important in the nonprofit medical realm, where external fundraising via equity division is not allowed. Instead, funds come from operations, debt, and philanthropy. In this light, costs that do not contribute to revenue are necessarily minimized. The lack of consideration of revenue generation in facilities modeling has resulted in infrastructure projects being delayed and unfunded. The scale of delays and unfunded infrastructure investments is approximately $243 billion across the United States (Morgan, 2021).

The methodologies presented in this chapter consider which facility factors are relevant to revenue generation and then proceed to introduce a model to integrate facility conditions, revenue, and patient risk. To find factors relevant to revenue generation,

multiple linear regression (MLR) was employed. To construct an integrated model, binary integer programming (BIP) was used. The BIP model used a case study to select a subset of projects from a group of potential projects. Section 3.2 discusses the data used in this research. Section 3.3 discusses MLR and its application to the selected data set. Section 3.4 discusses using BIP principles and software to construct a prioritized project list. Section 3.5 presents validation efforts for the data. The methodologies sought to address two hypotheses:

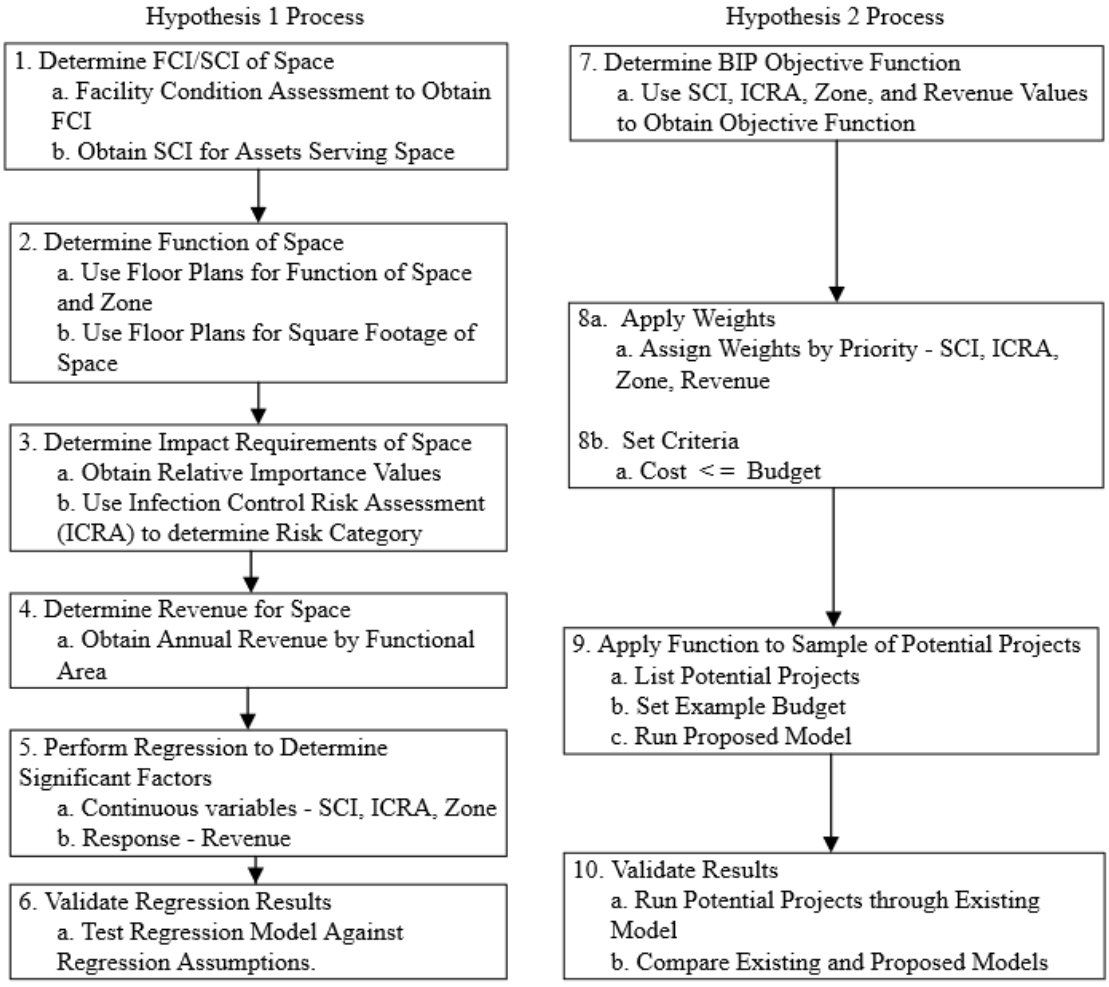
Hypothesis 1: Factors of system condition index, zone classification, and patient risk classification lead to the selection of projects that will yield the highest revenue.

Hypothesis 2: A decision model can provide a list of potential facility projects that will increase revenue while decreasing operational risk.

3.1.1 Process Overview

Two key questions arise when analyzing outputs from a medical FCA. First, if FCI and the systems condition index (SCI) are used primarily for facilities infrastructure criticality rankings, how should facilities infrastructure projects be differentiated in a healthcare context? Second, for facilities infrastructure projects with the same or similar condition indices, how should projects be prioritized? To answer the first question, scholars such as Ali (2013), Salem, and Elwakil (2020) added factors to assess asset performance and criticality. The second question goes one step further and considers the criteria for selecting projects with similar conditions. This research sought to move facilities management toward alignment with the revenue generation purposes of the business, so revenue is considered as a differentiator.

Figure 3.1
Methodology Process Flow



MLR allows the consideration of the relationship between several continuous variables and one response. As shown in Figure 3.1 above, Hypothesis 1 was tested using several factors in addition to FCI to determine, when given a set of potential projects, which factors relate to revenue generation. MLR allowed the analysis of the significance of the selected factors and their relevance to revenue generation. The significance level used in this research was a p value < 0.05. With respect to Hypothesis 2, competing

factors were introduced and balanced to construct a model that considers the project cost, condition index, patient risk, zone classification, and revenue.

3.1.2 Data Source

The data for this research came directly from a hospital FCA, functional use, revenue, and floor plans. To comply with data use agreements, all identifying information for the medical system has been removed. The assets under consideration were mechanical systems. Mechanical systems were utilized because of the particular impact that heating, ventilating, and air-conditioning (HVAC) systems have on patient care and safety in a medical context. The selection of HVAC components, relative to other American Society for Testing and Materials Uniformat II elements, such as superstructure or plumbing, allowed a discrete view of the link between component, safety, and revenue. Major elements such as superstructure or plumbing systems provide general services to support the entire facility, such as a roof or domestic water distribution system. In contrast, while HVAC components do contain common building systems, such as the duct distribution system, many HVAC components are particular to patient service areas and, therefore, a direct link to revenue loss or generation opportunities.

The FCA provided the building name, project number, functional system, system replacement cost, system deficiency cost, and SCI. The FCA also classified the category of project. The categories for the data set included lifecycle, reliability, integrity, building code, life safety, and hazardous material. Lifecycle classifications are based on end of service life. Reliability classifications are based on consistency of function. Integrity classifications are based on component failure. Building code

classifications are based on projects that are necessary to meet federal, state, and local requirements. Life safety classifications are components that represent a threat to safety and human life. Components with a hazardous material classification have impacts on the storage, handling, or movement of hazardous materials.

The FCA also determined the priority for projects. Priorities are based on timeframe. Priority 1 projects need to be conducted immediately. Priority 2 projects should be completed within 1 year. Priority 2 projects should be completed in the next 2 to 5 years. Priority 4 projects should be completed in 6 to 10 years. Priority 5 projects are not time bound but based on the preference of the project selection team. Table 3.1 on the next page displays results from a sample FCA query.

3.2 Variables

This section describes how data for specific variables used in the research were collected.

3.2.1 Facility Condition Index and System Condition Index

All assets from the most recent FCA were extracted from a 2022 database. The database returned over 4,500 system components. Each component was classified using the American Society for Testing and Materials Uniformat II Standard, as shown in Table 2.2. The FCA database contained the component, component replacement cost, component deficiency cost, SCI, and FCI. The replacement costs were determined by RSMeans, a widely used resource in North America that contains a database for construction estimating. The deficiency costs were determined by the FCA component assessment team. The aggregate of SCIs per building was used to calculate the FCI.

Table 3.1
Sample Facilities Condition Assessment Query Results for Building 1A

Proj No.	System name	System replacement cost	Estimated deficiency cost	Category	Priority level (years)	SCI	FCI
1	AHU-52	$124,968	$156,209	Lifecycle	3 (2-5)	1.25	0.26
2	AHU-56	$158,698	$198,373	Lifecycle	3 (2-5)	1.25	0.26
3	AHU-57	$107,382	$134,228	Lifecycle	3 (2-5)	1.25	0.26
4	Ductless mini split - 2-ton	$7,753	$9,691	Lifecycle	3 (2-5)	1.25	0.26
5	Ductless mini split - 1-ton	$16,840	$21,050	Lifecycle	3 (2-5)	1.25	0.26
6	DX split system - thermal zone	$9,005	$11,257	Lifecycle	3 (2-5)	0.00	0.26
7	Exhaust system - hazardous/isolation rooms	$95,950	$119,937	Lifecycle	3 (2-5)	1.25	0.26
8	DDC/pneumatic controls – hybrid	$1,170,690	$1,463,362	Lifecycle	4 (6-10)	0.00	0.26
9	Air compressor - pneumatic controls	$34,373	$42,966	Lifecycle	3 (2-5)	1.25	0.26
10	Ductless mini split - 2-ton	$7,753	$9,691	Lifecycle	4 (6-10)	0.00	0.26
11	AHU-55	$74,494	$93,118	Lifecycle	3 (2-5)	1.25	0.26
12	AHU-59	$47,999	$59,999	Lifecycle	3 (2-5)	1.25	0.26
13	DX split system	$10,962	$13,703	Reliability	2 (0-1)	1.25	0.26
14	Exhaust system - fume hood	$62,476	$78,095	Lifecycle	4 (6-10)	1.25	0.26
15	Exhaust system - duct distribution	$851,956	$1,064,945	Lifecycle	3 (2-5)	1.25	0.26
16	Exhaust system - general/restroom	$57,959	$72,449	Lifecycle	3 (2-5)	1.25	0.26
17	Fan coil system - cabinet - elevator equip rooms	$24,699	$30,874	Lifecycle	3 (2-5)	1.25	0.26
18	Four pipe distribution system	$3,133,112	$3,916,390	Lifecycle	4 (6-10)	0.00	0.26
19	Heat exchanger - liquid/liquid - plate and frame	$13,521	$16,901	Lifecycle	3 (2-5)	1.25	0.26
20	Paddle fans - ceiling mounted	$12,313	$15,392	Lifecycle	4 (6-10)	0.00	0.26

3.2.2 Function of Spaces and HVAC Area

Two sets of floor plans were obtained for each area of the selected facilities. The functional floor plan identified floor, function, and square footage. The HVAC floor plans identified which HVAC component served each area of the facility. Information from the two floor plans was combined to align the function, HVAC service area, and square footage of each space.

3.2.3 Area Importance

Each area was ranked by relative importance. The relative importance of each space was obtained from Ali and Hegazy (2014). First, the hospital was divided into three zones: clinical, nursing, and support. The zones are based on medical facility design guidance from James and Noakes (1994). Each zone was ranked against the other two zones. Table 3.2 shows the relative importance scales developed by Ali and Hegazy (2014). This information was included to be considered along with the SCI to provide a view of how important an HVAC asset is to continuity of operations and patient care.

Table 3.2
Relative Importance Areas

System	Clinical (20%)	Nursing (20%)	Support (60%)
Civil	25	25	25
Architectural	90	70	40
Electrical and communication	100	100	80
Mechanical	100	100	80
Equipment	100	N/A	90

Note: Reprinted from Ali and Hegazy (2014) with permission from the American Society of Civil Engineers.

3.2.4 Patient Risk Areas

Patient risk in each area is classified by The Joint Commission utilizing a tool called the infection control risk assessment (ICRA). The ICRA has four risk classifications: low, medium, high, and highest risk. The risks are relative to patients. Table 3.3 displays the ICRA matrix. This matrix was chosen to display the choice to select or not select, since an HVAC project has not only operational risks, but specific risks to patients.

Table 3.3
Infection Control Risk Assessment Risk Classifications

Low Risk	Medium Risk	High Risk	Highest Risk
• Office areas	• Cardiology • Echocardiography • Endoscopy • Nuclear Medicine • Physical Therapy • Radiology/MRI • Respiratory Therapy	• CCU • Emergency Room • Labor & Delivery • Laboratories (specimen) • Newborn Nursery • Outpatient Surgery • Pediatrics • Pharmacy • Post Anesthesia Care Unit • Surgical Units	• Any area caring for immunocompromised patients • Burn Unit • Cardiac Cath Lab • Central Sterile Supply • Intensive Care Units • Medical Unit • Negative pressure isolation rooms • Oncology • Operating rooms including C-section rooms

Note: Reprinted from Centers for Disease Control and Prevention (https://www.vendorportal.ecms.va.gov/FBODocumentServer/DocumentServer.aspx?DocumentId=451009&FileName=VA259-12-R-0369-0003002.PDF); not under copyright.

3.2.5 Revenue

The revenue for each space was determined using four factors: the functions of the spaces, the square footage of the areas, the revenue generated for the functions, and the HVAC component serving the functional areas. Revenue values were for 1 year of operations. The function and square footage of each space were determined from existing

floor plans provided by the organization. The revenue for each function was provided by the organization. The revenue attributable to the HVAC component was determined by using floor plans to determine which functional area and associated square footage was supported by each HVAC component. The proportion of the square footage supported by the HVAC component to the total square footage of the function was multiplied by the total revenue for the function. This calculation allowed the determination of the revenue supported by each HVAC component. If a space did not directly contribute to patient care, a negative revenue value was recorded.

3.3 Data Analysis

3.3.1 Multiple Linear Regression

MLR was chosen to determine the manner and significance of the relationship between the selected variables and the revenue generated by the area served. The MLR method allows the selection of independent continuous variables. The independent variables take the form of X. The independent variables are multiplied by regression coefficients from β_0 to β_p (Hadi & Chatterjee, 2012). There is also an error term, ε, which expresses random error. The dependent variable, Y, is expressed as the sum of the β_0, $\beta_p X_p$terms, and the error term and takes the form of

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \quad 3.1$$

As shown in Equation 3.1, the equation is written in slope-intercept form. The constant, β_0, will cross the Y intercept when all other X terms equal 0. Because the true relationship between X and Y may not be linear and there may be other variables that cause variation in Y, a catch-all error term, ε, is employed (James et al., 2013). In other

words, Y is approximately a linear function of X, and ε represents the discrepancy in that approximation (Hadi & Chatterjee, 2012). Initially, the values for coefficient terms were unknown. In seeking to describe a linear relationship between X and Y, the coefficients were estimated using the least squares method (James et al., 2013). This was done by finding the straight line that best fit the response versus predictor value (Hadi & Chatterjee, 2012). The least squares method seeks to minimize the error term and minimize the sum of the squares of the vertical distance from each point to the line (Hadi & Chatterjee, 2012).

3.3.2 Assumptions of Multiple Linear Regression

For MLR results to be reliable, several assumptions must be satisfied. The first assumption is a linear relationship between predictor and response. If the true relationship is far from linear, then virtually all conclusions drawn from the fit are suspect (James et al., 2013). One way to test linearity is to plot the residuals versus the predicted values (James et al., 2013). A random distribution of residual versus predicted values indicates linearity. In the case of multiple regression, checking the linearity of the predictor versus response is more difficult due to the high dimensionality of the data (Hadi & Chatterjee, 2012). This research used Minitab to perform an analysis of linearity.

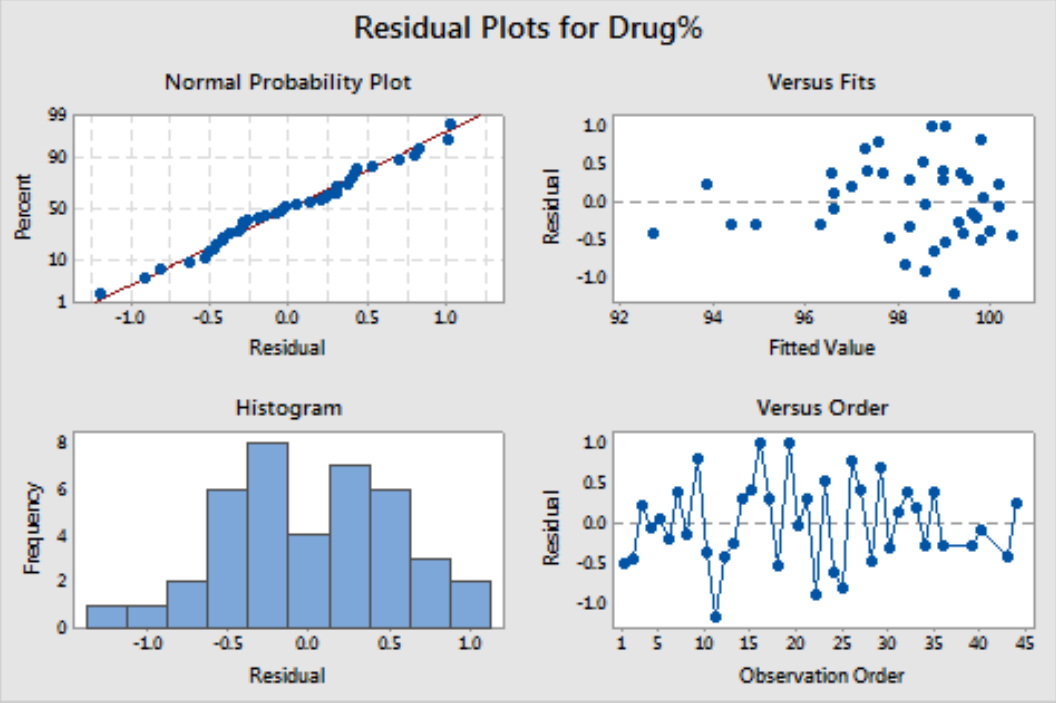
The second assumption is that the residuals must be independently and identically distributed. Four characteristics are necessary to satisfy this assumption (Hadi & Chatterjee, 2012):

a. The residuals are normally distributed.
b. The errors have a mean of zero.
c. The residuals have constant variance (homoscedasticity).

d. The residuals are independent.

Assumptions regarding residuals were checked via a Minitab four-in-one graph. This graph checks normality, constant variance, independence of residuals, and a histogram of the residuals. Normality was checked using a normality plot set at a significance level of $p < 0.05$. A p value greater than 0.05 indicates normality. The residuals versus fits graph checks for constant variance. A random pattern of values indicates constant variance. The residuals versus order graph checks for independence of residuals. A random pattern of values indicates independence of residuals. Figure 3.2 shows a sample four-in-one graph obtained from Minitab.

Figure 3.2
Sample Minitab Four-in-One Graph



3.3.3 Variable Reduction

A third assumption is that the predictors must be predetermined, error free, and linearly independent (Hadi & Chatterjee, 2012). Fixed and error-free assumptions cannot be validated (Hadi & Chatterjee, 2012). However, independence of predictors can be checked by analysis. Collinearity is a situation in which two or more predictor variables are closely related to each other (James et al., 2013). In the case of MLR, where multiple predictors were employed, multicollinearity was tested using the variance inflation factor (VIF). Any VIF values more than 5 warrant investigation because they point to a high amount of collinearity (James et al., 2013). The collinearity assumption was checked using the Minitab regression routine. Variable coefficients with VIFs higher than 5 were checked one at a time for removal from consideration. After each variable was removed, the MLR routine was run again to determine if there were any remaining variable coefficients with VIFs higher than 5. The process of removing variables was continued until only variable coefficients with VIFs lower than 5 remained.

After VIFs higher than 5 were removed, the MLR model was analyzed to test predictor variables against the null hypothesis (H_0). The null hypothesis states the selected predictor variables have no relationship with the response variable. The alternative hypothesis, H_a, is that at least one variable has a relationship with the response variable. The hypothesis test takes the form of the following two equations:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0 \quad 3.2$$

$$H_a: At\ least\ one\ \beta_p \neq 0 \quad 3.3$$

The hypothesis test was performed using Minitab. The method of determining the significance of the predictor variables was done by observing the p value of the predictor

variables (Illowsky & Dean, 2013). The significance value was set at $p < 0.05$. Variables with values higher than the significance value were removed one at a time, beginning with the variable with the highest *p* value. After each variable was removed, the MLR routine was run again and observed for variables with *p* values > 0.05. The variable reduction process continued until the remaining predictor values displayed a significance of $p < 0.05$.

A fourth assumption is the absence of outliers and high leverage points. While outliers occur when there is an unusual response to a given predictor, high leverage points have unusual predictor values (James et al., 2013). These unusual points are visible on the MLR fitted line plot. Each unusual point was investigated and, if necessary, removed. The determination of whether to remove an unusual point was whether the outlier was the result of an error. If the point is not the result of the error, the point may remain in the data set (Illowsky & Dean, 2013).

3.3.4 Binary Integer Programming

For project selection, an integer programming algorithm was employed. Integer programming is "a linear program with the requirement that all or some of the decision variables must be integers" (Baker, 2011, Chapter 6, para. 1). In the case of BIP, decision variables to select projects take the form of 0 or 1 (Marcondes et al., 2019). A classic application of BIP is for project selection, called the "capital budgeting problem." The model, adapted from Chen, Batson, and Dang (2013), takes the following form:

$$\begin{gathered} \text{Maximize } z = \sum_j C_j X_j \\ \text{Subject to } \sum_j a_j X_j \leq b \\ X_j = 0 \text{ or } 1 \; j = 1, 2, \ldots, n \end{gathered} \tag{3.4}$$

where z is the variable to be maximized, C_j is an input parameter, X is a binary decision variable, a is the cost of each item, j indicates the project number, and b is the total budget. For this research each project had a C_j score, which is the sum of the products of the normalized scores for each criterion and preselected criteria test weights for the jth project. The normalized score for each criterion was calculated by using the following equation, where $criteria_j$ is the value of a criterion (e.g., ICRA rating):

$$Normalized\ Condition\ Score\ criteria_j = \frac{criteria_j}{\sum criteria_j} \quad 3.5$$

Each test case was assigned a weight based on priority. An example of criteria weights is shown in Table 3.4.

Table 3.4
Sample Criteria Weights

Criteria	Condition	Zone	ICRA	Revenue
Test weights	0.1	0.4	0.4	0.1

The Microsoft Excel algorithm SOLVER was used to evaluate Equation 3.4. In a hospital setting, patient care and safety are the most important criteria; therefore, a constraint was that the weights of SCI, zone classification, and revenue ICRA could not exceed the ICRA weights. Weights were assigned at initial values of at least 10% to determine optimal values. The constraint for Equation 3.4 is that the sum of the costs of the projects must be less than the total budget available. The SOLVER algorithm was run twice. The first run was to determine the weights that would produce the highest *C* scores for the projects. The weight and ICRA criteria were input into SOLVER, and SOLVER was run to vary the weights to produce the highest *C* scores for the projects. Then, the SOLVER algorithm was run using the BIP described in Equation 3.4. The SOLVER

algorithm produced decision variables for X where 0 indicated not selecting the project and 1 indicated selecting the project.

3.3.5 Assumptions of Binary Integer Programming

For a BIP model to be valid, several linear programming assumptions must be satisfied. The assumptions for linear programming are as follows (Chen et al., 2013):

1. Divisibility: Each continuous variable must be nonnegative ($x \geq 0$).
2. Certainty: Each input parameter must be constant.
3. Proportionality: The total contribution to a function is proportional to the values of a variable.
4. Additivity: Every function (in the objective or in the constraints) can be expressed as the sum of several functions, each containing a separate variable.
5. Single objective: The optimization function must have one objective.
6. Simultaneousness: A feasible solution cannot violate any constraints equations.

3.4 Model Validation

The results of MLR indicated the predictive value of the evaluated model. Model validation was done by checking the results of the regression routine against the assumptions in Section 3.3.3. If the results indicated collinearity, unusual points, and insignificant variables, those variables were removed, and the routine was run again. The R-squared value of the final model was recorded to observe how much variation in the response variable was based on the variation of the predictor variable (Illowsky & Dean, 2013). The final model was used to test Hypothesis 1.

The BIP model was validated by comparing two existing methods for project selection against the proposed model. A two-step model for validating linear programming models was proposed by McCarl and Apland (1986). The first step is validation by construct. This method is commonly used for linear programming (McCarl & Apland, 1986). The linear programming model may use a combination of experience, prior modeling, and theories based on real-world observations to develop procedures deemed appropriate by the builder of the model (McCarl & Apland, 1986). A second step, validation by results, compares the proposed model to real-world outcomes (McCarl & Apland, 1986).

The first real-world model is the existing model used by the organization. Project selection was as follows. The first priority was age. Each project was ranked in ascending order in terms of existing useful life. The second priority was condition. After age sorting was completed, each project was ranked in descending order in terms of SCI. The final priority was patient risk. After determination of equipment condition was completed, each project was ranked in descending order in terms of ICRA score. After the three rankings were completed, projects were selected in descending order until the budget limit was reached. The first existing model was classified as Case I.

The second real-world model was selected from the literature. The selected model was published by Salem and Elwakil (2000) in "Asset Condition Assessment Model for Healthcare Facilities." This model was designed to consider 16 factors over physical, environmental, general safety, and revenue loss categories. The optimized model included seven of the 16 factors and is listed in Equation 3.6:

$$(0.0152 + (0.0969 * \text{Redundancy Score}) - (0.00472303 * \text{Energy Efficiency Score}) + (0.00226719 * \text{Environmental Consideration Score}) + (0.05727405 * \text{Life Safety Score}) + (0.05342182 * \text{Physical Safety Score}) + (0.07966991 * (\text{Labor Hour Score}-1)) + (0.05920107 * (\text{Number of Work Order Score}-1)))) * 10 \quad (3.6)$$

The second real-world model was classified as Case II. The results and implications for both MLR and BIP methods are discussed in Chapter 4.

CHAPTER 4: RESULTS

4.1 Introduction

The research aimed to aid facility managers in selecting projects in a context where capital renewal requirements exceed the available budget. The proposed model adds revenue generated as a discriminator when the system condition index (SCI) and condition of the space may prove insufficient. The variables chosen were explored using weights calculated by the SOLVER function in Microsoft Excel. An important constraint in weighting was that patient safety always takes precedence over other factors. This is consistent with the core mission of a healthcare institution and its providers. Two hypotheses were explored to arrive at the proposed model:

Hypothesis 1: Factors of system condition index, zone classification, and patient risk classification lead to the selection of projects that will yield the highest revenue.

Hypothesis 2: A decision model can provide a list of potential facility projects that will increase revenue while decreasing operational risk.

Hypothesis 1 was explored using the method of multiple linear regression (MLR). Proposed factors were selected to demonstrate the relationship between current factors used by managers to select projects and revenue preserved. Following exploration of factors, Hypothesis 2 was analyzed using binary integer programming (BIP) to construct a model that allowed the selection of a portfolio that maximized revenue preserved while accounting for operational risk to patients.

4.2 Results for Hypothesis 1

4.2.1 Hypothesis 1 Data Set

From the available data, only two connected buildings contained records that included the revenue generated by each function, the square footage of each space, and the facility infrastructure serving each space. The selected facilities provided a combined 28 patient care service areas with an annual revenue of approximately $2B. These two facilities provided a diversity of services ranging from minor outpatient services to major inpatient services. The two selected facilities had FCI scores of 25% and 26%. The range of SCIs for the combined 375 components in the two facilities ranged from 0% to 125% across 6 values, 0.00, 0.01, 1.06, 1.12, 1.25, and 2.15. Of the 375 components, 267 had an SCI of 0.00 and 99 had an SCI of 1.25. The list of HVAC components was primarily filtered by components that were recommended to be replaced within the next 5 years. For comparison consistency, component categories outside of the lifecycle classification were removed. The primary filter resulted in 41 components. Each component was compared to existing floor plans to determine which functional area it served. The floor plans were not linked to the FCA. Missing or conflicting information for each component was removed. Components less than the organizational capital threshold of $25,000 were removed. To diversify the data set, six components that needed replacement beyond the 5-year window were included. These components were added to allow for analysis of the SCI as a project discriminator. After all filters were applied, the list of potential projects was narrowed to 30. Table 4.1 displays the data set used for Hypothesis 1.

Table 4.1
Costs, Condition Index, Zone, Risk, and Revenue for the Selected Projects

Project	Replacement Cost	SCI	Zone (Clinical = 0.2, Nursing = 0.2, Support = 0.6)	ICRA Risk (Lowest = 1, Highest = 4)	Dollars of Revenue Generated (Lost)
1	$34,261	1.25	0.6	1	$(34,261)
2	$34,373	1.25	0.6	4	$(34,373)
3	$40,037	1.25	0.6	1	$(40,037)
4	$41,985	1.25	0.2	2	$2,116,212
5	$47,999	1.25	0.6	1	$(47,999)
6	$54,901	0.00	0.2	3	$(54,901)
7	$56,594	0.00	0.6	1	$(56,594)
8	$57,959	1.25	0.6	1	$(57,959)
9	$68,247	1.25	0.6	1	$(68,247)
10	$71,617	1.25	0.2	2	$2,086,580
11	$71,962	1.25	0.6	4	$(71,962)
12	$74,494	1.25	0.6	1	$(74,494)
13	$87,090	1.25	0.2	4	$2,151,619
14	$95,950	1.25	0.2	3	$(95,950)
15	$107,382	1.25	0.2	4	$98,446,790
16	$111,730	1.25	0.6	1	$(111,730)
17	$122,412	0.00	0.2	4	$66,714,107
18	$122,412	0.00	0.2	4	$66,714,107
19	$124,968	1.25	0.2	4	$20,818,455
20	$125,723	1.25	0.2	4	$8,063,805
21	$126,771	1.25	0.2	4	$2,219,000
22	$153,591	1.25	0.6	1	$(153,591)
23	$158,698	1.25	0.2	4	$12,082,723
24	$189,223	1.25	0.2	4	$25,482,210
25	$248,134	0.00	0.2	4	$4,243,749
26	$326,186	1.25	0.6	4	$(326,186)
27	$851,956	1.25	0.6	4	$(851,956)
28	$1,000,353	1.25	0.6	4	$(1,000,353)
29	$1,170,690	0.00	0.6	4	$(1,170,690)
30	$1,374,606	1.25	0.6	4	$(1,374,606)

4.2.2 Multiple Linear Regression Analysis

MLR was conducted for this phase. The continuous variables of SCI, service zone, and ICRA were selected. Revenue gained or lost was selected as the response. Minitab was used to run the MLR analysis. The significance level was set at $p < 0.05$.

Multicollinearity was checked by observing variance inflation factors. The threshold for removal was a variable with a corresponding variance inflation factor over 5. None of the variables resulted in coefficients greater than 5. The next step was to observe the significance of the variables using *p* values. The threshold for removal was a variable with a corresponding *p* value greater than 0.05. The removal was conducted via model reduction, where the variables with the highest associated *p* values were removed. The variable with the highest *p* value was removed, and the model was run again until the remaining variable or variables had associated values less than 0.05, or no variables remained. Table 4.2 provides a summary of the initial model run.

Table 4.2
Initial Results for Multiple Linear Regression

Term	*p* value	VIF
SCI	0.339	1.05
Zone (C = 0.2, N = 0.2, S = 0.6)	0.060	1.30
ICRA Risk (1-4)	0.460	1.28

Note. Sample size = 30. All *p* values were above 0.05 and do not reject the null hypothesis. No variables were statistically significant. VIF indicates variance inflation factor.

The initial model resulted in no variables being significant. The model was reduced by removing the variable with the highest *p* value, ICRA risk. The model was run again using zone classification and SCI as predictor variables. The resulting *p* values for zone classification and SCI were 0.015 and 0.306, respectively. The model was again reduced by removing SCI and then rerun with zone classification as the predictor variable. The resulting *p* value for zone classification was 0.008, within the *p* -value < 0.05 significance level. The R-squared value shows the predictor variable had a 22.59% probability of predicting a response. The results are displayed in Table 4.3.

Table 4.3
Final Results for Multiple Linear Regression

Term	*p* value	VIF	R-squared
Zone (C=0.2, N=0.2,S=0.6)	0.008	1.00	22.59%
Zone (C=0.2, N=0.2,S=0.6)	Revenue generated (Lost) = 33491292 – 56389137*Zone		

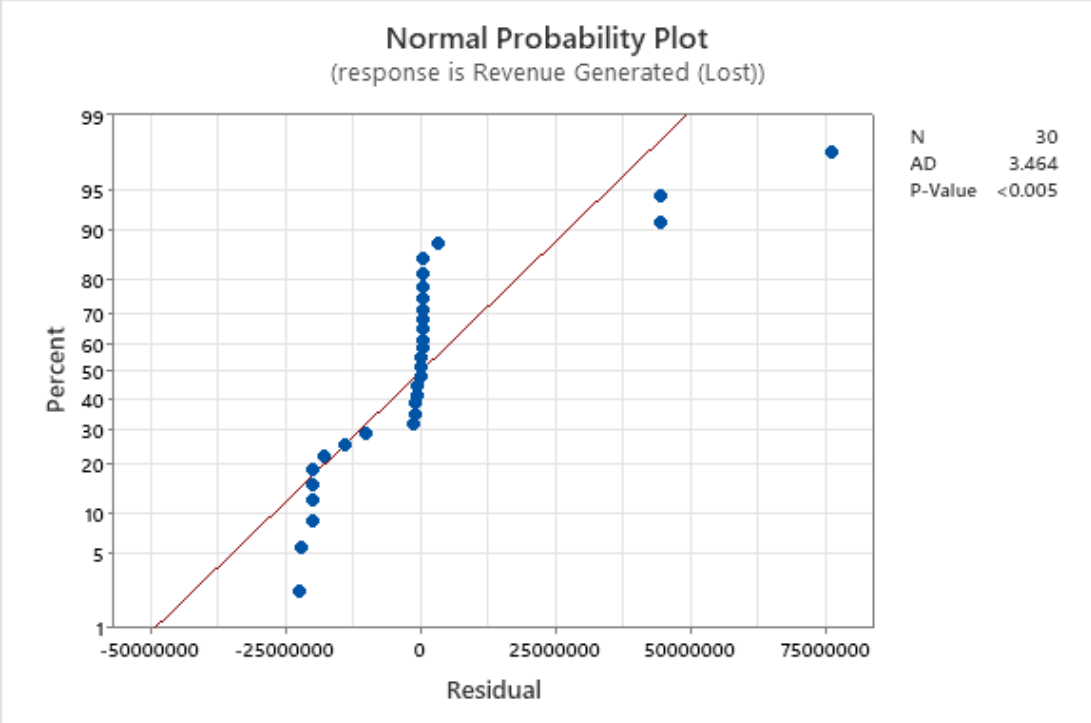
Note. Result: *p* values above 0.05 reject the null hypothesis. Zone classification was statistically significant. VIF indicates variance inflation factor. The R-squared value indicates that approximately 22% of the variation in revenue could be predicted by zone classification.

4.2.3 Multiple Linear Regression Validation

The resulting model was evaluated against MLR assumptions for validation. The assumptions for MLR were tested as described in Section 3.3, with the following results.

a. Normality was evaluated using the normality plot in the four-in-one graph in Minitab. A *p* value > 0.05 indicated normality. As shown in Figure 4.1, the *p* value was below 0.005. The assumption for normality was not met.

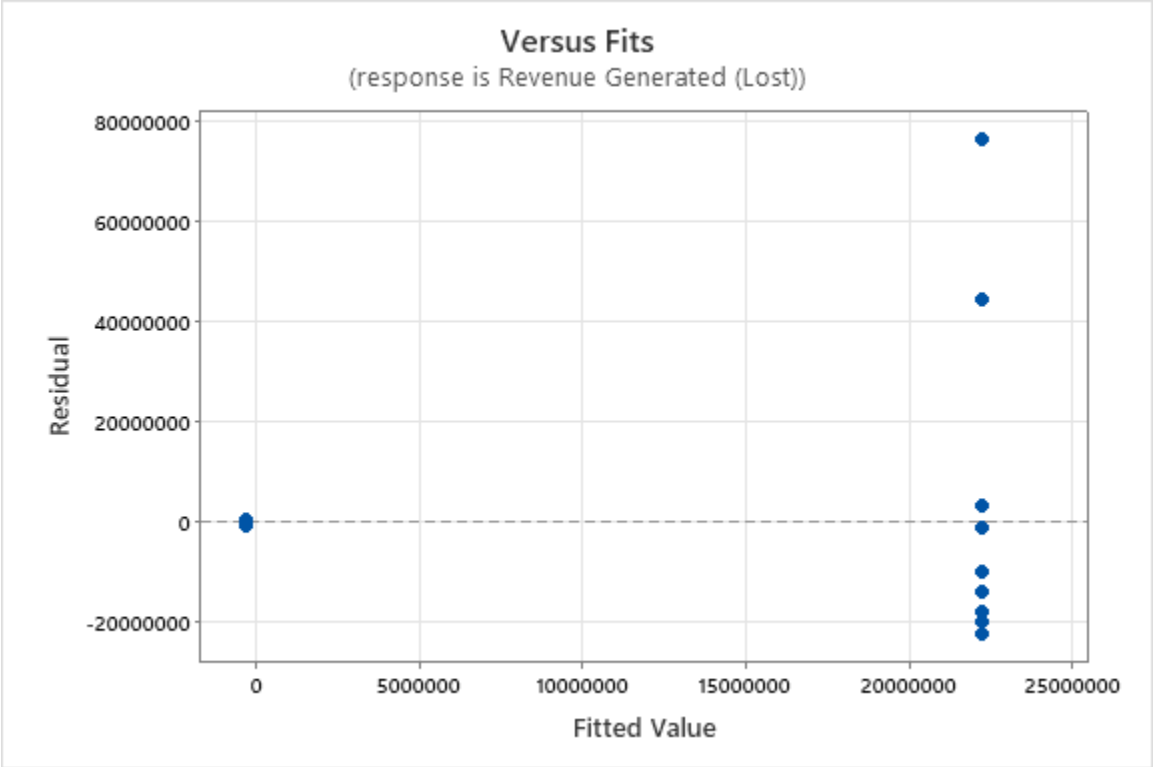
Figure 4.1
Results for Multiple Linear Regression Normal Probability Plot



b. Linearity was evaluated using the residuals versus fits plot in the four-in-one graph in Minitab. A random pattern indicates linearity. The residuals versus fits plot did not produce random points, as shown in Figure 4.2. The linearity assumption was not met.

Figure 4.2

Results for Multiple Linear Regression Versus Fitted Value

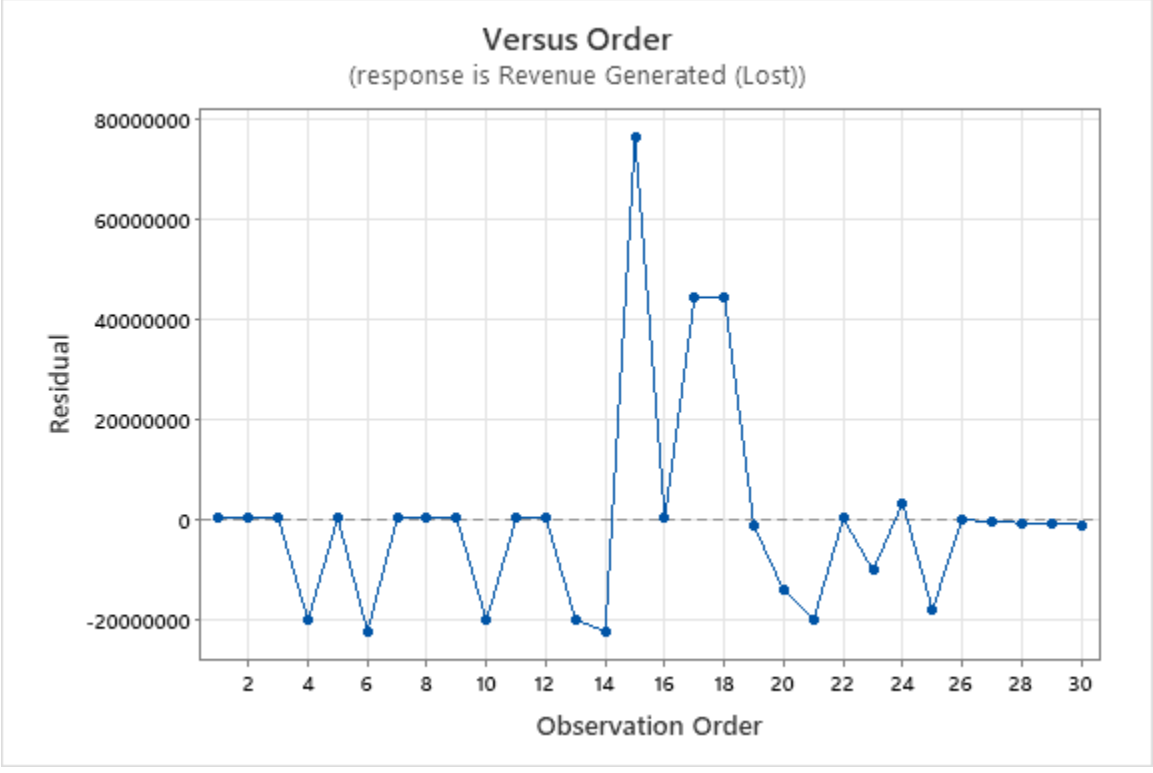


c. Residuals must have a mean of zero and were evaluated using the residuals versus fits plot in Figure 4.2. The residuals should not display a pattern and should be randomly distributed around zero. By observation, the residuals versus fits plot did not produce random points distributed around zero. The assumption for residuals with a mean of zero was not met.

d. Constant variance was evaluated using residuals versus fits plot in the four-in-one graph in Minitab. The residuals should display a constant variance around zero with no visible patterns. By observation, the residuals versus fits plot did not produce points with constant variance around zero and patterns were observed. The assumption of constant variance was not met. Figure 4.2 displays the residuals versus fits graph.

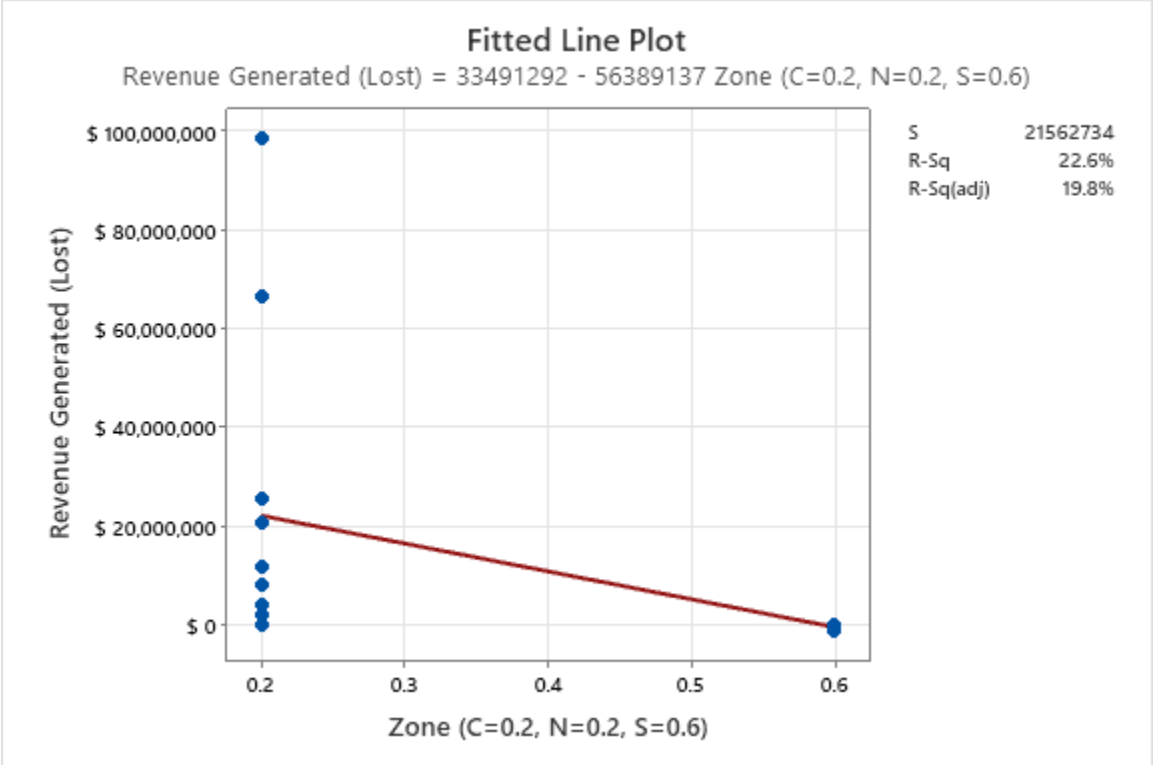
e. Independent residuals were evaluated using the residuals versus order plot in Figure 4.3. Residuals must be randomly distributed. By observation, the residuals versus order plot did not produce random points. The assumption of independent residuals was not met.

Figure 4.3
Results for Multiple Linear Regression Residuals Versus Order



f. Absence of outliers can be evaluated using a fitted line plot in Minitab. Since the model had one predictor and one response, the fitted line plot is as shown in Figure 4.4. Since the linearity assumption was not met, Figure 4.4 shows two points observed well outside the range of responses between 0 and approximately $25 million at approximately $66 million and $98 million. Removal of the outliers could change the response. However, the outliers in the selected data set were not incorrect. The outliers represented areas where the revenue generated for a space directly attributable to an HVAC component was far in excess of other components.

Figure 4.4
Outlier Analysis for Revenue



4.2.3.1 Model Transformation Results

The model produced one significant factor, zone classification, but did not meet the assumptions of linear regression. The initial construction of the model assumed linear associations between predictors and responses (Pardoe, 2020). However, since this was not the case, transforming or applying different formulas to the data could result in more linear associations between predictor and response (Pardoe, 2020). There are many formulas to transform data, but the transformations apply to either the predictor, the response, or both predictors and response (Pardoe, 2020).

To evaluate transformations for the model data set, Minitab was used to evaluate the data. The individual distribution identification routine in Minitab determines the most appropriate distribution or transformation for a data (Minitab, 2022). The individual distribution identification routine was run for both predictor and response. The model was run after attempting to transform the predictor, then the response, and then the predictor and response using Box-Cox or Johnson transformations. The results are summarized below. Additional detail can be found in the Appendix.

a. Predictor: No transformation resulted in a *p* value greater than the normality threshold of 0.05. The Box-Cox transformation resulted in a lambda value of 0.5, indicating a square root transformation. The model was run using the transformed data. The results of the model run using the Box-Cox transformed predictor did not satisfy the assumptions of linear regression.
b. Response: No transformation resulted in a *p* value greater than the normality threshold of 0.05.

c. Predictor and response: This option was not applicable due to the inability to successfully transform the response.

4.2.4 Correlation Analysis

Following attempts to construct a model using multiple linear regression, correlation analysis was performed to observe the relationship between the predictors and response. While correlation tests show significance and the strength of relationships between variables, the tests do not indicate causality (Campbell & Swinscow, 2009). For quantitative normal and quantitative nonnormal data, correlation analysis, along with linear regression, is a recommended form of analysis (Campbell & Swinscow, 2009). Two commonly used correlation tests are the Pearson's and Spearman's test. In order to use Pearson's correlation, Campbell and Spearman (2009) indicated that three assumptions must be met:

1. Comparison variables must be normally distributed.
2. Comparison variables have a linear relationship.
3. The null hypothesis is that there is no association between comparison variables.

If the three assumptions are not met, Spearman's correlation should be used. Spearman's correlation provides a nonparametric test in which observations are replaced by ranks (Campbell & Swinscow, 2009). The SCI, zone classification, ICRA, and revenue scores were tested for normality using the Anderson-Darling normality test routine in Minitab. Each of the four variables failed the normality test.

A Spearman's correlation routine was run in Minitab. Table 4.4 shows the results of the correlation analysis. The relationships between ICRA risk/zone classification, revenue generated (lost)/zone classification, and revenue generated (lost)/ICRA risk were

all below the *p* value significance level of 0.05. The strongest correlation was between revenue and zone classification, with a -0.764 value.

Table 4.4
Results of Spearman's Correlation Analysis

Sample 1	Sample 2	Correlation	*p* Value
Zone	SCI	0.325	0.079
ICRA risk	SCI	-0.344	0.063
Revenue generated (lost)	SCI	-0.106	0.576
ICRA risk	Zone classification	-0.497	0.005
Revenue generated (lost)	Zone classification	-0.764	<0.001
Revenue generated (lost)	ICRA risk	0.391	0.033

4.2.5 Summary of Hypothesis 1

Hypothesis 1. *Factors of SCI, zone classification, and patient risk classification lead to the selection of projects that will yield the highest revenue.*

The goal of Hypothesis 1 was to identify how SCI along with other factors related to revenue generation or preservation. The factors were limited to the condition of components, safety risk, and relative importance of the space. The results showed that only one factor, zone classification, demonstrated significance relative to the response. The predictive power of zone classification was approximately 20%, and the assumptions to validate the MLR model failed. Transformation attempts failed to produce a model that satisfied assumptions of MLR. The nonparametric correlation analysis showed a significant relationship, but a causal relationship between the variables could not be modeled through MLR. Hypothesis 1 was not confirmed.

4.3 Results for Hypothesis 2

BIP was used to analyze a selection of projects to determine if a model, within a given budget, could maximize revenue while accounting for condition index, patient safety risk, and condition of the building component. First, a set of 24 projects was selected from the data set. Projects with a 0.00 SCI were not in a deferred status and were removed. The attributes of each project were the cost of component replacement, the SCI of the component, the zone classification of the space, the ICRA patient risk, and the revenue preserved or lost for the space. Table 4.5 displays the data set used for analysis.

Table 4.5
Project Analysis Data Set for Binary Linear Programming

Project	Replacement Cost	SCI	Zone (Clinical = 0.2, Nursing = 0.2, Support =0.6)	ICRA Risk (Lowest = 1, Highest = 4)	Revenue Generated (Lost)
1	$189,223	1.25	0.2	4	$25,482,210
2	$158,698	1.25	0.2	4	$12,082,723
3	$124,968	1.25	0.2	4	$20,818,455
4	$68,247	1.25	0.6	1	$(68,247)
5	$47,999	1.25	0.6	1	$(47,999)
6	$74,494	1.25	0.6	1	$(74,494)
7	$107,382	1.25	0.2	4	$98,446,790
8	$126,771	1.25	0.2	4	$2,219,000
9	$71,617	1.25	0.2	2	$2,086,580
10	$40,037	1.25	0.6	1	$(40,037)
11	$111,730	1.25	0.6	1	$(111,730)
12	$34,261	1.25	0.6	1	$(34,261)
13	$41,985	1.25	0.2	2	$2,116,212
14	$87,090	1.25	0.2	4	$2,151,619
15	$125,723	1.25	0.2	4	$8,063,805
16	$34,373	1.25	0.6	4	$(34,373)
17	$1,374,606	1.25	0.6	4	$(1,374,606)
18	$851,956	1.25	0.6	4	$(851,956)
19	$1,000,353	1.25	0.6	4	$(1,000,353)
20	$57,959	1.25	0.6	1	$(57,959)
21	$71,962	1.25	0.6	4	$(71,962)
22	$95,950	1.25	0.2	3	$(95,950)
23	$326,186	1.25	0.6	4	$(326,186)
24	$153,591	1.25	0.6	1	$(153,591)

To analyze the information, the BIP method used was Equation 3.4, where C is the combined scoring for the jth project, a is the cost of the jth, and b is the fixed allocated budget. The variable X represents a binary choice of either 0 or 1. A value of 0 means the project was not selected, while a value of 1 means the project was selected.

The combined normalized score was calculated in two steps. The first step was to make the model factors consistent. The factors of SCI, zone classification, ICRA, and revenue used integer text, noninteger text, and financial values. The difference of values needed to be transformed into consistent units and scales in order to obtain a value for C. To obtain a consistent scale, the values of SCI, zone, ICRA, and revenue generated or lost were normalized between 0 and 1 using Equation 3.5. The resulting scores are displayed in Table 4.6.

Table 4.6
Normalized Data for Binary Linear Programming

Project	Normalized SCI Scale	Normalized Zone Scale	Normalized ICRA Scale	Normalized Revenue Scale
1	0.042	0.019	0.060	0.150672
2	0.042	0.019	0.060	0.071443
3	0.042	0.019	0.060	0.123096
4	0.042	0.058	0.015	-0.000404
5	0.042	0.058	0.015	-0.000284
6	0.042	0.058	0.015	-0.000440
7	0.042	0.019	0.060	0.582099
8	0.042	0.019	0.060	0.013121
9	0.042	0.019	0.030	0.012338
10	0.042	0.058	0.015	-0.000237
11	0.042	0.058	0.015	-0.000661
12	0.042	0.058	0.015	-0.000203
13	0.042	0.019	0.030	0.012513
14	0.042	0.019	0.060	0.012722
15	0.042	0.019	0.060	0.047680
16	0.042	0.058	0.060	-0.000203
17	0.042	0.058	0.060	-0.008128
18	0.042	0.058	0.060	-0.005037
19	0.042	0.058	0.060	-0.005915
20	0.042	0.058	0.015	-0.000343
21	0.042	0.058	0.060	-0.000426
22	0.042	0.019	0.045	-0.000567
23	0.042	0.058	0.060	-0.001929
24	0.042	0.058	0.015	-0.000908

The second step was to apply a weight for each criterion. Applying various weights allows trials to be run to obtain the model described by Hypothesis 2. Because the SCI score for each project was the same, the SCI score was excluded as a criterion. The constraint on the weights was that all criteria would be at least 10% and the ICRA value would always be equal to or greater than the zone and revenue values. The reason for the constraint was to ensure the model did not prioritize any factor higher than patient health. A violation of this constraint would produce a model that may in fact maximize revenue but risked doing so at the expense of the patient.

The C score, or combined score, for each project in the model was the sum of the products of each of the normalized SCI, zone, ICRA, and revenue scores for the jth project and the weights using the process described in Section 3.3.4. An example test set is shown in Table 4.7. The sample table for the results of combined scores can be found in the Appendix.

Table 4.7
Example of Proposed Model Scores for Data Set

Project	Model Score
1	0.096591
2	0.060938
3	0.084182
4	0.012304
5	0.012358
6	0.012287
7	0.290733
8	0.034693
9	0.020908
10	0.012379

After the combined scores were obtained, the next step was to conduct the BIP analysis. The SOLVER function in Microsoft Excel was used to execute Equation 3.4 for

each test case. The total cost of the 24 projects was approximately $5.4 million. Once the hypothesis was to create a model that selected the best subset of projects from the 24 projects, the budget constraint was set at less than the amount to fund every project. The selected budget constraints was 75% of the total cost of the projects. Additionally, the total cost, total revenue, and total risk values for each trial were calculated. The total cost was obtained by calculating the sum of the products of the cost of each selected project and the binary X value for each trial. The total revenue was obtained by calculating the sum of the products of the revenue generated or lost by each selected project and the binary X value of each trial. The total risk value was obtained by calculating the sum of the products of the ICRA risk value of each project and the binary X value obtained from each trial. The results for selected projects are shown in Table 4.8.

Table 4.8
Selected Projects from Proposed Model

Project	Proposed Model
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1

Using the weights produced by SOLVER, 23 projects were selected. Project 17 was not selected. The associated objective function score, total cost, total revenue, total risk, and total zone classification scores are shown in Table 4.9.

Table 4.9
Optimal Weights and Scores for Projects from Proposed Model

Weights	Proposed Model
Zone	0.1
ICRA	0.45
Revenue	0.45

Results	Proposed Model
Objective	0.971023
Cost	$4,002,555
Revenue	$170,498,295
Risk (ICRA)	63
Zone	9.8

4.3.1 Binary Linear Programming Validation

For a BIP model to be valid, several assumptions must be satisfied. The assumptions for BIP are as follows (Chen et al., 2013):

1. Divisibility: Each continuous variable must be nonnegative ($x \geq 0$). For the BIP, variable X takes the value of 0 or 1. The divisibility assumption was validated.
2. Certainty: Each input parameter must be constant. Values of C_j, a_j, and b were constant. The certainty assumption was validated.
3. Proportionality: The total contribution to a function is proportional to the values of a variable. The contribution to the objective function by X was 0 or 1. The proportionality assumption was not violated.
4. Additivity: Every function (in the objective or in the constraints) can be expressed as the sum of several functions, each containing a separate variable. The objective function only contained one variable, X, with a value of 0 or 1. The additivity assumption was not violated.
5. Single objective: The optimization function must have one objective. The objective function used had one objective.
6. Simultaneousness: A feasible solution cannot violate any constraints equations. The use of the Microsoft Excel SOLVER function consistently produced feasible

solutions that satisfied all budget constraints. The simultaneousness assumption was not violated.

To validate the model, alternate project lists were created to observe any differences between existing methods and the model. The project list selected contained 24 projects, all with the same relative component condition and an SCI of 1.25. The budget constraint for project selection was 75% of the total cost of the projects, or $4,032,871. The question to resolve is how to discriminate between projects with the same condition. All components need to be replaced, and estimates can be made based on individual facility managers. However, those estimates use subject matter expertise, are not formalized, and cannot be replicated in a systematic fashion. Replacements can be made based on criteria such as component breakdown, CMS standards, or user preference.

To obtain comparative lists, two existing models were chosen. The first existing model was used by the medical system from which the data were sourced. The second existing model was found in existing literature. Both models were described in Section 3.4. To maintain consistency of comparison with the model, the cost, revenue generated, and risk of the selected projects was calculated.

4.3.1.1 Case 1

Results for the Case I budget are shown in Table 4.10. Additional detail can be found in the Appendix.

Table 4.10
Results for Case 1 at 75% Budget Limit

Case 1	
Project	Rank
18	1
19	2
24	3
10	4
12	5
14	6
17	7
2	8
8	9
15	10

The differences in the results for the proposed model and Case I are shown in Table 4.11. The results show the model providing, within the same fixed budget constraint, a selection of projects that produced more revenue and accounted for more risk than the Case I model.

Table 4.11
Binary Linear Programming Model Versus Case I Results for 75% Budget

Factor	Proposed Model	Case I	Percentage Difference
Total cost	$4,002,555	$3,953,086	1.3%
Total revenue	$170,498,295	$21,062,343	709.5%
Total risk	63	28	125.0%
Total zone	9.8	4.4	122.7%
		Average	240%

4.3.1.2 Case II

Results for the Case II budget are shown in Table 4.12. Additional detail can be found in the Appendix.

Table 4.12
Results for Case II at 75% Budget Limit

Case II	
Project	Rank
4	1
19	2
22	3
16	4
1	5
2	6
3	7
18	8
20	9
21	10
23	11
24	12

The differences in the results for the proposed model and Case I are shown in Table 4.13. These results show the model providing, within the same fixed budget constraint, a selection of projects that produced more revenue and accounted for more risk than the Case II model.

Table 4.13
Binary Linear Programming Model Versus Case II Results for 75% Budget

Results	Proposed Model	Case II	Percentage Difference
Total cost	$4,002,555	$3,133,466	27.7%
Total revenue	$170,498,295	$55,722,811	206.0%
Total risk	63	38	65.8%
Total zone	9.8	5.6	75.0%
		Average	94%

4.3.2 Summary of Hypothesis 2

Hypothesis 2. *A decision model can provide a list of potential facility projects that will increase revenue while decreasing operational risk.*

The goal of Hypothesis 2 was to determine if a model could be constructed to address system component condition while also accounting for patient risk and revenue. Patient risk, function of space, and revenue are nonsubjective factors and can be applied in a systematic way and replicated across hospitals. The results showed that a weighted model using patient risk, function of space, and revenue could outperform the existing model used by the organization and a model found in the literature. The design of the model applied real-world data and processes in use today that produce real-world solutions, which makes the model valid by construct. The optimum result weighed revenue and patient risk the highest, while assigning a lower value to the function of the space. The proposed model was validated against the actual project selection methodology used by the organization that provided the data and against a comparable healthcare infrastructure investment model found in recent literature. The proposed model outperformed both the existing model used by the organization and the model from the literature, which made the model valid by results. Hypothesis 2 was confirmed.

CHAPTER 5: DISCUSSION AND CONCLUSIONS

5.1 Discussion

This research determined that the training for facility managers is not aligned with the business objectives of healthcare systems. Revenue is not typically considered in the capital renewal models facility managers use when constructing, prioritizing, and presenting project requests. Nonprofit hospitals typically defer facility infrastructure requirements in pursuit of positive operating revenue. This misalignment has resulted in underinvestment in physical infrastructure, which continues to increase patient safety risk and negatively impacts the financial bottom line of healthcare organizations. Given a deferred maintenance backlog in the United States of $243 billion, growing at approximately $15 billion per year, the need to correct this misalignment and improve capital renewal models will remain for the foreseeable future (Morgan, 2021).

The result of this research is a validated decision model to aid facility managers in selecting projects that consider the revenue objectives of a medical system. In addition to the component condition, this research added patient safety by using classifications from The Joint Commission and revenue information from an existing medical system. An additional factor, zone classification, was also added. The values for zone classification were based on research from Ali (2013). The zone classification and patient safety criteria used in this study are publicly available and can be used by facility managers in all U.S. nonprofit healthcare systems.

5.2 Summary of Results for Each Hypothesis

Hypothesis 1 analyzed the relationship between the condition of the component, the zone supported by the component, and the patient safety risk associated with the

component as predictor variables against revenue as the response variable. Multiple linear regression demonstrated that the relationship between predictor and response variables could not be proven. Attempts to transform predictor and response variables did not result in a model that could meet the assumptions associated with regression. Correlation analysis was able to indicate a significant relationship between revenue, zone classification, and ICRA risk values. The strongest correlation was between zone classification and revenue, which matched the significant relationship in the multiple linear regression analysis. Even though a causal link between the predictors and response could not be modeled through multiple linear regression, the correlation analysis was useful in demonstrating the relationship between the variables utilized in the analysis of Hypothesis 2. Hypothesis 1 was not confirmed. The failure to effectively model a relationship between factors used by facility managers and the revenue recognition for the health care systems, the correlation between predictor and response variables, and the research gap demonstrated in the literature review provided adequate justification for the exploration of Hypothesis 2.

Hypothesis 2 explored if a decision model could maximize revenue while accounting for the component risk. Binary integer programming was used to select projects for each combination of weighted criteria and to find an optimum set of weights. The proposed decision model was run to select projects from a budget limit of 75% of the total cost of available projects. The projects selected by the decision model were tested against the existing project method used by the organization that contributed the data as well as a model from the current literature. Hypothesis 2 was confirmed.

5.3 Contributions to the Body of Knowledge

The study makes two main contributions to address deferred maintenance investment needs. First, this research demonstrated that it is necessary for facility managers in a healthcare setting to use both patient safety and revenue considerations as discriminators for project selection. Chapter 2 described the gap between the ways facility managers and healthcare systems view facilities investments. Professional training for healthcare facility managers in the United States is provided by the American Society of Healthcare Engineers (ASHE). The professional training for a facility manager culminates in certification of and designation as a Certified Healthcare Facility Manager. The training for this certification does not reference the business of healthcare (ASHE, 2022). This research expands the body of knowledge for the facility manager by placing capital renewal concerns at the core of hospital operations, patient safety, and business concerns. Facility managers who integrate an understanding of the healthcare business into project selection considerations can target capital renewal toward revenue-generating areas. More revenue generated for the system means more dollars available for buy-down of the deferred maintenance backlog.

The second contribution of this research is the production of a decision model that combines factors from facilities management, occupational health and safety, compliance, patient service, and finance teams into a common operating picture. The model proposed by this study builds on the extensive research of Ali (2013) and Salem and Elwakil (2020) by extending facility investment models to account for and balance patient safety and revenue. The ability of healthcare facility managers to view the relationship between component condition, patient risk, and revenue impacts as an

interrelated system will aid in future research to build better models to address the growing costs of deferred maintenance.

5.4 Recommendations for Future Research

The healthcare business will remain a complex system. The nature of the business presents opportunities for facility managers to increasingly adopt a systems engineering approach to address healthcare challenges (Cudney & Kovach, 2015). In the future, facility managers may build on the concepts introduced in this research to include other factors. Capital renewal models can be revisited to account for revenue. For example, the 2018 Capital Renewal Playbook published by ASHE and used by current healthcare facility managers can add revenue considerations to its current suite of facilities investment criteria (Flannery et al., 2018). Other factors such as revenue per square foot or historical costs for operations and maintenance can be used to improve the model introduced in this research.

The concepts of healthcare patient rationalization presented by Taheri (2020) can be applied to healthcare real estate rationalization. As the healthcare field continues to utilize technology for remote medical appointments and distributes care to point-of-service locations, the proper utilization of space will increase in importance. The high fixed costs for legacy institution-owned facilities will create opportunities for consolidation and disposal of space. Facility managers can further develop the concepts used in this research to help build out not only the first costs for space conversion but also long-term operational costs.

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APPENDIX

Table A.1

Project Attribute Data for MLR Data Set

Proj no	System Name	Replacement Cost	Requirement Estimated Cost	SCI	Zone[a]	ICRA Risk[b]	Annual Revenue	Revenue Generated (Lost)
1	AHU-33	$ 34,261	$ 42,827	1.25	0.6	1	$ -	$ (34,261)
2	Air compressor - pneumatic controls	$ 34,373	$ 42,966	1.25	0.6	4	$ -	$ (34,373)
3	AHU-5	$ 40,037	$ 50,046	1.25	0.6	1	$ -	$ (40,037)
4	Chiller - Air-Cooled	$ 41,985	$ 52,481	1.25	0.2	2	$ 2,158,197	$ 2,116,212
5	AHU-59 - Penthouse	$ 47,999	$ 59,999	1.25	0.6	1	$ -	$ (47,999)
6	Exhaust system - fume hood - ductwork/fan	$ 54,901	$ 68,626	0.00	0.2	3	$ -	$ (54,901)
7	AHU-3	$ 56,594	$ 70,743	0.00	0.6	1	$ -	$ (56,594)
8	Exhaust system - general/restroom	$ 57,959	$ 72,449	1.25	0.6	1	$ -	$ (57,959)
9	Exhaust system - general/restroom	$ 68,247	$ 85,309	1.25	0.6	1	$ -	$ (68,247)
10	AHU-2A	$ 71,617	$ 89,521	1.25	0.2	2	$ 2,158,197	$ 2,086,580
11	Exhaust system - hazardous/ solation rooms	$ 71,962	$ 89,953	1.25	0.6	4	$ -	$ (71,962)
12	AHU-55	$ 74,494	$ 93,118	1.25	0.6	1	$ -	$ (74,494)
13	AHU-4	$ 87,090	$ 108,863	1.25	0.2	4	$ 2,238,709	$ 2,151,619
14	Exhaust system - hazardous/ solation rooms	$ 95,950	$ 119,937	1.25	0.2	3	$ -	$ (95,950)
15	AHU-57	$ 107,382	$ 134,228	1.25	0.2	4	$ 98,554,172	$ 98,446,790
16	Chilled water pump - CHWPs-1, 2, and 3	$ 111,730	$ 139,663	1.25	0.6	1		$ (111,730)
17	AHU-39A	$ 122,412	$ 153,015	0.00	0.2	4	$ 66,836,518	$ 66,714,107
18	AHU-39B	$ 122,412	$ 153,015	0.00	0.2	4	$ 66,836,518	$ 66,714,107
19	AHU-52	$ 124,968	$ 156,209	1.25	0.2	4	$ 20,943,423	$ 20,818,455
20	AHU-18	$ 125,723	$ 157,153	1.25	0.2	4	$ 8,189,527	$ 8,063,805
21	RTAHU-38	$ 126,771	$ 158,464	1.25	0.2	4	$ 2,345,771	$ 2,219,000
22	Stairwell pressurization - Unit-1 & 2	$ 153,591	$ 191,989	1.25	0.6	1	$ -	$ (153,591)
23	AHU-56	$ 158,698	$ 198,373	1.25	0.2	4	$ 12,241,421	$ 12,082,723
24	AHU-1	$ 189,223	$ 236,528	1.25	0.2	4	$ 25,671,433	$ 25,482,210
25	RTAHU-4-1	$ 248,134	$ 310,167	0.00	0.2	4	$ 4,491,883	$ 4,243,749
26	Smoke extraction fans	$ 326,186	$ 407,733	1.25	0.6	4	$ -	$ (326,186)
27	Exhaust system - duct distribution	$ 851,956	$ 1,064,945	1.25	0.6	4	$ -	$ (851,956)
28	Exhaust system - duct distribution	$ 1,000,353	$ 1,250,442	1.25	0.6	4	$ -	$ (1,000,353)
29	DDC/pneumatic controls - hybrid	$ 1,170,690	$ 1,463,362	0.00	0.6	4	$ -	$ (1,170,690)
30	DDC/pneumatic controls - hybrid	$ 1,374,606	$ 1,718,257	1.25	0.6	4	$ -	$ (1,374,606)

[a] Clinical = 0.2, Nursing = 0.2, Support = 0.6.

[b] Lowest = 1, Highest = 4.

Table A.2

Box-Cox Transformation Attempt for Zone Classification

Coefficients	P-Value	VIF
Constant	0.002	
Zone Box-Cox Transformation	0.008	1

Figure A.1

Residual Plots for Revenue Generated (Lost)

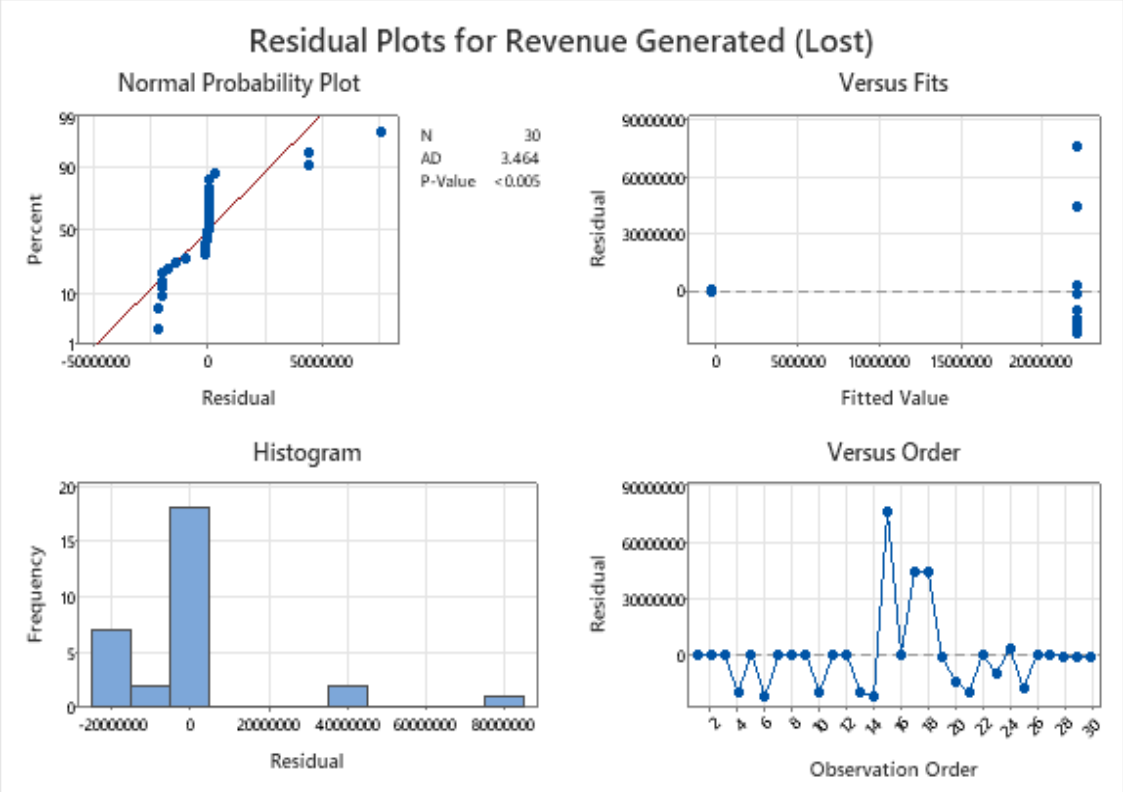

Figure A.2

Johnson Transformation Attempt for Revenue

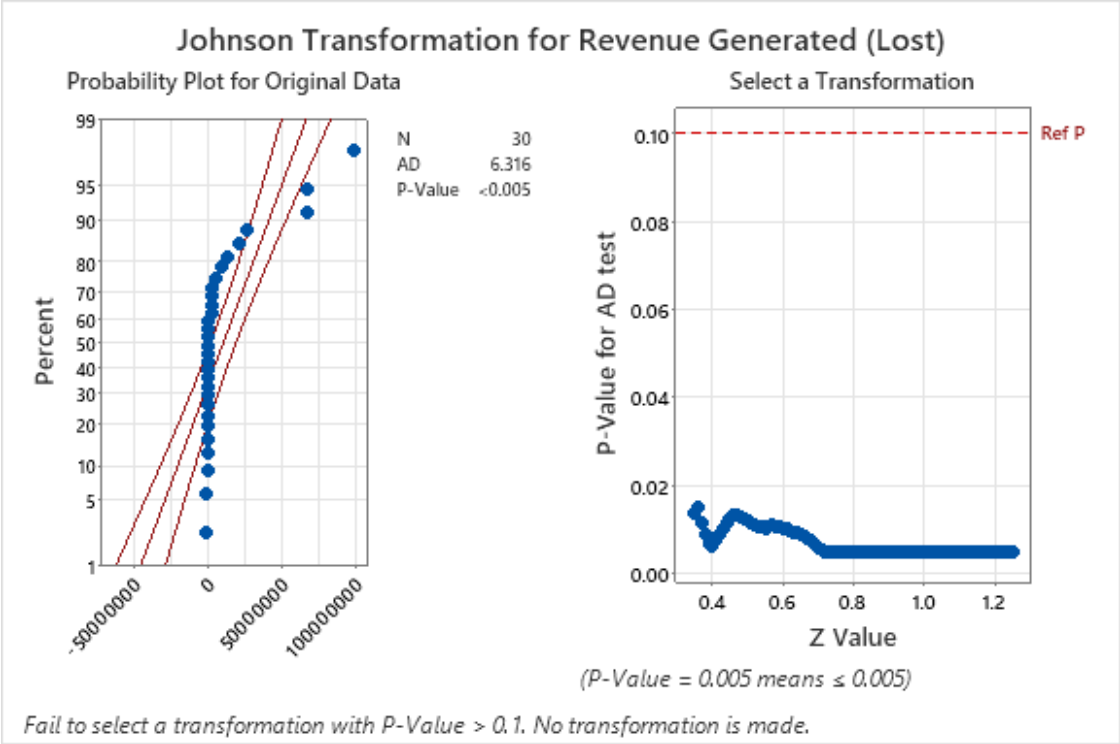

Table A.3

Sample Data for Case I Budget

Project	Replacement Cost	Remaining Years	SCI	Zone (Clinical = 0.2, Nursing = 0.2, Support = 0.6) [a]	ICRA Risk (Lowest = 1, Highest = 4)[b]	Dollars of Revenue Generated (Lost)
1	$189,223	4	1.25	0.2	4	$25,482,210
2	$158,698	-5	1.25	0.2	4	$12,082,723
3	$124,968	-5	1.25	0.2	4	$20,818,455
4	$68,247	-2	1.25	0.6	1	$(68,247)
5	$47,999	-5	1.25	0.6	1	$(47,999)
6	$74,494	-5	1.25	0.6	1	$(74,494)
7	$107,382	-5	1.25	0.2	4	$98,446,790
8	$126,771	-5	1.25	0.2	4	$2,219,000
9	$71,617	-5	1.25	0.2	2	$2,086,580
10	$40,037	-6	1.25	0.6	1	$(40,037)
11	$111,730	0	1.25	0.6	1	$(111,730)
12	$34,261	-6	1.25	0.6	1	$(34,261)
13	$41,985	4	1.25	0.2	2	$2,116,212
14	$87,090	-6	1.25	0.2	4	$2,151,619
15	$125,722.65	-5	1.25	0.2	4	$8,063,805
16	$34,373.08	4	1.25	0.6	4	$(34,373)
17	$1,374,605.69	-5	1.25	0.6	4	$(1,374,606)
18	$851,955.91	-10	1.25	0.6	4	$(851,956)

19	$1,000,353.32	-10	1.25	0.6	4	$(1,000,353)
20	$57,959.13	0	1.25	0.6	1	$(57,959)
21	$71,962.32	-2	1.25	0.6	4	$(71,962)
22	$95,949.76	0	1.25	0.2	3	$(95,950)
23	$326,186.12	0	1.25	0.6	4	$(326,186)
24	$153,590.87	-10	1.25	0.6	1	$(153,591)

[a] Clinical = 0.2, Nursing = 0.2, Support = 0.6.
[b] Lowest = 1, Highest = 4.

Table A.4
Sample Data for Case II

Project	Redundancy	Energy Efficiency	Environmental Considerations	Life Safety	Physical	Labor Hours	No of Work Orders	Score
1	3	0	1	1	0	2	1	4.4511115
2	3	0	1	1	0	2	1	4.4511115
3	3	0	1	1	0	2	1	4.4511115
4	3	0	0	1	0	2	1	4.4284396
5	3	1	1	1	0	2	1	4.4038812
6	3	1	1	1	0	2	1	4.4038812
7	3	1	1	1	0	2	1	4.4038812
8	3	0	1	1	0	1	1	3.6544124
9	3	0	1	1	0	1	1	3.6544124
10	3	0	1	1	0	1	1	3.6544124
11	3	0	1	1	0	1	1	3.6544124
12	3	0	0	1	0	1	1	3.6317405
13	3	0	0	1	0	1	1	3.6317405
14	3	1	1	1	0	1	1	3.6071821
15	3	1	1	1	0	1	1	3.6071821
16	3	1	1	1	0	1	1	3.6071821
17	3	1	1	1	0	1	1	3.6071821
18	3	1	1	1	0	1	1	3.6071821
19	3	1	1	1	0	1	1	3.6071821
20	3	1	1	1	0	1	1	3.6071821
21	3	1	1	1	0	1	1	3.6071821
22	3	1	1	0	0	1	1	3.0344416
23	3	1	1	0	0	1	1	3.0344416
24	3	1	1	0	0	1	1	3.0344416