

THE PENNSYLVANIA STATE UNIVERSITY  
SCHREYER HONORS COLLEGE

DEPARTMENT OF SUPPLY CHAIN AND INFORMATION SYSTEMS

Inventory Stocking Policies, Transportation Costs and Order Fill Rates

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FALL 2024

A thesis  
submitted in partial fulfillment  
of the requirements  
for a baccalaureate degree  
in Supply Chain and Information Systems  
with honors in Supply Chain and Information Systems

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## ABSTRACT

Inventory decision making is the focus for Company A, a fashion and body care retailer. The primary issue Company A wants to address is split orders due to the nature of their demand and the industry which drives high units per order. Company A is challenged by seasonal demand and promotions which exasperate the challenge of order fulfillment for their e-commerce fulfillment channel. Company A wants to understand if inventory positioning will improve their outbound order fulfillment targets and reduce their split orders.

The research conducted for this thesis utilized sales data from a five-day promotional event of Company A. After data cleaning and pre-processing, the data was analyzed through a market basket analysis conducted through data mining software. The analysis uncovers items that are frequently purchased together and can be used for inventory placement decision making.

The result of this research is a repeatable process for analyzing customer order profiles and uncovering inventory trends. The recommendation is to adjust inventory stocking policies by stocking high volume and velocity items frequently purchased together in the same fulfillment center to reduce split orders. For this thesis, only one demand season was used and additional data could provide a more comprehensive understanding of ordering trends. Different desired attributes, confidence and support levels can be assigned for further analysis. Additional recommendations include a financial analysis of the cost and benefit of implementing changes based on market basket analysis results.

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## ACKNOWLEDGEMENTS

I would like to thank the many people who have supported me while writing this thesis. First and foremost, thank you to my thesis supervisor, Dr. Robert Novack. From my first supply chain course at Penn State to finding internships to finishing my thesis, Dr. Novack has mentored me and shared his wisdom and support. It has been an honor to learn from an expert in supply chain management who is devoted to teaching and helping others. Thank you for giving your time and energy to invest in your students and truly prepare them for their years beyond college.

Next, I would like to thank Company A and the contacts I had the privilege of working with on this project. Thank you for providing the data and information used to complete the methodology and analysis of this research. It was a pleasure working with you for the past year to answer prevalent questions about your supply chain.

Finally, thank you to the Center for Supply Chain Research at Penn State for pairing me with Company A. I appreciate your partnership with companies to provide students with practical learning opportunities and exposure to current issues in supply chains today. Thank you for inviting me to share my thesis research and providing feedback at the Corporate Sponsor Meetings in both Fall 2023 and Spring 2024.

## **Chapter 1**

### **Introduction**

In retail, whether it be through brick-and-mortar or e-commerce, inventory availability is vital to completing orders for the customer. Optimizing inventory placement is beneficial for businesses to ship products more efficiently, improve accuracy, and therefore reduce costs. Complexity is driven for Company A by their distribution centers not having full parity between the two facilities, the stock keeping unit breadth and depth, and high average units per order. Demand seasons and promotional pricing exasperate these challenges, highlighting the importance of forecast accuracy and inventory placement. As a result of these challenges, Company A has seen order fulfillment impacted. Improvements to inventory positioning will aid in the achievement of outbound order fulfillment targets and the reduction of split orders.

The data for this thesis will be provided by Company A, which is a retailer in the fashion and body care industry. This data will consist of a portion of their customer orders through the online retail end of their business and will focus on demand captured during promotion and holiday sales. The regular volume for their demand averages a high number of units per order, only increasing during sales and seasonal demand periods. With high volumes moving through their network, inventory placement and customer behavior are critical to improving order fulfillment targets.

The remainder of this thesis will proceed as follows: background, methodology, analysis, conclusion and recommendations. The background section will look at inventory placement strategies and factors to consider, and the beneficial uses of customer order basket analysis. The

methodology will discuss the different steps that were taken to reach the conclusion of this thesis. A significant piece of this will identify and justify the statistical modeling used. The analysis portion of this thesis will discuss the results of the model and what it reveals about the data from customer orders. Lastly, the conclusion and recommendations will summarize how the results found can be utilized by Company A and ways that they can be applied to their inventory positioning decisions now and adapted for continued use in the future.

## **Chapter 2**

### **Background**

#### **Inventory in the Economy**

The Gross Domestic Product (GDP) of a country measures the final goods and services at a monetary value. The GDP is the sum of the consumption, investments, government spending and net exports of a nation for the year. Inventory is considered a form of investment and in 2022, the total business inventory as a percentage of nominal GDP was 14.6 percent (Kearney, 2023). Changes in inventory levels also impact other components of GDP and can signal future changes. Inventory is a leading indicator of GDP because it predicts changes in consumption and demand within the economy.

The economic tradeoff of supply and demand can be understood by the ratio of inventories and sales and how it is changing. A decline of inventory compared to sales indicates that demand is greater than supply. This signals growth as consumption is high and indicates that production will increase. In contrast, a rise in inventory levels compared to sales communicates low demand compared to supply. With a greater supply than demand, production is likely to fall. The inventory levels and production are closely aligned in an inverse relationship. In addition, predicting production is beneficial to the economy because of other factors such as employment and consumption.



## **Inventory vs Transportation**

Inventory is at the center of decision making for retailers because their purpose is to store and sell products to their customers. Not only does this require inventory availability, but also it requires access to the right inventory. Without the right items in the right place and available at the right time, retailers are unable to meet the demands of their customers. One of the most important decisions that must be made by a business is the trade-off between inventory and transportation. Different departments within a business have different motivations for balancing inventory and transportation. Finance is focused on the cost and cash flow, preferring to keep low inventory levels. Marketing is concerned about meeting customer needs and tends to be in favor of holding extra inventory to always meet demand. Manufacturing is interested in production efficiency through producing the same product for a long period of time to minimize cost per unit from labor and changeover costs.

Two key questions that need to be answered about inventory are how much to make and determine what are the optimal inventory stocking levels. There must be a compromise between the most cost-effective levels and the ability to meet customer demand. A few inventory cost factors that should be considered here are inventory carrying costs and stockout costs. On one end, inventory carrying cost is the cost of holding inventory and waiting for it to be sold, and on the other end stockout costs are the costs of not having the right inventory needed for a sale. Both inventory carrying costs and stockout costs are beyond the production cost or selling price of the item.

The nature of a product is responsible for the variability in inventory costs. Determined by the consumers, the level of substitutability is the willingness of a consumer to purchase a similar, alternative item if the originally desired item is out of stock. A few factors that help

determine substitutability include the value of the product and its uniqueness. In general, the more valuable or unique a product is, the less willing a consumer would be to choose a substitute item. In contrast, the more generic, common, or low value a product, the more likely a consumer is to substitute it if the original product is unavailable but there is a next best option available. Not every consumer is the same, which means there is variation between consumers on what they view as substitutable and to what extent.

Seasonality of products is an additional component to understand substitutability and stockout costs. In business, seasons are identifiable periods of increased demand. In many cases these demand fluctuations are associated with major holidays and the shopping leading up to the holiday. Seasons do not always align with holidays and their timelines vary because they are specific to their individual industry, product attributes, and demand patterns. Factoring in the seasonal demands of a product is critical for inventory management and it influences the cost of holding it in inventory and the cost of potential stockouts.

Shelf life is the length of time a product can sit before it becomes obsolete and can no longer be sold. The shelf life of products varies by the nature of the product, ranging from short shelf life items such as produce that are inedible after a few days or weeks to long shelf life items such as toilet paper that lasts years. Shelf life can also be determined by the amount of time it can be sold before it is out of trend or out of season. Seasonal items that cater to a specific holiday, event, or time of year can usually only be sold during that season. Many seasonal products have short shelf lives and tend to have low substitutability crossing between seasonal and regular items and thus have high stockout costs.

Calculating inventory needs and the costs associated is a balancing act. High inventory levels of slow-moving items can result in obsolete inventory and high inventory carrying costs,

but too low can result in high stockout costs. The shelf life, level of substitutability, and seasonality of products are overlapping factors that influence one another and must be considered in tangent.

Transportation is on the opposite end of the trade-off between inventory and transportation because they have an inverse relationship. If shipment frequency increases, transportation costs increase as well, but inventory storage costs will decrease. Inventory carrying costs decrease with an increase in transportation costs because less inventory needs to be held at once if there are more frequent shipments. Assuming demand remains the same, the customer needs the same amount of inventory, and the only factors that change are how much is in each shipment and when it is shipped.

Like inventory decisions, there are multiple layers to decision making for transportation. Transportation costs can be influenced by the nature of the product, time versus cost, and its physical position in the network. As with other inventory decisions, the shelf life of a product might determine at what frequency deliveries would be needed. A short shelf life product would require higher frequency of deliveries whether it must be consumed in a short time frame or it is needed within a seasonal time frame. Economies of scale would be less important to consumers in these situations because a short lead time is a higher priority than cost. When cost is prioritized above a short lead time, economies of scale for transportation can be used to take advantage of cost efficiency. The more items on an order, the higher the total transportation cost, but the lower the transportation cost per item.

Location is important to consider because it is best to fulfill orders from distribution centers closest to the customer. The closer the product is to its destination, the lower the transportation costs will be. Assume Store A is five miles away, Store B is two miles away, and

Store C is eight miles away, and assume all three stores have the same items in inventory. In this situation, the best choice would be to ship the order from the store that is closest to the destination because it would be the shortest time and lowest transportation cost.

An additional factor to consider with transportation costs is how carriers charge by parcel. There are two primary methods, dimensional and weight pricing. Dimensional pricing charges by the dimensions of a parcel package regardless of the weight, whereas weight pricing charges by the weight of the package rather than the physical size of the parcel. This is important to consider because if the carrier charges by dimensional pricing, it is favorable to take advantage of the space available in each parcel. The number and the weight of the items does not change the cost to ship a package under dimensional pricing, therefore it is more efficient to ship as many items in that parcel to lower the transportation cost per unit.

### **E-Commerce**

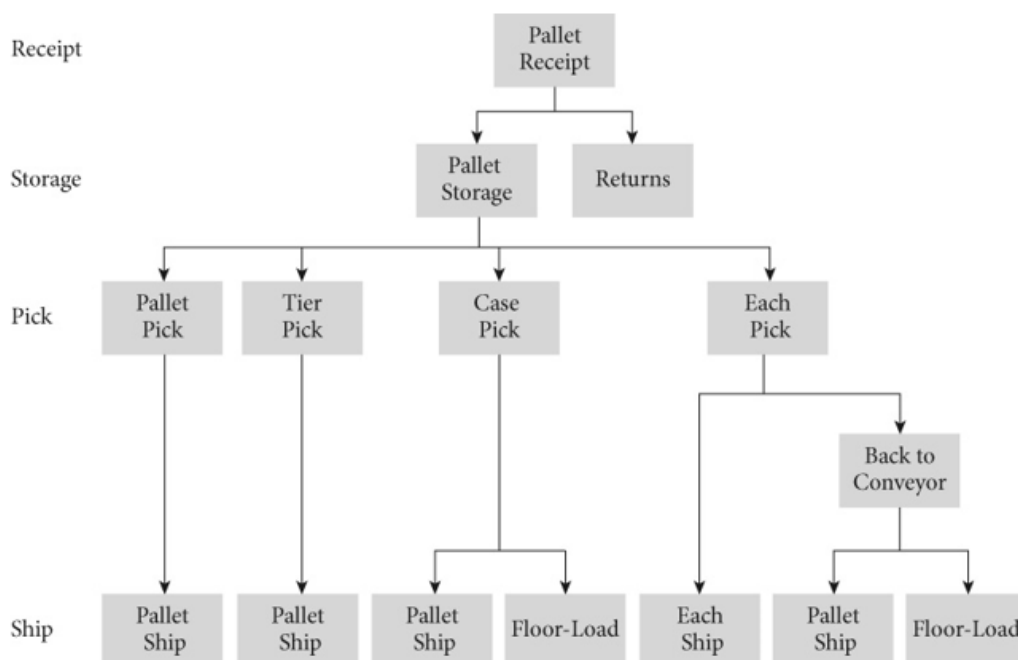
Another segment of inventory that may be considered is e-commerce, its relevance, and its complexities which must also be considered. E-commerce has seen positive growth trends and has become a staple in consumer purchasing habits, which in turn impacts how supply chains have adapted and changed their network designs. One variation in the design of a network is based on how product is received in and shipped out. In this discussion, the focus will be on fulfillment centers rather than distribution centers. Fulfillment centers are designed to receive orders for customers, pick and pack individual stock-keeping units (SKUs) from the orders, and ship these orders directly to customers. Whereas distribution centers are designed to receive large

volumes of products from suppliers and ship out high volumes to retailers. Both receive finished good products by pallet, but the differentiator is the pick, pack, and ship of eaches, or SKUs.

The distribution flow difference can be observed in the similarities and differences between the distribution from Unilever to Walmart and from Amazon to the consumer. For a relationship like Unilever and Walmart where high volumes are shipped in and out, a distribution center would follow the left-hand process flow in Figure 1, pallet receipt, pallet storage, pallet pick, and pallet ship. While Amazon also receives and stores a high volume of products, Amazon ships direct to consumers and follows the path of pallet receipt, pallet storage, each pick, and each ship seen in Figure 1.

Figure 1

## Distribution Center Process Flow Chart



Cost is associated with all aspects of how products are touched throughout the supply chain. Using an activity based costing method is beneficial because it is a more precise than traditional costing which can be generalized estimations. In comparison to a distribution center, a fulfillment center incurs greater costs because of the touchpoints required for each shipment out. Activity based costing allocates the indirect and overhead costs based on their consumption of these costs. This is driven by order profiles, which indicates order composition. What and how much is on an order will influence how inventory decisions are made such as where it is positioned.

For companies with multiple channels, both e-commerce and brick-and-mortar store platforms, the choice is mainly between omnichannel networks where there are integrated fulfillment processes, or to have separate processes for each respective type of fulfillment process. Regardless, both types of networks share many overlapping characteristics.

Most notably is the duality of inventory management for omnichannel businesses with both online and brick-and-mortar stores is that they must consider the issue of order crossovers. Order crossover problems can occur when both online and in-store orders are being fulfilled from the same inventory pool, and the same individual item is allocated to multiple orders. There are also benefits to pooled inventory such as the safety stock required is lower than the if each lane held its own, separate, inventories. An appropriate safety stock level can be calculated and the effect of increasing stocking points can be illustrated by the square root rule. Adding stocking points, places at which inventory is held such as a fulfillment center or distribution center, increases the amount of safety stock required to be held. This is why serving two sources of demand from the same inventory pool is beneficial to safety stock levels as it decreases when inventory is consolidated.

### **The Consumer of Company A**

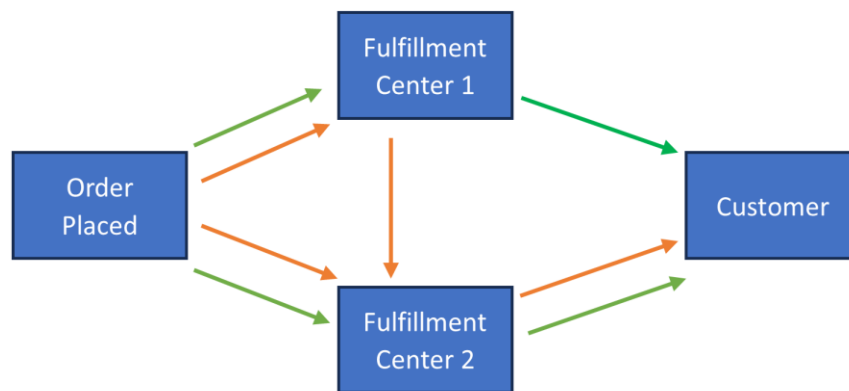
Consumers, their interests, and behavior are crucial to consider for making well informed business decisions. Because demand is dictated by consumers, it is important to identify their priorities and expectations to best meet their needs. Studying the consumer profile of a product or industry allows for improved forecasting abilities. A few ways that a company can measure how well they are meeting their consumers' needs is through various key performance indicators such as delivery time which measures the number of orders delivered on time compared to the promised delivery date, order accuracy of whether items shipped matches the items ordered, and fill rate which reflects whether the overall output of a company is meeting customer orders.

Consumer tendency to purchase more than one item at once, or multi-line-item orders, are frequent for numerous reasons. Whether it is because consumers find additional items to purchase along with their originally intended item, or it is their intention to purchase multiple items. This prompts the question for Company A of whether promotional events, deals, and priced items drive people to shop or if they are secondary purchases. If promotions do carry influence, what types do and how can this be taken advantage of? By studying customer orders of Company A, independent and dependent demand items can be identified and intentionally slotted accordingly.

In general, any given consumer desires to receive the correct goods which they have purchased as quickly as possible and for as cheap as possible. Both supply chains and customers would like to achieve high on time and in full orders, with no or minimal split orders. A split

order occurs with multi-line orders when a single order is delivered in more than one shipment. Most often this is due to outages or in multi-node networks, the items are not located in the same fulfillment center and must be shipped separately. If products are held in separate fulfillment centers, additional transportation costs will be exerted regardless of if the customer receives the products in one or more shipments. Either products accumulate to one location to ship to the consumer in one package or each fulfillment center ships a package to the consumer directly. Figure 2 illustrates the two ways to resolve an order that requires products from two separate fulfillment centers. The orange arrows in Figure 2 represents when the products accumulate to one location to ship to the consumer, and the green arrows represent an order that is shipped in two packages from both fulfillment centers.

Figure 2



Inventory positioning is a decision and strategy based on information gained from consumer purchasing patterns and order profiles that can improve output, cost, and customer satisfaction rather than hinder operations. There are two perspectives to inventory positioning to consider, the first is the placement of inventory in the supply chain network and distance to customers, and the second is the selection and placement of product within a fulfillment center.



When there are numerous fulfillment centers located nationally or globally, the business ought to consider geographic demand in deciding where to stock different products. It would not be logical to stock a product further from the demand point, consumers, because it would result in higher than necessary transportation costs. Similarly, leveraging information on geographic demand allows a business to best prevent split orders. Within an individual fulfillment center, inventory positioning can also be used to improve picking efficiency. By improving picking efficiency, a business can save both time and money. These factors open opportunities for a competitive advantage through intentional product allocation in facilities and optimal inventory levels aiding in achieving high velocity.

Company A currently operates out of two regional fulfillment centers for their e-commerce orders. Considering the importance of inventory to order fulfillment and the issue of split orders, Company A is faced with the question of where to place their inventory and how to effectively determine this. To answer these questions, the approach taken in this research is based on order profiles drawn from historical sales data of Company A.

## **Chapter 3**

### **Methodology**

#### **Context**

The data used to complete this research was a snapshot of orders from a promotional event for Company A that spanned five days. All e-commerce sales within this period were included in the dataset delivered. The data on orders fulfilled includes both single and split shipments. These shipments were fulfilled through a network of two distribution centers.

The objective of this data analysis is to create a repeatable method for identifying items frequently purchased together to inform decision making for inventory placement between distribution centers with the goal of reducing split shipments. With the goal of identifying patterns, data mining is a good fit for conducting this analysis. The focus will be on a data mining technique called market basket analysis which allows purchasing patterns to be uncovered from historical orders.

#### **Data Preparation**

The raw data was delivered as five separate excel files divided by each day of the promotional event. Verifying the quality of the data was usable was the first step before moving forward with the analysis. The datasets were combed through to ensure that there were not values missing and that the data values listed aligned with their column categories and formatting was consistent. Each file was identical in what raw data columns were included. Each row identifies each unique item type on an order. Figure 3 shows the seventeen column headers of the raw data

received: WHSE\_NUM, ORD\_NBR, ITM\_NBR, ORD\_CRE\_DT, SHP\_TO\_CTRY\_CD, ORD\_LN\_PRC\_IND, UNT\_ALLOC\_CNT, DEMAND, STYLE\_CHOICE, PROD\_DESC, SIZE, SZ1\_CD, SZ2\_CD, VS\_SUBCATEGORY, PROD\_LIFECYCLE, FLDIDACATEGORY, and ITM\_COLOR\_FAM\_DESC.

**Figure 3**

|   | A        | B       | C       | D          | E              | F              | G             | H      | I            | J         | K    | L      | M      | N           | O              | P              | Q                  |
|---|----------|---------|---------|------------|----------------|----------------|---------------|--------|--------------|-----------|------|--------|--------|-------------|----------------|----------------|--------------------|
| 1 | WHSE_NUM | ORD_NBR | ITM_NBR | ORD_CRE_DT | SHP_TO_CTRY_CD | ORD_LN_PRC_IND | UNT_ALLOC_CNT | DEMAND | STYLE_CHOICE | PROD_DESC | SIZE | SZ1_CD | SZ2_CD | SUBCATEGORY | PROD_LIFECYCLE | FLDIDACATEGORY | ITM_COLOR_FAM_DESC |

Out of the seventeen given data column types, ten were initially highlighted to answer questions and to further analyze. These ten in figure 4 include warehouse number, order number, item number, sale type, style, size, style subcategory, product lifecycle, category, and color. Warehouse number and order number were key components to identifying split shipment orders. Drilling further the item numbers and remaining item characteristics could be used to look for frequently occurring items on these split shipment orders.

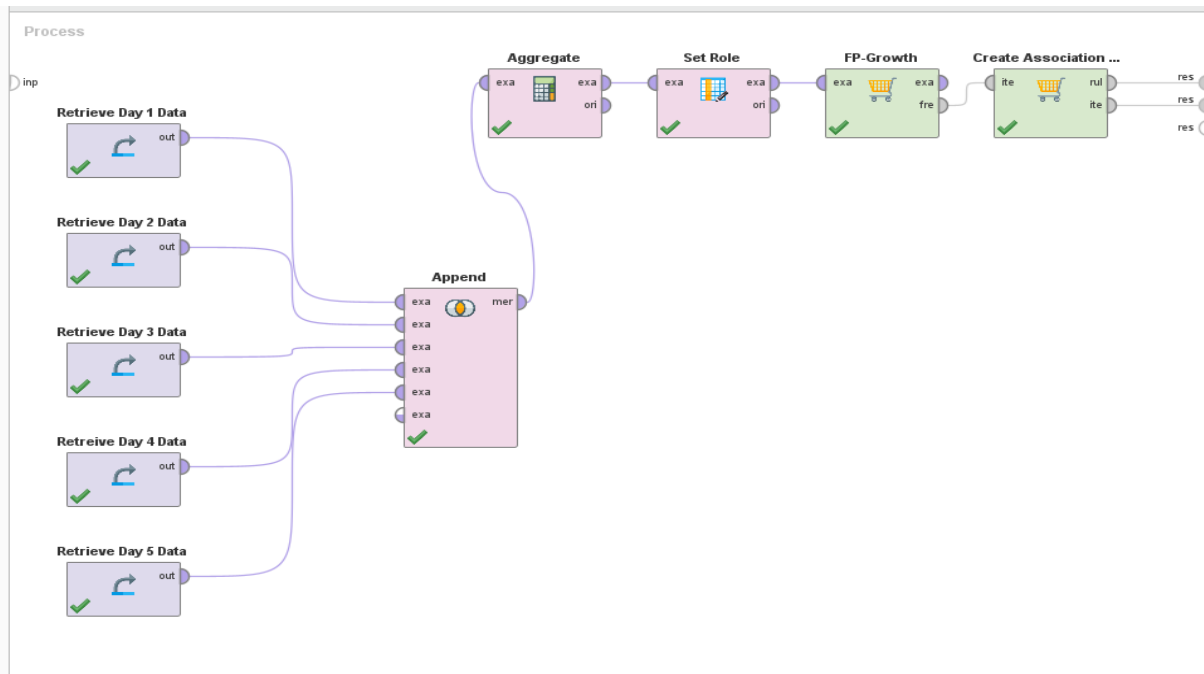
**Figure 4**

|   | A        | B       | C       | D              | E            | F    | G           | H              | I              | J                  |
|---|----------|---------|---------|----------------|--------------|------|-------------|----------------|----------------|--------------------|
| 1 | WHSE_NUM | ORD_NBR | ITM_NBR | ORD_LN_PRC_IND | STYLE_CHOICE | SIZE | SUBCATEGORY | PROD_LIFECYCLE | FLDIDACATEGORY | ITM_COLOR_FAM_DESC |

### **Data mining process**

The data mining process included retrieving and combining the raw data, aggregation and grouping, assigning special roles to attributes, identifying patterns of item combinations, and creating useful rules about these patterns. Figure 5 shows the six operators used to complete the steps: “Retrieve,” “Append,” “Aggregate,” “Set Role,” “FP-Growth,” and “Create Association Rules.”

Figure 5



The “Retrieve” operator allows the raw data to be pulled from the provided excel datasets. One “Retrieve” operator is used for each excel workbook needed. The “Append” operator is a preprocessing tool that merges compatible datasets into one. The requirements for this operator is all datasets must have the same number of attributes, and the names and roles of these attributes are consistent across each dataset input. This allows the analysis to pull as many datasets as needed and makes this process easily repeatable in the future.

From the merged dataset that was created, the data is next aggregated using the “Aggregate” operator. This operator takes the given dataset and creates an aggregated dataset that is created by a designated aggregation function. The first parameter selects the aggregation attribute and aggregation function to be applied. The aggregation attribute can be broad or narrow from size to SKU item number. The aggregation function used for all aggregations was the concatenation function.

The second parameter of this operator is “group by attributes” which creates a grouping of the dataset based on the selected attribute. This is similar to the “group by” clause used in the Structured Query Language (SQL) programming language used in relational databases. For this analysis, the “group by attribute” parameter is grouping the data by Order Number. Figure 6 shows the parameters for the aggregation operator.

Figure 6

Figure 7 is the settings used in the “Set Role” operator which allows an attribute to be assigned a special role. This does not rename the attribute, rather it instructs other operators on how to process the attribute. For this analysis, the special role that needs to be assigned is “id” to the attribute Order Number. This is important to do because “id” is used as the unique identifier for each order in the dataset.

Figure 7

| attribute name | target role |
|----------------|-------------|
| ORD_NBR        | id          |

The data is now prepared for analysis, starting with the “FP-Growth” operator. This is a frequent pattern tree algorithm that identifies the frequency of item sets purchased in a large dataset. Items in this analysis can include the specific SKU item, or item characteristics such as a size or color. Item sets are defined as the subset of items in the same order.

To focus on relevant items and item sets, a minimum support can be set to exclude items or item sets that do not appear frequently. Support is the number of orders with both Item A and Item B divided by the total number of orders in the dataset. Minimum support is used rather than frequency because frequency is the number of occurrences of an item set where as support is a ratio of frequency to the data set. Figure 8 includes the “FP-Growth” parameters set for this analysis. The output of the “FP-Growth” operator is frequently occurring item sets which is the input required for the last operator, “Create Association Rules.”


Figure 8





| Parameter                   | Value                               |
|-----------------------------|-------------------------------------|
| input format                | item list in a column               |
| item separators             |                                     |
| use quotes                  | <input type="checkbox"/>            |
| escape character            | \                                   |
| trim item names             | <input checked="" type="checkbox"/> |
| min requirement             | support                             |
| min support                 | 0.002                               |
| min items per itemset       | 1                                   |
| max items per itemset       | 0                                   |
| max number of itemsets      | 1000000                             |
| find min number of itemsets | <input checked="" type="checkbox"/> |
| min number of itemsets      | 100                                 |
| max number of retries       | 15                                  |
| requirement decrease factor | 0.9                                 |
| must contain list           | Edit Enumeration (0)...             |

The frequently occurring item sets can be expressed as association rules in an if/then statement format which describe the relationship between the two items. In addition to support, confidence is a parameter set in the “Create Association Rules” operator which indicates how true each if/then relationship is. Confidence is calculated by the number of orders with both Item A and Item B divided by the number of orders with Item A. By setting the minimum confidence to 0.8, as seen in Figure 9, the results are filtered to relationships where eighty percent or more of the time when Item A is purchased, Item B is also purchased.

Figure 9

**Parameters** ×

 **Create Association Rules**

|                       |   |   |
|-----------------------|---|---|
| <b>criterion</b>      | <input type="text" value="confidence"/> |  |
| <b>min confidence</b> | <input type="text" value="0.8"/>        |  |
| <b>gain theta</b>     | <input type="text" value="2.0"/>        |  |
| <b>laplace k</b>      | <input type="text" value="1.0"/>        |  |



## **Chapter 4**

### **Analysis and Results**

The data mining process established in the methodology of this research remains the same and was run numerous times for the analysis. Different parameters can be assigned to further understand the data and analyze the inventory questions of Company A based on different attributes. The parameters include confidence and support levels. There are advantages and disadvantages to both which were considered for this recommendation. Insights on the results from analyzing different attributes were provided. The range of attributes to choose to analyze ranged from wide to narrow. In addition to these insights, the last deliverable to Company A is a repeatable process. As a retailer in the fashion industry, the nature of Company A's trends in demand vary greatly year to year and season to season. For this reason, regularly analyzing their order profiles is beneficial to evaluate their inventory positioning decisions.

#### **Answering Pre-Processing Questions**

The first piece of information to determine was the total number of orders placed during these five days. To find the total number of unique orders, a copy of all order numbers listed for all five days was compiled. Removing duplicates leaves the unique order numbers which totaled 479,123 orders over all five days. Next the average number of units per order was determined using the same list of unique order numbers. The total units on each order were pulled by a SUMIF function to include multiples of the same SKU as well. The average was calculated with an average function, resulting in eleven units per order on average.

Additional insights that could be drawn from an initial look at the data was the number of orders that were split and shipped from both distribution centers. Using a pivot table the data could be viewed as: order number as rows, warehouse number as columns, and a count of item numbers as values. This

provides how many items came from each distribution center on each order. Split orders could be identified from this data pivot by further filtering to orders where there was at least one item shipped from both distribution centers. The total number of split shipment orders was 62,007 orders. Of these split shipment orders, 55,486 orders were split because of one SKU item. This was calculated by the quantity shipped from each distribution center for all split shipment orders filtered to only one item coming from one or both distribution centers. A small portion of these orders, 175 orders, were two SKU item orders.

### **The Split Orders**

From the pre-processing analysis of the data, it was established that of the total number of split orders in the dataset, 89.48 percent of split orders were split by one item. These single item split orders were the orders prioritized in this analysis. First, the data mining process was run using an aggregation at the SKU level of the data attributes. The first question looked at is whether there were identifiable patterns of key items causing the split orders. With an average of eleven items per order, there was not a select few SKU items that could be identified as the cause for the majority of the split orders observed. The single items being split from orders neither were a single item nor from one fulfillment center. There was an even distribution of which fulfillment center the single item was coming from.

### **Support and Confidence Levels**

Support and confidence are parameters of the process operators “FP-Growth” and “Create Association Rules” which identify the relevant items and item sets in the data. The minimum support parameter is the minimum ratio of frequently occurring item sets from the dataset. These item sets can be expressed as If/Then statements. The process returns association rules based on these statements using the minimum confidence which is the accuracy level of these If/Then statements.

Conceptually the closer to 100 percent support and confidence the better the model is because these item sets are highly occurring and there is high certainty that Item B will be bought if Item A is bought. Practically support and confidence set too high can limit the scope of results. If support is too high, it assumes that these items would need to be on almost every orders. With a large breadth and depth of SKUs, it is impossible for every order to contain the same item sets. Similarly, if confidence is too high, it assumes that this relationship must always be true. In certain circumstances a confidence close to 100 percent can be used, but for the purpose of this research a moderately high confidence level still provides a strong understanding of the association between items bought together.

In this research, minimum support was .002 and confidence was 0.8 for the analysis of the given data set. A minimum support of .002 was necessary because of the wide scope of item attributes and specifications. The minimum confidence of 0.8 is a moderately high confidence level that would create high accuracy association rules.

### **Scope of Attributes**

There are both advantages and disadvantages to choosing either a wide or narrow scope based on the product attributes. As Company A is a fashion retailer, the data can be analyzed by a single attribute such as color or size, a category or product family, or a SKU item. The SKU item is the most detailed criteria that can be drilled down to because it specifies criteria for all attributes. Focusing on a category such as size is an advantage because it provides the broadest results. The disadvantage is that this is not the most practical approach to positioning inventory across different fulfillment centers. Looking at order profiles by specific SKUs is more precise than looking at size, but it can be too meticulous and time intensive to analyze each SKU when there are a high number of total SKUs available. Product categories are useful attributes to focus on because these have a moderate range of possible combinations. For this

research all given attributes were considered, and the best results were from product category types and from overlapping a few broad attributes which produced interpretable results.

## Results

Each data mining process iteration produces association rules and measures. The results in Figure 10 include premise, conclusion, support, and confidence. For direction in the item set relationship, premise indicates Item A lead to Item B, the Conclusion item. Additional information which can be used for information gain, direction, and probability includes LaPLace, gain, p-s, lift, and conviction are listed in Figure 10.

**Figure 10**

| No. | Premises | Conclusion | Support | Confidence | LaPlace | Gain   | p-s   | Lift  | Conviction |
|-----|----------|------------|---------|------------|---------|--------|-------|-------|------------|
| 13  |          |            | 0.004   | 0.812      | 0.999   | -0.006 | 0.001 | 1.545 | 2.520      |
| 14  |          |            | 0.002   | 0.812      | 0.999   | -0.003 | 0.001 | 1.546 | 2.521      |
| 15  |          |            | 0.003   | 0.813      | 0.999   | -0.005 | 0.001 | 1.548 | 2.536      |
| 17  |          |            | 0.008   | 0.815      | 0.998   | -0.012 | 0.003 | 1.552 | 2.566      |
| 18  |          |            | 0.004   | 0.816      | 0.999   | -0.006 | 0.001 | 1.555 | 2.586      |
| 19  |          |            | 0.002   | 0.817      | 1.000   | -0.003 | 0.001 | 1.556 | 2.594      |
| 20  |          |            | 0.002   | 0.818      | 0.999   | -0.003 | 0.001 | 1.559 | 2.616      |
| 21  |          |            | 0.030   | 0.821      | 0.994   | -0.044 | 0.011 | 1.564 | 2.653      |
| 22  |          |            | 0.004   | 0.824      | 0.999   | -0.005 | 0.001 | 1.568 | 2.691      |
| 23  |          |            | 0.006   | 0.824      | 0.999   | -0.009 | 0.002 | 1.569 | 2.699      |
| 24  |          |            | 0.004   | 0.827      | 0.999   | -0.006 | 0.001 | 1.576 | 2.751      |
| 25  |          |            | 0.004   | 0.829      | 0.999   | -0.006 | 0.002 | 1.579 | 2.780      |
| 26  |          |            | 0.005   | 0.831      | 0.999   | -0.006 | 0.002 | 1.582 | 2.804      |
| 27  |          |            | 0.005   | 0.833      | 0.999   | -0.006 | 0.002 | 1.587 | 2.849      |
| 28  |          |            | 0.002   | 0.837      | 1.000   | -0.003 | 0.001 | 1.595 | 2.920      |

The result of this research is a repeatable process for analyzing customer order profiles and uncovering inventory trends. This research analyzed the orders of a single promotional event for Company A. The information gained can guide Company A in inventory positioning decisions. This

process can be repeated in the future by Company A with additional data sets across numerous seasons or for an annual sales scope of their order profiles.

## Chapter 5

### Conclusion and Recommendations

The research conducted for this thesis was intended to provide insights for inventory positioning and stocking policies for Company A. Understanding the significance of inventory and its influence on the economy and supply chain underscores the importance of inventory decisions. From the data set provided by Company A, a thorough dissection of split orders was conducted in addition to the market basket analysis of order profiles. Deductions from this research include specific item sets frequently purchased together.

The primary conclusion reached was that this is a value-add process that provides Company A information on their customer order profiles to better inform their inventory stocking policies. Based on frequently purchased item sets Company A should stock the high velocity and volume item sets together in their fulfillment centers to reduce split orders. To identify which attributes to focus on, Company A should run a Pareto analysis for which few item attributes drive the most profit. These attributes should then be used to aggregate the order data. This will produce the item sets that will drive inventory stocking policies for their fulfillment centers.

Limitations include the time range of the data set only looked at a single promotional event of Company A. As a fashion retailer, Company A has numerous seasons and the order profiles are potentially not identical from season to season. Recommended further research is to conduct this analysis for each season to understand incongruencies in ordering patterns across seasons.

Additional further research recommended include is a financial cost-benefit analysis of the current inventory positioning to compare cost savings from repositioning inventory based on the results of the order profile analysis. Current costs to consider would include the split shipment costs of additional parcels shipped and transportation costs between fulfillment centers.

**BIBLIOGRAPHY**

Kearney. 34th ed., Penske Logistics, 2023, p. 58, *Council of Supply Chain Management Professionals State of Logistics Report*.



# ACADEMIC VITA

## Grace Moyer

### EDUCATION

**The Pennsylvania State University***Smeal College of Business and Schreyer Honors College*

Bachelor of Science in Supply Chain and Information Systems

Minors in International Business, and Information Systems Management

**University Park, PA***December 2024*

Dean's List 7/7 semesters

### RELEVANT EXPERIENCE

**Honeywell***Sales Inventory Operations Planning Intern***Atlanta, GA**  
*June 2024 – August 2024*

- Improved inventory and order fulfillment efficiency through redistributing excess finished good inventory to distribution centers with firm orders. Calculated opportunities globally within and across regions for a total of \$2.4M in inventory rebalanced
- Identified inventory and demand levels by SKU through a widely-distributed report twice a week. Worked to create automatic data pulls available to planning and sales

**The Hershey Company***Customer Supply Chain Co-Op***Hershey, PA***January 2022 – July 2022*

- Uncovered and analyzed ordering inefficiencies to create and implement recommendations to the sales team to improve the ordering process by reducing supply chain complexity and maximizing container efficiency for a \$20+ million customer
- Simplified and standardized reports for ordering that improved visibility
- Leveraged various data sources to create reports that improve item visibility for customer managers
- Created a new disclosure on Hershey's supply chain water footprint and water scarcity impacts that was included in the 2022 ESG report

**Verizon***The Future of Transportation Project***University Park, PA***August 2022 – December 2022*

- Analyzed current transportation network and cost benefit of small parcel transportation to provide short-term and long-term recommendations based on competitive advantages

**Unilever***New Product Innovation Project***University Park, PA***August 2021 – December 2021*

- Proposed a new product including a market analysis, launch strategy, marketing strategy, and financial analysis

### LEADERSHIP AND INVOLVEMENT

**Centre Region Down Syndrome Society***Treasurer***State College, PA***August 2021 – June 2024*

- Created annual budgets forecasting the income and expenses for a the year
- Managed and improved payment efficiency for a \$42,000 fundraiser

**Institute for the International Education of Students***Emerging Economies Studies***Argentina and Chile***February 2023 – June 2023*

- Analyzed the economic and social impacts of different government and economic systems
- Exposure to how South American businesses operate and grow in global markets

### ADDITIONAL LEADERSHIP/HONORS/SKILLS/INTERESTS

**Leadership:** Chi Alpha *President* May 2023 – December 2024, Omega Chi Sigma *Membership Chair* March 2021 – May 2021**Honors:** Stuart and Michele Rothstein Study Abroad Initiative Scholarship, Schreyer Scholarship for 8 semesters**Skills:** Microsoft Applications (Excel, Access, Power BI, PowerPoint, Word, Teams), SAP, Kinaxis RapidResponse, SQL, Tableau, RapidMiner**Interests:** Photography, Hiking, Board Games, Baking, Basketball, *Psych*, Sudoku, Tradle