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GOODWILL SAN ANTONIO PROJECT

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Executive Summary

The Goodwill San Antonio Project 2023 seeks to provide insights on the impact of Goodwill San Antonio's new production process on accuracy levels in keeping track of items from production to their end designations. To meet this objective, we obtained data for items produced under the Wares department by Goodwill San Antonio from January 2021 to January 2023 and created 3 performance metrics to measure the accuracy levels. These performance metrics measure the discrepancy between item count at production point and at end designation (production percentage error), the percentage of batches with constant item count throughout the production process (percentage of perfect batches), and the percentage of items at the ideal end designation (percentage of sold items).

Our performance metrics showed that despite the production process being an influential factor on accuracy levels, the sensitivity of accuracy levels to the new model implementation varied by store. Certain stores experienced major improvement in production accuracy while other stores continued to experience pre-implementation accuracy levels. As a result, for certain stores, the new model implementation was only somewhat effective in reducing the number of misreported items. However, it significantly increased the percentage of perfect batches. This report presents our findings on the accuracy levels in Goodwill San Antonio's operations across store locations, employees, and product categories within the Wares department using statistical analysis and visualization dashboards. The development of dashboards serves as a tool to provide Goodwill San Antonio with a visual demonstration of its operational performance in terms of both quality and quantity. Additionally, these dashboards are intended to encourage friendly competition amongst stores, departments, and employees.

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I. Introduction

1. Client Organization - Organization’s Purpose & Business Model

Founded in 1945, Goodwill San Antonio is a charity organization that sets out to help the underprivileged of San Antonio by selling repaired used goods and using such earnings to provide them career guidance (Goodwill SA, 2022). After 75 years of operation, the organization currently has services expanding across 24 counties (Goodwill SA, 2022). Through its products and services, Goodwill San Antonio seeks to “help change lives through the power of work” and empowers the community with a skilled workforce and successful businesses (Goodwill SA, 2022).

Despite being a charity organization, Goodwill SA seeks to do good for the people by doing well itself. The organization self-sustains by sourcing local donations and reselling those items in its retail chain. Goodwill employees are trained to classify, repair, and reintroduce products to consumers who then have the opportunity to purchase unique items. As a result, the organization does not rely on suppliers for its inputs and is not subject to the costs of goods sold. The low cost allows Goodwill to offer merchandise at below-market prices to meet the needs of its target individuals. The revenues generated from Goodwill stores then fuel its operations as well as funding for community services.

The combination of all the steps from receiving donations to repurposing them and putting them back on the shelves is referred to as the production process by Goodwill SA. In 2022, Goodwill SA adopted a new production model which is believed to have improved the level of accuracy in its process. The discussion and comparison of Goodwill SA’s old model and new model is detailed in Section 2 - Study of Contextual Information. After an item is produced and put on sale, its shelf life and any related discounts are determined by Goodwill SA’s color system and rotational schedule, which are explained in Section 2 - Study of Contextual Information.

The GoodwilSA system operates as a decentralized network with highly localized stores. Goodwill SA currently has 29 donation locations, 24 retail locations, and an online retail channel on eBay (Goodwill SA, 2022). In addition, the organization has 5 career centers and 5 career academies specifically for their vocational services (Goodwill SA, 2022). While a retail location can also be a donation location and a career center, each physical address of Goodwill SA operates independently, offering a different set of items or specializing in a niche category. Due to their reliance on donations, items are often unique and cannot be found in more than one store. Out of all retail locations, the Fredericksburg Road store has the biggest sales floor and possibly the most diverse product mix, allowing it to become the pilot location for Goodwill SA's new production process.

2. Study of Contextual Information

Rotational Schedule & Color System

Goodwill SA's color-rotational system determines the shelf life and the discounts of each item. The current version of Goodwill SA's color-rotational system has five colors in rotation: orange, yellow, pink, green, and blue. All items processed within one week are assigned to the same color. Items processed the following week will be assigned to the next color in rotation. Once each week's items are assigned a color, they are placed on the retail floor where they have a 5-week shelf life. The items are sold at full price throughout all weeks except for the fourth week when there is a 50% discount. As the 5-week period ends, the remaining items are pulled from the floor. Figure 1 is an example of an advertisement used to announce Goodwill SA's Color of the Week.

Figure 1: *Color of the Week Advertisement*

Table 1: 5-Week Color Schedule

Week One	Items are processed and assigned orange sales tags; these items are then introduced to the retail floor at their full price.
Week Two	Orange-tagged items continue to be on sale at full price.
Week Three	Orange-tagged items continue to be on sale at full price.
Week Four	Orange-tagged items are discounted at 50% off.
Week Five	Orange-tagged items return to full price; all orange-tagged items should be pulled from the floor by the end of the week.

Table 2: Colors' Staggered 5-Week Example Schedule

Week of Year	Orange	Yellow	Pink	Green	Blue
1/1/2023	Week One				
1/8/2023	Week Two	Week One			
1/15/2023	Week Three	Week Two	Week One		
1/22/2023	Week Four	Week Three	Week Two	Week One	
1/29/2023	Week Five	Week Four	Week Three	Week Two	Week One
2/5/2023		Week Five	Week Four	Week Three	Week Two
2/12/2023			Week Five	Week Four	Week Three
2/19/2023				Week Five	Week Four
2/26/2023					Week Five

Note. Table highlighting the staggered starts of each color's 5-week period. No two colors will be on the same week of their 5-week rotational schedule.

Description of the Production Process

Goodwill SA receives donated items from San Antonio locals at designated locations. These items are then pre-sorted into wares, apparel, shoes, books, electronics, or online sales at retail stores that are close to the donation locations. The employees, or "producers," restore the products to their best possible condition and attach Stock Keeping Unit (SKU) tags. These tags allow the products and their associated prices to be scanned into an inventory system, allowing the organization to keep track of the store's inventory levels. At the end of the 5-week period of a batch, SKU tags will have been either sold, pulled, or reconciled. An item is sold if it was purchased by a customer. When an item is pulled, the item is taken off shelves to either be disposed of or sent to Goodwill SA's warehouses for by-the-pound sale. Reconciled items are excess SKU tags that were never assigned to a product and need to be canceled out or reversed in the inventory system. Reconciled items are treated as a unique product category that needs to be removed from the system entirely. Producers are generally assigned to specific departments, so the producers responsible for processing, tagging, and placing Wares goods are the same producers responsible for pulling Wares goods.

Narrow-Scope of Focus - Wares

Our scope of research is restricted to the Wares department of goods processed by Goodwill San Antonio. Wares, short for Housewares, is an extensive department that includes the following SKUs: Dishes, Cups & Glasses, Pots & Pans, Vases & Figurines, Woods, E-Comm, Games, LG Toys, SM Toys, Pictures & Frames, Seasonal, Bed & Bath, Office, Sports, Wicker, Metal, and Plastic.

As early as May 2022, Goodwill SA began implementing a new production model across its stores. With the Wares department being the first and only department to have undergone the transition to the new production model, our research will strictly focus on Wares. Serving as the pilot department, the Wares' success in implementing the new production model and achieving greater accuracy will be the deciding factor for the application of the new production model to other departments.

Old vs. New Production Model

Under the old production model, SKU tags were produced in batches, leading to the issue of unassigned SKU tags. Overtagging requires producers to cancel the excess tag and reassign them as reconciled items. Figure 2 shows how SKU tags are produced in batches under the old production model. Under the new production model, producers only print one SKU tag per item to prevent excess tags. While the new production process is used by the Wares department, the old production model continues to be used by all other departments.

Figure 2: SKU Tags

The new production model was first applied to the Fredericksburg store's Wares department in May 2022. The remaining San Antonio locations waited until October 2022 to transition to the new production model. When each store location transitioned to the new model, the store underwent a migration phase period of four weeks.

II. Research Questions

As mentioned in the previous section, Goodwill SA's stores began transitioning to a new tag-per-item production model in 2022. The goal of our report is to determine how effective this new production model is in improving the accuracy of items' end destinations. Goodwill SA stores frequently deal with issues that result in "missing items.", which may result from scanning errors by cashiers. For instance, if a customer is purchasing five t-shirts and all the t-shirts are priced at $3.99, a cashier might scan one t-shirt five times rather than scan each of the five t-shirts one time. As a result, Goodwill SA will see that a unique item was purchased five times and the remaining four items were never purchased, implying that they are still for sale on the retail floor. Due to human errors, Goodwill SA now has a discrepancy between the collected data and reality. We want to see if discrepancies such as this one are minimized under the new tag-per-item model in comparison to the batch-based model.

Goodwill SA is also interested in having us develop metrics surrounding the production process. Using measures such as total units sold and total sales, Goodwill SA would like to better understand production performance at the levels of store, department, and employee. Once we identify and develop the relevant metrics, we are to create dashboards that display these metrics to employees. These dashboards are intended to encourage healthy competition among individual employees, departments, and store locations. Ideally, the dashboards would be connected to Goodwill SA's database servers, allowing the dashboards to be updated in real-time.

RQ1: Does the new tag-per-item model minimize inaccuracies in the production process?
RQ2: If so, how does the number of inaccuracies in the new production model compare to the number of inaccuracies in the old model?
RQ3: What production process metrics can we identify or develop to encourage friendly competition among employees, departments, and even store locations? With these metrics are we able to answer questions such as "Which employees are producing the most items?" and "Which items sell the most in terms of generated revenue?"

III. Data Overview

For our research, Goodwill SA provided us with five relevant tables: tbl_ProductionSkuAgent, tbl_ProductionBin, tblEmployee, tbl_Stores, and tblColorSched. The tables are listed below in Table 3.

Table 3: Data Overview

Table	Columns	Rows
tbl_ProductionSkuAgent	21	1,572,627
tbl_ProductionBin	5	1,544,665
tblEmployee	17	2,544
tbl_Stores	28	3
tblColorSched	7	3,161

1. tbl_ProductionSkuAgent

The ProductionSkuAgent table provides information on individually tagged batches produced by various Goodwill SA stores and keeps track of the total number of produced tags within a batch and the total value of the batch. The ProductionSkuAgent table includes a batch's intended production date, actual production date, system production ID, the ID of the employee responsible for the batch, the ID of the store responsible for the batch, and the assigned SKU. The assigned value of a single item is the total production value divided by the total number of produced tags. Other important variables corresponding to the end designation of produced tags include the number of pulled tags, the number of reconciled tags, and the number of sold tags.

The ProductionSkuAgent table is central to creating our performance metrics. We will be using the columns ProdAmount, PullAmount, ReconAmount, and SoldAmount to calculate our production accuracy measure. Figure 3 presents the percentage error formula that we will use to create our accuracy measures.

Figure 3: Percentage Error Formula

$$\sigma = \left| \frac{(Pull + Sold + Reconciled) - Produced}{Produced} \right| \times 100\%$$

Given that the sum of values from the PullAmount, ReconAmount, and Sold amount columns should equal the value of ProdAmount, our formula measures whether there is a difference between the two. Any difference other than 0 will be measured against the number of total batch produced, or ProdAmount. **In other words, the production percentage error represents the inaccurately recorded amount as a portion of the expected amount produced.**

The value for production percentage error be as low as 0% but can exceed 100%. A production percentage error of 0% represents perfect batches, or batches where the sum of Pull, Sold, and Reconciled equals the ProdAmount. Using the ProdPercError variable, we created PerfectBatch - a binary variable with two factor levels 0 and 1 to indicate whether a batch is perfect or not. **The PerfectBatch variable allowed us to calculate the percentage of perfect batches among all the batches produced by each employee in each SKU at each store by day or month.**

2. tbl_ProductionBin

The ProductionBin table provides information on individual production bins. The ProductionBin table includes details such as the system production ID, the corresponding line number, the ID of the store where the bin was originally produced, the bin color, and the bin's item price.

The ProductionBin table is relevant in identifying potential inaccuracies related to item pricing based on the table's Price column. While an equivalent column is not included in the ProductionSkuAgent table, we calculated the value or price of a produced item using the columns ProdAmount and ProdValue. Theoretically, this calculated price should be the same as the given price provided by the ProductionBin table. If the given price and calculated price are not equal, then there is an inaccuracy in the system. Similar to the production amount accuracy measure discussed above, we will also use the percentage error formula which is shown in Figure 4 to measure the inaccurate amount. **This price accuracy measure represents the difference between the expected price and the actual price of a batch as a percentage of the expected price.**

Figure 4: Price Accuracy Measure

$$\sigma = \left|\frac{Price - (Production\ Value\ \div Production\ Amount)}{(Production\ Value\ \div Production\ Amount)}\right| \times 100\%$$

3. tblEmployee

The Employee table provides information on individual Goodwill SA employees, including the employee's ID, first name, last name, user ID on the production system, corresponding StoreID, and contact information. Contact information does not contribute to addressing our research questions, so columns such as Addr1, Phone and Email will be dropped from our final combined table. The main purpose of the Employee's table is to provide us with employees' IDs and their names, the latter of which will be beneficial in creating dashboards for our performance metrics. The addition of this table's data in the merged data frame will enable store employees to identify their performance figures and measure them up against their coworkers' numbers.

One important detail to note for this table is that UserID is a unique key while EmpID is not. EmpID can change if an employee changes store locations or resumes working after a prolonged period of absence, leading to an employee being associated with multiple EmpIDs. Unlike EmpID, an employee's UserID does not change across different store locations or timeframes. UserID refers to the ID an employee uses to log into the PoS system and also serves as an employee's HR badge number. Consequently, there will only ever be one UserID per Goodwill SA employee.

Other variables that may be relevant in our analysis are an employee's security level and whether or not an employee is disabled within the Point-of-Sale (PoS) system. Security level directly relates to an employee's position and his access to the PoS system. For example, 0 indicates no form of security access, 50 is associated with a cashier position, and any number above 70 is associated with a managerial position. A zero in SecLevel translates to a one in DisabledYN as 1 indicates an employee is disabled within the PoS system. Any non-zero value in SecLevel translates to 0 in DisabledYN, meaning that the employee is not disabled within the system. Utilizing either SecLevel or DisabledYN will be useful in analyzing the effect of employees' access to the PoS system on inaccuracies in Goodwill SA's database.

4. tbl_Stores

The Store table provides information on Goodwill SA's individual stores and only contains three columns: StoreID, StoreName, and Address. The Store table mainly serves to provide store names, which are not available in ProductionSkuAgent. Having stores' names will be beneficial in creating dashboards for our performance metrics.

5. tblColorSched

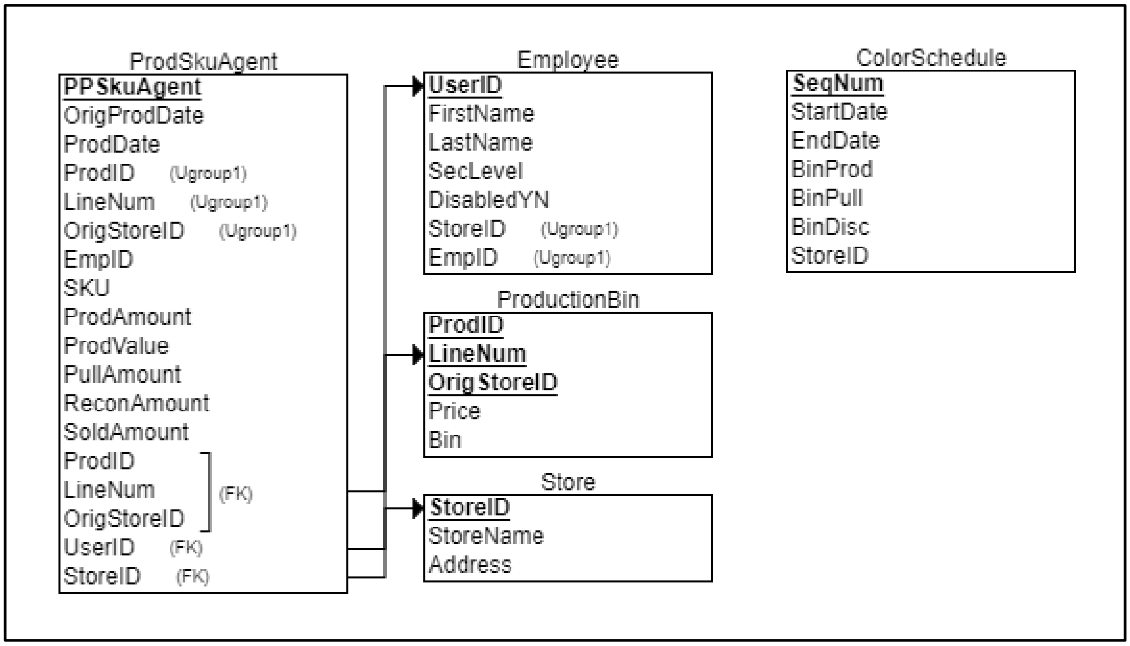
The ColorSchedule table provides information on Goodwill SA's color schedule. Information from the ColorSchedule table includes details such as the bin colors being produced, pulled, and discounted for a particular week of the year. While Color of the Week is likely to not be relevant in addressing our research questions, it serves to help us better understand a product's lifecycle.

IV. Merging of Data

In Microsoft SQL Server Management Studio (SSMS), we merged four of the five tables together to form one larger table. We did not merge the ColorSchedule table with the other tables as ColorSchedule's data was not relevant to addressing our research questions. The ProductionBin table already provides the bin colors associated with individual tag batches and further addition of ColorSchedule columns will cause redundancy.

We performed left joins to merge the tables ProductionSkuAgent, ProductionBin, Employee, and Store into one consolidated table using Microsoft SSMS. The left joins allowed us to maintain all 1,572,627 tag batch records of ProductionSkuAgent which was important as our research's scope focuses on the individual tag batches. Figure 5 shows the relational schema of the given Goodwill tables and how four of the five tables were joined together. The Relational Schema contains the most relevant columns for our analysis.

Figure 5: Goodwill SA Relational Schema



After performing the merge, we eliminated observations with physical production dates (OrigProdDate) after December 17, 2022, as they represented batches with incomplete 5-week cycles. The number of observations reduced from 1,572,627 rows to 1,176,950 rows. Had we included these observations, our results would have projected higher error rates and consequently, inaccurately represented the overall data.

V. Data Cleaning

1. Data Exploration

An overview of all columns in the consolidated table that are relevant to addressing the research questions is summarized in Table 4 below. The table consists of 5 columns, including the variable names, the data type of each variable, the number of unique values and missing values per variable, and the corresponding missing value percentages. All information included in Table 4 describes raw data or data before the cleaning process.

Table 4: Variable Overview

Column	Data Type	Total Unique Values	NA count	NA percentage
PPSKUAgnt	integer	1,572,627	0	0
OrigProdDate	date	707	0	0
ProdDate	date	712	0	0
Month	integer	12	0	0
Year	integer	3	0	0
ProdID	integer	96,612	0	0
LineNum	integer	459	0	0
EmpID	character	1,150	0	0
StoreID	integer	24	0	0
SKU	character	16	0	0
ProdAmt	numeric	212	0	0
ProdValue	numeric	3,553	0	0
PullAmt	integer	68	0	0
ReconAmt	integer	107	0	0
SoldAmt	integer	258	0	0
Bin	character	7	102	0.01
Price	numeric	572	0	0
StoreName	character	24	0	0
Address	character	24	0	0
FirstName	character	564	62	0.01
LastName	character	579	261	0.02
UserID	character	864	0	0
SecLevel	character	12	705	0.06
Disabled-Y/N	character	3	705	0.06

2. Addressing NA Values (Missing Values)

NAs or missing values were addressed on a column-by-column basis. A summary of columns with NA values and descriptions of our approach to each case is provided in Table 5 below.

Table 5: Handling NA Values

Column	Data Cleaning
Bin	Replaced NA values with "No Color".
Price	Replaced NA values with the quotient of ProdValue divided by ProdAmount correspondingly.
FirstName	All NA values were associated with two employees who also had LastName NA values. We retained these observations and impute “Unnamed” for the FirstName NA values.
LastName	All NA values were associated with three employees: the two employees mentioned under FirstName and a third employee who did have a first name. For the two employees that had NA values for both FirstName and LastName, we imputed “Employee One” and “Employee Two.” For the third employee, we will impute “Unknown” .
SecLevel	Replaced NA values with level 0 (no security access) and grouped individual levels into bigger groups.
Disabled-Y/N	Replaced NA values with level 1 (access disabled due to security level 0).

3. Identifying & Addressing Outliers

For numerical variables including ProdAmount, ProdValue, PullAmount, SoldAmount, ReconAmount, and Price, we calculated the Lower Bound and Upper Bound for each variable using the Interquartile Range. We then used density plots and box plots to observe data distribution. Any values to the left of the Lower Bound and to the right of the Upper Bound were replaced with the mean of values within the two bounds of each variable.

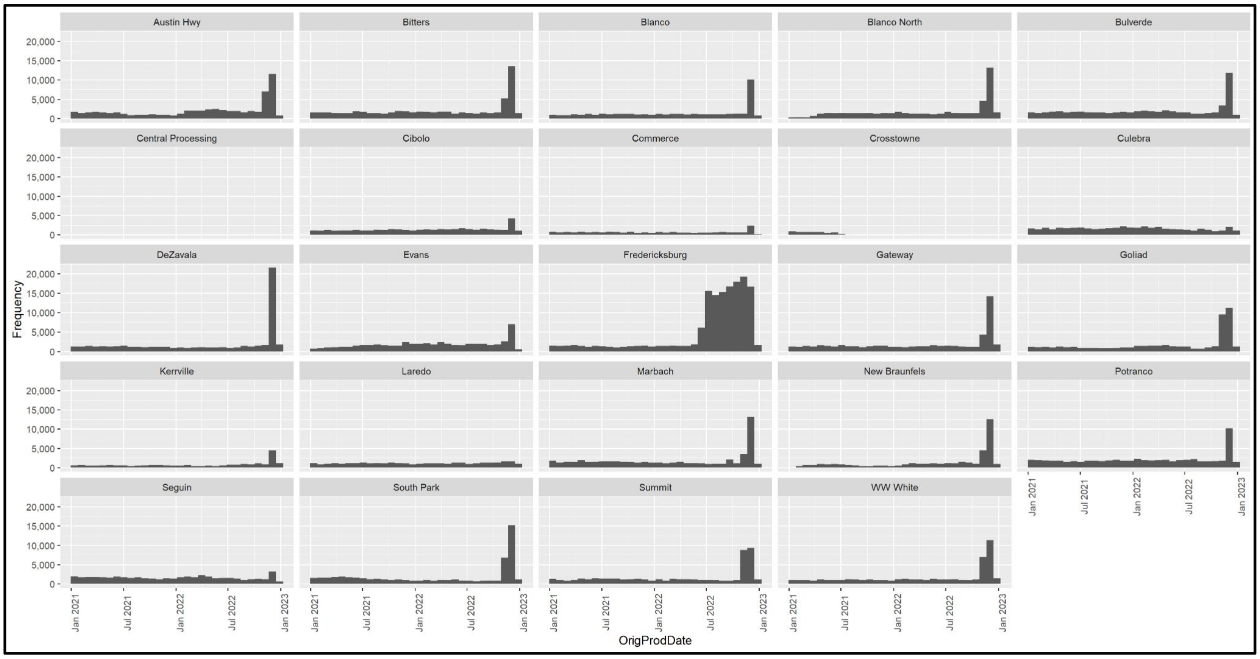
4. Transformations

We performed data transformations related to the creation of new variables: ProdPercError, PricePercError, and PrePostModel. ProdPercError and PricePercError were the coded variable names for the production and price accuracy measures discussed earlier in the Data Overview section. The third variable, PrePostModel, was created using data not from the five given tables so it was not introduced with a particular table.

We created PrePostModel after noticing a pattern in the frequency of OrigProdDate. When looking at the frequency of OrigProdDate by store, we saw that prior to a particular date, the frequency never exceeded a certain threshold. However, past that particular date, OrigProdDate's frequency immediately shot up and exceeded the threshold. We believed this jump in production was associated with the implementation of the new production model across Goodwill SA's stores: stores began transitioning from a model where employees were producing multiple tags per batch to a model where employees were producing only one tag per batch. Consequently, we created a variable related to this change to provide valuable insight for our analysis.

Figure 6 displays OrigProdDate histograms faceted by StoreName, allowing us to directly observe when batch production rapidly increased for a store and indirectly observe when a store implemented the new production model. Since estimating the transition date for each store can affect the accuracy of our analysis, we asked Goodwill SA to provide us with the formal model implementation dates.

Figure 6: Frequency of Produced Batches



Goodwill SA provided us with the new production implementation dates shown in Table 6. Using these implementation dates with the corresponding store locations, we were able to create PrePostModel through the use of a conditional ifelse statement.

Table 6: Model Implementation Dates by Store

Date	Store ID	Store Name
6/23/2022	154	Austin Hwy
6/19/2022	150	Bitters
7/12/2022	125	Blanco
6/26/2022	146	Blanco North
8/3/2022	159	Bulverde
7/1/2022	188	Cibolo
6/18/2022	128	Commerce
6/24/2022	157	Culebra
8/17/2022	152	DeZavala
7/14/2022	160	Evans
6/18/2022	120	Fredericksburg

Date	Store ID	Store Name
9/19/2022	158	Gateway
9/25/2022	155	Goliad
9/7/2022	186	Kerrville
12/13/2022	156	Laredo
6/20/2022	127	Marbach
7/12/2022	151	New Braunfels
7/13/2022	183	Potranco
6/18/2022	126	Seguin
7/10/2022	153	South Park
6/18/2022	129	Summit
11/8/2022	184	WW White

5. Other Cleaning Methods

We checked for typos in all categorical variables and made corrections as appropriate.

During the data cleaning process, we applied binning to the SKU column. The original categorization of SKU contained certain categories that were more detailed and narrowly focused relative to the other categories. Narrowly-focused categories such as “bike”, “Bike Accessories”, and “Wares blue bin” only contained 19, 1, and 1 instances, respectively. When a column contains categories with very low frequencies, those categories will not have a significant effect on a response variable. Binning addresses this issue by consolidating similar categories into a single category to improve overall model quality.

Another reason we applied binning to the SKU column was the new production model itself. Prior to the new production model’s implementation, the only SKU that should have existed under the Wares department was “Wares.” and new SKUs should only appear after the new model’s implementation. However, some SKUs with few observations existed prior to the implementation binning allowed us to consolidate these problematic SKUs under “Wares”. As a result, we were able to resolve model quality issues and adjust the SKUs to reflect the pre- and post-implementation reality.

Table 7 provides a list of original SKU Categories and their corresponding frequencies within the dataset. The red-highlighted categories were combined into the green-highlighted Wares category.

Table 7: Original SKU Categories

SKU Category	Count
Bed/Bath	13,689
bike	19
Bike Accessories	1
Bikes	10
Cups/Glass	31,610
Dishes	25,114
EASTER499	120
EASTER699	236
EASTER999	123
EasterBasket	207
EASTEROPEN	10
Games	5,750
Metal	29,010

SKU Category	Count
Office	13,943
Pictures/Frames	26,028
Plastic	29,940
Pots/Pans	15,302
Seasonal	28,859
Sports	7,473
Toys	42,246
Vases/Figurines	40,763
Wares	837,047
Wares blue bin	1
Wicker	7,795
Wood	21,654

6. Descriptive Statistics

Descriptive statistics for both numeric and categorical variables in the consolidated table are provided in Tables 8 and 9 below. All information included in both tables describes raw data or data before the cleaning process. The statistics for numerical variables include the minimum value, the median, the mean, and the standard deviation. The statistics for categorical variables include only their relative total number of levels. We did not provide the proportions of individual levels due to the large number of levels some factors have. Variables that are not listed in either Table 8 or Table 9 are data that do not directly contribute to addressing the research questions but serve to further clarify the observations (metadata). Such data include ID columns (PPSKUAgnt, ProdID, EmpID, UserID, StoreID), time stamps (OrigProdDate, ProdDate), and employees' additional information (FirstName, LastName).

Table 8: Descriptive Statistics for Numerical Variables

Variable	Min	Median	Mean	Stdev	Max
ProdAmt	1	2	10.89	19.95	5,050
ProdValue	0	17.94	41.23	142.07	62,860
PullAmt	0	0	0.15	1.15	263
ReconAmt	0	0	0.36	2.43	246
SoldAmt	0	1	7.41	13.26	772
Price	0	3.99	6.62	31.7	19,399

Table 9: Descriptive Statistics for Categorical Variables

Variable	Total Levels
Month	12
Year	3
SKU	25
Bin	7
StoreName	24
Address	24
SecLevel	12
Disabled-Y/N	3

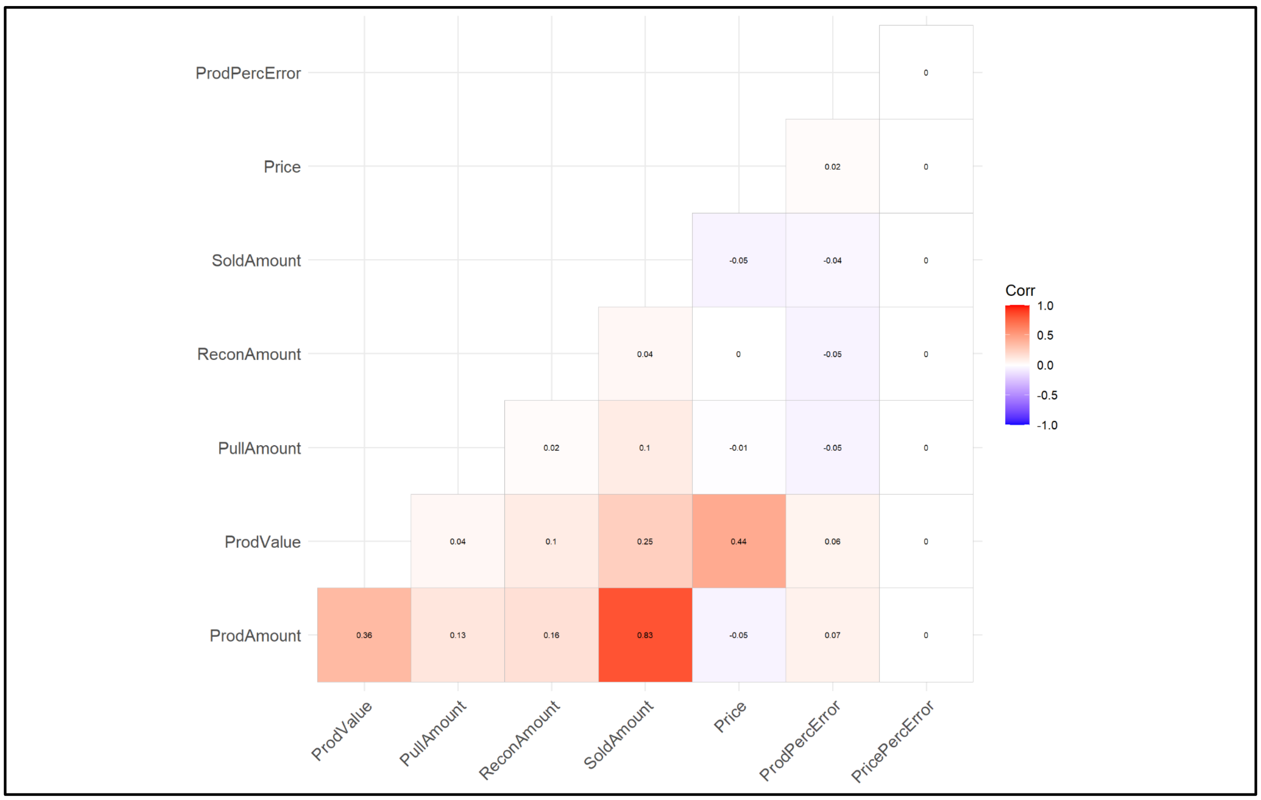
7. Bivariate Analysis

After cleaning the original variables and creating new variables, we performed bivariate analysis on our numeric variables: ProdAmount, ProdValue, PullAmount, ReconAmount, SoldAmount, Price, ProdPercError, and PricePercError. For the bivariate analysis, we created a correlation matrix to see the correlation coefficients between all the possible pairs of our numeric variables. This correlation matrix is displayed below as Figure 7.

In the correlation matrix, vibrant red tiles indicate a strong, positive correlation between two variables whereas vibrant blue tiles indicate a strong, negative correlation.

Pale-colored or white tiles indicate a weak correlation between two variables. Looking at Figure 7, only three of the twenty-eight correlation coefficients have absolute values greater than 0.30. These correlation coefficients are 0.36, 0.44, and 0.83 for the pairs ProdAmount-ProdValue, ProdValue-Price, and ProdAmount-SoldAmount, respectively. Consequently, we know there are weak, positive correlations between ProdAmount and ProdValue and between ProdValue and Price; the only high, positive correlation exists between ProdAmount and SoldAmount. The remaining twenty-five correlation coefficients imply a negligible correlation for the other variables pairs, especially correlation coefficients relating to PricePercError as they are all 0.

Figure 7: Post-Data Cleaning Correlation Plot



VI. Analytical Methods

This section discusses the analytical methods used to address our three research questions. Research Questions One and Two are addressed together as we mainly used a regression-based model to answer these two questions. Research Question Three is addressed on its own as this question is more closely related to our production process metrics and dashboards.

1. Research Questions One & Two

To answer our first two research questions, we chose to build regression-based models with either ProdPercError or PricePercError serving as a model's response variable. In terms of predictor variables, we limited the model to those that could 1) potentially impact ProdPercError and PricePercError and 2) allow for a reasonable level of interpretability with our model. For instance, while we thought including an employee's unique UserID could provide some insight into whether or not certain employees generate inaccuracies, our model would be inundated with 886 UserID factor levels. As a result, we decided not to include UserID as a predictor in our model. The final variables included as predictors in our model are the following: ProdAmount, Month, Year, StoreID, SKU, SecLevel, and PrePostModel.

Factor Releveling

We assigned a base level to all unordered factors as it could prove useful to the interpretation of the model's coefficients. Using a factor level related to the pre-implementation period as the base means that all the generated post-implementation level coefficients would be in reference to the pre-implementation base level.

Assuming that the new model minimizes inaccuracies, we would expect post-implementation level coefficients to be negative to indicate either a lower production or price percentage error. A positive, post-implementation level coefficient indicates an increase in production or price percentage error in the post-implementation period, implying the new model does not minimize but increases inaccuracies in the production process. We assigned a base factor level to four of the model's categorical variables: StoreID, SKU, SecLevel, and PrePostModel. For the variables StoreID, SKU, SecLevel, and PrePostModel, we assigned “120,” “Wares,” “0,” and “Pre” as the base factors levels, respectively.

2. Research Question Three

Metrics Development

To track performance as well as encourage healthy competition among employees, departments, and store locations, we have developed several performance metrics that measure production value, production error percentage, and percentage of perfect batches by employees, SKUs, and stores. We implemented the performance metrics using the given data, specifically the PrePostModel, OrigProdDate, StoreName, SKU, UserID, FirstName, LastName, ProdAmount, ProdPercError, and PerfectBatchPerc variables. The numerical variables (ProdAmount, PullAmount, ReconAmount, ProdPercError) were grouped by a combination of day, store location, SKU, and employee to calculate an aggregated sum or average of each grouping. The aggregated sum is applied to ProdAmount whereas the aggregated average is applied to ProdPercError and PerfectBatchPerc.

Metrics Visualizations

The results from developing performance metrics are then visualized using Tableau worksheets and dashboards. We present the sum or average of numerical variables aggregated by categorical variables and include filters such as Month, Year, StoreName, or SKU to allow for drilling down into a specific category. Additionally, we separated several of the aggregated results by pre- and post-model implementation, allowing us to easily highlight the impacts of the new model. Our visualizations employ bar charts, column charts, bubble charts, and line graphs for an intuitive read of the data by viewers. This report contains two main types of visualizations: those whose main purpose is to highlight the impacts of the newly-implemented production model, and those that provide a snapshot of Goodwill SA’s performance organization-wide and by store, SKU, and employee.

VII. Results & Discussion

This section discusses the results obtained from the analytical methods used to address our three research questions. Research Questions One and Two are addressed together as we mainly used a regression-based model to answer these two questions. Research Question Three is addressed on its own as this question is more closely related to our production process metrics and dashboards.

1. Research Questions One & Two

Most Influential Variables Affecting Production Accuracy

Our first two research questions were 1) Does the new tag-per-item model minimize inaccuracies in the production process? and 2) If so, how does the number of inaccuracies in the new production model compare to the number of inaccuracies in the old model? To address these questions and see how components of Goodwill SA's production process influenced system inaccuracies, we created two regression-based models: one with the response as ProdPercError and one with the response as PricePercError. With ProdPercError, we sought to understand which production process components encouraged or prevented the number of sold, pulled, and reconciled items from equaling the number of produced items. We used PricePercError to examine which components prevented an item's assigned price from being the same as the item's corresponding per-item batch production value.

For our ProdPercError model, all but one of the variables' factor levels were determined to be statistically significant at an alpha level of 0.001. The lone factor level, StoreID155 or Goliad, had negligible statistical significance. The statistically significant factor levels were related to the following categorical variables: OrigProdYear, StoreID, SKU, SecLevel, and PrePostModel. As discussed in the section *Analytical Methods*, we assigned "120," "Wares," "0," and "Pre" as the base factors levels for StoreID, SKU, SecLevel, and PrePostModel, respectively. The model's intercept of 43.798 is developed around these base levels, so we can interpret 43.798% as the production percentage error for batches produced at 1) Fredericksburg 2) prior to the store's implementation date 3) under the Wares SKU 4) when the producing employee's SecLevel is 0. Consequently, the model's intercept serves as a base case that we can relate back to when analyzing changes in categorical variables. For instance, when comparing the factor level StoreID112 to the base case, we would interpret StoreID112's coefficient estimate, 23.172, as a 23.172 percentage point increase in production percentage error for batches produced at Crosstowne relative to those produced at Fredericksburg. Consequently, we would say Crosstowne on average has a production percentage error of 66.97% and is associated with higher percentage errors relative to Fredericksburg given all other variables are held constant.

Since we had a total of 56 statistically significant factor levels, we did not include the OrigProdMonth factor levels in Table 10 as they all indicated a decrease in percentage error of around 9.5 to 13%. In Table 10, we see the first variable listed is ProdAmount. As a numeric variable, ProdAmount's coefficient tells us that for every 100 items produced within a batch, ProdPercError increased by 3.8%. As the new model had employees move away from producing many items per batch to only producing one item per batch, this result implies an improvement in the production process in terms of minimizing inaccuracies. Rather than producing a batch of 100 items that increases production percentage error by 3.8%, we instead produce a batch of one item that only increases production percentage error by 0.038%.

In Table 10, we also see that whereas some stores experienced a decrease in production percentage error, other stores were associated with an increase in production percentage error relative to Store 120 or Fredericksburg. Specifically, looking only at the stores statistically significant at 0.001 and not including Central Processing (Store 1154), Store 112 or Crosstowne experienced the greatest increase, 23.17%, in production percentage error relative to Store 120's production percentage error. The store with the greatest decrease in production percentage error relative to Store 120 was Store 156 or Laredo, with a decrease of 16.32%.

In terms of SKUs, relative to the original Wares SKU, all other SKUs were associated with a decrease in production percentage error. For instance, several SKUs such as Dishes and Pots/Pans had decreases in production percentage error as large as 11.61% and 13.86%, respectively. The fact that all of the SKUs implemented with the new production model experienced a decrease in production percentage error relative to the pre-implementation SKU of Wares implies an accuracy improvement in the production process following the new model's implementation.

Looking at our created variable PrePostModel in Table 10, we see that batches produced in the post-implementation period experience a decrease in production percentage error of 2.84%. Along with the coefficients of ProdAmount and SKU factor levels, the coefficient of the factor level Post further suggests that Goodwill SA's production process experiences an improvement in accuracy with the implementation of the new production model.

Table 10: ProdPercError Model Results

Factor Level	Coefficient Estimate	Significance Level
(Intercept)	43.798	***
ProdAmount	0.038	***
OrigProdYear2022	3.047	***
StoreID112	23.172	***
StoreID125	8.525	***
StoreID126	-5.922	***
StoreID127	-3.995	***
StoreID128	16.674	***
StoreID129	2.155	***
StoreID146	-1.303	***
StoreID150	-2.712	***
StoreID151	-1.992	***
StoreID152	-3.953	***
StoreID153	-8.683	***
StoreID154	11.355	***
StoreID155	-0.044	
StoreID156	-16.329	***
StoreID157	-8.853	***
StoreID158	-7.029	***
StoreID159	5.145	***
StoreID160	1.457	***
StoreID183	-11.464	***
StoreID184	-5.805	***

Factor Level	Coefficient Estimate	Significance Level
StoreID186	2.018	***
StoreID188	-7.485	***
StoreID1154	24.871	***
SKUBed/Bath	-2.910	***
SKUCups/Glass	-10.084	***
SKUDishes	-11.618	***
SKUGames	-7.867	***
SKUMetal	-9.749	***
SKUOffice	-3.347	***
SKUPictures/Frames	-7.085	***
SKUPlastic	-10.853	***
SKUPots/Pans	-13.869	***
SKUSeasonal	-10.126	***
SKUSports	-2.159	***
SKUToys	-5.702	***
SKUVases/Figurines	-9.336	***
SKUWicker	-10.563	***
SKUWood	-9.935	***
SecLevel10to25	-2.993	***
SecLevel50	-4.753	***
SecLevel70andAbove	-4.572	***
PrePostModelPost	-2.849	***

Note. Under the Significance Level column, \`***\`, \`**\`, \`*\`, and \`.\` indicate a factor level is statistically significant at alpha levels of 0.001, 0.01, 0.05, and 0.1, respectively.

For our PricePercError model, there were only two statistically significant factor levels in comparison to the ProdPercError model: StoreID127 (Marbach) and StoreID188 (Cibolo). Store 127 was significantly significant at an alpha level of 0.01 whereas Store 188 was only significantly significant at an alpha level of 0.1.

Below in Table 11, both Stores 127 and 188 experience an increase in price percentage error relative to Store 120 or Fredericksburg by 0.0021% and 0.0014%, respectively. While our PricePercError model is overall inconclusive, the statistically significant increases in price percentage error experienced by Stores 127 and 188 imply that these two stores have pricing inaccuracy issues not experienced by other stores. Consequently, we suggest further investigation into Stores 127 and 188 to obtain a better understanding of why these stores are struggling in terms of pricing accuracy.

Table 11: PricePercError Model Results

Factor Level	Coefficient Estimate	Significance Level
StoreID127	0.0021054205	**
StoreID188	0.0014313191	.

Note. Under the Significance Level column, \`***\`, \`**\`, \`*\`, and \`.\` indicate a factor level is statistically significant at alpha levels of 0.001, 0.01, 0.05, and 0.1, respectively.

Measure Production Accuracy Pre- and Post-Implementation

To best gauge the new model's effect on inaccuracies in the production process, we created visualizations showing the production percentage errors of three store groups: the new model's early adopters (June-July transition), followers (August-October transition), and late adopters (November-December transition). Two representative stores were chosen from each group: Fredericksburg and Bitters represent the early adopters, Bulverde and De Zavala represent the followers, and WW White and Laredo represent the late adopters.

Figure 8 shows the average error in production amount by store before and after the implementation of the new production model using clustered columns. For 5 out of 6 stores, the inaccuracies in production amounts have decreased after the adoption of the new model. While the drop was slight for the Fredericksburg and the Bulverde locations, the percentage error for Bitters decreased by half. Laredo was the only store (among the 6 locations) showing no improvement in accuracy after the new production process implementation. The percentage error jumped from 13.61% to 17.28%, meaning that on average, for every 100 items, the number of inaccurately recorded items is ±14 pre-implementation and ±17 post-implementation. This store, however, was the latest store to adopt the transition from the old model to the new model.

Figure 8: Average ProdPercError by Store Pre- and Post-Implementation

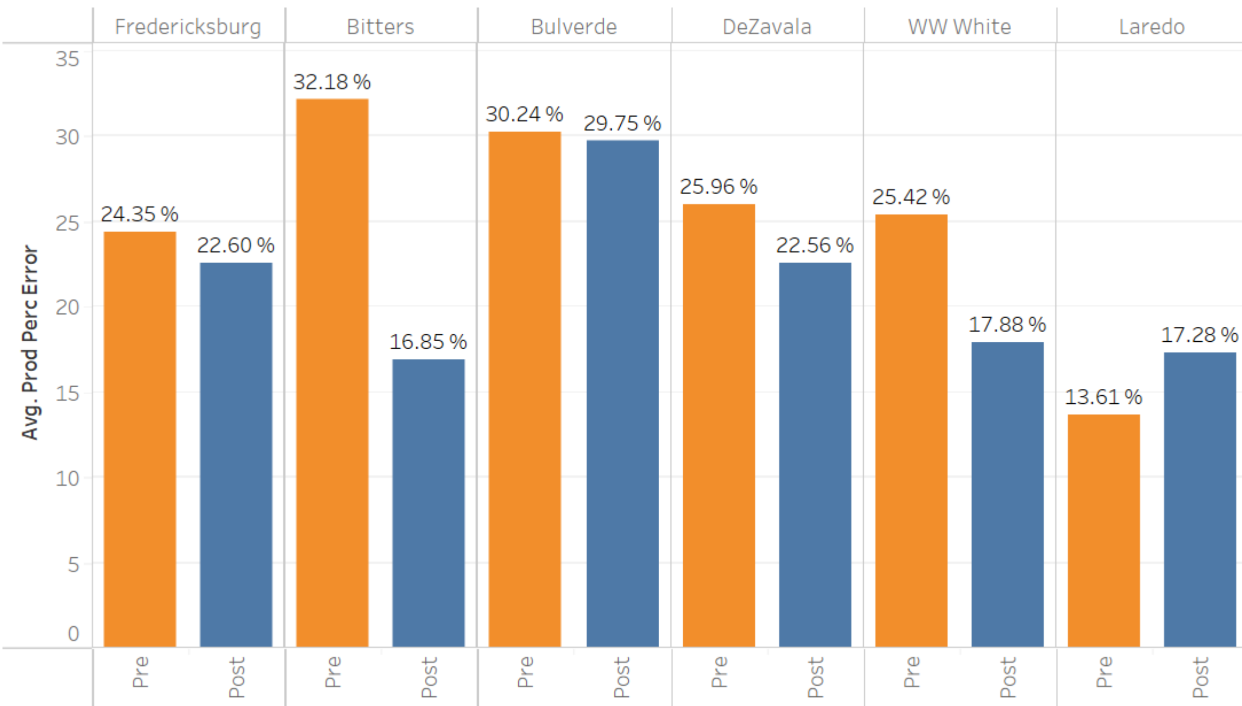
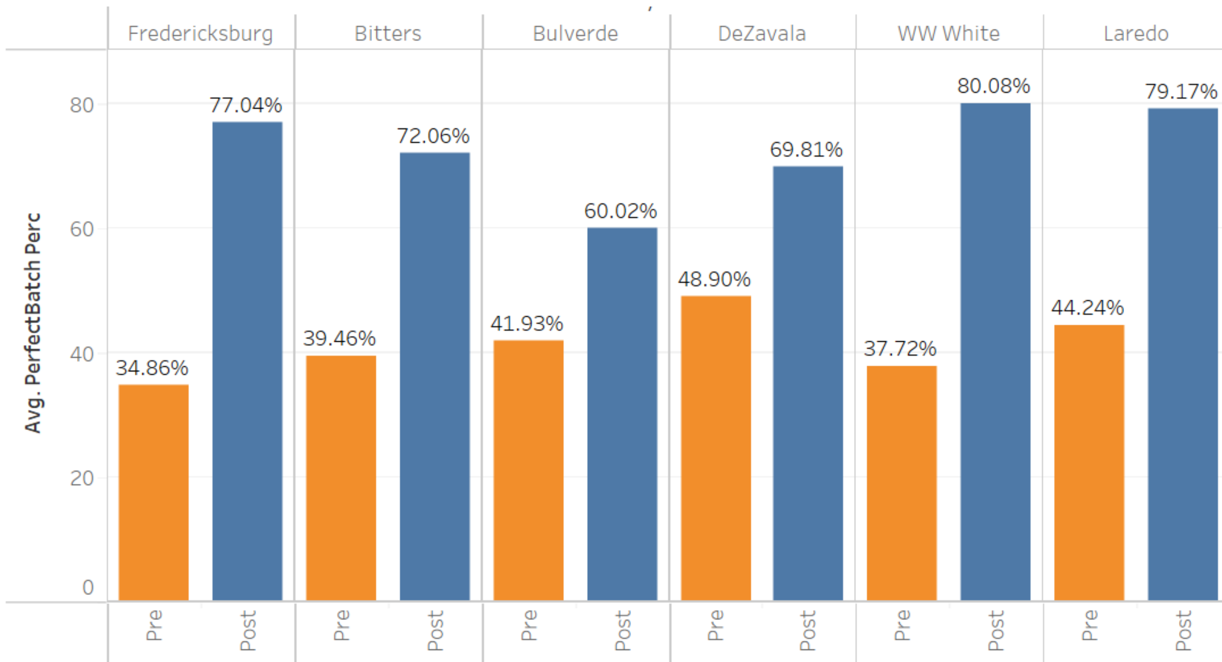


Figure 9 shows the average percentage of perfect batches among all batches produced both before and after the new process implementation. All 6 stores experienced an evident increase in the proportion of perfect batches, or batches with all accurately reported items. The increase was staggering for Fredericksburg and WW White - the percentage of perfect batches more than doubled for both stores. Fredericksburg went from 34.86% to 77.04% while WW White went from 44.24% to 80.08%. Even for the store with the least improvement, De Zavala, the rise in the number of perfect batches was 19%, which was still significant. While the reduction in production percentage errors only showed a somewhat positive trend among the 3 store groups, the improvement in the percentage of accurately reported batches was distinct.

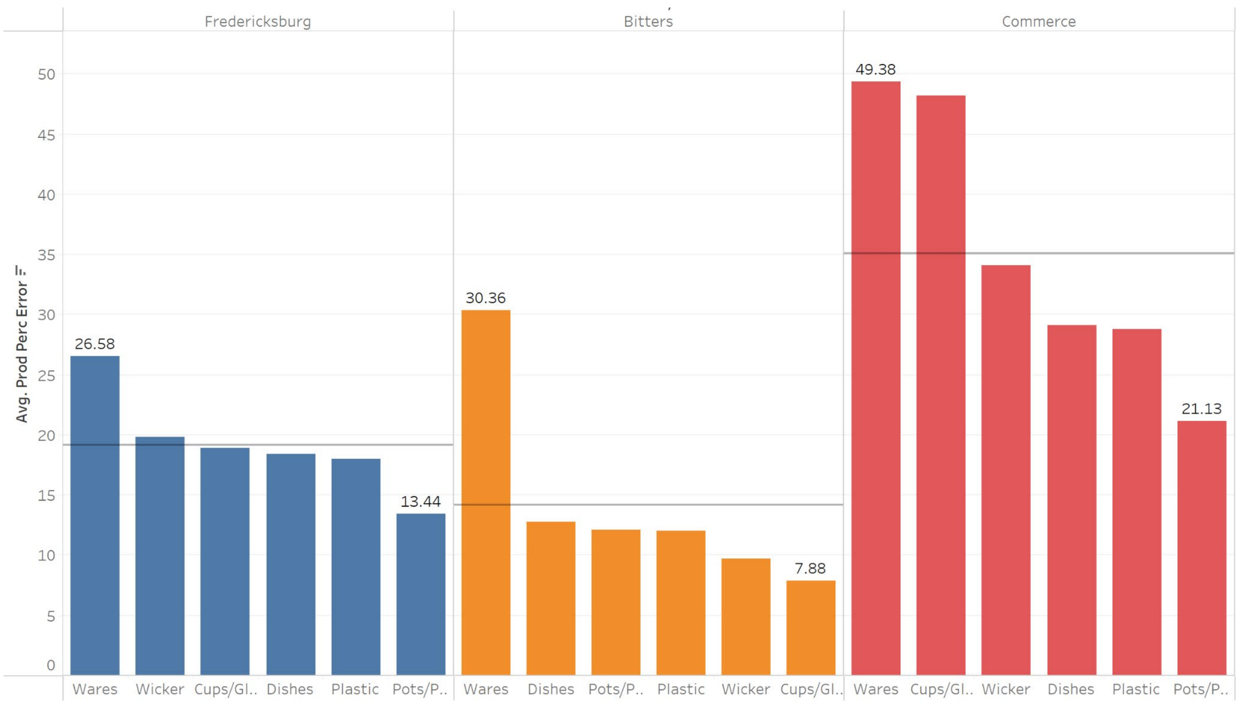
Figure 9: Average Percentage of Perfect Batch by Store Pre- and Post-Implementation



To further observe the new model's impact on accuracy levels, we also compared three early adopter stores as they all had substantial time to adapt to the new model. Fredericksburg, Bitters, and Commerce transitioned to the new process at roughly the same time, with the transition dates being June 18, 2022, for the first two stores and June 19, 2022, for the last store. Figure 10 shows the average production percentage error across the early adopter stores by influential SKUs. The overall trend across these three stores is a decrease in production percentage errors with the new model's implementation.

For Figure 10, across all three early adopter stores, the Wares column is evidently higher than the other SKUs. Given that Wares was the only SKU with pre-implementation data, we see that the post-implementation SKUs have a lower average production percentage error. In fact, for Fredericksburg and Bitters, the newer SKUs' production percentage errors fall below the store's average line whose value was skewed by the high percentage error of Wares. For these two stores, the Ware's production percentage error is responsible for raising a store's overall production percentage error.

Figure 10: Average ProdPercError of Early Adopting Stores by Influential SKUs



2. Research Question Three

We created three dashboards, each with three visualizations to track the performance of the overall Goodwill SA organization, each individual store by employee, and each individual store by SKU. For the purpose of demonstrating the performance metrics, the Fredericksburg location is used as an example of the individual store dashboards.

Organizational Performance Metrics

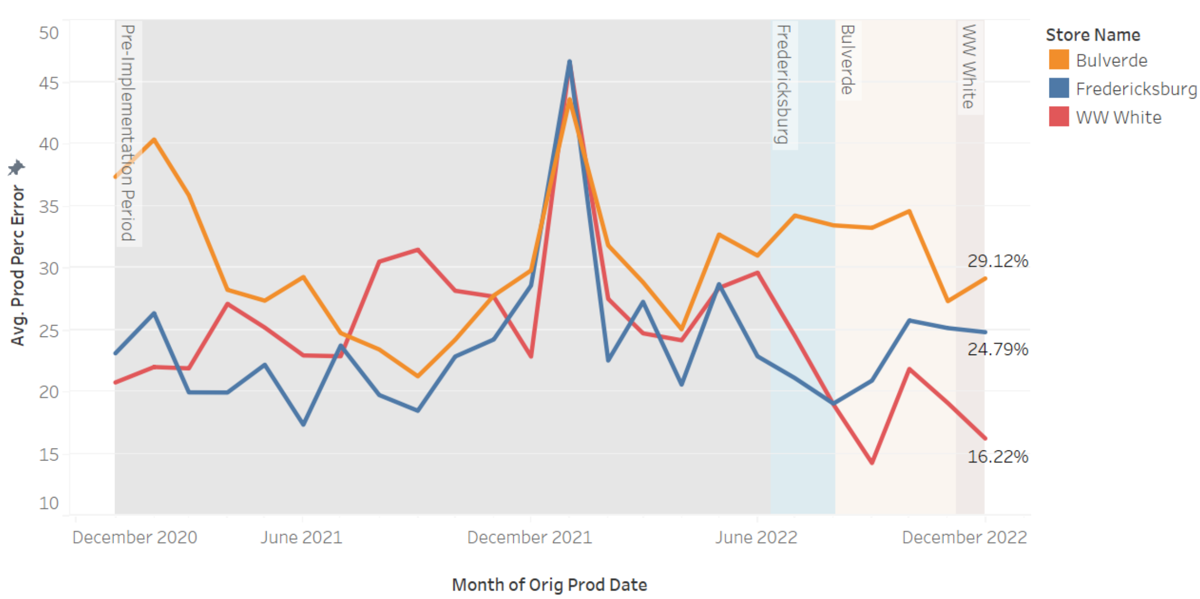
The organizational performance metrics we recommend are as follows:

- Average production percentage error by early, mid, and late adopting stores over time (Figure 11)
- Average production percentage error by influential SKUs over time (Figure 12)

- Average production percentage error relative to production amount by store (Figure 13)
- Sold amount relative to production amount by store (Figure 14)
- Average percentage of perfect batches by store (Figure 15)
- Average percentage of items sold by employee across all stores (Figure 16)

Below in Figure 11, the visualization shows the average production percentage error by three representative stores: Fredericksburg as an early adopter, Bulverde as a mid-adopter, and Laredo as a late adopter. Background reference bands are included in the visualization to highlight when each of the three stores began to implement the new production model. The gray, blue, orange, and red reference bands correspond to the pre-implementation period, Fredericksburg's post-implementation period, and Bulverde's post-implementation period, and WW White's post-implementation period, respectively. For all three stores, we see an abnormal spike in production percentage error around January 2022, with production percentage error reaching as high as 46.64%. We also see production percentage error decrease to a certain extent for each of the stores during their respective post-implementation periods. This trend indicates that the stores' production processes experience an improvement in accuracy with the implementation of the new production model.

Figure 11: Average ProdPercError by Early, Mid, & Late Adopting Stores



In Figure 12, we see the average production percentage error by five representative SKUs: the original SKU Wares, Cups/Glass, Plastic, Vases/Figurines, and Wicker. Background reference bands are included in the visualization to highlight when the first stores began to implement the new production model. The gray reference band corresponds to the pre-implementation period and the blue reference band corresponds to when stores began implementing the new model. Similar to Figure 11, we see an abnormal spike in Wares' production percentage error around January 2022, with a production percentage error of 44.93%. For all of the newer SKUs, we see production percentage error decrease from the start to the end of the post-implementation period. This trend of improvement in production percentage error with the newer SKUs further substantiates Goodwill SA's production processes experience an improvement in accuracy with the implementation of the new production model.

Figure 12: Average ProdPercError by SKUs for All Stores Pre & Post-Implementation

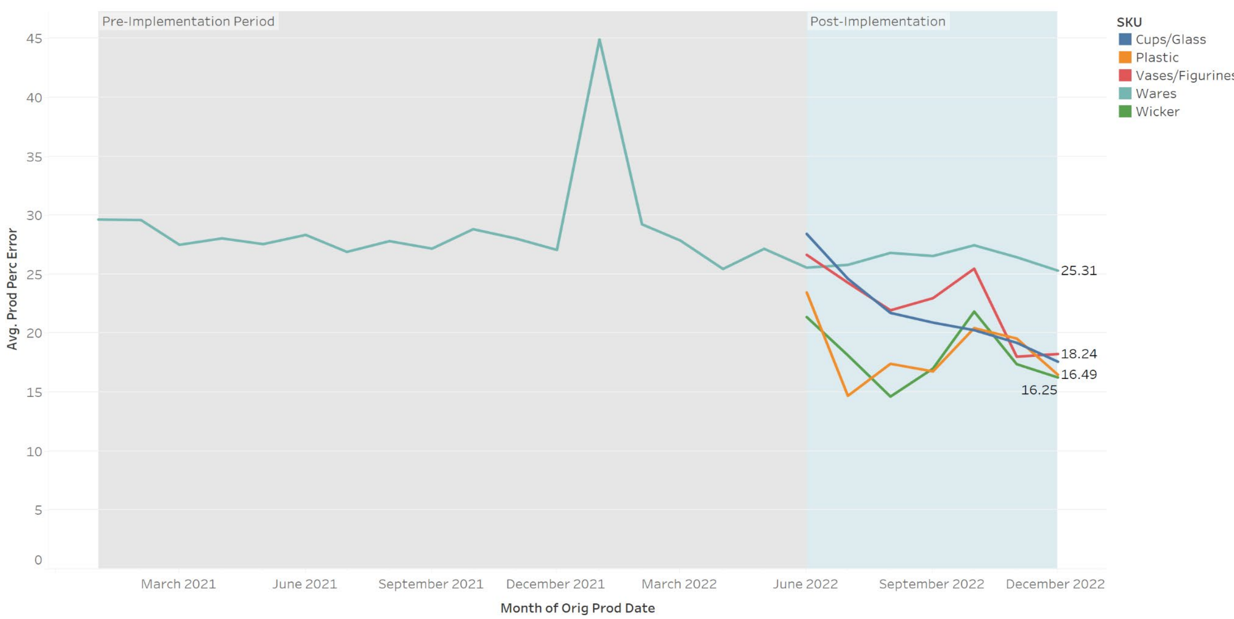


Figure 13 shows the average production percentage error relative to the production amount in May 2022 by store. Figure 13 contains a snapshot of the historical data to highlight store performance one month prior to June 2022, the month when the new production model began being implemented at Goodwill SA's stores. A bar's height represents the total amount of items produced by a store, whereas a bar's color represents the average production percentage error. Vibrant blue corresponds to a low production percentage error, vibrant magenta corresponds to a high production percentage error, and gray references an assigned production percentage error threshold of 25 percent. Based on this visualization, an ideal store would be represented by a tall, vibrant blue bar, suggesting that the store produces more items than its counterparts and sustains a lower percentage error.

Figure 13 indicates that all but four stores have a production percentage error of 20 percent or higher in May 2022. These four stores are Bitters, Potranco, South Park, and Laredo. While these stores may not have the highest production levels, they have relatively impressive percentage errors: Bitters with 19.91%, Potranco with 16.30%, South Park with 16.90%, and Laredo with only 10%. In terms of this group's production levels, Laredo has the lowest production level with 19,887 produced items and Bitters has the highest production level with 32,552 produced items. Looking at stores with the highest production percentage errors, we see that these stores fall on both ends of the spectrum in terms of production output. The two stores with the lowest production levels, Commerce and Kerville, have percentage errors of 53.04% and 30.24%, respectively. With the highest production levels, Austin Hwy and Bulverde have percentage errors of 48.41% and 32.67, respectively. While there is no store with ideal performance in both production level and percentage error for May 2022, more than half of the stores were associated with a gray bar, indicating that the stores' percentage errors were ±5 percentage points from the threshold value of 25 percent.

Figure 13: Average Percentage Error Relative to Production Amount in May 2022

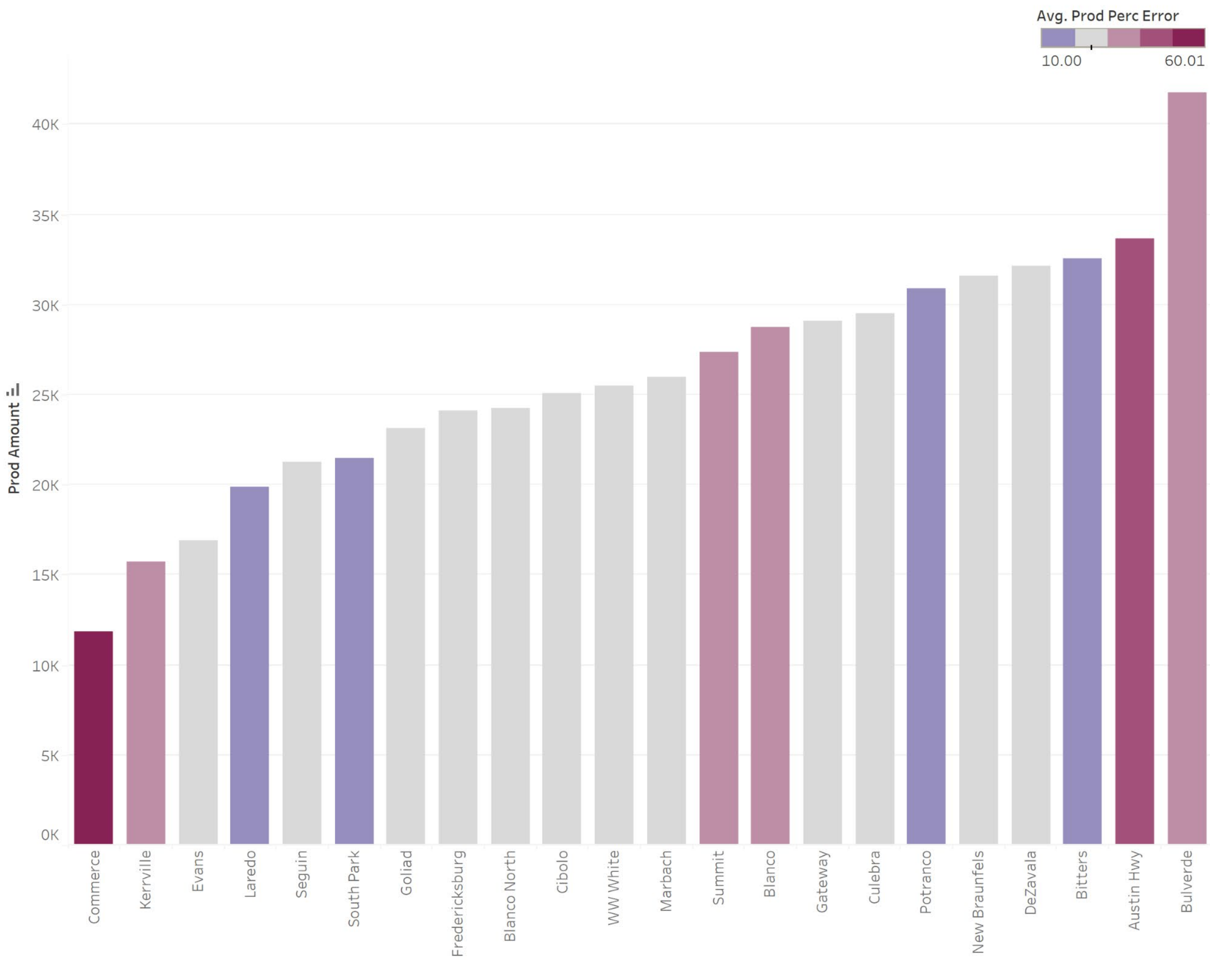


Figure 14 shows the average production percentage error relative to the production amount in November 2022 by store. Figure 14 contains a snapshot of the historical data to highlight store performance in the months following June 2022, the month when the new production model began being implemented at Goodwill SA's stores. A bar's height represents the total amount of items produced by a store, whereas a bar's color represents the average production percentage error. Vibrant blue corresponds to a low production percentage error, vibrant magenta corresponds to a high production percentage error, and gray references an assigned production percentage error threshold of 25 percent. Ideally, we want to see a store represented with a high bar and vibrant blue color, implying the store not only has a high level of production but also a low production percentage error.

Figure 14 indicates that only four stores have a production percentage error of 28 percent or higher in November 2022. Struggling in terms of production accuracy, these four stores are Blanco, Austin Hwy, Kerville, and Commerce with percentage errors of 37.93%, 33.28%, 27.87%, and 37.63%, respectively. These four stores have either low or relatively moderate production levels; the group's lowest output is tied to Commerce with 8,896 items and the group's highest output tied to Blanco with 23,799 items. The remaining stores and their performance tell an impressive story: thirteen stores had production percentage errors equal to or less than 21.38% and five stores had percentage errors less than 27.85% but greater than 21.38%. Comparing November 2022's production percentage errors against those of May 2022, we see a major improvement in production accuracy across most stores. The two stores with the lowest percentage errors and consequently, the best production accuracy are Gateway with 12.05% and Blanco North with 14.09%. In terms of these two stores' production output, Gateway produced 22,664 items and Blanco North produced 21,884 items in November 2022.

Figure 14: Average Percentage Error Relative to Production Amount in Nov 2022

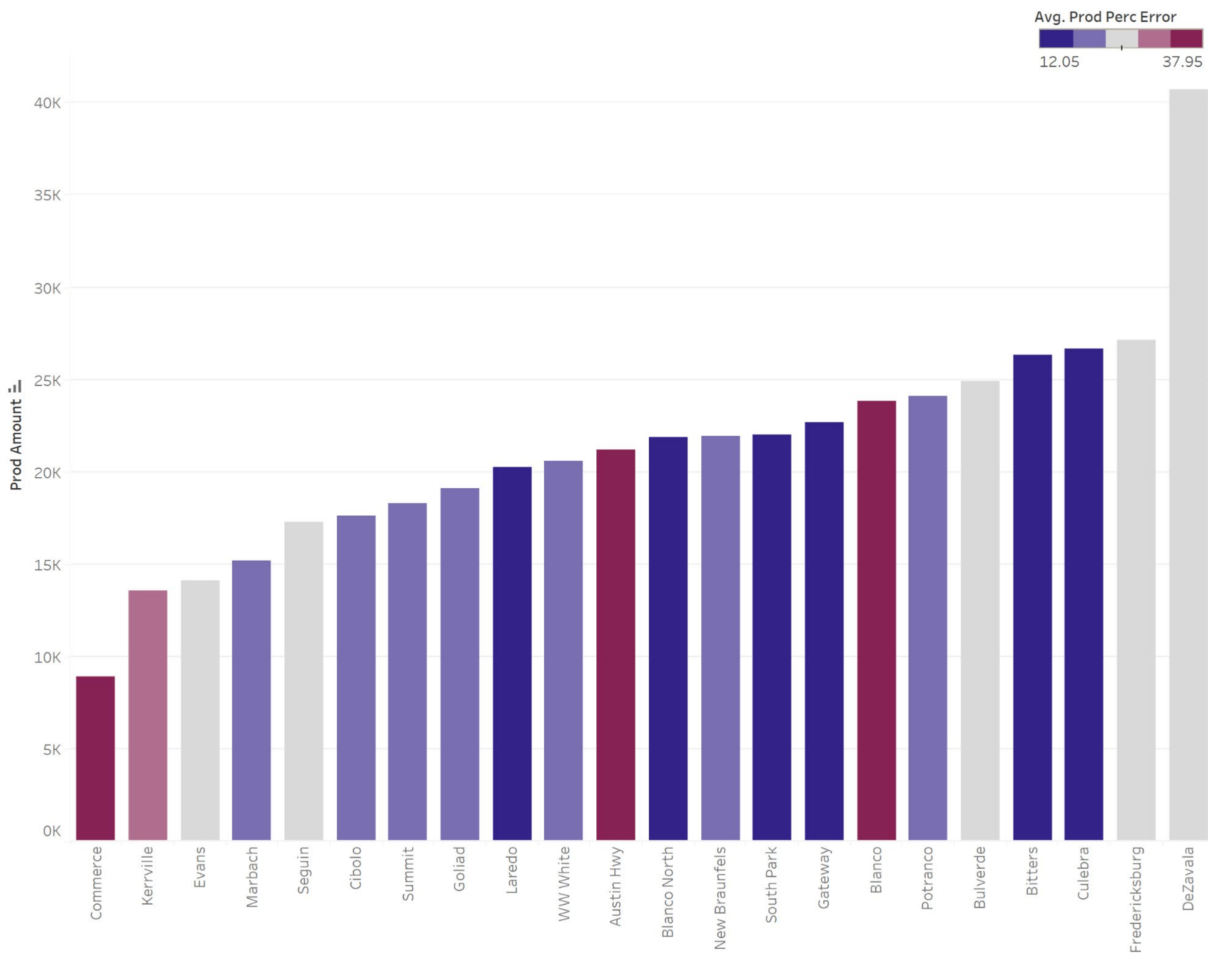


Figure 15 shows all of Goodwill SA's stores and their corresponding production and sales levels in May 2022. A bar's height represents the total amount of produced items by a store, whereas a bar's color represents the average percentage of produced items that were eventually sold by the store. Vibrant blue indicates that a high percentage of produced items were sold, vibrant magenta indicates that a low percentage of produced items were sold, and gray references an assigned threshold where 70 percent of produced items were sold by a store. Ideally, we want to see a store represented with a high bar and vibrant blue color, implying the store not only has a high level of production but also is able to sell most of its produced items.

In Figure 15, we see that De Zavala and Potranco have relatively high production levels and moderate sale rates during May 2022. De Zavala produced a total of 32,152 items and was able to sell 73.99% of those items. While Potranco had only produced a total of 30,880 items, Potranco was able to sell a greater percentage of these items at a rate of 79.28%. The stores Bulverde, Austin Hwy, and Bitters had higher production levels than De Zavala; however, these stores had significantly worse sale rates. Bulverde, Austin Hwy, and Bitters produced 41,753, 33,769, and 32,552 with low sale rates of 64.68%, 50.21%, and 62.77%, respectively. Looking at the poorest performing store in both production and sales, Commerce produced a total of 11,871 items and only managed to sell 49.96% of those produced items.

Figure 15: Sold Amount Relative to Production Amount in May 2022

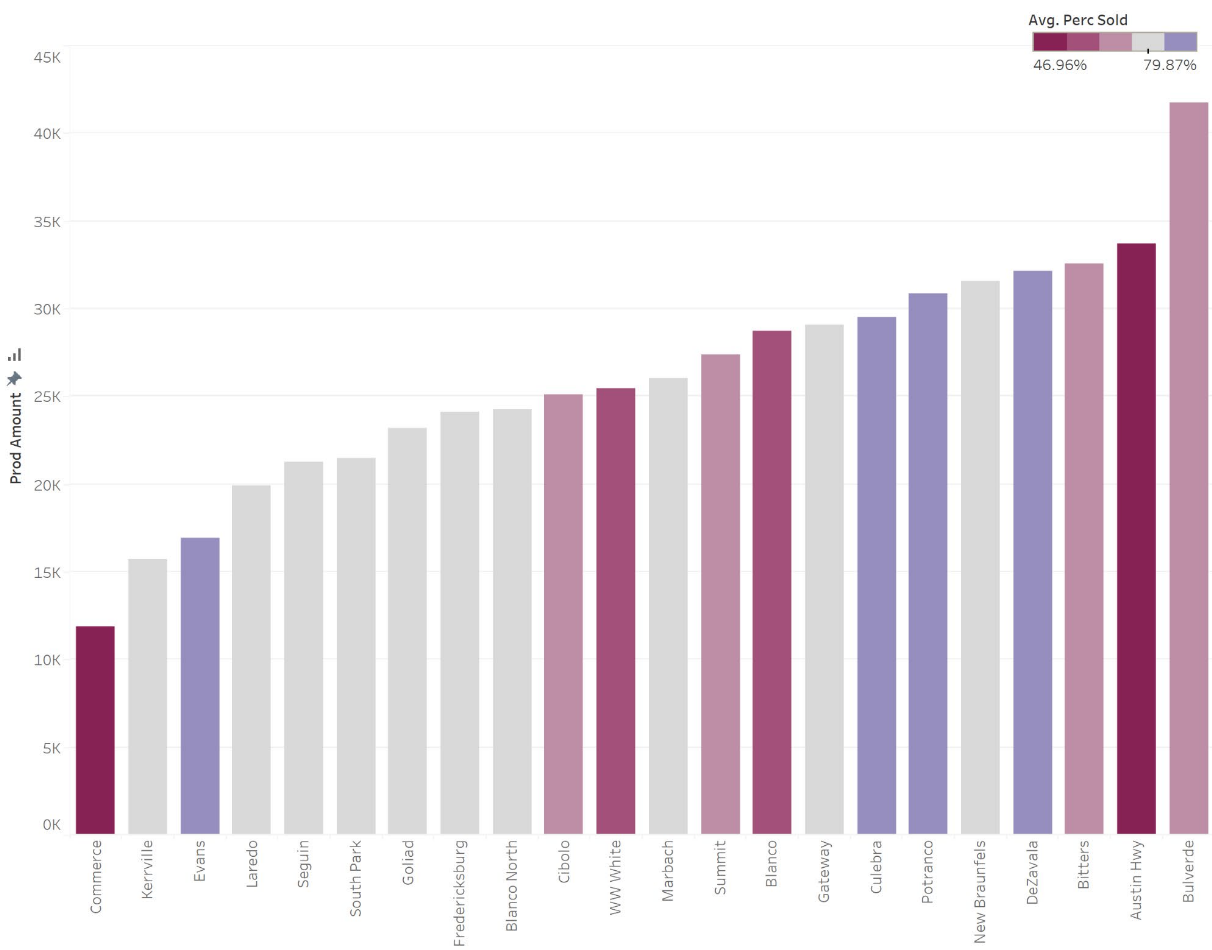


Figure 16 shows all of Goodwill SA's stores and their corresponding production and sales levels in November 2022. A bar's height represents the total amount of produced items by a store, whereas a bar's color represents the average percentage of produced items that were eventually sold by the store. Vibrant blue indicates that a high percentage of produced items were sold, vibrant magenta indicates that a low percentage of produced items were sold, and gray references an assigned threshold where 70 percent of produced items were sold by a store. Ideally, we want to see a store represented with a high bar and vibrant blue color, implying the store not only has a high level of production but also is able to sell most of its produced items. In Figure 16, we see that De Zavala had the highest production level and a moderate sale rate during November 2022. De Zavala produced a total of 40,693 items and was able to sell 70.43% of those items. The second leading store in terms of production was Fredericksburg, producing a total of 27,118 items. While Fredericksburg produced less items than De Zavala, Fredericksburg was able to sell a greater percentage of these items at a rate of 73.71%. In terms of production levels, the store with the most concerning performance is Commerce, producing only 8,896 items or around two-thirds of the second-lowest producing store's output. Additionally, Commerce had the second-lowest sale rate with a rate of 62.37%. Regarding sale rates, Blanco had the most concerning performance with the lowest sale rate, 51.27%, in November 2022. While Blanco had the lowest sale rate, Blanco managed to be the 7th highest producing store with 23,799 produced items.

Figure 16: Sold Amount Relative to Production Amount in Nov 2022

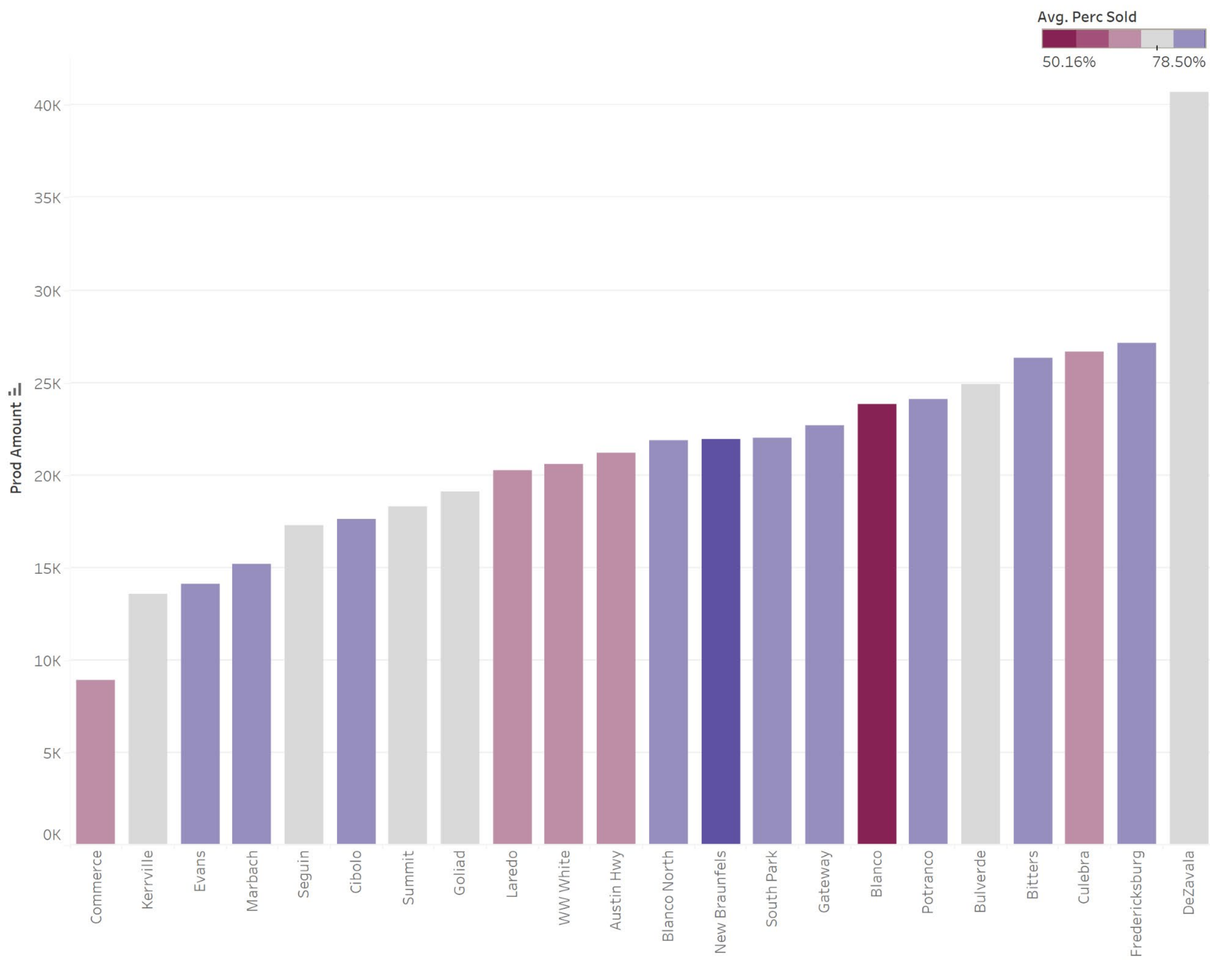


Figure 17 shows the average percentage of perfect batches by store. For example, a percentage of 68.13% for Fredericksburg means that on average, for every 100 batches the store produced, 68 of them were accurately accounted for and the store knew the proper end designations of those 68 batches' items (pulled, sold, or reconciled). Based on Figure 17, we can group the stores into 3 groups with the first five stores on the left having the highest percentage of perfect batches (56% and above) and the last four stores on the right producing noticeably fewer perfect batches on average (42% and below). The third group consists of all the remaining stores with the perfect batch percentages ranging from 45% to 54%. Fredericksburg stands out as the store with the highest percentage at 68.13% while the stores with the lowest percentages are Commerce, Blanco, and Crosstowne at

38.2%, 31.66%, and 26.57% respectively. There is little variance between the percentages for stores in the third group with the exception of Goliad, Bulverde, New Braunfels, and Laredo as their figures all fall just below 50%; the remaining stores within the third group all have an average percentage of perfect batches between 51% ad 54%.

Figure 17: Average Percentage of Perfect Batches by Store

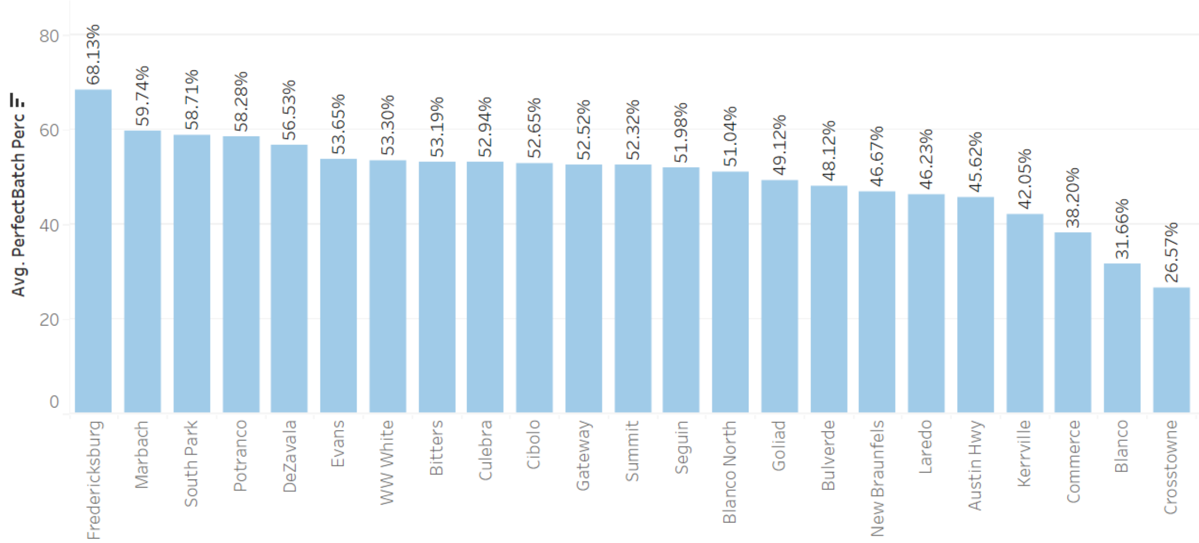
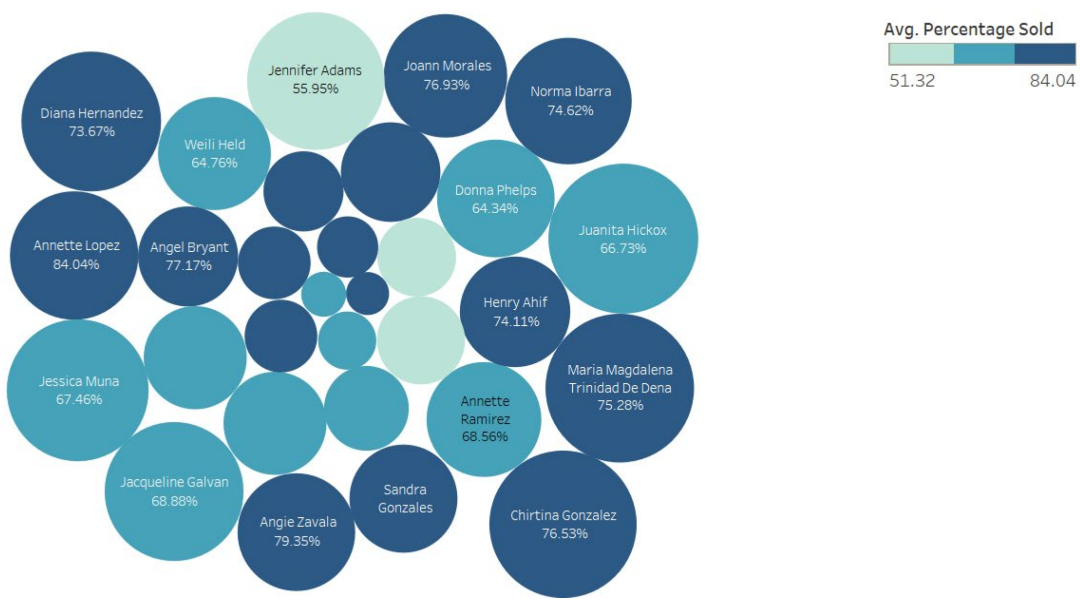


Figure 18 is a bubble chart that shows the average percentage of sold items by employee across all Goodwill SA stores in the Wares subcategory. Although some bubbles do not have a label due to their small size in Figure 18, the label appear when we hover over the bubbles in Tableau. We only compared employees within Wares to ensure an objective evaluation as different SKUs can have different influences over the number of items sold. The bubble size indicates the amount produced by an employee and the color indicates the average percentage of sold items among those produced by that employee. The darker the shade of blue, the higher the percentage sold. An ideal employee would be represented by a bigger-size bubble with a dark navy blue shade. With these points in mind, top performers Diana Hernandez, Annette Lopez, Angie Zavala, Christina Gonzalez, and along with several others represented by the biggest bubbles, not only produced the most items but also had a high percentage sold ranging from 73% to 84%. Jennifer Adams, on the other hand, only had an average percentage sold of 55.95% despite being one of the top producers. Several other top producers such as Juanita Hickox, Jessica Muna, and Jacqueline Galvan rank in the middle in terms of percentage sold, which indicates that while they may have produced significantly more than others, the quality of performance could be improved. Producers with the lowest percentage sold are represented by bubbles with the mint green shade, which include Jennifer Adams, Yolanda Patterson, and Refugio Llanas. Yolanda Patterson and Refugio Llanas were also among the employees who produced the least, meaning that they were falling behind compared to colleagues in terms of both quality and quantity.

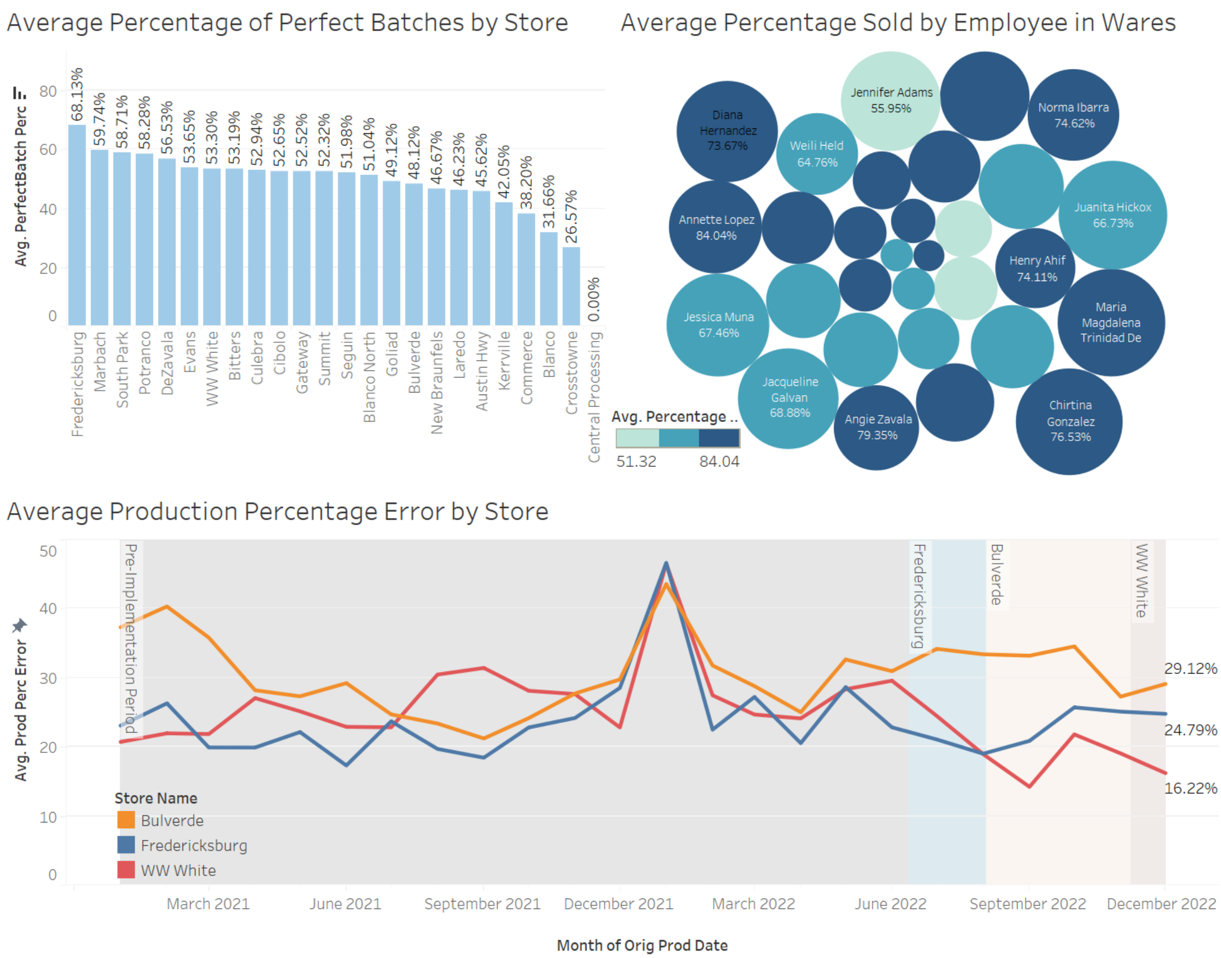
Figure 18: Average Percentage Sold by Employee in Wares across All Stores



Example of Organizational Dashboard

Figure 19 shows an example of the organizational dashboard with a selected group of performance metrics. We only included 3 visualizations out of the total 6 organizational visualizations to avoid repetition of metrics and ensure dashboard interpretability while staying informative. We chose the following visualizations: average percentage of perfect batches by store, average percentage sold by employee in Wares across all stores, and average production percentage error by store, or Figure 12, Figure 17, and Figure 18, respectively.

Figure 19: Organizational Dashboard Performance Metrics



Individual Store Performance Metrics by Employee

Based on the visualizations built in the Organizational Dashboard, each store can drill down and navigate its own performance metrics according to preference. We chose Fredericksburg to provide a concrete example of the individual store dashboard by employee. As the individual store dashboard serves to capture the performance after a set period of time such as a week or a month, the visualizations introduced below present a snapshot of Fredericksburg's operations over four weeks, beginning 11/17/2022 and ending 12/17/2022. The individual store performance metrics by employee are as follows:

- Top 10 employees with the lowest production percentage error (Figure 20)
- Average percentage of sold items by employee (Figure 21)

- Total perfect batch relative to total batch by employee (Figure 22)

Figure 20 shows the top 10 employees at the Fredericksburg store location with the lowest production percentage error. We only included the top 10 employees as the purpose of this visualization was to encourage friendly competition rather than singling out individuals for lower performance. The height of the columns indicates the average percentage error of the respective employee while the color indicates whether that employee produced more, the same as, or less than his/her colleagues. An ideal employee would be represented by a low column (low percentage error) that is colored navy blue (high production). All employees in this chart had production percentage errors below 30% with 7 out of 10 employees performing better (having lower percentage error) than the store post-implementation average (22.60% - see Figure 12). Figure 19 indicates that the employees who made the least mistakes were also the ones who produced the least, with the exception of Sandra Gonzalez, Angie Zavala, and Norma Ibarra who produced a total of 6,401, 8,683, and 7,214 batches respectively. However, only Sandra Gonzalez had a lower percentage error (22.57%) than the store average (22.60% - see Figure 12). The top employee with the lowest error was Ricardo Zavala at 0%, but he only produced 1 item in the month from 11/17/2022 to 12/17/2022.

Figure 20: Top 10 Employees with the Lowest Percentage Error - Fredericksburg

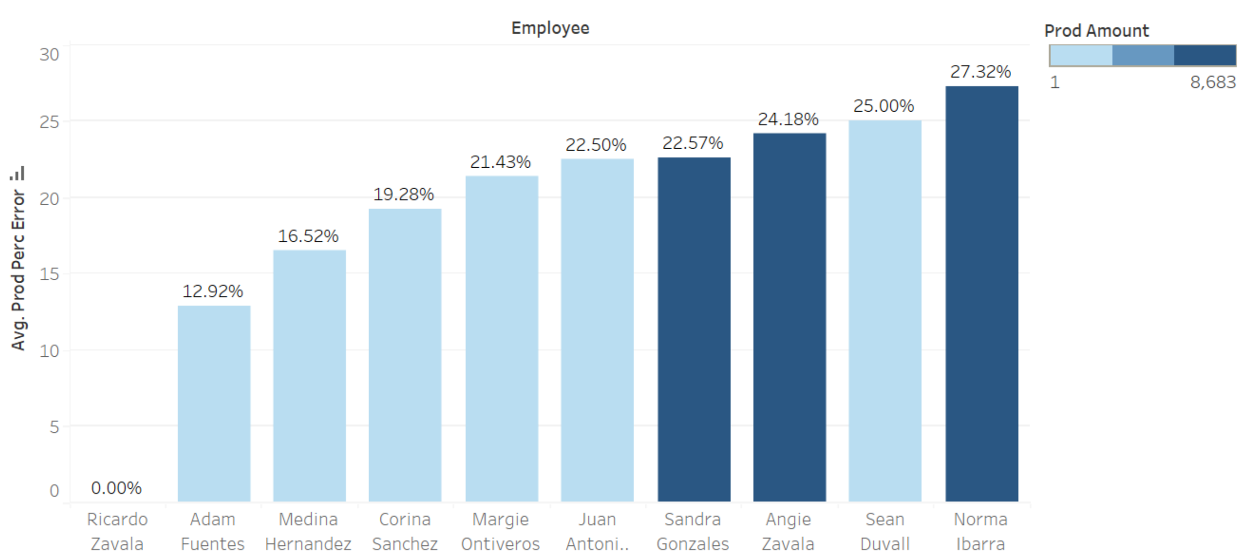


Figure 21 shows the average percentage of items sold by employee at the Fredericksburg store location using a bubble chart. Although some bubbles do not have a label due to their small size in Figure 21, the label shows once we click on them in Tableau. The bubble size indicates the average production amount of the respective employee while the color indicates whether the percentage sold of the respective employee was high, medium, or low compared to his/her colleagues. An ideal employee would be represented by a larger-size bubble with a navy blue color. As pointed out in Figure 20, Angie Zavala, Norma Ibarra, and Sandra Gonzales were the top producers at Fredericksburg. However, Zavala and Gonzales were only average in terms of the percentage sold among Fredericksburg's employees and Ibarra had a lower sold rate than her colleagues. Figure 21 suggests that while top producers might have been ahead in terms of quantity, there was still room for improvement in product quality. Olivia Garcia, the runner-up after Zavala, Gonzales, and Ibarra, was also the employee with the lowest percentage sold. The employees with the highest percentage sold were Adam Fuentes and Ricardo Zavala at 87% and 100% respectively, represented by navy bubbles. However, Fuentes only produced 3 batches and Richard Zavala only produced 1 batch per day on average.

Figure 21: Average Percentage Sold by Employee - Fredericksburg

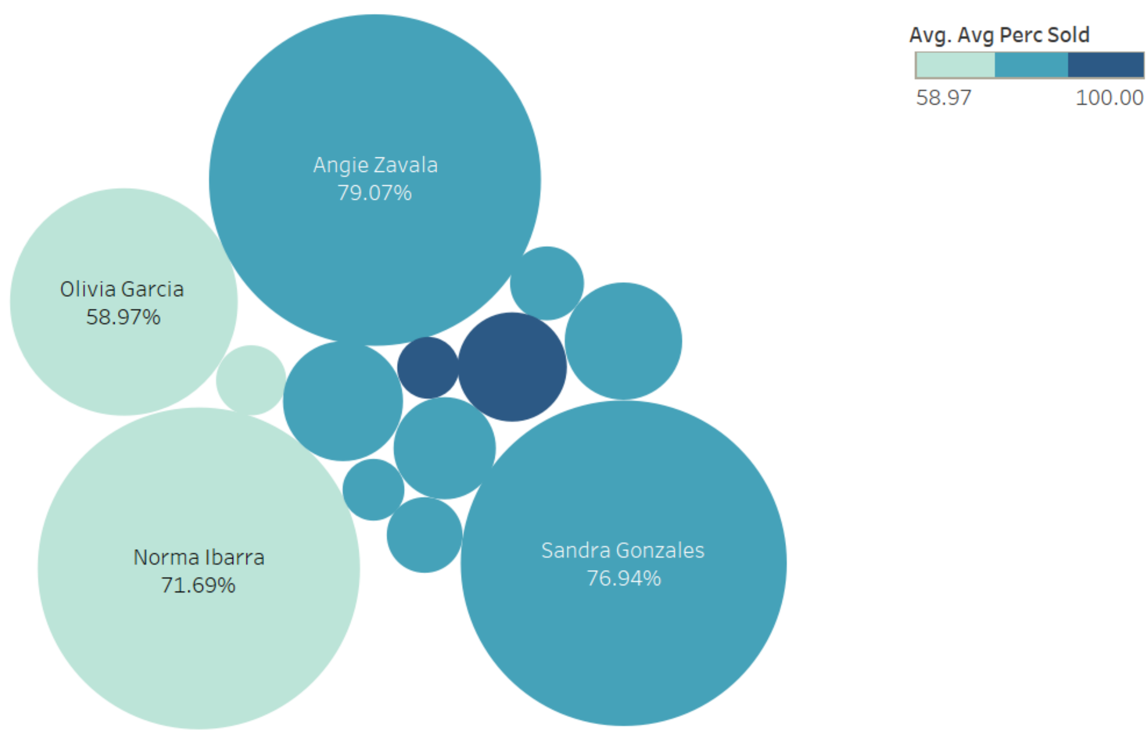
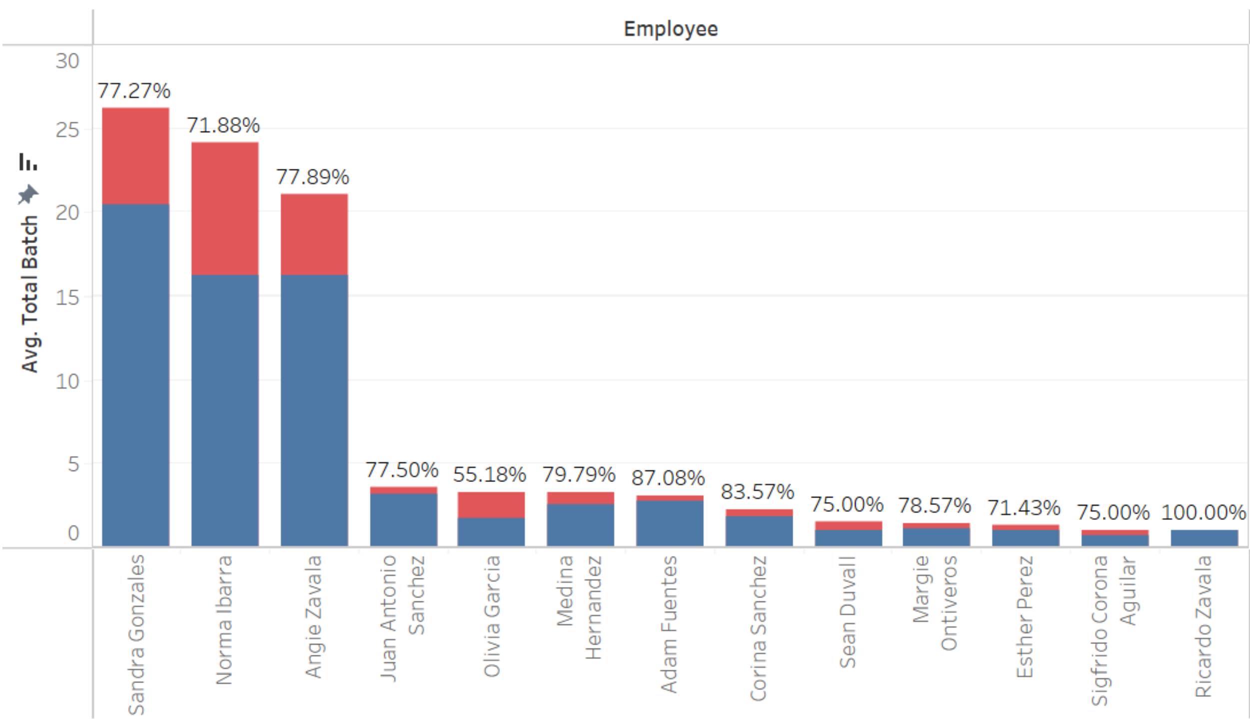


Figure 22 shows the average number of perfect batches relative to the average number of batches produced by each employee at the Fredericksburg store location using a stacked bar chart. The blue portion of the bar represents the perfect batches whereas the red portion represents the imperfect batches and the label at the top of each bar represents the percentage of perfect batches produced by the respective employee. Consistent with Figures 20 and 21, Figure 22 continues to point out Sandra Gonzales, Norma Ibarra, and Angie Zavala as top producers. On average, they produced 26, 24, and 21 batches per day respectively, which are 6.5, 6, and 5.25 times more than the fourth-highest producer Juan Antonio Sanchez who produced 4 batches per day. Gonzales, Ibarra, and Zavala were also leading in terms of the average percentage of perfect batches with Gonzales and Zavala averaging 77 perfect batches for every 100 batches they produced, and Ibarra with 72 batches. However, the employees with the highest percentage of perfect batches were Ricardo Zavala, Adam Fuentes, and Corina Sanchez at 100%, 87%, and 84% respectively. They ranked 13th, 7th, and 8th in terms of production amount among the total 13 employees of Fredericksburg shown in Figure 22.

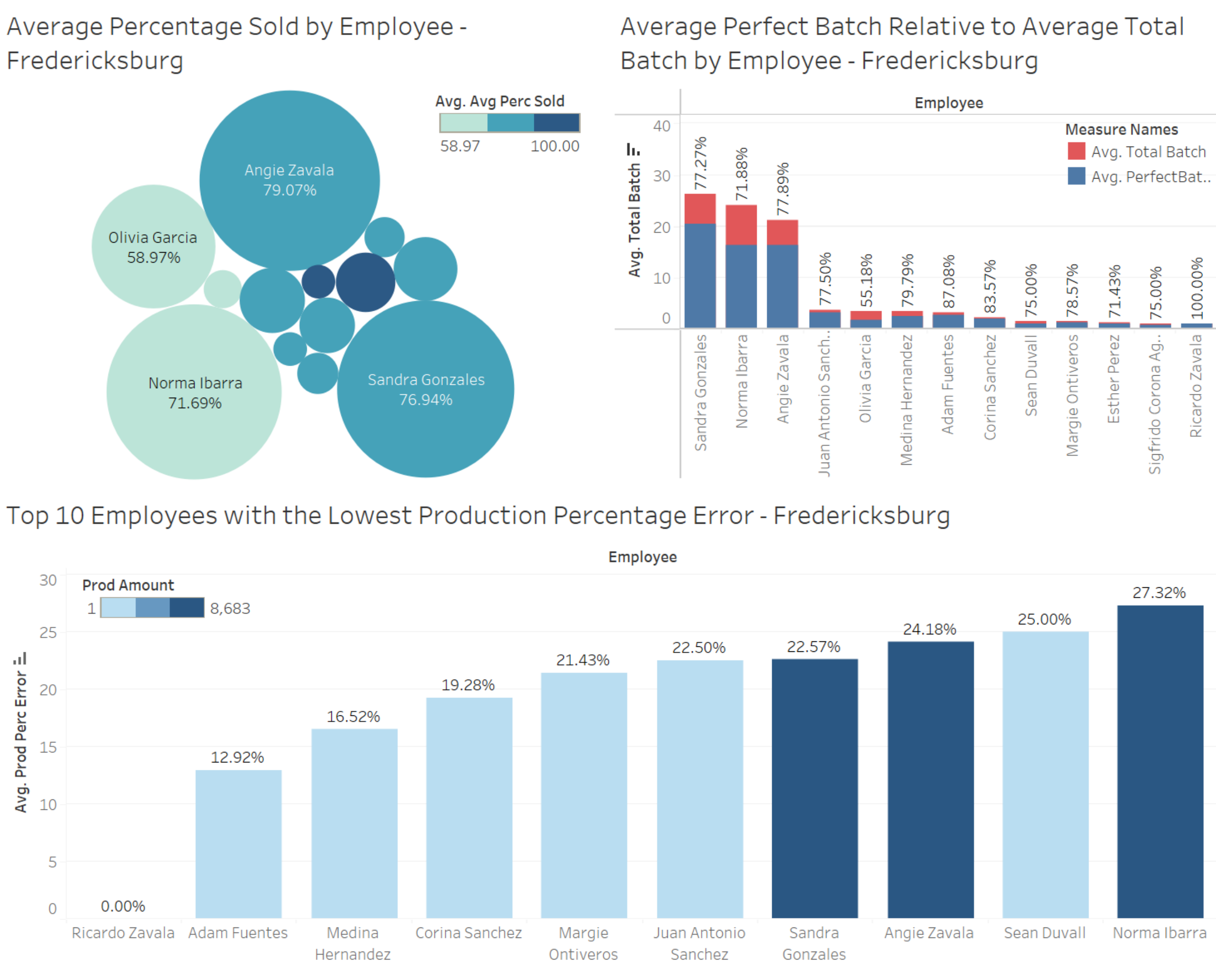
Figure 22: Average Perfect Batch Relative to Average Total Batch by Employee - Fredericksburg



Example of Individual Store Dashboard by Employees

Figure 23 shows an example of the individual store dashboard with performance metrics to encourage healthy competition among employees for the Fredericksburg location. It serves as a snapshot of the store's performance during the month from 11/17/2022 to 12/17/2022. This dashboard includes all performance metrics in Figures 20, 21, and 22.

Figure 23: Store Dashboard Performance Metrics by Employee - Fredericksburg



Individual Store Performance Metrics by SKU

Figure 24 shows the average production percentage error relative to the total production amount by SKU for the Fredericksburg store location during the month from 11/17/2022 to 12/17/2022. The height of the bar indicates the total batches produced under a specific SKU while the bar color indicates whether the average percentage error of the respective SKU was high, medium, or low among all SKUs. The ideal SKU would be represented by a taller bar with orange coloring. The number of batches produced under the Wares subcategory still significantly exceeds that of other categories with the amount for Wares more than tripled the amount for Toys, the second highest SKU. However, its relative production percentage was medium compared to other SKUs, suggesting that Wares was leading in quantity but not quality. Other SKUs leading in terms of production amount were Toys and Vases/Figurines at 2,728 and 2,391 batches respectively, but they only ranked slightly above medium among all SKUs in average percentage error. The SKUs with the lowest production percentage errors that were also top producers include Cups/Glass with 18.43% error and Plastic with 20.82% error. Seasonal, on the contrary, was not only the lowest producer among all SKUs, but it also had the highest error rate at 52.55%.

Figure 24: Average Percentage Error Relative to Production Amount by SKU

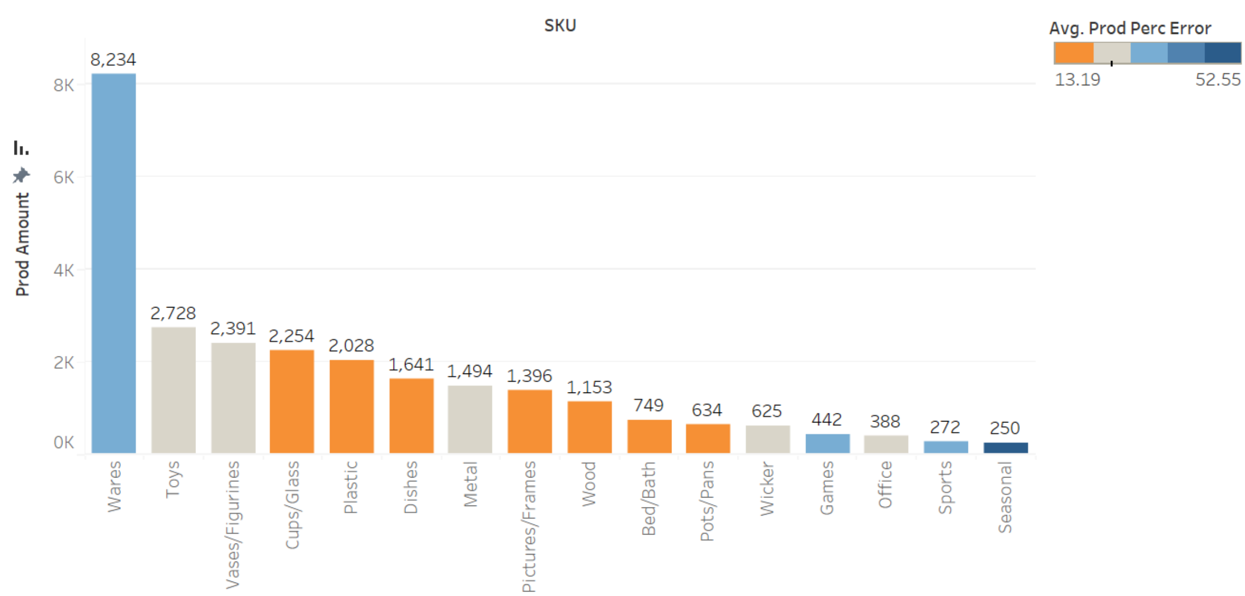


Figure 25 shows the average percentage of perfect batches relative to the total batches produced by SKU at the Fredericksburg store location from 11/17/2022 to 12/17/2022 using a bubble chart. Although some bubbles do not have a label due to their small size in Figure 25, the label shows once we click on them in Tableau. The bubble size indicates the total batches produced under each SKU while the color indicates whether the average percentage of perfect batches of that SKU was high, medium, or low among all SKUs. An ideal SKU would be represented by a larger-size bubble with a navy blue color. Despite producing the most number of batches, Wares only ranked below medium in terms of the percentage of perfect batches at 65%. Other top producers including Cups/Glass, Dishes, and Plastic were also leading in the percentage of perfect batches. The second-highest producer, Toys, was slightly above average in terms of perfect batches rate at 75%. Games and Seasonal were the lowest performers as their percentage of perfect batches was below medium compared to other SKUs, and they produced the least number of batches.

Figure 25: Average Percentage of Perfect Batch Relative to Production Amount by SKU

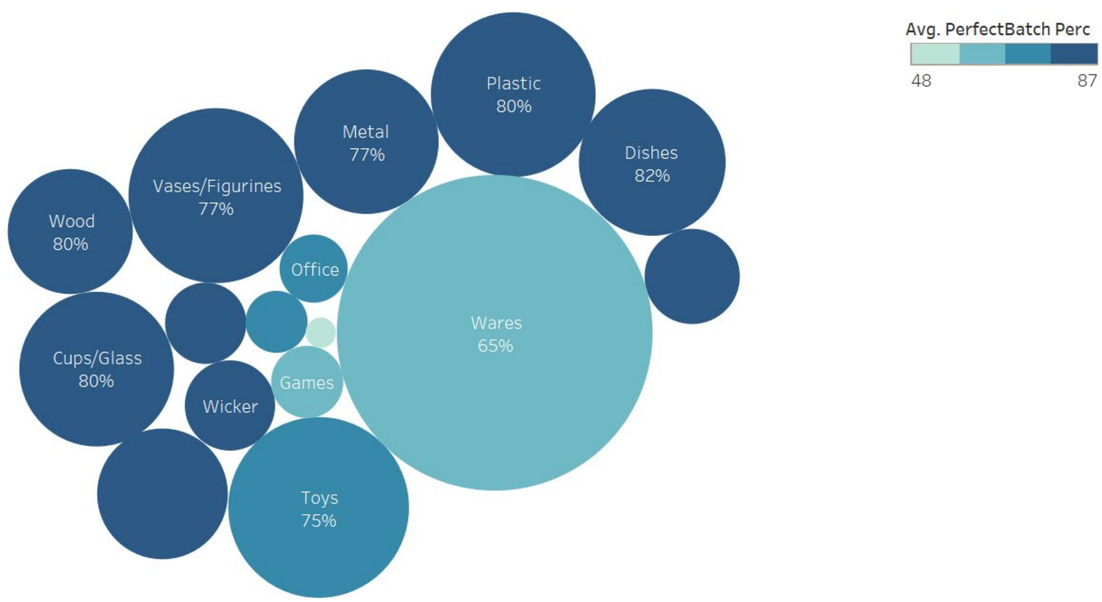
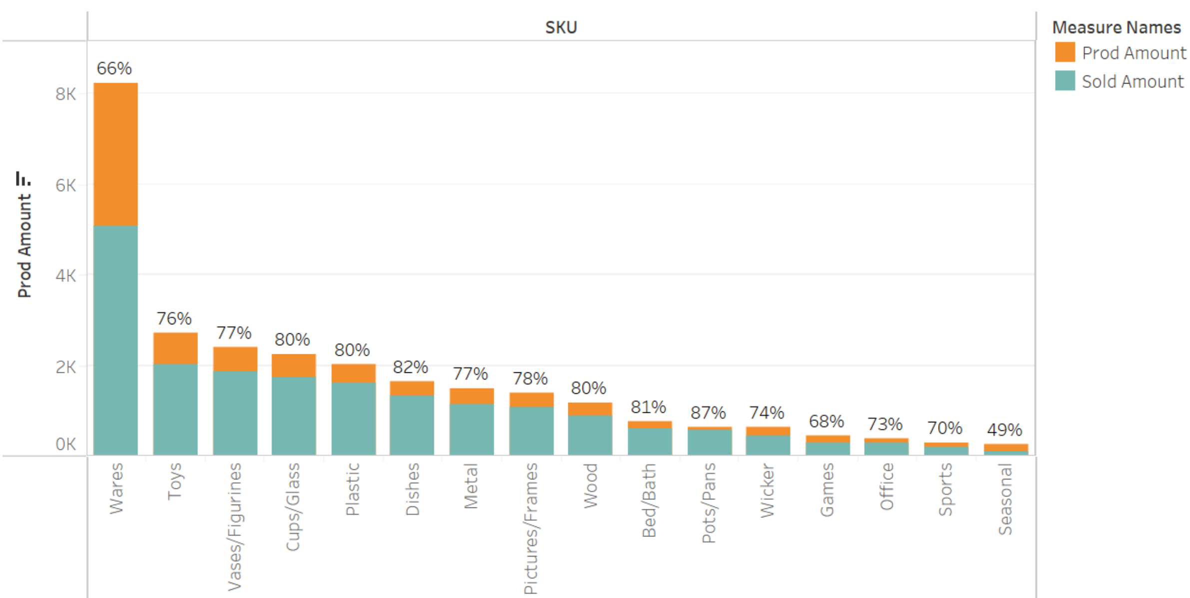


Figure 26 shows the total sold amount relative to the total production amount and the average percentage sold by SKU at the Fredericksburg store location from 11/17/2022 to 12/17/2022. The green portion of the bar represents the sold amount and the orange portion represents the items that were pulled, reconciled, or unaccounted for. The label at the top of each bar is the average percentage of sold batches relative to each SKU. While Wares produced the most batches, its sold percentage was only 66% which was the third lowest among all SKUs. Pots/Pans, Dishes, Bed/Bath, and Plastic, had the top sold percentages at 87%, 82%, and 81% respectively. Among the SKUs with the higher sold rates, Cups/Glasses, Dishes, and Plastic were also in the leading group for production amount. The lowest producers, Sports and Seasonal, ranked in the bottom two for average percentage sold. This finding suggests that these SKUs were not only falling behind in terms of production amount, their items were also the least likely to be bought by customers.

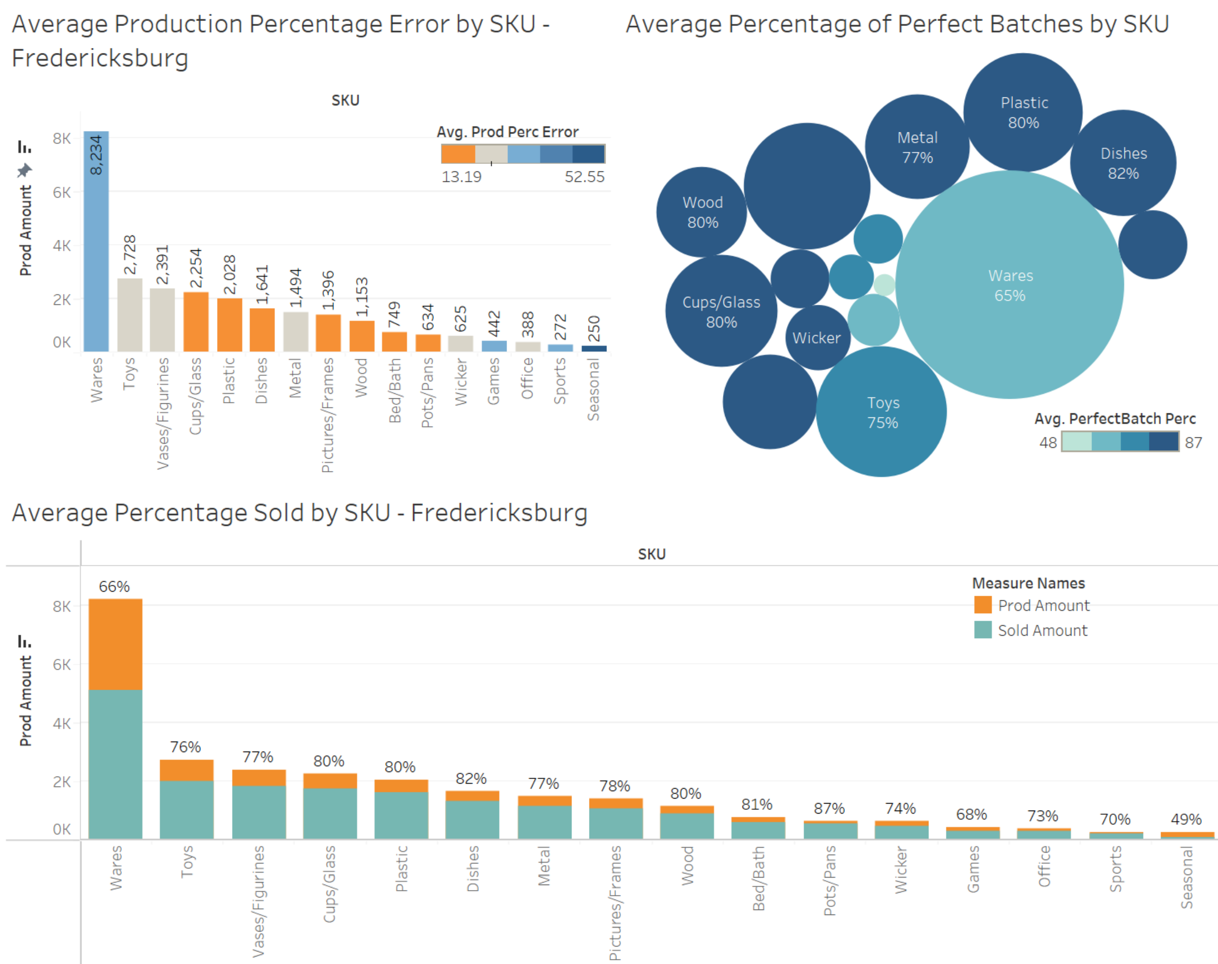
Figure 26: Average Percentage Sold by SKU - Fredericksburg



Example of Individual Store Dashboard by SKU

Figure 27 shows an example of the individual store dashboard with performance metrics to encourage healthy competition among departments for the Fredericksburg location. It serves as a snapshot of the store's performance during the month from 11/17/2022 to 12/17/2022. This dashboard includes all performance metrics in Figures 24, 25, and 26.

Figure 27: Store Dashboard Performance Metrics by SKU- Fredericksburg



VIII. Conclusion

Overall Conclusions

Based on our analysis, we were able to draw conclusions from Goodwill SA's data that remain consistent across all performance metrics and visualizations. The general conclusions are as follows:

- The most influential factors regarding the accuracy in the reporting of production amount are production date, store location, security level, and the implementation of the new model.
- Marbach and Cibolo are struggling the most among all store locations to accurately report the price of produced items.
- The new model reduced the production percentage error for most stores and significantly increased the percentage of perfect batches across all stores.
- De Zavala, Bitters, Culebra, and Potranco were the top performers across the Goodwill SA chain due to their leading production amounts and lower production percentage errors.
- Crosstowne and Commerce are most in need of ramping up their performance because they produced the least number of items with the highest production percentage error and the least percentage of perfect batches.
- Top employees who produced the most at Fredericksburg tend to have a higher percentage error but also a higher rate of perfect batches. They do not necessarily have the highest sold rate.
- Employees who produced less at Fredericksburg tend to have a higher sold rate.
- Fredericksburg produced the most batches under Wares but Wares' sold rate, percentage of perfect batches, and production percentage error are medium compared to other SKUs.
- At Fredericksburg, Cups/Glass, Plastic, and Dishes are the leading SKUs in terms of sold rate and percentage of perfect batches. They also had the lowest production percentage error.

- Sports and Seasonal ranked bottom for both quality and quantity among all SKUs at Fredericksburg: they produced the least number of batches and had the lowest sold rate and percentage of perfect batches.

Limitations of Findings

While the level of inaccuracies displayed a general downward trend after the new model implementation, the degree of improvement varies by store and SKU. With our data's cut-off date set to 12-18-2022, we had little to no data to see how the new model affected late-adopting stores such as WW White and Laredo. As a result, the reduction in inaccuracies may not be as apparent for WW White and Laredo as it was for early-adopting stores.

We were unable to translate the rate of inaccuracies in production amount and product pricing to revenue due to the unavailability of revenue data. While we had the option to impute such data, we chose not to do so given that our calculation must take into account the discount by batch and the inaccurate pricing data, both of which may skew our results.

Project Reflection

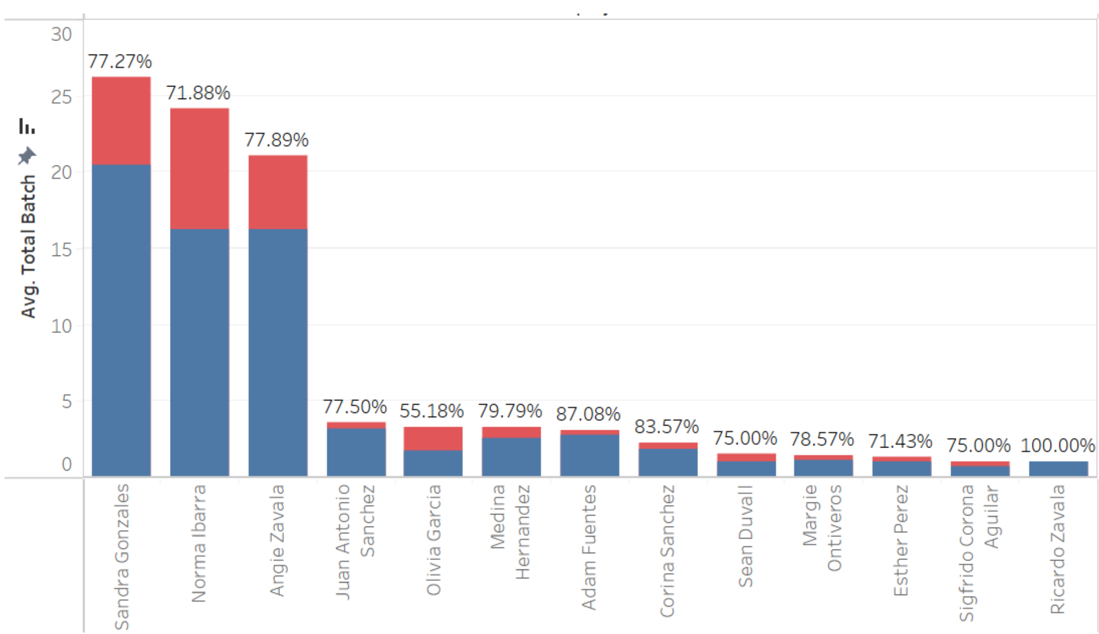
For this project, we spent the majority of our time gaining access to data, performing data exploration, and researching relevant information. The large amount of data (approximately 1.5 million observations) required a tremendous effort in moving the dataset around between the Microsoft SQL Server, RStudio, and Tableau without causing any unwanted changes. As a result, we gained experience working with handling a substantial amount of data as well as working on the VDI virtual server. The constraints in data access and the coding environment created many opportunities for creating solutions and critical thinking. Working as a team not only enabled us to enhance the quality of work but also allowed us to develop collaboration skills and offer different perspectives on problem-solving. We hope that our findings provide a source of insights for Goodwill with regard to their production process and drive part of their decision-making.

IX. Recommendations

Reviewing our analysis, we produced several recommendations that may prove useful for Goodwill SA in its future operations. Overall, we suggest Goodwill SA set metric thresholds that are tailored for each group of producers. These groups can be based on different variables, including store, SKU, and even past performance statistics taken from metric values.

For example, reviewing Figure 22 from the section *Individual Store Performance Metrics by Employee*, we see there are two distinct groups of employees: employees who on average produce 20 to 26 batches per day and employees who on average produce 1 to 4 batches per day. For the first group of employees, the percentage of perfect batches remains in the 70 to 80 percent range. For the latter group, there is greater variation in the percentage of perfect batches, ranging from 55.18 to 100%. Rather than set the same threshold for both groups of employees, each group could have its own threshold value. With its own threshold value, a group can gain valuable insight that specifically pertains to the group. Having thresholds or target values that are shared by employees across all stores, SKUs, and even performance levels can weaken whatever insight that is taken from performance metric data.

Figure 22: Average Perfect Batch Relative to Average Total Batch by Employee - Fredericksburg



The tailored threshold suggested above or target values can be applied to performance metrics such as total production amount, percentage sold, production percentage error, and number of perfect batches. Below are detailed suggestions relating to tailored threshold values:

- Set threshold values for quantity (e.g. ProdAmount) and quality (e.g. ProdPercError, PerfBatch) metrics, using progressive or regressive thresholds based on previous performance. Including both quantity- and quality-based metrics and thresholds allows for a more holistic view of a store's, SKU's category's, or even an employee's performance. For employee performance reviews, we highly suggest reviews that take on this holistic approach.
- Consider utilizing thresholds tailored to SKU groups to observe the trends and patterns of different SKUs. Similar to the case of employee performance reviews, to identify patterns related to different SKUs' performances, we suggest utilizing a holistic approach that is based on both quantity and quality measures.
- In conjunction with the previous point, establish stricter guidelines for classifying items into the different SKU categories. As stores implement the new production models, employees should reduce their reliance on the Wares SKU. During the analysis process, we noticed that the top producers were mostly producing batches under the Wares SKU rather than the newly-developed SKUs. Even at Fredericksburg, an early-adopting store well settled into the new production model, this trend was present in late 2022. We believe employees' reliance on the original SKU Wares could potentially be skewing metric insights and consequently, affecting how one might consider setting performance thresholds.

Our last recommendation is not related to developing tailored threshold values. Instead, this recommendation focuses on data validation when entering data into Goodwill SA's databases. Specifically, we suggest creating a validation process that checks the accuracy and quality of data related to the variables ProdAmount, PullAmount, ReconAmount, and SoldAmount. For a particular batch, we know that the sum of pull, reconciled, and sold items should never exceed the original number of produced items; however, our current dataset contains batches where this sum exceeds the original number of items. This accuracy issue was especially severe around January 2022 when the average production percentage error was approximately 45%. Many batches during this period were reported as having more items sold than the total number of items produced within a batch. If possible, we recommend Goodwill SA sets ProdAmount as the maximum value for the variables PullAmount, ReconAmount, and SoldAmount. Setting ProdAmount as a maximum for these variables would help minimize the production inaccuracies experienced by Goodwill SA.

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