Determining Centralized Inventory SKUs in a Space and Cost Constrained Hospital Environment using Binary Integer Programming

by

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I would like to dedicate this thesis first and foremost to God, for guiding me and strengthening me along the journey, and to my family, for everything you have done for me.

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Abstract

This research determines centralized inventory stock keeping units (SKUs) in a space and cost constrained hospital environment using Binary Integer Programming (BIP). The case study takes place at the IWK hospital in Halifax where the demands of consumable medical supplies significantly increased since the outbreak of COVID 19. Due to the increased demands, decision makers of the IWK wish to investigate how their centralized inventory space can be used more efficiently and effectively.

Therefore, this research proposes a generic BIP model to determine centralized inventory SKUs based on space, cost, and essentiality of SKUs. The model is generic and applicable to any health system by appropriately choosing its parameters. The model determines the list of centralized inventory SKUs with appropriate inventory policies: order quantity, reorder points and safety stocks. Furthermore, a case study at the IWK is completed with recommendation on setting inventory policies for new SKUs.

Acknowledgement

First of all, I would like to thank my supervisor Dr. Peter VanBerkel for his guidance, encouragement, and patience in helping me complete this work. Through his commitment in time and efforts to mentor me, I never felt distant even when we could not meet in-person. I greatly valued, appreciated, and will miss friendliness and collegiality of our discussions.

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1. Introduction

1.1 Context

The worldwide outbreak of corona virus also known as COVID in 2020 disrupted supply chain management in healthcare industries around the world. As the demands of personal protective equipment (PPE) and other necessities surged, the inventory specialists in the healthcare industries noticed the traditional Just-In-Time (JIT) strategy failed to meet patient demands without stockouts.[1] As the stockouts of consumable items in hospitals directly affect patient health, new approaches to inventory management became priorities of many hospitals.

Approaches of inventory management emphasized the importance of increasing the level of safety stocks (SS), order quantities (OQ), average inventory level (AIL) and diversifying suppliers to effectively meet the rapidly varying demands.[2,3] However, this indicated that more space and capital must be invested. Hospitals operate within limited budget and more space and capital for inventory cause decreased availability of funds for direct patient care activities. Therefore, setting new appropriate level of SS, OQ and AIL while minimizing the total cost to effectively prevent stockouts became a common challenge of hospitals in the post COVID era.

1.2 Overview of IWK's Supply Chain System

This research was conducted in the collaboration with the IWK Health Centre (IWK) located in Halifax, NS. The IWK is both a pediatric and obstetric hospital and consumes at least $17M of medical supplies each year to care and treat patients. Moreover, there are more than 9,500 unique number of stock keeping units (SKU) used by medical departments.

To provide medical supplies to their medical departments efficiently, the IWK manages the flow of supplies through two types of distribution centers:

1. Centralized inventory (CI)
2. Decentralized inventory (DI)

CI is the main warehouse managed by the supply chain specialists at the IWK. They manage approximately 1,400 unique SKUs that are shared by multiple medical departments. The selection of which SKUs are stored in CI is based on requests from the departments. CI orders SKUs from the suppliers and stores items in the warehouse until medical departments submit requests through online software to transfer SKUs into their own inventory: DI. Essentially, CI serves as a distribution center that stores the medical supplies for various departments' DI. Using an online software, supply chain specialists set replenishment order quantities, average inventory levels, and reorder points for each SKU and monitor them continuously to prevent stockouts.

DI, commonly known as 'lockers', are provided to each medical department at the IWK. The goal of the IWK is to supply medical supplies to each DI so healthcare professionals can successfully meet demands. DI is independently managed by medical departments, and they directly order SKUs from suppliers if CI does not manage the SKUs they seek. Since DI is decentralized, their average inventory level and reorder points are not recorded digitally.

A unique aspect of the IWK is that DI independently manages more portions of supply demands than CI due to their warehouse space constraints. From June 2017 to June 2021, four years of historic demands had been accumulated from both CI and DI, and CI managed demands of $19M whereas DI managed demands of $47M. Figure 1 illustrates the number of SKUs and demands that CI and DI control over 4 years. This indicates that the supply chain specialists oversee less than 30% of the total SKUs in IWK.

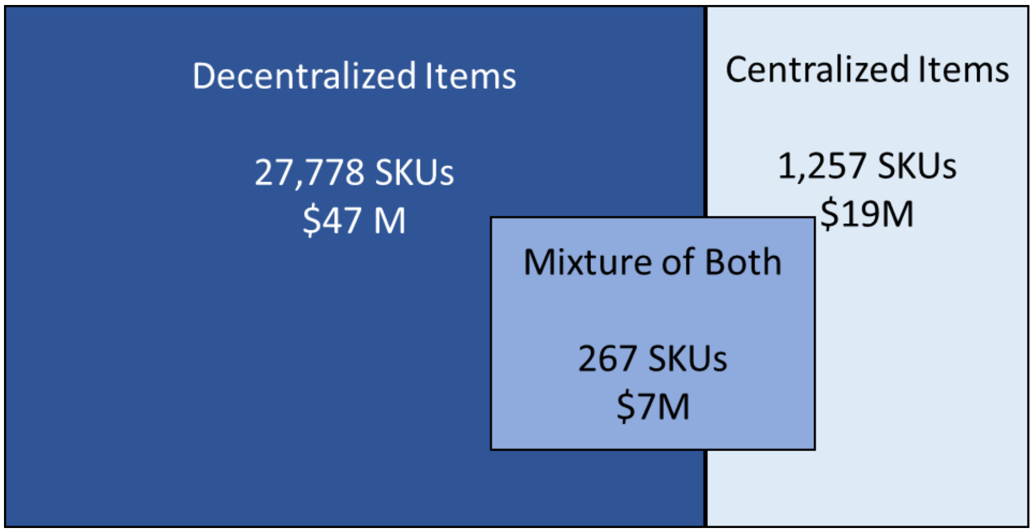
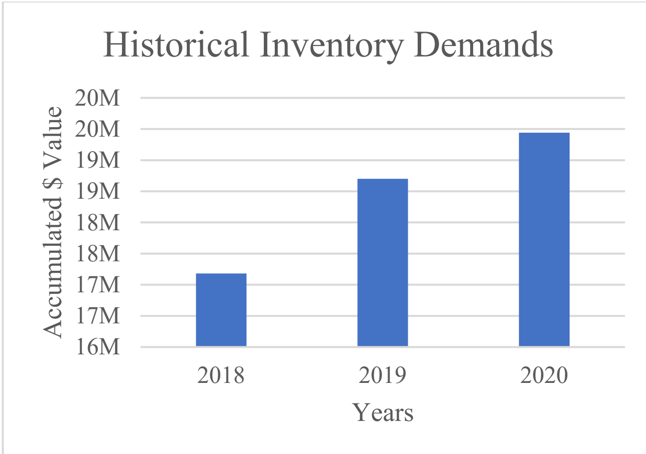


Figure 1 Historical Consumption of CI and DI in IWK

1.3 Impact of COVID 19 on IWK

As COVID 19 emerged and impacted the supply chain and distribution networks worldwide, the consumption of medical supplies in IWK significantly increased. From 2018 to 2020, the annual consumption of supplies increased from $17M to $19.5M which is approximately 15% increase. Although it is only 15% increase of total consumption, certain categories of SKUs such as PPE experienced incremental surge of demands.

As the consumption increased, the total number of SKUs IWK purchased increased as well. Similar to the surge of demands, the number of unique SKUs that the IWK purchase increased from approximately 9,500 to 10,800 which is a 16% increase. Figure 2 illustrates these increases below.



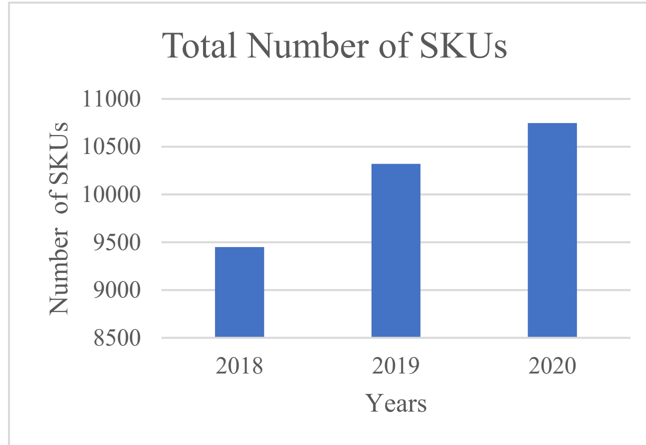


Figure 2 Historical Demands and SKUs Purchased in IWK (2018-2020)

1.4 Problem Statement

With surging demands, number of SKUs to manage, and potential exposure to overstocking and stockout occasions, IWK is challenged to:

1. Sort SKUs that belong in CI or DI
2. Store enough inventory in CI to prevent stockouts
3. Fit the SKUs into CI

The objective of this research is to develop an Binary Integer Programming (BIP) model that uses multiple criteria to determine the list of SKUs that CI should manage and develop appropriate inventory policies. The focus is on maximizing the availability of each SKU in CI based on cost and space constraints in the IWK to minimize supply and heir effects.

1.5 Overview

This thesis is organized as follows: Chapter 2 introduces a list of literature that adds functional characteristics to the model and summarizes trends in inventory policies. Chapter 3 introduces the data gathered from IWK with detailed analysis. Chapter 4 formulates the BIP model used in this research and Chapter 5 describes data preprocessing and feature engineering performed on the input data. Chapter 6 introduces results from the BIP model and sensitivity analysis. Lastly, Chapter 7 discusses the findings of the research and presents directions for future research.

2.0 Literature Review

The purpose of the literature review is to position this research within existing academic literature. Section 2.1 proposes the search strategy used to find related papers. Section 2.2 introduces the review of inventory classification trends in the reviewed articles. Similarly, Section 2.3 and Section 2.4 introduce the review of inventory centralization and management trends in the literature.

2.1 Search Strategy

Relevant studies were identified by searching the following online databases: Google Scholar and Novanet.[4] Search terms included "hospital inventory centralization", "hospital inventory management", "hospital inventory order quantity", "hospital inventory policy", "hospital supply chain resilience" and "hospital PPE inventory management". Forward and backward searches from identified papers were also conducted. Relevant grey literature had been included but studies published in languages other than English were excluded.

The search yielded approximately 500 articles. 19 records of duplicated literature had been eliminated prior to initial screening. After reviewing the abstracts, 427 records were excluded due to insignificant relevancy to the topic of the research, thus, leaving 66 articles to be assessed in full-text article reviews. Additionally, 6 articles were excluded due to lack of fit, leaving 60 articles to be included in this review. The search strategy and the results are shown in the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) flow diagram in the Figure 3.[5]

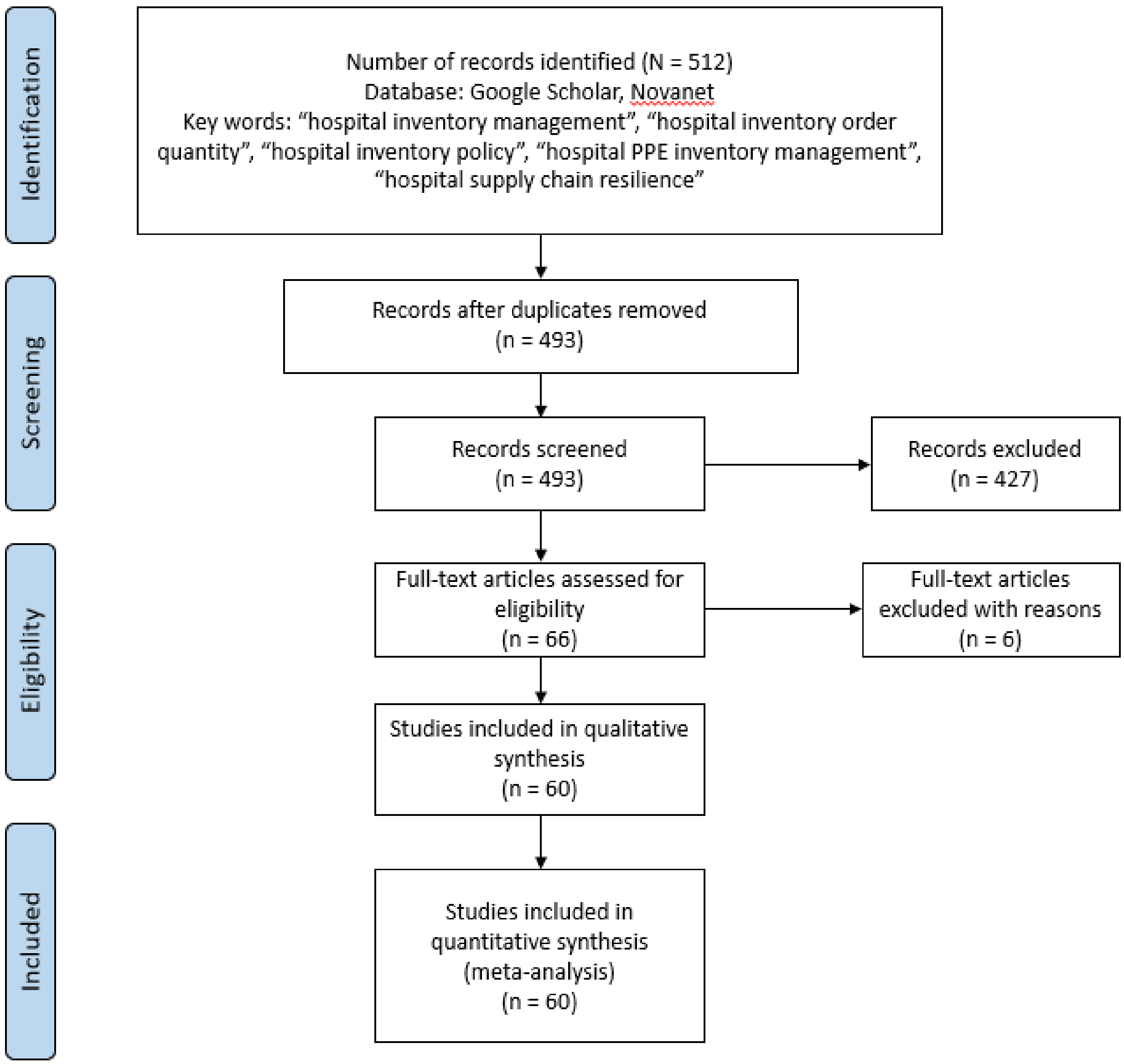


Figure 3 PRISMA Flow Diagram[5]

2.2 Focus

The searched articles were categorized into three sections: inventory classification, inventory centralization, and inventory management. These three categories are highly related to the purpose of research and provide characteristics of BIP model to be discussed in Chapter 4. There are 22 articles in the inventory classification section, 16 articles in inventory centralization, and 24 articles in hospital inventory management. The remaining articles were not easily grouped into the specified categories; however, they are still included in the overall reviews in Section 2.3 to 2.5.

2.3 Review of Inventory Classification Literatures

One of the most traditional inventory classification methods: ABC analysis focuses on historical demand of SKUs to categorize items into three sections: A, B and C from most prioritized to the least in an alphabetical order.[6–12] However, one criterion is insufficient to categorize the importance of items in real practice; therefore, many researchers performed Multi-Criterion Inventory Classification (MCIC) to determine how the priorities of management should be set up between SKUs.[6,8–11,13–17] To perform MCIC, there are two questions to be answered:

1. What criteria should be included?
2. What are the weights of the chosen criteria?

To answer these research questions, various approaches had been performed to find the best indicators to classify inventories. The following summarize the recent trends of the inventory classification research.

The importance of developing multi-criteria to classify priorities of SKUs have been expressed throughout many research articles. Although the traditional performance-based indicators such as unit cost, demand rate and lead times are important, more indicators are necessary to find logical results in practice.[18] One frequently mentioned indicator is the frequency of consumption. Mallick et al expresses the importance of considering not only the overall demand but the consumption rate of an item as well.[17] Furthermore, Danas et al highlight in their Ned-MASTA classification model for medicines within hospital environment where consumption rate of drugs showed significant relations to the criticality of items.[19] There are more indicators used in many articles but the dominant opinion is that each industry should consider and use different indicators to better report their operating characteristics.[11,18]

In healthcare articles, one of the popular approaches taken is adding qualitative measures to the ABC analysis.[20] One of examples, The VED analysis classifies the items into vital (V), essential (E) and desirable (D) categories, and cross-tabulating the result with ABC analysis, the new ABC-VED analysis considers both quantitative and qualitative measures to classify inventories.[7] However, it is difficult to remove subjectivity in measuring qualitative indicators as many articles used different weights in their classification.[21] Also, many difficulties were shown in determination of weights since practitioners valued items differently.[12] Almost all articles chose different weights in prioritizing which criterion is more important than another, showing that it is dependent on who is deciding the weights.[20]

A potential solution approach to deciding weights involves the machine learning. Cui L et al approaches inventory classification problem with machine learning application where a back-progation neural network (BPNN) is applied.[13] Using unit value, ordering cost, demand and lead time as criterion, the machine learning algorithm finds the best weight to distinguish SKUs into A, B and C categories. In another research, Lolli et al used the supervised classifiers from the machine learning to classify inventory items and develop re-order policies from the inventory-cost perspective.[22] However, to perform machine learning algorithms, well maintained sets of data are necessary but often in healthcare, data is noisy.[23] Therefore, operation research models are common.

2.4 Review of Inventory Centralization Literatures

Inventory centralization and decentralization provide different pros and cons to the overall system. To optimize the supply chain networks in various industries, finding the right balance of centralization and decentralization became the research question in multiple articles. In the following articles, the recent research trends of methods and benefits of inventory centralization are summarized.

In many articles, centralized inventories (CI) often provide continuous review whereas decentralized inventories (DI) provide periodic review.[24–26] In continuously reviewed inventory, average inventory level (AIL) is constantly monitored to react effectively to any unpredictable event to occur; therefore, it is more suitable for SKUs with stochastic demands to be put under continuous review.[27–29] Conversely, periodically reviewed inventory monitors AIL at specific time intervals between, causing the inventory to be more exposed to stochastic demands.[1] Therefore, the periodic review is more suitable for SKUs with deterministic demands.

Although, the CI with continuous review requires more labor costs than DI, it is more cost efficient if practiced effectively. Adade et al assessed the cost savings that inventory centralization brought to the sample hospital in Morocco and concluded that inventory centralization improved the waste reduction by 80% on average, resulting in significant cost savings.[24] They concluded that establishing efficient management in centralized inventory can lead to cost benefits. Another healthcare inventory centralization article, Iannone et al found economic convenience of centralizing the hospital's inventory decisions where centralization minimized the holding and penalty costs of inventory and shared supply chain risks.[28]

Additionally, inventory centralization can establish increased sustainability, availability and supply chain resiliency in the system.[30–32] Hosseinifard et al studied the significance of inventory centralization at the blood supply chain with perishable items and found that it increases sustainability and resiliency of the supply chain.[33] The numerical study suggests that reducing the number of hospitals that hold inventory from 7 to 3 decreases outdate and shortage in the supply chain by 21% and 40%. This is a significant improvement as any shortage in supplies within healthcare can lead to critical medical consequences on patients. In another study, Duan et al studied centralizing inventory of several different departments to improve efficiency on blood supply chain and concluded that it reduced blood shortage and wastage in hospital by 72% to 90% respectively.[34] In the post-COVID era, improving supply sustainability, availability and resiliency of supply chains became essential to reduce supply shortages in healthcare.[32] Inventory centralization shows a promising direction to match the evolving recent trends of supply chain in the world.

To centralize inventories, various approaches have been taken in research. The most popular approach is using optimization tools developed from operation research. Essoussi and Ladet developed an optimization tool using Mixed Integer Linear Programming (MILP) to minimize the total cost of inventory while maximizing the supply chain network reactivity where it reduces the traveling distance between hospitals and depots[29]. Similar to Essoussi's approach, there are many previous historical research records where operation research had been used effectively to solve inventory centralization.

Another popular inventory centralization method is developing heuristic algorithms.[26,35–38] Guerrero et al in their optimization of inventory policies in pharmaceutical system, heuristic algorithms were developed to minimize the stocks and determine order quantities for each product controlled.[26] Although developing heuristic algorithms in previous research have been successful, it proved difficult for practitioners to use in their work environment.[28] In practice, circumstances often change, and heuristic algorithms became too complicated for practitioners to utilize and rearrange.

2.5 Review of Inventory Management Literatures

There are two main objectives in the inventory management: minimizing the costs of inventory and maximizing the availability of supplies. Finding the right balance of these objectives has been the focus of the research historically. There is a wide range of approaches taken to achieve this goal and this section summarizes the recent trends of optimization tools used in the research.

2.5.1 ABC Analysis and Variations

The most practical inventory management method in the literatures is ABC analysis and their variation. As discussed in the Section 2.3, ABC analysis is more convenient for practitioners to use because mathematical methods such as operation research and heuristics algorithms require extensive work in developing models.[39] In one application, Bialas et al, developed ABC-VED-XYZ analysis to develop inventory policies based on their relative importance, clinical criticality and consumption pattern.[40] By adding XYZ onto ABC-VED analysis, it measures each SKU's consumption pattern which is essential in predicting fluctuations in demands for the future. However, ABC analysis and their variations can only focus on few variables whereas operation research and heuristics algorithms can accommodate as many variables as is tractable to develop inventory policies[3,41].

2.5.2 Operation Research and Heuristic Algorithms

Another approach is developing mathematical optimization models to find a solution. These are mainly divided in creating an optimization tool using operation research or heuristics algorithm models from Markov chains. Most of the articles reviewed in this section used this approach as 13 articles out of 24 articles used either operation research or heuristics algorithm to develop inventory policies. Commonly, the objective function minimizes the cost amid various constraints to reflect circumstances at the practice.[42] The reorder point and safety stocks are estimated based on lead time, safety factor, mean and standard deviation of demands. Furthermore, economically efficient replenishment quantities are determined through economic order quantities (EOQ) method using historical demands of SKUs with ordering and carrying costs.[43] However, this method is often difficult to use in hospitals as it is difficult to assess the ordering and carrying costs of SKUs.[44] Moreover, circumstances routinely change at the practice, requiring mathematical modes to be modified. Therefore, it is difficult for the current mathematical models to be utilized consistently in healthcare sector to determine inventory policies.[45–48]

2.5.3 Lean Six Sigma Process Optimization

Lean Six Sigma process optimization (LSS) provides continuous improvement to the system by eliminating wastes in the process. This method is commonly for developing inventory policies since reducing wastes result in improving inventory efficiency. The application of LSS in inventory management led a trend of Just-In-Time (JIT) inventory replenishment strategy to minimize space and cost.[1,46] SKUs with deterministic demands can benefit from this method; however, as most SKUs have stochastic demands, LSS and JIT inventory strategy reduces overall supply chain resilience and can be exposed to inventory shortages.[49]

2.5.4 Machine Learning Application

There are many cases of machine learning and deep learning applications of developing inventory policies in hospitals. In one example, Zwaida et al studied a hospital supply chain system where they noticed the need of efficient inventory management to avoid drug shortage problems[2]. They used a Deep Reinforcement Learning (DRL) model to develop an online solution that can automatically make a drug refilling decision to prevent a drug shortage, and this resulted in better performance compared to the previous setup. However, machine learning applications often required various classifiers with clean data and weights to distinguish relative importance between classifiers. In healthcare research, determining weights proved difficult and differentiate between research; indicating that it is hard to remove subjectivity [9,19]. Without removing the subjectivity in weights of classifiers, it is hard to conclude that machine learning is the optimal inventory management strategy.

2.6 Conclusion and Research Gaps

Here are the key findings from reviewing literatures in fields of inventory centralization, classification, and management:

1. CI is preferred for SKUs under stochastic demands by providing continuous review on their average stock level. Under efficient management, CI brings supply chain resiliency and sustainability while minimizing wastes and shortages to save costs.
2. Historical demands and consumption rate of SKUs are important indicators to set level of priorities in inventories. However, qualitative measures need to be accounted as well but it is difficult to determine weights to balance both quantitative and qualitative measures.
3. Mathematical optimization tools such as operation research and heuristics algorithms provide effective strategies but can be difficult to implement.
4. Practical tools such as ABC analysis and LSS provide simpler approaches for practitioners; however, it is less comprehensive compared to mathematical models and can be biased.
5. There are many cases of machine learning applications in literatures, but they require clean data and set of weights to determine prioritized classifiers.

The research gap found between literatures is that there are not enough applications of mathematical models designed for practitioners to use routinely. Many articles highlight their models' effectiveness but not on approachability for practitioners. They experienced difficulties on removing bias in their weights of classifiers to objectively classify SKUs when qualitative measures are considered. Using the key findings from the literature review, this research seeks to fill in the research gaps by developing a generic BIP model that is designed for practitioners. The BIP model is developed generic and practical that practitioners would only have to control parameters to reflect their current state of inventory rather than rearranging objective function and constraints. This model in contrast to the current research would provide more approachability to the practitioners.

3.0 Descriptive Analysis

The purpose of the Descriptive Analysis is to provide a detailed overview on the current state of IWK's historical demands on medical supplies and their patterns. Section 3.1 provides the overview of IWK's data, and Section 3.2 comments on the data cleanliness of classifiers. Then, Section 3.3 and Section 3.4 provide detailed analysis on the IWK's medical supply demand characteristics and ordering patterns. Section 3.5 concludes the chapter by providing analysis on why BIP is an appropriate tool for this research.

3.1 Overview

As IWK's medical supply consumptions has been constantly increasing over the last few years, an inefficient ordering pattern developed. Since most of medical supplies are independently managed in decentralized inventory without supervision from supply chain specialists, there are many new SKUs ordered and never purchased again. Of 9,500 unique SKUs that IWK annually purchases, only 2,184 SKUs had been consistently purchased between 2018 and 2020. Figure 4 illustrates this result.

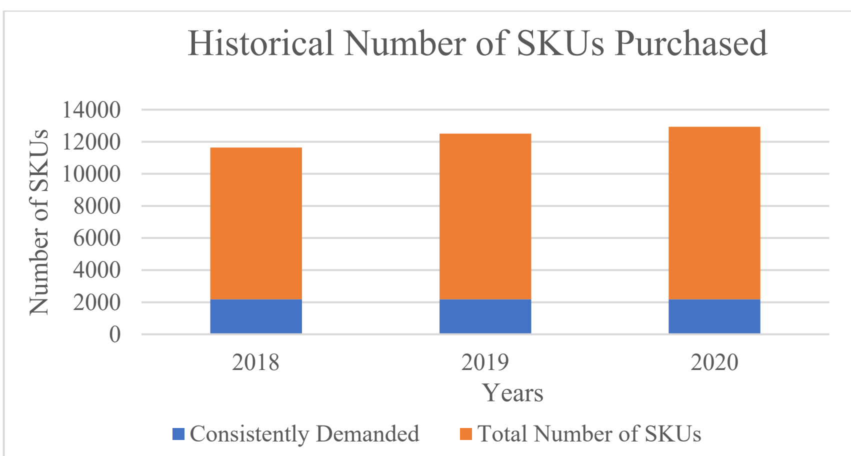


Figure 4 Consistently Purchased SKUs in IWK (2018-2020)

Since there is not a historical record of consuming these newly bought SKUs in the decentralized inventory, it raises a concern for inefficient utilization of storage space, cases of overstocking and wasting capital. To determine how many SKUs had been exposed to this concern, this analysis focuses on two characteristics of each SKU:

1. Historical demand
2. Ordering frequencies

Historical demand and ordering frequencies reflect an aspect of essentiality of the SKU within the supply chain system. Focusing on these characteristics, various demand and ordering patterns had been observed.

3.2 Data Quality

Before beginning on the result of demand and order frequency analysis, it is important to comment on the quality of the data. IWK provided 67 classifiers of data related to their supply chain system and four years of historical records from June 2017 to June 2021. However, most of these classifiers missed data entries, provided duplicated information or were unrelated to assessing status of supply chain network. This left only 9 classifiers to be analyzed. The classifiers used for this research had at least 95% of data entries filled.

Using Excel VBA, these classifiers were analyzed to determine the characteristics of demands. After analysis, data were preprocessed and feature engineered to be used in the BIP model. This will be further discussed in Chapter 5.

3.3 Demand Analysis

In this analysis, data were processed to reflect the historical demands of each SKU accumulated from 2017 to 2021. Each demand is measured in financially ($) and categorized based on significancy of capitals spent thus far. There are four different levels: 1. When demand of SKU_i (D_i) < \$1,000, 2. \$1,000 < D_i < \$10,000, 3. \$10,000 < D_i < \$100,000 and 4. D_i > \$100,000. The analysis overviews the historical demands of all SKUs, then divides into how CI and DI are managing differently.

The result of the analysis on all SKUs is organized in the Table 1. Records of 29,300 SKUs were found and categorized. Results show that 74.79% of the SKUs recorded less than \$1,000 historical demands from 2017 to 2021, but only takes 6.90% of the entire accumulated historical demands. There are many SKUs that contribute tremendously to patients despite its low rate of usage and inexpensiveness compare to other SKUs; however, this result depicts that there are many unsupervised experimental purchases done within IWK. Additionally, there are few SKUs that are significantly more demanded than other SKUs. 92 SKUs have been consumed for over \$100,000 and accumulated historical consumptions of theses SKUs take up only 0.31% of the list but take 24.26% of total demands. These significant differences in demands between SKUs highlight level of priorities.

Table 1 Demand Analysis on All SKUs

D_i = Demand of SKU_i	**SKU # Count**	**ACC \$ Value**	**Percentages**	
			SKU # Count	**ACC \$ Value**
D_i < \$1000	21,913	\$5,115,322	74.79%	6.90%
\$1000 < D_i < \$10,000	6,085	\$18,610,828	20.77%	25.12%
\$10,000< D_i < \$100,000	1,210	\$32,382,025	4.13%	43.71%
D_i > \$100,000	92	\$17,975,253	0.31%	24.26%

The result of demand analysis on SKUs managed within CI is organized in the Table 2. Records of 1,256 SKUs have been found and categorized. Compared to the previous result, it shows difference in SKUs with historical demands less than $1,000. There are significantly lower number of SKUs managed within this category which states that these SKUs are more likely to be SKUs that are not in high demands but still are critically important for patient health. Furthermore, approximately 30 highly demanded SKUs are managed within CI taking up to 30% of entire accumulated historical demands.

Table 2 Demand Analysis on SKUs in CI

$\boldsymbol{D_i}$ = Demand of $\boldsymbol{SKU_i}$	SKU # Count	ACC $ Value	Percentages	
			SKU # Count	ACC $ Value
D_i < $1000	323	$123,739	25.72%	0.66%
$1000 < D_i < $10,000	550	$2,246,852	43.79%	12.00%
$10,000< D_i < $100,000	353	$10,744,665	28.11%	57.40%
D_i > $100,000	30	$5,603,410	2.39%	29.93%

Table 3 illustrates the result of demand analysis on SKUs managed within DI. As expected, the majority of SKUs purchased under $1,000 of historical demands have been purchased within DI. For SKUs with historical demands between $1,000 to over $100,000 follow similar patterns to previous results. A majority of SKUs are between $1,000 to $100,000 categories and there is a small number of 42 SKUs that take up a large portion of historical demand.

Table 3 Demand Analysis on SKUs in DI

D_i = Demand of SKU_i	SKU # Count	ACC $ Value	Percentages	
			SKU # Count	ACC $ Value
D_i < $1000	21,542	$4,969,729.59	77.55%	10.48%
$1000 < D_i < $10,000	5,435	$15,950,393.90	19.57%	33.65%
$10,000< D_i < $100,000	758	$18,442,661.90	2.73%	38.91%
D_i > $100,000	42	$8,036,970.02	0.15%	16.96%

Lastly, the analysis result of SKUs managed in both CI and DI show that there are not many SKUs in this category. The demand patterns for these SKUs follow similar to CI where large number of SKUs are located in between $1,000 and $100,000 of historical demands. Although there are only 267 SKUs, historical demand on these SKUs are significant. This depicts potential cases of overstocking on these SKUs since they are both managed in CI and DI where communications between maintaining overall average stock levels for these SKUs are uncertain.

Table 4 Demand Analysis on SKUs shared in CI and DI

D_i = Demand of SKU_i	SKU # Count	ACC $ Value	Percentages	
			SKU # Count	ACC $ Value
D_i < $1000	48	$21,791.19	17.98%	0.27%
$1000 < D_i < $10,000	100	$413,581.32	37.45%	5.19%
$10,000< D_i < $100,000	99	$3,194,697.71	37.08%	40.11%
D_i > $100,000	20	$4,334,872.30	7.49%	54.42%

3.4 Order Frequency Analysis

The demand analysis exposed 21,542 SKUs that have been purchased for less than $250 each year. As also mentioned in the Section 3.1, there are only 2,184 SKUs that are regularly demanded from 29,300 SKUs purchased from 2017 to 2021. This raises a concern that SKUs were purchased, did not find usage and end up taking spaces in the storage. This causes cases of overstocking as these SKUs prevent inventories from utilizing its space at the maximum capacity; therefore, an order frequency analysis is performed to observe the different rate of consumption for each SKU.

Data has been preprocessed to exclude SKUs that are no longer purchased in 2020 and 2021 to reflect the current state of inventory. This process excluded 15,216 SKUs, remaining 14,084 SKUs to be analyzed. The order frequency analysis divides SKUs into three categories: 1. When the historical number of orders for 2020 and 2021 (X) = 1, 2. 1 < X < 5, and 3. X > 5. The result of the analysis is shown in the Table 5.

Table 5 Order Frequency Analysis on All SKUs

X = # of Orders	SKU # Count	ACC $ Value	Percentages	
			SKU # Count	ACC $ Value
X = 1	9,408	$7,886,425	66.80%	27.80%
1 < X < 5	2,565	$5,322,955	18.21%	18.77%
X > 5	2,111	$15,154,467	14.99%	53.43%

The result shows that the majority of the SKUs had been purchased only once accumulating 66.80% of entire list of SKUs but accounting 27.80% of the total demand. This is a significant amount of capital invested; however, SKUs ordered more than 5 times during

2020 and 2021 accounted for more than 50% of the total demands. This illustrates the importance of ordering frequency to represent essentiality of a SKU.

Since SKUs that have been ordered once took significant portion of accumulated historical demands, a histogram is drawn to observe how data is distributed based on number of orders placed and total historical demand for every SKU. The result shows that there are many SKUs that have been purchased once but at a significantly higher cost.

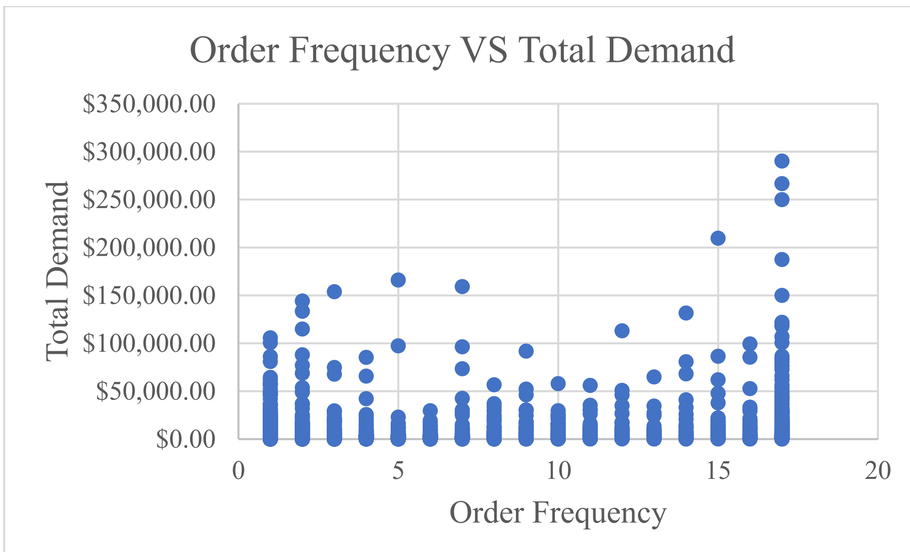


Figure 5 Order Frequency vs Total Demand Histogram

Figure 6 illustrates the number of orders placed versus the order amount in dollars. The result shows that most of expensive purchases are distributed among infrequently ordered SKUs. Tracking these purchase histories, it was discovered that these were software or equipment purchases which explain the expensive cost difference compare to other SKUs. Equipment and software installation are not within the scope of IWK's supply chain team to manage; therefore, these items had been excluded in the Chapter 5.

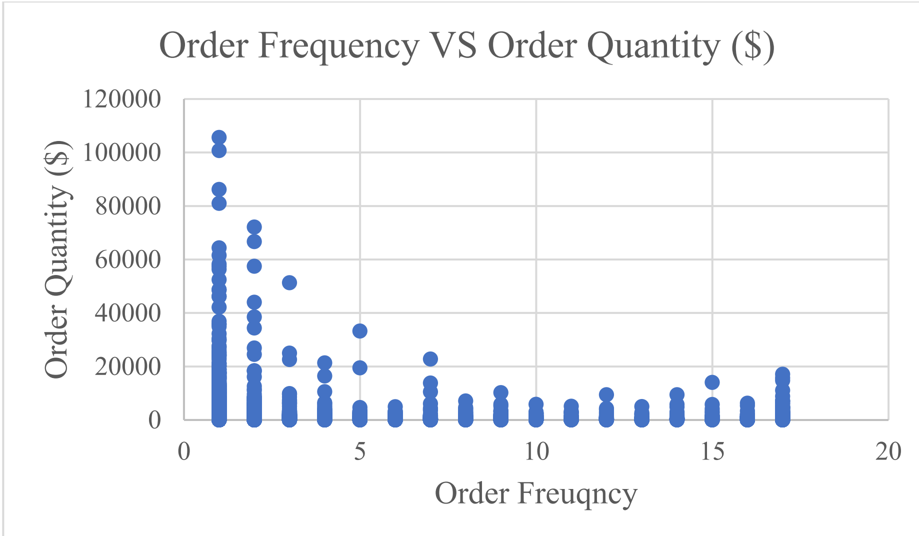


Figure 6 Order Frequency vs Order Quantity ($) Histogram

3.5 Summary

In conclusion, the descriptive analysis showed the following characteristics of IWK's medical supply consumptions:

1. Historically, most SKUs had been purchased once and never again.
2. Small portion of SKUs are regularly purchased, requested and used. These SKUs take up a large portion of the accumulated total consumption in IWK.
3. More frequently purchased SKUs are demanded more. Order quantities for these SKUs are on average lower than other SKUs.

Using the data characteristics in Chapter 3 and model characteristics in Chapter 2, the multi-criterion BIp inventory optimization model is developed and described in Chapter 4.

4.0 Method

This section formulates the multi-criterion BIP model to develop effective inventory policy for CI in IWK. It determines which SKUs should be included within CI and provides order quantity, reorder points, and level of safety stocks for those SKUs. Section 4.1 introduces the conceptual model where key considerations of the BIP model are explained. Section 4.2 and 4.3 introduce the notation and assumptions of the model. Section 4.4 to 4.6 discuss the objective function, constraints and calculation of reorder points and safety stocks. Section 4.7 determines the performance measures of the model and Section 4.8 introduces different approaches to determining ordering quantities where they are experimented in Chapter 6.

4.1 Conceptual Model – Key Considerations

The goal of this research is to develop a generic model that effectively reflect any hospital by rearranging parameters. This mainly concerns IWK's CI; however, application of this BIP model is not limited to only IWK but to any hospital with similar objectives. To achieve this goal, the four key considerations accounted for in the BIP model are:

1. Essentiality of SKUs
2. Perishability of SKUs
3. Physical Limitations of CI
4. Inventory Policies

4.1.1 Essentiality of SKUs

Essentiality of SKUs defines different level of priorities of each SKU. Given the uniqueness of healthcare, every SKU cannot be categorized based on traditional performance factors such as historical demands. Even small demands of a particular SKU can be critical to patient health; therefore, in this research essentiality of SKUs is defined as following:

1. Consistency of demands
2. Significance of demands
3. Unique SKUs identified by IWK staff

Incorporating traditional approaches of identifying priorities of inventories, if a SKU is consistently and significantly demanded over the years, it is considered more essential and should be considered to store within CI. However, SKUs that are identified essential by IWK regardless of its consistency and significance of demands are also considered in this model to reflect the uniqueness of healthcare.

4.1.2 Perishability of SKUs

Perishable SKUs require extra attention due to their limited shelf life. There are many SKUs within IWK with different expiry dates that need supervision when stored within an inventory. Given the current state of inventory management, CI provides continuous review whereas DI provides periodic review for their inventories. Therefore, supervising perishable SKUs within CI is concluded to provide better service for the patients.

4.1.3 Physical Limitations of CI

With essentiality and perishability defined, it is also important that selected SKUs are stored in CI without exceeding physical limitations. To define physical limitations of CI, usable spaces within CI and physical size of SKUs in ordering size must be defined. The usable spaces within CI are defined by the managers in IWK; the physical sizes for are not known for all SKUs, thus a feature engineering approach was used. This process is further elaborated in the Chapter 5.

4.1.4 Inventory Policies

For each selected SKU in CI, an inventory policy must be developed where it determines order quantity, reorder points and safety stocks. Historically, CI relied on experience to develop inventory policies for each SKU but in this research, these policies are determined through the BIP. Currently, CI provides continuous review and has an order-up-to level for each SKU with reorder points allocated; meaning that it is a (s,S) system. The BIP model implements the safety factor (k_r) to determine the reorder points and safety stocks for each SKU. This is inspired from Silver et al's textbook on inventory management where they developed the mathematical models to develop inventory policies.[50]

4.2 Notation

The following notation is used to formulate the inventory optimization model for CI:

Sets

I	SKUs purchased in IWK that could be stored in CI
J	Order quantity strategies
R	Range of safety factors

Parameters

q_{ij}	Order quantity for SKU i using replenishment strategy j
μ_i	Average monthly demand for SKU i
σ_i	Average monthly standard deviation of demand for SKU i
k_r	Safety factors based on safety factor
$G(k_r)$	Normal distribution loss function based on k_r

FR_{ijr} Fill rates of SKU i based on inventory policy j and safety factor r

Q_{ijr} Total amount of inventory required for SKU i based on replenishment policy j and safety factor r

s_i Volume of ordering sizes for SKU i measured in inches

S_{IWK} Total volume of available space in CI measured in $inch^3$

α_i Minimum level of fill rate required for SKU i

δ_i $\begin{cases} 1 & \text{if SKU } i \text{ is considered perishable} \\ 0 & \text{otherwise} \end{cases}$

Decision Variable

x_{ijr} $\begin{cases} 1 & \text{if SKU } i \text{ needs to be stored at CI with replenishment strategy } j \\ & \text{and safety factor } r \\ 0 & \text{otherwise} \end{cases}$

4.3 BIP Model

The objective of the BIP model is to determine the list of SKUs to store in CI which maximizes the sum of their service levels. Unlike traditional inventory model, cost is not the primary focus of the model as IWK's priorities lie in ensuring the availability of SKUs at any time. Therefore, ensuring the service levels of SKUs in CI became the priority of the BIP model.

$$Maxmize \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} FR_{ijr}x_{ijr} \quad (1)$$

Fill rate represents the fraction of patient demand that is met routinely; that is, without backorders or lost sales which indicate stockouts.[50] Maximizing this indicator determines which level of safety stock, reorder points and order quantities which are essential information to developing inventory strategies. Derivation of fill rates are explained in Section 4.6. x_{ijr} is a binary decision variable that will determine which SKUs are selected for CI based on the various constraints.

The deterministic model is bound by constraints 2 – 5.

$$\sum_{j=1}^{J}\sum_{r=1}^{R} x_{ijr} FR_{ijr} \geq \alpha_i \qquad \forall i \in I \tag{2}$$

$$\sum_{j=1}^{J}\sum_{r=1}^{R} x_{ijr} \geq \delta_i \qquad \forall i \in I \tag{3}$$

$$\sum_{j=1}^{J}\sum_{r=1}^{R} x_{ijr} \leq 1 \qquad \forall i \in I \tag{4}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} x_{ijr} s_i Q_{ijr} \leq S_{IWK} \tag{5}$$

$$x_{ijr} \in \{0,1\} \qquad \forall i \in I, j \in J, r \in R \tag{6}$$

Constraint 2 ensures the inclusion of SKUs that are considered clinically critical SKUs at the IWK. This constraint originated from Section 4.1.1 where in healthcare some SKUs must be considered essential regardless of its demand and unit value due to their impact on patient health. Constraint 3 ensures the availability of SKUs that are considered perishable at the IWK. Similar to Constraint 2, practitioners have freedom to select any perishable SKU that they deem necessary to store within CI. Constraint 4 ensures that only one inventory policy and level of safety stock are selected per each SKU. Constraint 5 ensures that the SKUs that are selected fir within the physical space restrictions of the CI. Constraint 6 is the binary constraint.

4.4 Assumptions

This formulation makes the following assumptions:

1. A replenishment order of size q_{ij} is placed when the inventory position is exactly at the order point RP_{ijr}.
2. Lead time is assumed as one month for all suppliers.
3. Unit shortage costs (explicit or implicit) are assumed very high and immeasurable since unit shortage can lead to serious consequences for patient health.
4. From Silver et al's estimation of inventory policies, this research assumes that forecast errors are normally distributed as discussed in Section 4.6. [50]

4.6 Estimation of Fill Rates, Reorder Points and Safety Stocks

Estimating fill rates, reorder points and safety stocks heavily rely on an assumption that forecast errors are normally distributed with standard deviation σ_i and forecast demand over replenishment lead time μ_i over lead time. If the actual demand exceeds over $\mu_i + k_r\sigma_i$, stockout occurs. Therefore, using k_r as a safety factor, reorder points, safety stocks and fill rates can be estimated. Figure 7 shows a graphical representation of normally distributed forecast error assumption.

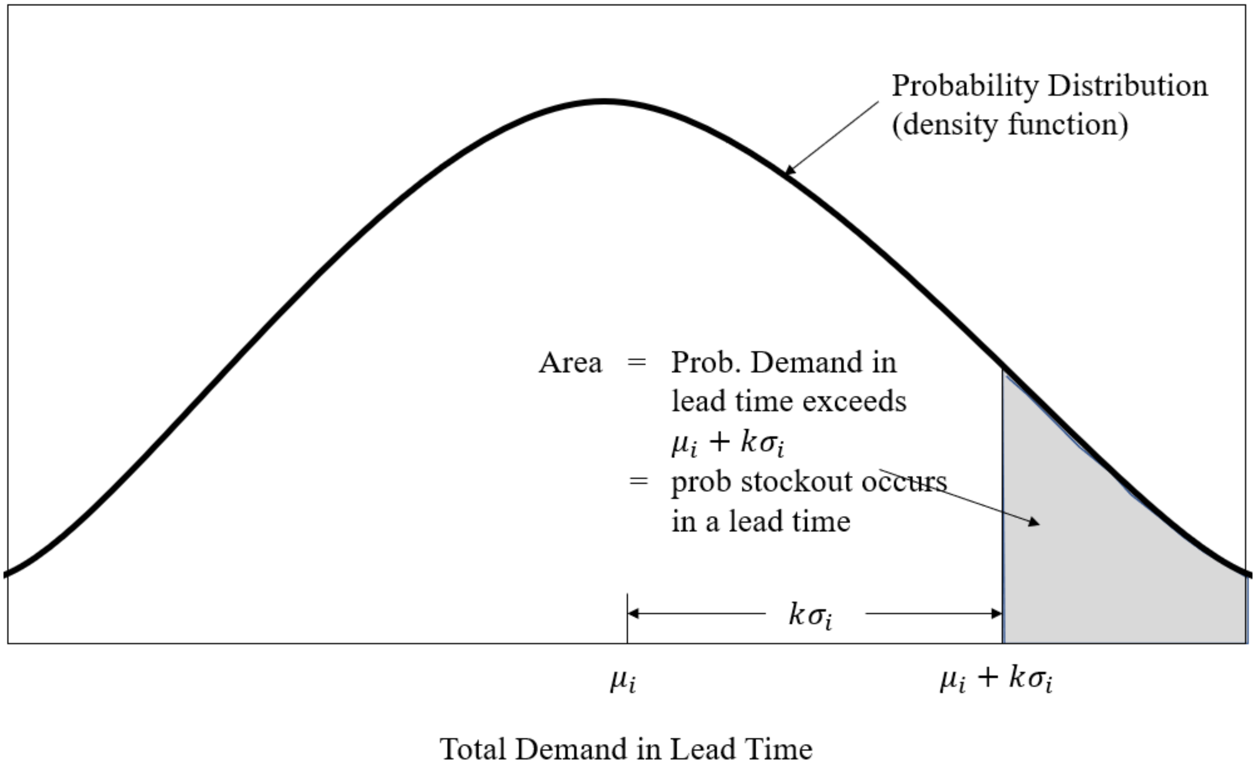


Figure 7 Normally Distributed Forecast Errors[50]

Also, Silver et al suggests that $G_u(k_r)$ can be used to find the expected inventory shortages per replenishment cycle.[50] $G_u(k_r)$ is defined in equation 10. By determining the expected inventory shortages, the fill rate for each SKU i can be estimated as following in equation 11.

$$G_u(k_r) = \int_{k_r}^{\infty} (u_0 - k_r) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u_0^2}{2}\right) du_0 \tag{6}$$

$$FR_{ijr} = 1 - \frac{G_u(k_r) \times \sigma_i}{q_{ij}} \tag{7}$$

Using the safety factor k_r, the level of safety stocks (SS_{ir}), reorder points (RP_{ijr}) can be calculated as shown in equation 12 and 13. In the calculation, average demand (μ_i) and its standard deviation (σ_i) of SKU i is necessary. μ_i and σ_i are measured in lead time; therefore, it is estimated monthly in this research. SS_{ir} is measured by multiplying the safety factor and the monthly standard deviation together so it can withstand varying monthly demands. RP_{ijr} is measured by adding μ_i to SS_{ir} so, when a replenishment order is placed, the inventory is enough to satisfy the demand during the lead time without consuming safety stocks. Safety stocks exist to demand during lead times. Equation 14 represents the maximum inventory level required for each SKU by combining the order quantity and reorder point.

$$SS_{ir} = \sigma_i \times k_r \tag{8}$$

$$RP_{ijr} = \mu_i + SS_{ir} \tag{9}$$

$$Q_{ijr} = q_{ij} + RP_{ijr} \tag{10}$$

4.8 Performance Measures

To further explore how the model performs, two additional measures have been chosen: Estimated Stockouts Per Year (ETSOPY) and Estimated Value Short Per Year (ETVSPY). ETSOPY determines the number of yearly potential stockouts that the current inventory policy for SKU i could experience and ETVSPY estimates the amount of financial value short per yearly potential stockouts. Equation 15 and 16 illustrate these two measures:

$$ETSOPY = \sum_i \frac{D_i}{q_{ij}} p_u(k_r) \tag{11}$$

$$ETVSPY = \sum_i \frac{D_i}{q_{ij}} \sigma_i v_i G(k_r) \tag{12}$$

ETSOPY is calculated from multiplying the annual number of replenishment periods (D_i/q_{ij}) by probability of a stockout in a replenishment cycle ($p_u(k_r)$). ETVSPY multiplies the annual number of replenishment periods by expected shortage per replenishment cycle ($\sigma_i\ G(k_r)$) and financial unit value (v_i).

These two measures are convenient indicators to observe how the BIP model performs because this model tests with different parameters of q_{ij} to find which setting of replenishment order policies is the best for IWK. ETSOPY provides the potential number of stockouts alongside with estimated financial value short per parameter of q_{ij}. Furthermore, these measures are highlighted in Silver et al's calculation of fill rates to observe the performance of an inventory; therefore, concluded to be used in the result section in Chapter 6.[50]

4.9 Order Quantity Test Scenarios

There are three different parameters of q_{ij} to be tested in the Chapter 6 to determine the optimal replenishment order quantities:

1. Model 1 – q_{ij} based on historical record in IWK (J = 1)
2. Model 2 – Model 1's q_{ij} with for variants (J = 4)
3. Model 3 – q_{ij} based on number of replenishment periods (J = 8)

In Model 1, q_{ij} for each SKU is determined based on historical record in IWK. The most common order quantity is selected and tested in the model. Model 2 tests Model 1's q_{ij} with four variants. With its variants, Model 2 has wider range of replenishment policies to choose from. The range is set as 50%, 100%, 150% and 200% of Model 1's q_{ij}. Lastly, in Model 3, q_{ij} is determined based on number of replenishment periods. Based on the historical demand, q_{ij} is determined by setting how many replenishment periods that the practitioners will order each year. The range of replenishment periods are set from twice per year to every three weeks.

With these three different parameters, the model is tested to determine which SKUs belong in the CI with optimal order quantity and inventory policy for each SKU i.

4.10 Model Formulation

The model was written in Python 3.7.3 using Jupyter Notebook. The binary integer programming (BIP) was implemented using Python MIP (Mixed-Integer Linear Programming) package, and Gurobi 9.1 license. Every parameter must be prepared and imported through Excel worksheet saved in csv format. Once the data is inputted into the model, it is processed to be set as parameters for the model.

The model then calculates every possible case of fill rates (FR_{ijr}) and total inventory amount (Q_{ijr}) for each SKU i based on ranges of order quantity j and safety factor r. After creating a matrix of every possible scenario of FR_{ijr} and Q_{ijr}, the model selects the list of SKUs to be stored within CI by using the listed constraints in Section 4.3.

The focus of model formulation is to minimize Python code interactions for the practitioners. By importing parameters through Excel which is a more familiar tool than Python, this model aims to be more approachable for practitioners to use. Furthermore, BIP model is formulated so that practitioners would have to rearrange parameters only to observe different results than changing constraints. The details of Python codes can be found in the Appendix.

5.0 Data Preprocessing and Feature Engineering

This section discusses how the data has been preprocessed and feature engineered prior to testing in Chapter 6. Section 5.1 discusses the necessity behind preprocessing data, which data type has been excluded from the study and the result of data preprocess for each model. Section 5.2 highlights the necessity of feature engineering, methodologies used in this research and the result.

5.1 Data Preprocessing

Section 4.1.1 highlighted the importance of inputting the essentiality of SKUs within the model. To incorporate consistency and significance of demands of SKUs, this research proposes a simple approach:

1. Any SKU purchased only in 2018 and 2019 are assumed not in demand anymore.
2. Any SKU purchased only once are assumed that they are either equipment, software installation or experimental purchases that are not likely to be purchased again.

With this approach, the BIP model considers consistency and significance of demands classifiers, but the model avoids using weights since they can be biased and hard to determine. To successfully apply this approach, Excel VBA is used to preprocess data prior to running models.

Total number of SKUs purchased in 2017 to 2020 is 31,295. With data preprocessing, 26,630 SKUs are found to be nonessential as they fit into the categories of exclusion. The remaining 4,665 SKUs are selected with enough essentiality and tested in the Chapter 6.

5.2 Feature Engineering

The physical size of each SKU is a critical measure to optimize the space constraints of CI. However, IWK only keeps record of SKUs that are stored in CI which counts at 1,268 SKUs. This is only approximately 27% of the entire list of potential SKUs; therefore, feature engineering became necessary to fill in the gaps between missing data.

When performing feature engineering, each SKU's material description has been labeled with multiple classifiers. Based on matching classifiers, their physical sizes are assumed as same as known physical sizes. For example, if multiple SKUs share a classifier: 'gloves' within material description, then it is assumed that all SKUs with the same classifier have similar physical sizes.

After feature engineering, 2,473 SKUs are assumed with physical sizes which is approximately about 53% of the entire list. For SKUs that did not share any classifier with other SKUs, feature engineering could not be performed. Through several discussions with IWK, the last 20% of unknown data has been assumed as median physical size value of known and assumed combined.

With feature engineering done, the data has been inputted into the model and tested with different order quantity parameters.

6.0 Model Results

Chapter 6 illustrates the runs of the BIP model with different parameters. The purpose is to determine which SKUs to keep in CI and the parameters for order quantities. This will result in efficient and cost-effective inventory policies in CI. Section 6.1 shows the result of Model 0 which reflects the current inventory management setup in CI. Section 6.2 to 6.4 show the results of Models 1, 2 and 3 with analysis on their selected inventory policies. Section 6.5 summarizes the performance of Models 1, 2, and 3 in comparison to Model 0. Lastly, Section 6.6 classifies selected SKUs in Models 1, 2, and 3 by ABC classification to observe which SKUs have been prioritized in selection process.

6.1 Model 0 Result

The objective of Model 0 is to replicate the current inventory management setting of CI and observe how it is performing. The result of Model 0 is to be compared with the actual test models later in the chapter. In the BIP model, 1,268 SKUs that are currently managed by CI are inputted to develop inventory policies for each SKU. The result is depicted in Table 6. Interestingly, the model developed inventory strategies for 98.3% of inputted SKUs but still failed to accommodate for all SKUs. This indicates that current setup in CI is exposed to the risks of understocking.

Table 6 Model 0: Test Result

Inventory Type	SKU Count	SKU Count (%)
Centralized Inventory	1,246	98.3%
Decentralized Inventory	22	1.7%

The primary focus of inventory management for supply chain specialists at IWK is to prevent stockouts at any given time. This translates into guaranteeing fill rates of each SKU above 90%. Result of the Model 0 shows in the current setting, their goal can be achieved. Furthermore, we see most SKUs are above 95% fill rates.

Table 7 Model 0: Range of Fill Rates for CI SKUs

Range of Fill Rates	SKU Count	SKU Count (%)
$FR_{ijr} \geq 95\%$	1,235	99%
$95\% > FR_{ijr} \geq 90\%$	18	0.8%
$90\% > FR_{ijr}$	3	0.2%

Currently, the average inventory level (AIL) of all SKUs in CI is uncertain. However, using the result of Model 0, this can be estimated. As illustrated in Figure 8, ratio between level of safety stocks and replenishment order quantities are roughly 1:3. As most of selected SKUs experience high standard deviation in average monthly demands, large amount of inventory is inevitable.

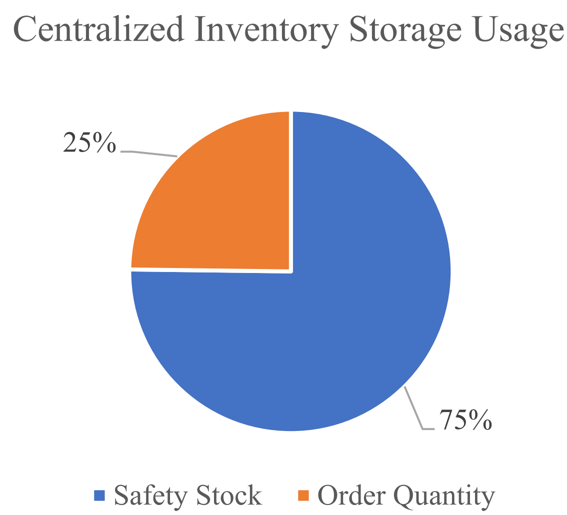


Figure 8 Model 0: Centralized Inventory Storage Usage

The histogram of safety factors (k_r) in Model 0 is also recorded and shown in Figure 9. The histogram looks normally distributed with safety factor 2.2 most frequently used. High range of safety factor indicates that more capital must be locked in inventory to prevent the stockouts. By comparing each model's histogram of k values with others, practitioners can estimate which is more efficiently managed.

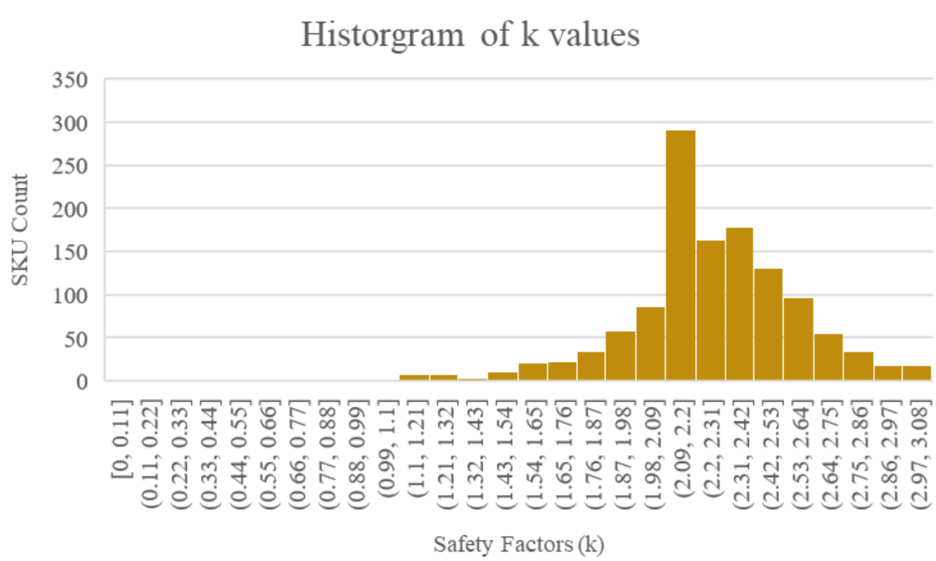


Figure 9 Model 0: Histogram of Safety Factors

Lastly, histogram of annual number of replenishments are recorded for Model 0 in Figure 10. The majority of SKUs currently controlled in CI are replenished at high frequency. This adds more explanations to why the BIP model chose high level of AIL for each SKU. Considering that ordering costs are not defined in IWK, high frequency of ordering can result in more financial commitment from CI. Therefore, similar histograms will be tested and compared to observe which model determines the most reasonable range of annual number of replenishments for each SKU.

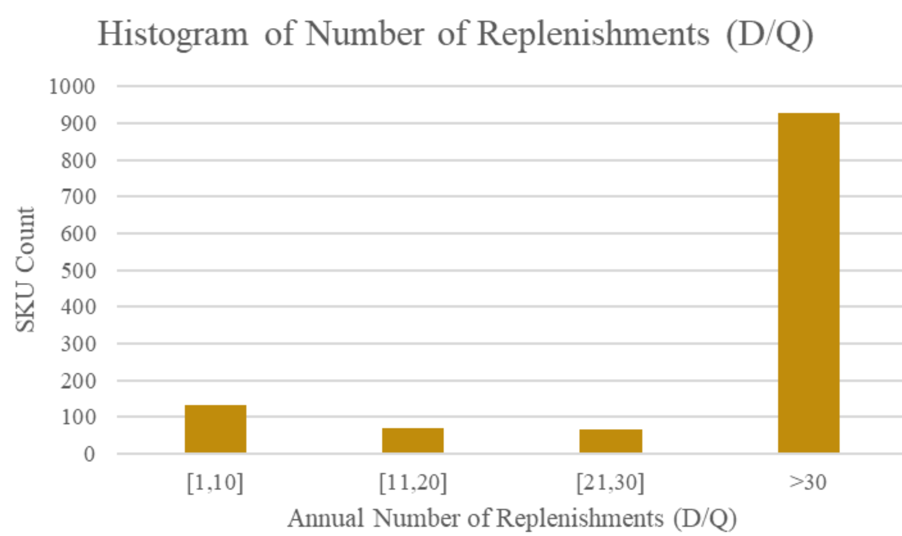


Figure 10 Model 0: Histogram of Number of Replenishments (D/Q)

6.2 Model 1 Result

With Model 1's parameters inputted; the BIP model produced the following result in Table 8. The model successfully accommodated 4,513 SKUs in CI which is 96.7% of all SKUs tested. This is more than 3 times the number of SKUs that are currently controlled in CI, indicating that this is a huge improvement for practitioners.

Table 8 Model 1: Test Result

Inventory Type	SKU Count	SKU Count (%)
Centralized Inventory	4,513	96.7%
Decentralized Inventory	153	3.3%

Similarly to Model 0, the range of fill rates are shown in Table 9 to observe if the selected SKUs are guaranteed with high fill rates. 4,254 SKUs which are 94.3% of all selected SKUs have fill rates above 95%.

Table 9 Model 1: Range of Fill Rates for CI SKUs

Range of Fill Rates	SKU Count	SKU Count (%)
$FR_{ijr} \geq 95\%$	4,254	94.3%
$95\% > FR_{ijr} \geq 90\%$	167	3.7%
$90\% > FR_{ijr}$	92	2.0%

Comparing to Model 0, Model 1's space usage differs considerably as well. Approximately 38% of the warehouse capacity is dedicated to replenishment order quantity whereas the remaining is allocated for safety stocks. This is a significant reduction in level of safety stocks compare to Model 0. Model 1's space usage is shown in Figure 11 below.

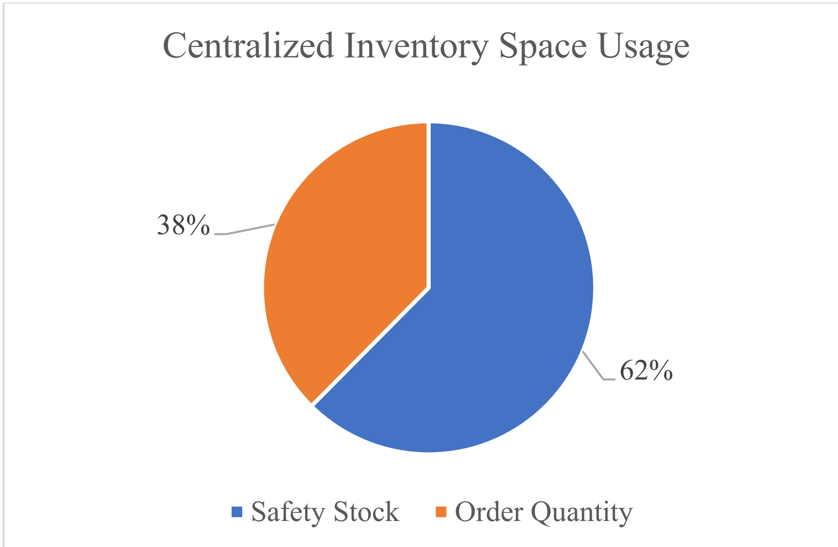


Figure 11 Model 1: Centralized Inventory Storage Usage

However, when looking at the distribution of safety factors (k_r) for the chosen SKUs in CI, they are ranged similar to Model 0. In Figure 12, the histogram of safety factors is shown and it is evident that similar range of safety factors are used but the median safety factor is more frequently used in Model 1 compare to Model 0.

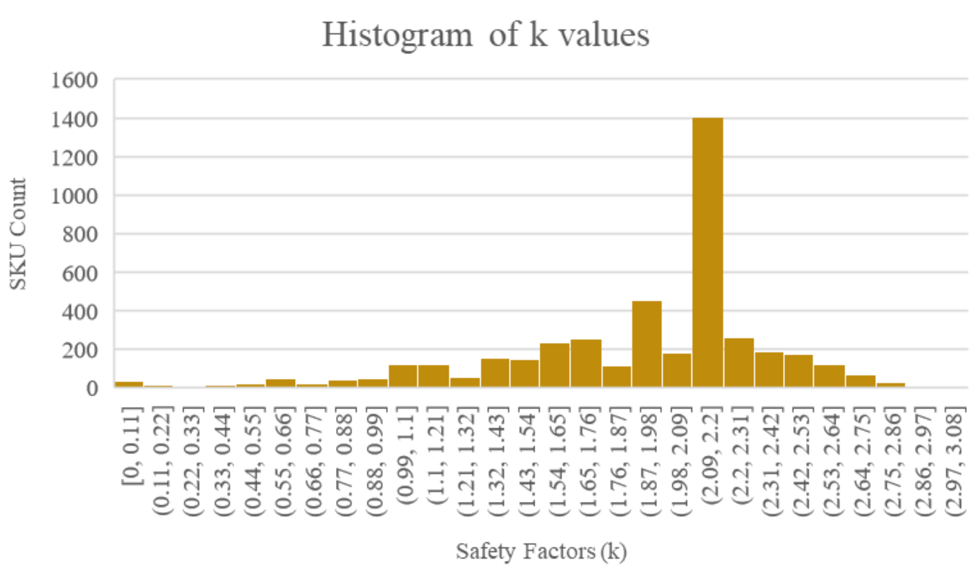


Figure 12 Model 1: Histogram of Safety Factors

To observe how safety factors for clinical critical SKUs and perishable SKUs are distributed, a box plot is drawn in Figure 13. As observed previously in Figure 12, similar range of k values is used for these specially categorized SKUs.

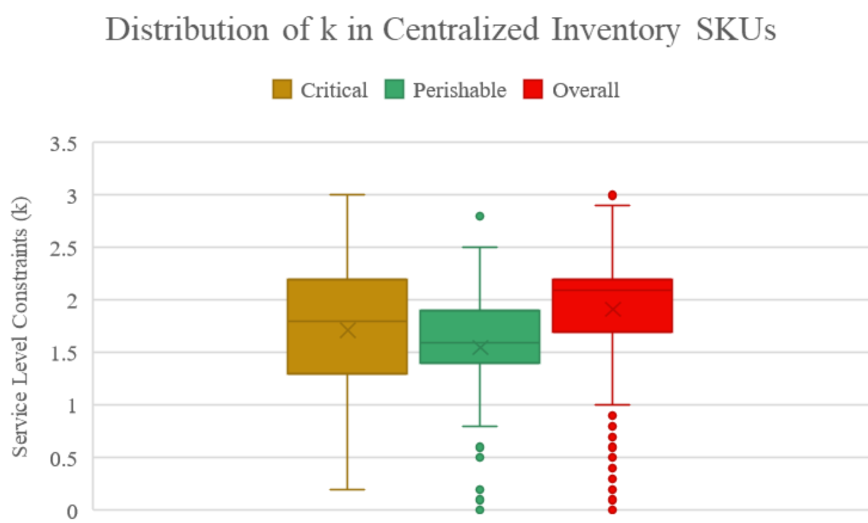


Figure 13 Model 1: Distribution of Safety Factors in CI SKUs

Lastly, the histogram in Figure 14 reveals that many of SKUs had been set with low replenishment frequencies to satisfy the demands. Since most of these SKUs are controlled in DI, they are maintained throughout with very low order frequency averaging around biannually or quarterly purchases every year. This explains the low amount of inventory allocated to safety stocks in Model 1 compare to Model 0.

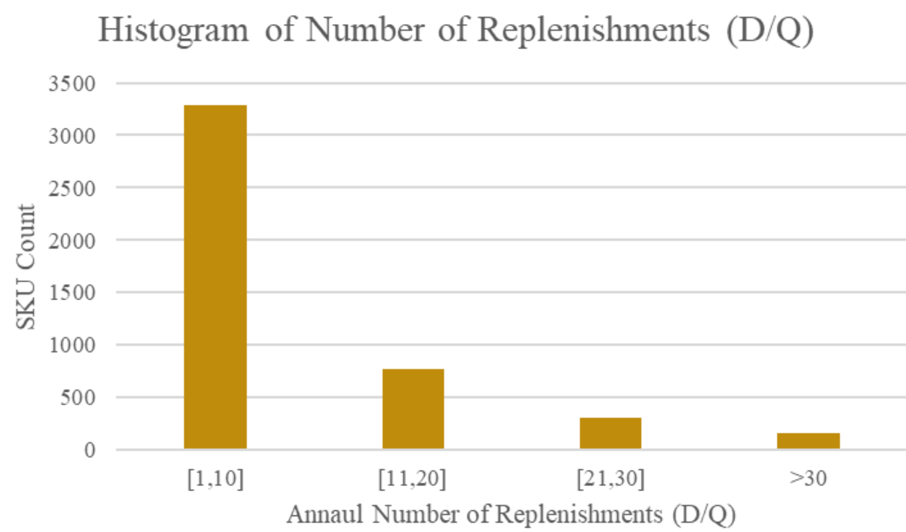


Figure 14 Model 1: Histogram of Number of Replenishments (D/Q)

6.3 Model 2 Result

In Model 1, it is seen that depending on annual number of replenishments for each SKU, warehouse capacities are differently utilized compare to Model 0. Therefore, the Model 2 tests different ranges of replenishment order quantities by using variations from Model 1's order quantity. Results of Model 2 are shown in the Table 10 as more SKUs have been selected to be managed in CI.

Table 10 Model 2: Test Result

Inventory Type	SKU Count	SKU Count (%)
Centralized Inventory	4,576	98.1%
Decentralized Inventory	90	1.9%

Furthermore, increased range of order quantities found better fill rates for the selected

SKUs as well. Table 11 shows the distribution of fill rates determined for each SKU in CI and it produced better result compare to previous models.

Table 11 Model 2: Range of Fill Rates for CI SKUs

Range of Fill Rates	SKU Count	SKU Count (%)
$FR_{ijr} \geq 95\%$	4,418	96.9%
$95\% > FR_{ijr} \geq 90\%$	99	2.2%
$90\% > FR_{ijr} \geq 95\%$	44	1.0%

With increased range of order quantities, Model 2's warehouse capacity utilization differentiates with Model 1 as well. It is similar to Model 0's state where the ratio between replenishment order quantity and level of safety stock is 1:3. Figure 15 shows the result in a pie graph.

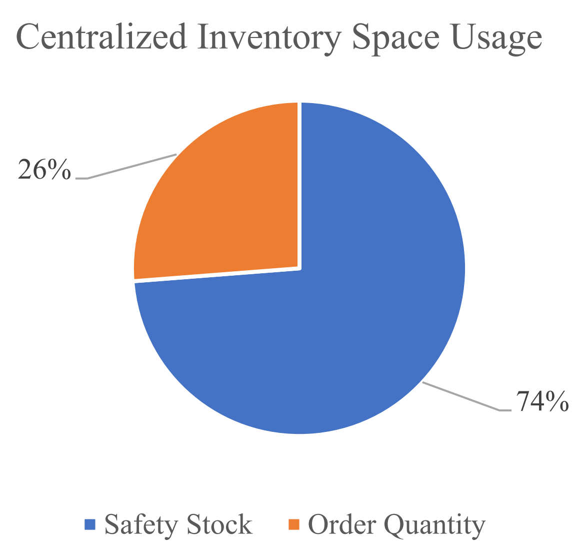


Figure 15 Model 2: Centralized Inventory Space Usage

Similar to previous model, histogram of safety factors is drawn to observe how they are distributed in the result, and it shows that Model 2 is more inclined to using various range of safety factors. It looks normally distributed with median safety factor ranging between 1.2 to 2.1. Additionally, distribution of safety factors in clinical critical SKUs and perishable SKUs shows that they are all in similar ranges as shown in Figure 16.

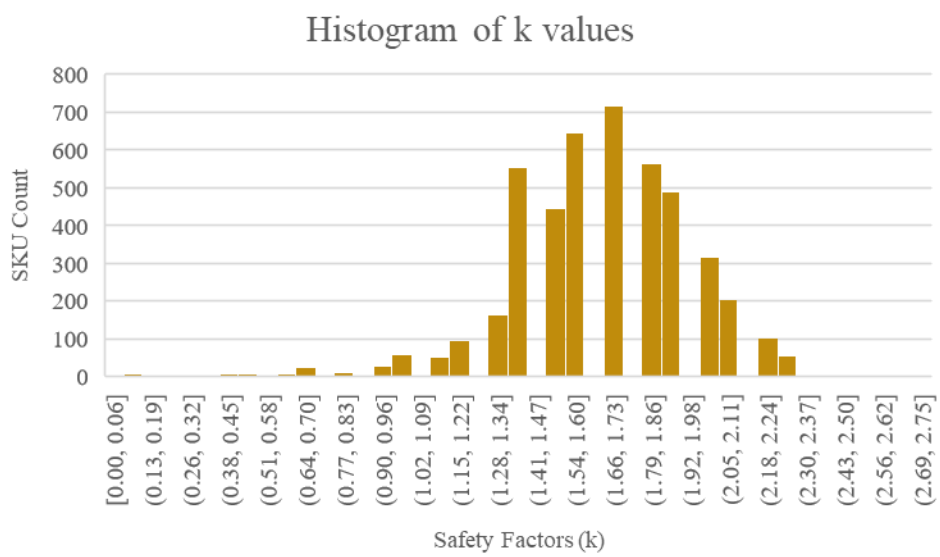


Figure 16 Model 2: Histogram of Safety Factors

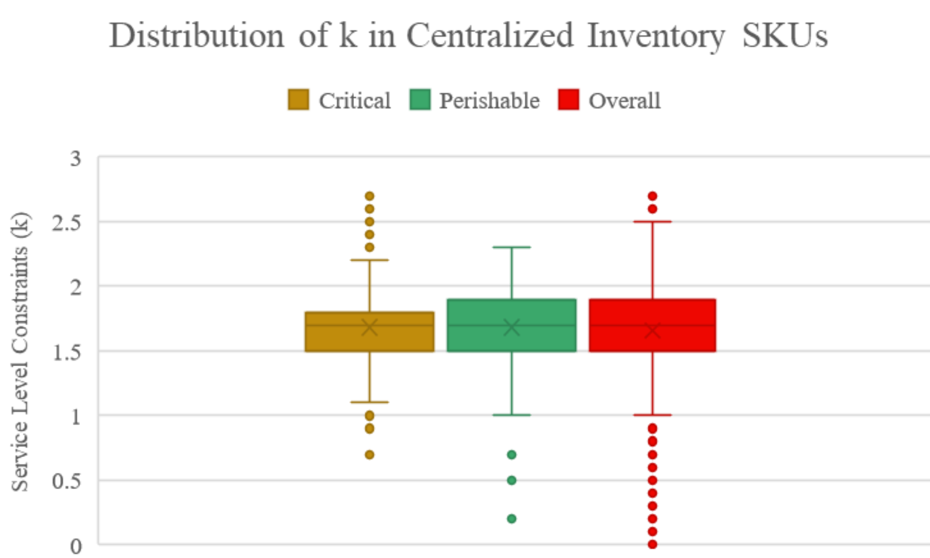


Figure 17 Model 2: Distribution of Safety Factors in CI SKUs

Similar to the boxplot in Figure 17, the histogram of annual number of replenishments in Figure 18 shows little difference compare to Model 1. In Model 2, the BIP model is more inclined to order more frequently, but most SKUs still maintain low number of replenishments per year.

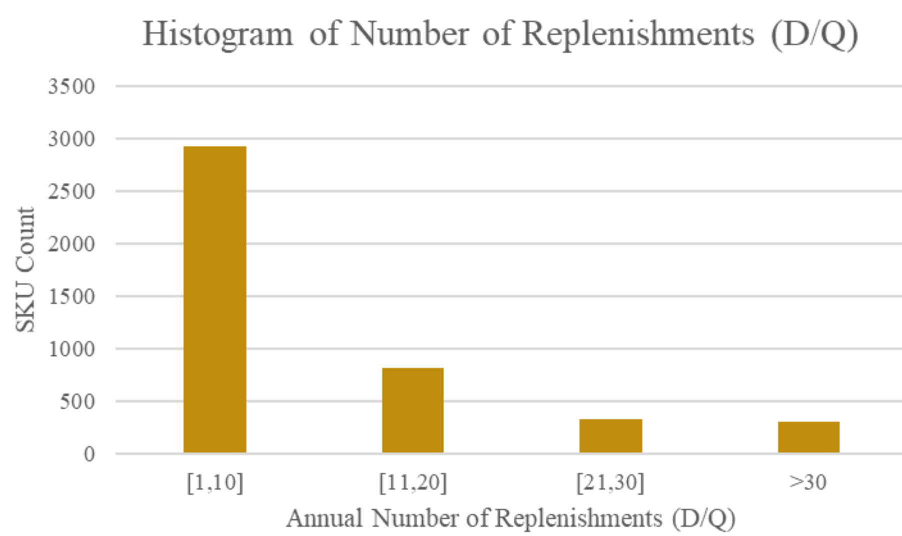


Figure 18 Model 2: Histogram of Number of Replenishments (D/Q)

6.4 Model 3 Result

Model 3 differentiates with the other models by determining replenishment order quantities of SKUs based on a range of annual number of replenishments. In Model 1 and 2, some selected SKUs had extremely small or large annual number of replenishments allocated which is a hard practice to follow. Therefore, a reasonable number of replenishments range from 2 to 18 are set to determine order quantities for each SKU selected. The result of the model is shown below in Table 12. Compared to Model 2, Model 3 underperforms by managing 12 SKUs less in CI.

Table 12 Model 3: Test Result

Inventory Type	SKU Count	SKU Count (%)
Centralized Inventory	4,564	97.8%
Decentralized Inventory	102	2.2%

Model 3's distribution of fill rates for selected SKUs follows similar trend to Table 13 where it selects less SKUs compare to Model 2. However, there are only 9 additional SKUs guaranteed with less than 90% fill rates, but this is only 1.2% of all selected SKUs.

Table 13 Model 3: Range of Fill Rates for CI SKUs

Range of Fill Rates	SKU Count	SKU Count (%)
$FR_{ijr} \geq 95\%$	4,391	96.2%
$95\% > FR_{ijr} \geq 90\%$	120	2.6%
$90\% > FR_{ijr}$	53	1.2%

Model 3's utilization of warehouse capacity shows that it allocated more space for replenishment order quantities compare to previous models. The ratio between safety stock and order quantity is 2:1 which means that less amount of inventory is required to achieve similar level of efficiency in Model 2.

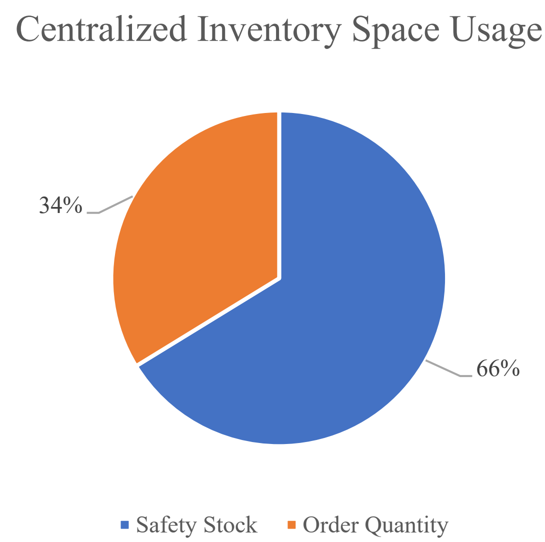


Figure 19 Model 3: Centralized Inventory Space Usage

Model 3's distribution of safety factors differs from previous models as well. The median safety factor is still ranged between 1.5 to 2; however, when different range of safety factors were selected for clinical critical SKUs and perishable SKUs. Clinical critical SKUs are mostly categorized as personal protective equipment (PPE) whereas perishable SKUs are categorized as chemical solutions or consumable medical supplies with serviceable life. These are easily distinguishable SKUs with different characteristics shown in various measures. This result shows that the BIP model is capable of categorizing SKUs based on data characteristics and develop different inventory policies for each category.

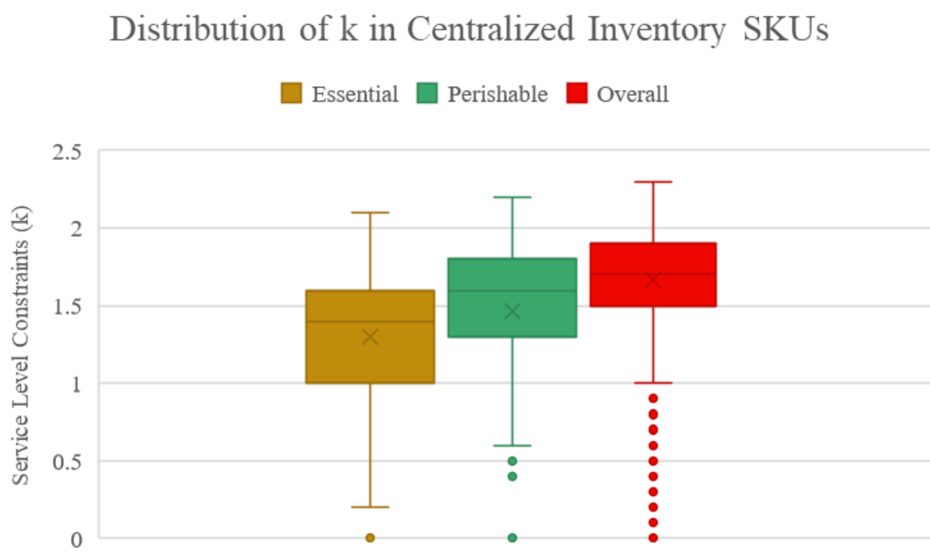


Figure 20 Model 3: Distribution of Safety Factors in CI SKUs

Model 3's capability to distinguish different categories of SKUs are further shown in Figure 20. Figure 20 is a box plot that illustrates the distribution of number of replenishments for clinical critical SKUs, perishable SKUs and overall SKUs. Overall, wide range of replenishment periods are allocated but it shows that different range of replenishment periods is selected for clinical critical and perishable SKUs.

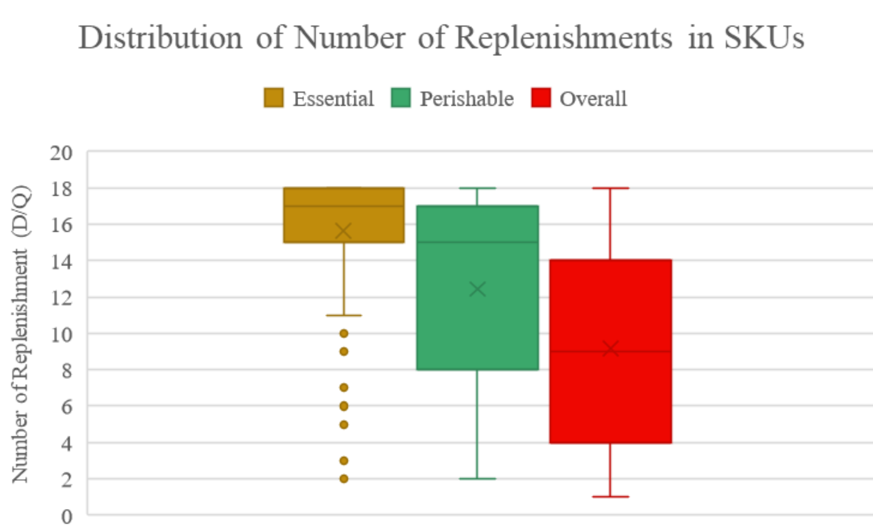


Figure 21 Model 3: Distribution of Number of Replenishments in SKUs

6.5 Model Result Summary

Summarizing the performance of Models 1, 2, and 3, they all outperform the current setup of CI in IWK. The result showed that warehouse capacity can be accommodated to manage at least 4,513 SKUs. This means that the CI can manage almost 97% of all frequently desired SKUs in IWK. The number of SKUs selected does not differ between models too much; however, Model 2 is more efficient in utilizing warehouse capacity than Model 1 and Model 3 is less onerous on inventory averages by requiring less frequent ordering.

Table 14 Results Summary of All Models

Inventory Type	SKU Count			
	Model 0	Model 1	Model 2	Model 3
Centralized Inventory	1,246	4,513	4,576	4,564
Decentralized Inventory	22	153	90	102

Furthermore, approximately 95% of all selected SKUs in Models 1, 2, and 3 are guaranteed with fill rates above 90% which is a desirable goal set by supply chain specialists at IWK. Similarly to Table 15, Model 0 is outperformed by all three models.

Table 15 Range of Fill Rates Summary of All Models

Range of Fill Rates	SKU Count			
	Model 0	Model 1	Model 2	Model 3
$FR_{ijr} \geq 95\%$	1,235	4,254	4,418	4,391
$95\% > FR_{ijr} \geq 90\%$	18	167	99	120
$90\% > FR_{ijr}$	3	92	44	53

Lastly, ETSOPY and ETVSPY for all models are calculated as performance measure and shown in Table 16. All three models outperform Model 0 where ETSOPY is reduced tremendously even through there are more SKUs to be managed. ETVSPY follows a similar trend compared to Model 0, the rest of the models' ETVSPYs are reduced by half. Comparing Models 1 and 2, Model 2 outperforms Model 1 because it has higher ETSOPY but lower ETVSPY. ETSOPY is inevitably larger than Model 1 because it manages more SKUs in the CI; however, lower ETVSPY means that the model can prevent stockouts on more expensive SKUs. Lastly, Model 3 is outperformed by both Models 1 and 2, but Model 3 is tested with reasonable range of order quantities whereas range of order quantities for certain SKUs in Model 1 and 2 is unachievable in real practice. Therefore, Model 3 is slightly underperforming but still provide better solutions than Model 0.

Table 16 ETSOPY and ETVSPY of Model 1, 2, and 3

	Model 0	Model 1	Model 2	Model 3
ETSOPY	11,211	1,967	2,573	2,479
ETVSPY	$933,836	$558,635	$504,264	$560,986

6.6 ABC Classification

To observe difference between selected and unselected SKUs in models, ABC classification has been applied. In all 4,666 inputted SKUs 442 SKUs are identified as A items, accumulating 70% of entire financial demands, 820 SKUs are identified as B items, accumulating the next 25% of the demands and the rest 3,404 SKUs are labeled C items. Table 17 shows the result of ABC classification.

Table 17 ABC Classification Result

	Cumulative Demand	SKU Count
A item	70%	442
B item	25%	820
C item	5%	3,404

In summary, it shows that Models 1, 2 and 3 selected more SKUs in all A, B, and C item categories than Model 0, indicating that they perform better in comparison. Even though most of SKUs in A items are selected but the result shows that the BIP model prioritized the selection of B and C items over A item. This is because SKUs in A item require more inventory capacity in average compare to SKUs in B and C items.

Table 18 Number of A, B and C items in All Models

	Model 0	Model 1	Model 2	Model 3
A item	232	370	395	387
B item	273	781	799	796
C item	762	3,362	3,382	3,381

Table 19 Percentage of A, B, and C items selected in ALL Models

	Model 0	Model 1	Model 2	Model 3
A item	52.5%	83.7%	89.4%	87.6%
B item	33.3%	95.2%	97.4%	97.1%
C item	22.4%	98.8%	99.4%	99.3%

7.0 Discussion

In this thesis, a generic BIP model is designed to develop inventory policies for the list of SKUs that should be managed in Centralized Inventory (CI) of IWK. Different parameters of replenishment order quantities are tested to optimize the order quantity and level of safety stock for each SKU.

7.1 Key Findings

The results in Chapter 6 showed that the current CI can store and manage more SKUs without additional warehouses. All three models showed that CI can manage 3 times more SKUs than their current setup and maintain above 95% fill rates on most of SKUs selected. Interestingly, the ABC classification showed that the BIP model prioritized in selecting C items over A items. This was observed because C items generally required less space to ensure high fill rates over A items. Therefore, this left decentralized inventories (DI) to manage unselected SKUs in mostly A items. Since decentralized inventories periodically reviews their inventories, reduced number of SKUs to manage is a good indicator to effectively prevent stockouts from occurring. Furthermore, DI has reduced risks of overstocking so warehouse capacities can be more efficiently utilized in departments.

Another finding in testing three models is that the BIP model consistently used similar ranges of safety factors. The range of safety factors for these models was between 1.5 to 2.5 as shown in Figure 9, 12 and 16. When the wider range of replenishment strategies (J) are provided in Model 3, the range of safety factor looked categorized between clinical critical SKUs and perishable SKUs. Clinical critical SKUs had lower range of safety factors compare to perishable SKUs but the overall range of safety factors remained between 1.5 to 2.5.

Similarly to range of safety factors, more trends could be discovered in the model results. Three models showed likely inventory ratio between order quantity and safety stock where safety stocks are usually stored 2 to 3 times more than order quantities. These trends in the model results are good indicators for newly purchased SKUs as they do not have historical demands or monthly standard deviation to determine appropriate inventory policies in the beginning.

7.2 Limitations

There are limitations of the data used in the case study that could be improved upon for more accurate modelling. As discussed in Chapter 5, data needed significant feature engineering to assume the physical size (s_i) of SKUs. 73% of physical sizes had to be assumed and if appropriate s_i was provided for all SKUs, the BIP model could have drawn more accurate results. Additionally, there were 67 different classifiers of data collected for each order history but most of these classifiers provide either duplicating information or left empty. This only left 9 classifiers to set parameters of BIP model. If there were more classifiers to address qualitative measures such as essentiality of SKUs, the BIP model could add more functional characteristics. Also with more classifiers, machine learning approach could be applied since various research supports the usage of machine learning to classify SKUs and develop inventory policies.

Another limitation with the data is that all lead time is assumed as 1 month. There are many suppliers connected with IWK and depending on suppliers and SKUs, the lead time can vary for each purchase. Differentiating lead time for SKUs affect level of safety stocks and reorder points but in this research, this aspect could not be covered. If lead times for suppliers and SKUs are recorded in future study, the BIP model could develop more detailed inventory policies for each SKU in CI.

Also, the traditional economic ordering quantity (EOQ) method is not used in this research because it must estimate the order cost and holding costs of the inventory. Order cost and holding costs are unknown in IWK and holding cost especially is difficult to estimate. Furthermore, literatures suggest that most hospitals have not yet measured holding costs; therefore, a different approach of determining the optimal ordering quantity is taken so practitioners can determine the optimal order quantity with less data.

Lastly, there may be practical issues with order quantities suggested in this research. Suppliers might have minimal order quantities that are bigger than the suggested order quantities from the model. This could impact the result of the model but can be adjusted in the parameters in future application.

7.3 Future Research

The case study indicates that the BIP approach is an effective method to classify SKUs into CI or DI and develop inventory policies to satisfy the patient demands. However, there are other considerations when addressing this problem that could be included in future work. These points are outside of the scope but may be considered in future research.

Firstly, the BIP model focused on maximizing the availability of SKUs selected in CI but does not minimize the overall costs of inventory. Although this was preferred by IWK staff, an objective function to minimize overall costs of inventory is a common function of inventory optimization model. This research explored options of reducing overall costs of inventory by applying different parameters of order quantities to reduce estimated value short per year (ETVSPY) in Section 6.5.

Another adjustment to the BIP model can be different sets of order quantity parameters. In this research, order quantities are retrieved from historical record or calculated based on bi-annual replenishments to monthly replenishments, but there are many more approaches to estimate order quantities in research. Moreover, if accurate lead times for suppliers can be obtained, the BIP model could acquire more accurate inventory policies for CI. In real life practice, lead time varies between suppliers and be stochastic based on circumstances. Lead time also greatly affects the calculation of safety stocks, reorder points and fill rates; therefore, accommodating stochasticity of lead time could improve the overall accuracy of the model.

It may also be appropriate to consider developing inventory policies for DI in future. In this research, the number of warehouses in DI and their capacities were unknown in IWK, excluding DI from the scope in developing inventory policies. However, optimizing inventory capacities for individual warehouses in DI would be very beneficial to hospital since most of the experimental purchases are done in DI by practitioners. Providing advice and guidance to DI's inventory management would greatly benefit the efficiency of supply chain in hospitals. Therefore, optimizing both DI and CI should be the next goal in improving the BIP model.

When classifying SKUs in this research, the most common classifiers in research: historical demands, order frequencies, essentiality of SKUs are used to determine which SKUs should belong in CI. This research differentiates with traditional inventory classification problem by not using the weight to create hierarchy of classifiers because determining weight between quantitative and qualitative classifiers are especially difficult in healthcare. However, there are many applications of machine learning where different set of weights had been tested for hospitals.[13,22,23] Using machine learning application, various sets of weights were found to reduce bias from practitioners. This indicates that including of machine learning application has a potential to add more functional characteristics to the BIP model.

To conclude, more research is needed on to add additional functional characteristics to the BIP model, but the current BIP model successfully determined the list of SKUs in CI and develop inventory policies for each SKU. In all proposed order quantity scenarios, the BIP model outperformed the current setting of CI by managing more SKUs while reducing estimated value short per year. By improving the overall efficiency of inventory control in healthcare service, the health outcomes are likely to improve.

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Appendix – Python Codes

```
In [2]: from itertools import product
        from sys import stdout as out
        from mip import Model, xsum, maximize, BINARY
        import matplotlib.pyplot as plt
        import pandas as pd
        import numpy as np
        import seaborn as sns

        Using Python-MIP package version 1.6.8

In [3]: data = pd.read_csv('IWKData4.csv')
        data2 = pd.read_csv('k & p(k) & g(k) values.csv')

In [34]: raw_mu = pd.DataFrame(data, columns= ['Demand']).to_numpy()
         raw_s= pd.DataFrame(data, columns= ['Size']).to_numpy()
         raw_OQ = pd.DataFrame(data, columns= ['q1','q2','q3','q4']).to_numpy()
         raw_StDev = pd.DataFrame(data, columns= ['StDev']).to_numpy()
         raw_Perish = pd.DataFrame(data, columns= ['Perish']).to_numpy()
         raw_Crit = pd.DataFrame(data, columns= ['CC']).to_numpy()
         raw_Value = pd.DataFrame(data, columns = ['Value']).to_numpy()
         raw_mean = pd.DataFrame(data, columns = ['mean']).to_numpy()
         raw_k = pd.DataFrame(data2, columns = ['k']).to_numpy()
         raw_pk= pd.DataFrame(data2, columns = ['p_k']).to_numpy()
         raw_Gk= pd.DataFrame(data2, columns = ['G_k']).to_numpy()

         S_IWK = 28168128

         flatten_mu = raw_mu.flatten()
         flatten_s = raw_s.flatten()
         flatten_StDev = raw_StDev.flatten()
         flatten_Perish = raw_Perish.flatten()
         flatten_Crit = raw_Crit.flatten()
         flatten_Value = raw_Value.flatten()
         flatten_mean = raw_mean.flatten()
         flatten_k = raw_k.flatten()
         flatten_pk = raw_pk.flatten()
         flatten_Gk = raw_Gk.flatten()

         mu= flatten_mu.tolist()
         s = flatten_s.tolist()
         OQ = raw_OQ.tolist()
         StDev = flatten_StDev.tolist()
         Perish = flatten_Perish.tolist()
         Crit = flatten_Crit.tolist()
         Value = flatten_Value.tolist()
         mean = flatten_mean.tolist()
         k = flatten_k.tolist()
         pk = flatten_pk.tolist()
         Gk = flatten_Gk.tolist()

         I, J, R = range(len(OQ)), range(len(OQ[0])), range(len(k))
```

```
In [36]: # Fill Rates for Items i and policy j
         FR = [[[1-(Gk[r] * StDev[i]/OQ[i][j])  for r in R] for j in J] for i in I]

          # Total Inventory Amount to Hold for Items i and Order Quantity j and Stock Strategy r
         TQ = [[[OQ[i][j]+mean[i]+k[r]*StDev[i]  for r in R] for j in J]for i in I]

In [37]: model = Model()

In [38]: # binary variables indicating which jth order policy for ith item

         x = [[[model.add_var(name="x({}{}{})".format(i,j,r), var_type=BINARY)
                for r in R] for j in J] for i in I]

In [39]: # Objective Function

         model.objective = maximize(sum(FR[i][j][r] * x[i][j][r]
                                        for r in R for j in J for i in I))

In [40]: # Pick One Order Policy Constraint

         for i in I:
             model += sum(x[i][j][r] for r in R for j in J) <= 1

In [41]: for i in I:
             model += sum(FR[i][j][r]*x[i][j][r] for r in R for j in J) <= 0.99

In [42]: # Perishable Item Constraint

         for i in I:
             model += sum(FR[i][j][r] * x[i][j][r] for r in R for j in J) >= 0.95 * Perish[i]

In [43]: # Physical Space Constraint

         model += sum(x[i][j][r]*s[i]*TQ[i][j][r] for r in R for j in J for i in I) <= S_IWK

In [44]: # Criticality Constraint

         for i in I:
             model += sum(FR[i][j][r] * x[i][j][r] for r in R for j in J) >= 0.95 * Crit[i]

In [45]: # Result

         model.optimize()

Out[45]: <OptimizationStatus.OPTIMAL: 0>
```

```
In [46]: for (i,j, r) in product(I,J, R):
             if x[i][j][r].x >= 0.99:
                 print("{} {} {}".format(i+1,j+1, r+1))
```

```
1 1 20
2 1 18
3 3 28
4 4 18
5 4 17
6 4 12
7 4 20
8 4 18
9 3 18
10 4 17
11 4 18
12 3 16
13 1 17
14 3 26
15 4 8
16 1 18
17 1 19
18 1 17
20 4 12
```