Customer Segmentation and Price Optimization Strategies for Singi's Kitchen

A final submission report for the BDM capstone Project

Submitted by

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Contents:

1. <u>Executive Summary</u>

This study presents a comprehensive data-driven analysis of Singi's kitchen, a community restaurant in Hyderabad, focusing on **menu optimization**, **pricing strategies** and **Inventory management** to enhance profitability and overall efficiency. A **primitive dataset** was developed through extensive fieldwork, which captured key features such as, **orders per month**, **revenue** and **profit margins**. Following this, an **Advanced datase**t was built, which consisted of 2 new additional features, incorporating **Phase potential score,** which assesses customer loyalty and a **Menu score** which is a heuristic model which evaluates the overall performance of the dish in the menu. **IQR analysis** (Inter Quartile Range) was performed to delegate four different categories to the menu scores, which are, **top-performing, moderately successful, mediocre** and **failed items**, which allow for strategic interventions.

Economic pricing strategies were implemented by using **Price Elasticity Demand (PED)** which are useful in enhancing overall sales profile of the restaurant. **Inelastic dishes** such as Butter chicken and Tandoori Chicken saw a price increment by 5-10% given the immense popularity and demand in the customer base. Whereas, **elastic dishes**, such as Fish fry and Vegetable biryani saw a price reduction by 5-15% to leverage more sales revenue and to enhance customer loyalty. **Menu engineering principles** were implemented to create **high-value combos** which paired moderately successful items with top performing items to enhance the appeal of the items.

A primitive inventory management dataset was developed to assess all the necessary ingredients, **total of 28 ingredients** were captured with respect to **14 different features** and then ultimately an Advanced inventory management dataset was developed which consisted of **19 different features** and most importantly, it revealed insights about the **underutilization of spices and beverages**, **overstocking of perishables** and about **Eggs having the highest stock per order.**

2. <u>Detailed explanation of Analysis Process</u>

The analysis process for this final submission has been conducted in various stages, which namely are **Menu analysis & Optimization, Inventory Management** and **Finalized optimized menu creation.** To be noted, Finalized optimized menu creation is simply an extension to Menu analysis & Optimization, starting with Menu analysis & Optimization:

(1) **Menu Analysis & Optimization**

Firstly, A dataset with all necessary key features regarding sales data of the items in the menu was surveyed upon, and after a month of tedious and rigorous work, a comprehensive dataset was created. The key features of the primitive dataset are:

- Dish name – name of item on the menu
- Most Ordered in Households – Number of Households where the dish was the frequently the most ordered item
- Total orders in a Month – total number of orders paced for the dish in a month

- Selling price – price at which the dishes were sold
- Cost to prepare – Cost incurred in making the dish
- Profit margin – percentage of profit per dish
- Total revenue – Overall earnings from that dish in a month
- Total profit – Total revenue subtracted from the preparation cost

This was the primitive dataset that was built upon rigorous surveying for exactly a month as the stipulated time period.

All of the collected data was collected physically, A register had been maintained and entries were rigorously introduced for a month's period of time. After physical data collection was completed, a lot of data cleaning was performed digitally. There were **63 total menu items**, before all of the feature selection and data cleaning was done, and after removal of items which were seasonal or had fluctuating pricings or were confectionaries, ultimately, **41 total menu items remained** including side dishes and drinks, this was the established **Primitive dataset**. (Link: https://docs.google.com/spreadsheets/d/1zxMH35PMIbYTz6iq8qj5lsdB-MtJzyxH/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

Now, this is foundation of the next more enhanced and advanced dataset. After the successful creation of the item sales dataset, I decided that the dataset would be more meaningful if it also contained **Phase potential scores** and **Menu score**, these two were the feature additions to the primitive dataset. To briefly recapitulate, Phase potential score would indicate the average customer loyalty of that particular phase in the community with respect to that particular item.

Now, the feature of **Menu score** and its mathematical formulation will be discussed. Menu score is the **target variable** of the **Advanced dataset**. Menu score is a rating of an item in the menu which would describe its overall performance considering the future as well. The total features considered here are, **Total orders per month, Phase potential score, total revenue generated from the dish and cost to prepare the dish**. The mathematical representation of the Menu score is given below and also appropriate justifications for developing the following heuristic formulation of the Menu score:

$$S(i) = W_1 O(i) + W_2 P(i) + W_3 R(i) - W_4 C(i)$$

Where:

$O(i)$: Total number of orders per month for dish i

$P(i)$: Average potential score of the phase where this dish is most ordered

$R(i)$: Total revenue generated from dish i

$C(i)$: Total preparation cost for dish i

W_1, W_2, W_3, W_4 : Appropriate weights for the given features, to be found experimentally.

Before calculating the values of the weights, its important to understand how such a heuristic score was developed at the first place. The assignment of these particular features was done after referring to many **research papers in economics and Business analytics**.

A research paper published by Kaj Storbacka, Tore Strandvik, and Christian Grönroos in 1994, discusses about importance of monitoring order volumes and how order volumes can directly affect the business health. This research paper was crucial in developing the mathematical formulation of menu score and helped in realizing that total number of Orders per month ($O(i)$) is crucial in determining the overall success of the menu and business in general. (Research paper link : https://www.researchgate.net/publication/235281531_Managing_Customer_Relationships_for_Profit_The_Dynamics_of_Relationship_Quality)

Similarly, research paper published by Barak Libai was also quite significant as this research paper directly correlates to the concept of Potential score and how it affects customer loyalty and overall success of the businesses. The most important takeaway point for Barak Libai's work is, customer loyalty to a certain product from a business can ultimately enhance overall business's profitability. This implies that, the Phase potential score ($P(i)$) is quite significant for determining the menu score and the overall success of the business. (Research paper link: https://journals.sagepub.com/doi/10.1509/jm.10.0209?icid=int.sj-abstract.citing-articles.388)

Lastly, research paper by Claes Fornell, suggests that, businesses that have a satisfied customer base can maintain higher profit margins, contributing sustainable growth for the business. The research paper states that successful businesses often display higher profit margin. This in this case, reinstates that, total preparation cost and total revenue generated ($C(i)$, $R(i)$) are two very important features for determining the success of the menu or of the business as well. (Research paper link: https://www.researchgate.net/publication/228233854_Customer_Satisfaction_and_Stock_Prices_High_Returns_Low_Risk)

Now, Weights of the features can be discussed, where weights of the features in the heuristic Menu score are assigned on the basis of their relative importance in determining menu success and business profitability. Based on experimental analysis over the primitive dataset, Logical considerations and feasible assumptions, the following weights were established:

Total orders per month ($O(i)$) – Weight W_1 = 0.25: this feature directly impacts the menu's success but this feature is too simplistic in nature and doesn't account for future events and due to which, the appropriate weight assigned here is moderate in value.

Phase Potential score ($P(i)$) – Weight W_2 = 0.4: This feature is absolutely significant, as this feature considers the customer loyalty and also considers whether the customers from a specific phase will remain loyal or not in the future, which makes this feature very crucial. It's not a naïve feature and is considering future events and hence weight parameter will have a very high value.

Total Revenue Generated ($R(i)$) – Weight W_3 = 0.2: Revenue generation is a key feature and will help in determining the success of the business but higher revenue alone doesn't guarantee higher profitability. Hence, revenue's weight parameter is assigned a lower value.

Total Preparation Cost ($C(i)$) – Weight W_4 = 0.3: Claes Fornell's research paper does reinforce the fact that successful and sustainable businesses do have higher profit margins and hence, lower preparation cost. The weight parameter assigned to Total preparation cost is also high to showcase that higher preparation costs will only lead to lower profit margins and that is reason a high value has been set, to penalize the items with lower profit margins.

So ultimately, the **finalized Menu score formulation** is given as:

$$S(i) = 0.25O(i) + 0.4P(i) + 0.2R(i) - 0.3C(i)$$

This formulation ensures that dishes with higher Order Frequency, Phase Potential scores are awarded robustly but also making sure that the dishes with low profit margins are penalized heavily, which would result in a consistent and accurate menu score model.

After the features of the Advanced dataset have been properly defined, the two new columns were inserted into the primitive dataset via MS EXCEL and then using Excel's formula functions command, the column of Menu score was populated accordingly. All measures have been taken to ensure that there are minimal errors within the dataset.(Link to advanced dataset:https://docs.google.com/spreadsheets/d/14DNe_Ua1qAOpU4SikwJjolNLyyBmefFr/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

Once the dataset was properly organized, further analysis had been performed on the obtained menu scores to understand items that have good performance level and the items that have a low performance level. During the analysis it was found that items which had a good word of mouth like Tandoori chicken had a very high menu score and items which had almost negligible publicity like momos had a low menu score. This reinstates the fact that menu score is well aligned to sales data, publicity and customer loyalty, making it a good performance indicator.

It was then decided to categorize the dishes based on their menu score. Firstly, during the analysis part, it was realized that the numerical range of menu scores was $[266,14126]$. But purely considering this as the actual range of menu scores is not logically sound, as the dishes on the lower end were mainly breads, desserts and drinks. Side dishes like breads, desserts and drinks, are often paired with other main dishes for consumption, these alone do not generate any traction, therefore these items are not considered as many of these have very low menu score which is expected. But side dishes which have performed well when compared to main dishes, have been considered for analysis too.

The excluded side dishes from the analysis are:

- Breads – Naan, Tandoori roti
- Desserts – Gulab Jamun, Rasgulla, Falooda
- Beverages – Masala Tea, Mango Shake, Lassi

Now, on performing **Interquartile Range analysis** (IQR), we obtain the following three given quartiles:

- Q_1 (25th Percentile): 2648.63
- Q_2 (Median/ 50th Percentile): 4729.59
- Q_3 (75th Percentile): 6764.74
- IQR (Inter Quartile Range): $Q_3 - Q_1 = 4116.11$

A graph has been shared in the Results section for better understanding of the quartiles and categorizations in a more graphical way.

Now based on the statistical framework, we can construct Four appropriate categorizations based on the numerical values of the quartiles we have found. The ranges of Four categorizations and its essential implications are provided down below:

- **Top Performing category** (All menu items with score above Q_3 / Score $\geq$ 6764.74): These are the most successful dishes which have garnered exceptional sales, customer loyalty and profitability. These items don't need any major adjustments, these items are already performing exceptionally well, but if needed slight increments in prices will not really damage the economics of the business as these are the signature dishes of the restaurant which provide the fundamental traction for the restaurant.
- **Moderately Successful Category** (all menu items with score between Q_2 and Q_3 / 4729.59 $\leq$ Score < 6764.74): These are moderately successful dishes which have performed decently in terms of sales, revenue, customer loyalty and profitability. Minor adjustments such as price tweaking and portion size changes will be sufficient.
- **Mediocre category** (all menu items with score between Q_1 and Q_2 / 2648.63 $\leq$ Score < 4729.59): These are the dishes which are neither strong performers nor failures. These dishes need a lot of strategic modifications which includes, Major price adjustments, rebranding of the dishes, bundling these dishes with other successful dishes as a part of a combo and discount vouchers.
- **Failed items Category** (all menu items with score less than Q_1 / Score < 2648.63): These dishes have failed to generate satisfactory customer loyalty, sales and profitability. These items will require major restructuring which includes revamping the ingredients of the dish, implementing a new recipe and changing the way in which its promoted and branded, and if none of them are applicable, removal of the dish is the best way forward.

Once the categories are devised and established, using Excel's in-built functions, the dishes have to be placed within their appropriate categories, the result of this can be found in results category of the report. Now, focusing on Menu Optimization, which will primarily include mathematical framework and concepts in economics for a robust and sound analysis.

Menu Optimization strategies using theory of price elasticity & demand:

In economics, the **Price Elasticity of Demand (PED)** measures how the quantity demanded of a certain item responds to a change in the price. This is a key concept; it helps in understanding whether an item's price should go up or down and what could be the consequences of increasing or decreasing the price of a good. The mathematical representation of this concept is given by:

$$PED = \frac{\%\Delta Q}{\%\Delta P}$$

Where, $\%\Delta Q$: Percentage change in quantity demanded & $\%\Delta P$: Percentage change in price

For this restaurant menu, classification of items is done based elasticity, **elastic demand** (PED >1) and **inelastic demand** (PED < 1). Elastic items require careful pricing adjustments, decreasing the prices by a notch can increase the sales by a lot but can damage the revenue. Inelastic items on other hand, allow for increasing prices up by a notch which wouldn't alter the sales by a lot.

Implementation strategy for Top performing category items: As observed in the primitive and advanced dataset, the overall sales and menu score is particularly very high, which suggests maximum customer engagement. This means $\%\Delta Q$ is slightly **net positive** in many cases, due to which it is known that the demand here is inelastic and based on that, **a moderate increment by 5-10% can be applied to extract more revenue**.

Implementation strategy for moderately successful category items: The items in the category when observed using primitive and advanced dataset, both showcase decent sales capacity and menu scores, but the demand curve of the product is a regressive one, which means $\%\Delta Q$ is slightly **net negative**, due to which it is an elastic good. **Slight decrement of the prices by 5-10% can be applied to extract more sales** without compromising the revenue.

Implementation strategy for Mediocre category items: The items in this category have average sales and menu scores, the items in this category have a steeply falling demand. $\%\Delta Q$ in this case is net negative but with a good margin and due to which, **pricing adjustments are not useful in this case, instead, bundling these as a combo** to a top-performing item will help in gaining traction within the customer base.

Implementation strategy for Failed items category: These items have no customer loyalty and these generate absolutely no revenue or sales. **These dishes need a complete repositioning or rebranding** to stay in business and if no such interventions are possible, removing these dishes from the menu is also another important option.

Now, discussing about items in the mediocre category, and developing a proper mathematical framework to deal with combo offers using **menu engineering** and **consumer psychology**. A perceived deal value of combining n mediocre dishes achieve an ideal perceived deal value is given by:

$$V_b = \sum_n P_i - d\left(\sum_n P_i\right)$$

Where:

V_b : Value of the combo, P_i : Individual price of the (i)th item, d : discount percentage (optimally 5-15% for maximum effect)

This is a common formula used in menu engineering, where the sum of all individual items is subtracted from weighted sum of items. This formula can be used to create appropriate deals which include 2 or 3 mediocre items paired with a successful item to increase the sales and engagement of mid-tier items. New combos constructed using the formula and for $d = 10\%$, one example of such combo bundling can be given as:

- Breakfast delight (200 rupees) – 1 Masala dosa + 1 Idly + 1 Lassi

These are all the combos which must be a part of the finalized menu as the weaker items in each combo will **indirectly get its sales increased** which otherwise struggle a lot individually.

Now discussing about items in the failed items category, the strategy for optimization which should be employed here is **removal and replacement strategy**. Items such as Momos, Tea, Lassi and Naan should be removed for their unsatisfactory performance and **new remodels** should be launched for few of those such as, Masala Tea, Punjabi Lassi and Cheese Garlic Naan will ensure that these new items will once again gain traction in the customer base.

Minor optimization strategies such as, **Decoy strategy** and **Charm pricing** are introduced, where Hyderabadi dum Biryani is being sold for 300 rupees, Chicken biryani is introduced for 220 rupees for chicken biryani's price to look way cheaper than its counterpart and Masala dosa instead for being sold at 100 rupees is sold at 90 rupees, it's a psychological trick to make the prices look more attractive and to enhance customer perception.

Ultimately, by implementing Price Elasticity of Demand (PED), Price tweaking, Menu engineering, removal and replacement strategy, Decoy strategy and Charm pricing, a finalized optimized menu can be constructed. The finalized optimized menu can be found in the results section of this report. Now focusing on the last stage of analysis which is inventory management.

Inventory Optimization Strategy

I have extensively collected inventory data from the restaurant for a period of one month. A **total of 28 ingredients** have been observed with respect to **19 different metrics**. Sensitive metrics such as stock pillage loss and waste percentage have been observed and noted diligently ensuring there are minimal errors in the final Optimized inventory dataset. In the primitive Inventory management dataset, there are **14 features** and they are:

- **Ingredient**: Name of the raw material (e.g., Onion, Chicken, etc.)
- **Category**: Whether it's Vegetable, Meat, Dairy, Grain, Spice, etc.
- **Cost per KG**: Price per kilogram of each ingredient
- **Stock Usage per Day**: The amount of each ingredient used in daily cooking.
- **Stock Purchased per Order**: The weight of the ingredient bought per order
- **Purchase Frequency**: The number of days in which stock gets replenished
- **Reorder Level**: The safety threshold at which stock is reordered

- **Monthly Consumption**: Total quantity used in a month
- **Monthly Purchase Cost**: The amount spent per month on buying the ingredient.
- **Waste Percentage**: Total percentage of stock being wasted
- **Stock Spoilage Loss**: Amount of total stock lost to rotting and spoiling
- **Stock Usage Efficiency (%)**: Ratio of usable stock and wasted stock
- **Days Until Stockout**: The number of days current stock will run before exhausting
- **Stock Value in Inventory**: Value of ingredients currently available in stock

Now, to optimize the Inventory, there are several strategies which have been implemented by applying the **theory of Inventory management and demand forecasting.** The strategies implemented are: (Primitive dataset link: https://docs.google.com/spreadsheets/d/110V1WVGEdaZM7lWpZ9kXa-Aj0sZJbcM4/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

- **Stock usage and overstocking:** The ingredients are categorized into 2 broad categories, highly perishable items, which includes, vegetables, fresh dairy, meat and etc. and less perishable items, which includes, Rice, spice, oil and etc. For highly perishable items, stock purchase frequency should be for every 3-5 days, whereas for lesser perishable items, it should be for every 15-30 days. Lesser perishable items do not have to worry about reordering level calculation, but for higher perishable items, it is given by the formula:

$$RL = (DU \times LT) + SS$$

  Where:
  RL : Reordering Level, DU : Daily Usage, LT : Lead Time, SS : Safety Stock
- **Wastage & Spoilage:** Items with high waste percentage (>10%) should reduce the wastage by cutting down on the order quantities. For calculating stock spoilage loss, the formulation is given as:

$$SSL = \left(\frac{WP}{100}\right) \times MC$$

  Where:
  SSL : Stock Spoilage Loss, WP: Watse Percentage, MC: Monthly Consumption
  And, in the case of stock usage efficiency, the formulation is given as:

$$SUE = \left(1 - \frac{WP}{100}\right) \times 100$$

  Where:
  SUE : Stock Usage Efficiency, WP: Waste Percentage
  Additionally, if Stock Usage Efficiency is below 85%, then, **increase purchase frequency to prevent spoilage** and **decrease order quantity by a notch**.
- **Modifying Order quantities based on market trends**: For readjusting the Order quantities, the mathematical formulation is given by:

$$NOQ = COQ + \left(\frac{WP}{100} \times COQ\right)$$

  Where:
  NOQ : New Order Quantity, COQ : Current Order Quantity, WP : Waste Percentage

Few points that should be considered, in the case of frequent stock outs, that is if **days until stockout < 3**, increase the order quantity and if there is too much inventory left at the end of the stipulated period of time that is, if **stock value > 20,000 Rupees**, reduce the order quantity.

- **Practical Adjustments**: By applying some logical considerations and few rules of thumb used frequently in demand forecasting, it could be said that, for vegetables frequent purchases are a must, **for every 3-5 days to prevent spoilage**. Whereas for, Oils, spices and grains, **buying once in a month in bulk is preferable** given negligible spoilage. In case of meat, **buying fresh every 2-4 days** is a must, and to reduce purchase size if the spoilage > 5% and finally for dairy products, **buying once in every 3 days** is preferable but to be purchased in smaller amounts.
- **Threshold setting**: Some final adjustments such that the inventory management is code ready. Some general principles which must be followed for any given ingredient irrespective of its nature, if SUE < 85% reduce orders, if SSL > 5 Kg per month then reduce the orders and if Days until stockout < 3 days then increase the orders. Items that are frequently ordered should have their orders increased and vice-versa. Maintain up to 5-10 % of goods which constitute under grains, spices and oils. Whereas, maintain 2-5 % of goods which constitute under meat and dairy to avoid excess spoilage.

Now, using these strategies a code was written such that it returns an Optimized Inventory management dataset, which would include additional features in the dataset which are, Order Quantity Adjustment, Optimized Purchase Frequency, Optimized Order Quantity, Optimized Reorder Level and Optimized Waste Percentage (Expected waste percentage after implementation of the strategies). This Code was executed in google Colab and its link has been provided in the results section of this report. The **Optimized dataset** is a very rigorous dataset with 38 ingredients and 19 Features, which has been finalized and established. (Link: https://docs.google.com/spreadsheets/d/1UjMzjAkQn49jd0ZCPVr6RGVTXb1oZhuV/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

3. Results and Findings

The final stage of this project yielded critical insights that have significantly enhanced the overall menu structure, inventory efficiency, pricing strategies in Singi's kitchen and ultimately designing a finalized optimized menu for the restaurant. All the major takeaway points realized in the final submission report are as follows:

(1) **Finalized Primitive menu analysis dataset and Advanced menu analysis dataset**:

After extensive fieldwork of over a month, A primitive dataset with **8 features and 41 dishes** which included main dishes, side dishes, breads, deserts and beverages. The primitive dataset provides all the necessary elementary sales related features such as, Total orders in a month, cost to prepare, Profit margin and etc. (Primitive dataset link:

https://docs.google.com/spreadsheets/d/1zxMH35PMIbYTz6iq8qj5lsdB-MtJzyxH/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

After this, an advanced dataset was also created considering two more features, Phase potential score and Menu score. As explained in detail in earlier section, Phase potential score measures the customer loyalty of a phase within the community which has the most number of orders for a given item. Whereas, the menu score is a heuristic model developed as a weighted sum of four different parameters which includes, Orders per month for a dish, average phase potential score for that dish, Revenue generated by that dish and Cost to prepare the dish. The advanced dataset is of paramount importance as it serves as a cornerstone for understanding the overall profile of dishes, their historical performances, and their possible performance in future. (Advanced dataset link: https://docs.google.com/spreadsheets/d/14DNe_Ua1qAOpU4SikwJjolNLyyBmefFr/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

(2) **Developing a menu score**:

To predict the performance of an item on the menu and to quantify the customer loyalty that particular item brings, A menu score heuristic model was developed. The menu score was primarily built as a weighted sum of four important parameters which are, average phase potential score, Total orders in a month, Total revenue generated by the item and Total cost to prepare the item. The menu score aligns well with the sales data, customer loyalty and individual publicity to each dish. The mathematical formulation of the score is given by:

$$S(i) = 0.25O(i) + 0.4P(i) + 0.2R(i) - 0.3C(i)$$

Where:

$O(i)$: Total number of orders per month for dish i

$P(i)$: Average potential score of the phase where this dish is most ordered

$R(i)$: Total revenue generated from dish i

$C(i)$: Total preparation cost for dish i

(3) Categorization of menu items:

Based on the menu score, An Inter Quartile Range analysis (IQR) was performed to find four different quartiles in menu score feature. The **overall range** of the menu scores was [266,14126], considering all items including side dishes. Ultimately for analytical purposes, the outliers that is the side dishes which are often ordered rarely on their own and often ordered as a complement to the main dish, were excluded from the process of analysis as they skew the dataset. Side dishes that were excluded are, Tandoori roti, Naan, Gulab Jamun, Masala Tea, Lassi, Rasgulla and mango shake. Side dishes that performed well (score > 2000) were included for the analysis. Ultimately after performing the IQR analysis, the quartiles observed were, Q_1 = 2648.63, Q_2 = 4729.59 and Q_3 = 6764.74. Based on the quartiles, four broad categorizations were created, which are:

- **Top performing category**: All menu items with score above Q_3,where the menu score ≥ 6764.74. The most successful category in the menu.
- **Moderately successful category**: All menu items with score between Q_2 and Q_3, where the menu score is defined as, 4729.59 ≤ menu score < 6764.74. Decently successful items with decent customer base and profitability.
- **Mediocre category**: all menu items with score between Q_1 and Q_2, where the menu score is defined as, 2648.63 ≤ Score < 4729.59. Items which have neither failed nor succeeded, A lot of reforms are needed to increase profitability of the dishes.
- **Failed items category**: all menu items with score less than Q_1, where menu score is defined as, menu score < 2648.63. Items which have failed to generate revenue or customer loyalty. Major rebranding or removal are the only two choices for these dishes.

A visual representation is shared below for a more graphical understanding of the four categories (All codes for the graphs is provided in this google colab worksheet, link: https://colab.research.google.com/drive/1uVTjeAamSRRFAuMKcTWrMW21vuKISlDp?authuser=0&pli=1#scrollTo=1Ox1S9mXnglR)

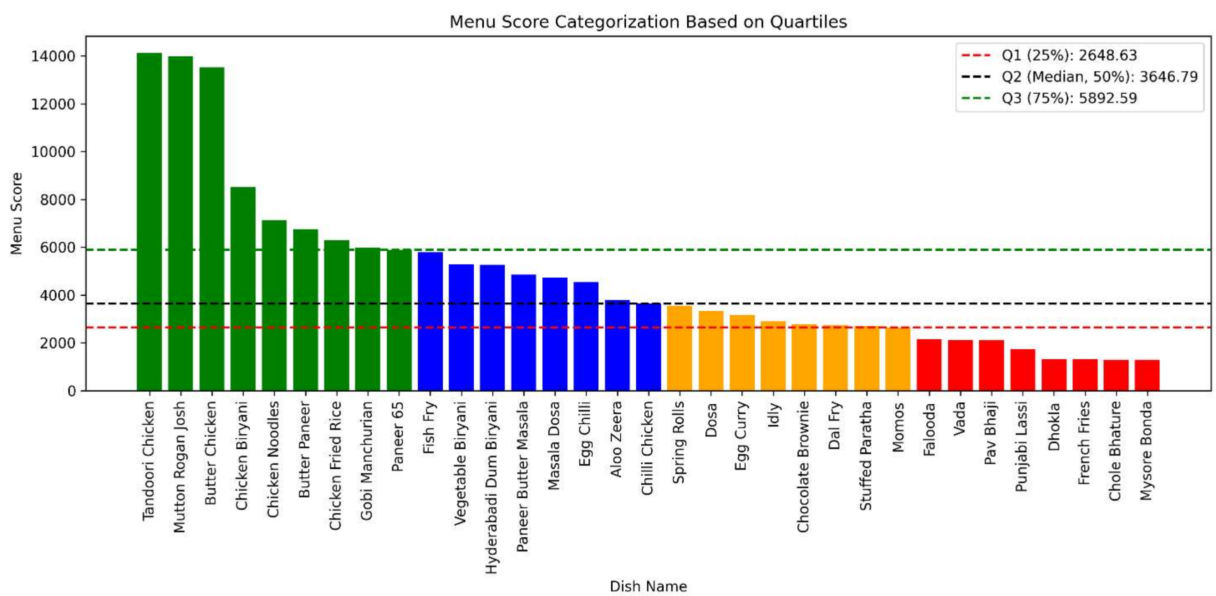

Figure 3.1: Bar graph on menu score categorization

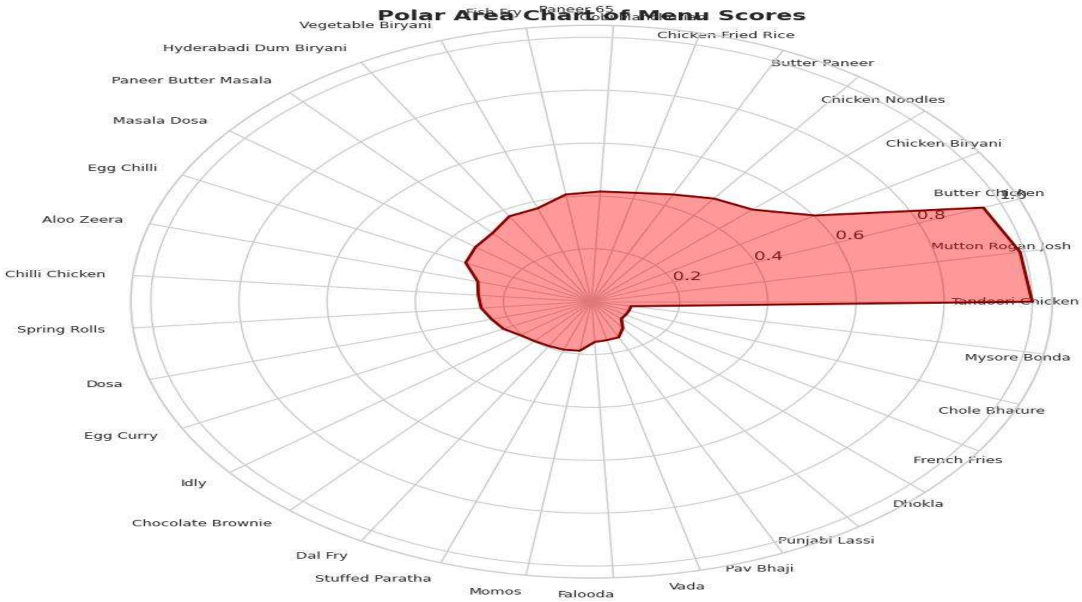

Figure 3.2: Polar area chart of menu scores

Where Green represents Top performing category, Blue represents Moderately successful category, yellow represents Mediocre category and red represents failed items category in the bar graph, whereas the radial distance covered in polar area chart shows performance of items with respect to their menu scores. From the analysis here are few important insights on the items based on the graphs:

- Dishes like **tandoori chicken dominate sales and profitability**, the demand here is likely inelastic, prices could be slightly increased for better profitability.
- Dishes like Fish fry and veg biryani are performing decently well. Demand here is likely elastic, **price decrement will be the key**.
- Dishes like **Dosa, Egg curry and idly are not performing satisfactorily**. Demand here is likely elastic but just a change in price will not help with the profitability.
- Dishes like Vada, French fries, dhokla and Mysore Bonda have failed immensely. **rebranding/reposition is one of the viable choices** or removal is another viable choice.
- The menu primarily needs to focus on increasing prices on successful items, Apply minor tweaks to decently successful items, **apply bundling strategy to mediocre items** and **possibly remove majority of the failed items**.

(4) **Implementation of pricing strategies using theoretical techniques**:

Using economical framework, many formulations were derived in the earlier section. Most importantly using, **Price Elasticity Demand (PED)** and **menu engineering** formulations, items in different categories are dealt with different frameworks, and below is the implementation of all of the mathematical framework derived.

Items in top performing category: As discussed earlier, using PED, **5-10% of increment** in pricing the items will be maximize revenues as the demand is inelastic. Implementing that to old menu we have:

- Tandoori chicken's new price will be 310 rupees instead of 300.
- Mutton Rogan Josh's new price will be 420 rupees instead of 400.
- Butter chicken's new price will be 290 rupees instead of 280.
- Chicken biryani's new price will be 260 rupees instead of 250.

Items in moderately successful category: As discussed, using PED, **5-15% of decrement** in pricings will maximize revenues as suggested by empirical evidences. Implementing that to old menu we have:

- Fish fry's new price will be 330 instead of 350.
- Vegetable biryani's new price will be 160 instead of 180.
- Hyderabadi Biryani's new price will be 280 instead of 300.
- Paneer butter masala's new price will be 200 instead of 220.

Items in Mediocre category: Using menu engineering, effective combo bundles need to be constructed using dishes in mediocre category such that their sales increase indirectly which also increases customer loyalty. Implementing that to old menu we have:

- Breakfast delight (200 rupees) – 1 Masala dosa +1 Idly + 1 Lassi
- Mutton Jumbo pack (1500 rupees) – 3 portions of Mutton rogan Josh + 6 naans
- Economic Combo delight (120 rupees) – 2 Idlys + 1 Vada
- Biryani Special Combo (370 rupees) – 1 Chicken Biryani + 1 Falooda
- Butter chicken meal (380 rupees) – 1 Butter chicken + 2 Tandoori roti +1 Lassi

Items in failed category with decoy strategy and price charming included: Many of the items in this category should be removed and if not a serious rebranding of the item is required. Implementing that strategy we have:

- Naan is now repositioned to Cheese garlic naan sold for 100 rupees.
- French fries are now repositioned to Masala fries sold for 120 rupees.
- Tea is now repositioned to Masala tea for 40 rupees.
- Momos are now repositioned to Tandoori momos for 100 rupees.
- Many items such as dhokla, pav bhaji, chole bhature and Mysore Bonda are now removed from the new menu.
- Dosa is now sold for 90 rupees instead of 100 using the price charming strategy, Chicken biryani is sold at 250 rupees where Mutton rogan josh is sold for 400 rupees using the decoy strategy.

Majority of the menu items were covered in here, for few items that aren't mentioned here will be explicitly covered in the **finalized optimized menu**, where a completely organized and optimized menu with all the required strategies induced will be shared.

(5) **Finalized optimized menu strategy**:

The final optimized menu is the culmination of data-driven analysis, which had been diligently researched upon using various socio-economic strategies as well as psychological and marketing strategies. A link of the finalized optimized menu is given below, followed by key insights and details in the final menu:

Finalized optimized menu dataset link: https://drive.google.com/file/d/1pOeM74VoGC83wBfGiKvEudSlo0yp8SR0/view?usp=sharing

Key insights for the finalized optimized menu are:

- Most successful items had their pricings increased by 10/20 rupees based on inelastic demand, whereas moderately successful items pricings have been decreased by 10/20 rupees based on elastic demand.
- Underperforming dishes were bundled with successful ones into Combo meals, increasing perceived deal value and gaining customer loyalty.
- Few of the failed items have been rebranded and repositioned to more appealing variations such as, **Tandoori momos**, **Masala Fries**, **Cheese Garlic naan** and etc., to leverage more popularity and demand from the customer base.
- Decoy and price charming strategies have been used effectively over items such as dosa and chicken biryani, to ensure that there is always a psychological appeal for the consumers.
- The finalized menu is compact, concise and efficient, from a huge menu of 41 items the finalized menu has **only 26 items**, which only focuses on **high-performing** and **high-value dishes** while leaving some room for experimentation.

(6) **Primitive Inventory management dataset**:

After an extensive fieldwork of exactly one month, A primitive Inventory management dataset was established which covers all the necessary aspects of ingredients which has been explained in detail in the preceding section. The primitive dataset contains 28 ingredients and 14 different features. Visual representations of few key features within the primitive dataset are provided below, and key insights based on the figures is discussed as well (Primitive Dataset Link:https://docs.google.com/spreadsheets/d/110V1WVGEdaZM7lWpZ9kXa-Aj0sZJbcM4/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

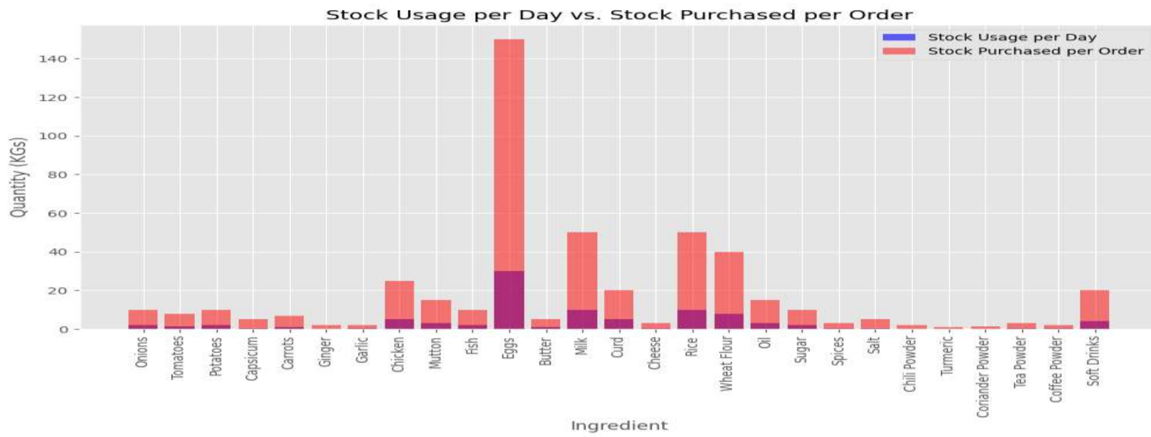

Figure 3.3: Stock usage per day vs. Stock purchased per order

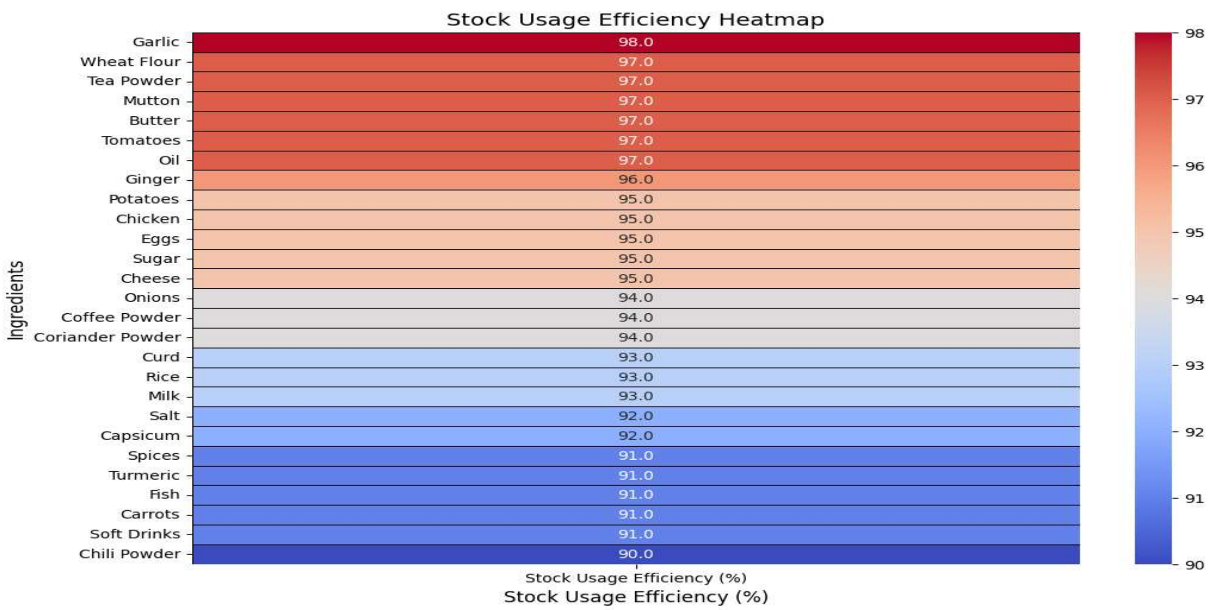

Figure 3.4: Stock usage Efficiency Heatmap

Based on above visual representations, the following key insights can be observed:

- There is a high stockage efficiency in essential ingredients, in items such as garlic, wheat flour, tea powder and mutton exhibit highest stock usage efficiency (~97-98%). This indicates essential items optimally utilized with minimal wastage
- In figure 3.3, it could be observed that Eggs, butter and rice have a substantially higher purchase quantity compared to their daily usage. Optimized purchase frequency is needed to avoid overstocking and stock spoilage loss.
- Items related to spices and seasonings have a very low stock usage efficiency (~90-91%), this highlights the fact that excess stock is maintained and demand is not aligning with purchases. Readjustments are needed to reduce the storage costs.

- Higher perishable items are showing lower stock usage efficiency whereas Lesser perishable items are showing higher stock usage efficiency, which suggests negligence and possible higher order purchases exceeding the demands.
- Total stock usage per day compared to stock purchases per order is relatively very small, this suggests a possible issue of overstocking in multiple departments which needs to be addressed via optimized procurement planning.

(7) **Advanced Inventory management dataset**:

Building upon primitive Inventory management dataset, an advanced inventory dataset was developed integrating multiple strategies which includes, improving procurement efficiency and minimizing inventory wastage. This dataset applies all the frameworks discussed in the preceding section, Modifying Order quantities based on market trends formulation, waste & spoilage-based formulation, practical adjustments and etc. The dataset introduces 5 additional features which optimizes the ordering frequency, threshold frequency stock usage efficiency and minimizing waste percentages. The 5 additional features are explained in detail below, and after applying and implementing all the applied framework, the following Advanced Inventory management dataset was established (Code of this can be found in the provided google colab notebook link):

- **Order Quantity Readjustment (KGs)**: Readjusts stock levels by reducing excessive inventory and making purchases which align to the required demand.
- **Optimized Purchase Frequency**: Adjusts restocking intervals to prevent over-stocking and to reduce storage costs.
- **Optimized Order Quantity (KGs)**: Dynamically readjusted to align with demand fluctuations, reinforcing sustainable inventory management.
- **Optimized Reorder Level (KGs)**: Maintaining precise stock thresholds to trigger timely replenishments without acquiring surplus stock.
- **Optimized Waste Percentage (%)**: By adhering to balanced procurement based on actual consumption and sales profile, to minimize the material spoilage which in turn reduces financial losses.

After implementing all the necessary Inventory and socio-economic strategies as discussed in preceding sections, and after establishing this dataset via programming, A finalized Inventory management dataset is created with **28 ingredients and 19 features**.

(Link : https://docs.google.com/spreadsheets/d/1UjMzjAkQn49jd0ZCPVr6RGVTXb1oZhuV/edit?usp=sharing&ouid=104943617588248477463&rtpof=true&sd=true)

4. Interpretation of Results and Recommendations

This section consolidates all findings from previous analyses, interprets business and social implications, provides data-backed recommendations for Singi's kitchen to optimize its menu offerings, price strategies economic profile and inventory management. This section is divided into two categories, where firstly key results will be interpreted and presented and in the second category key recommendations will be presented and discussed:

(1) Interpretation of key results:

- **Menu performance Insights**: The menu score model effectively identified high-performing, moderately successful, and underperforming items. **Tandoori chicken**, **Mutton Rogan Josh**, and **Butter Chicken** emerged as the top-performing dishes with robust sales and customer loyalty. The menu score also effectively highlighted items which have failed to gain traction in both sales and customer loyalty, items with a very low performance, which included items like **Vada**, **Pav Bhaji**, **Momos**, **Lassi** which needs restructuring or removal to reap any economic benefits out of these items.
- **Impact of price elasticity on revenue**: By referring to various economic texts, the Price Elasticity of Demand (PED) model revealed that, there are two categories of items, where inelastic items can withstand moderate price hikes because of their prominent demand and immense customer loyalty which includes dishes like Tandoori chicken and Butter chicken, whereas, elastic items benefited from slight reduction in pricings, which would enhance their demand and revenue which includes items such as Fish fry and Vegetable Biryani.
- **Impact of Menu Engineering & Combo building**: With the help of formulations for consumer economics and Menu design engineering, introduction of combo meals significantly boosts sales for mid-tier items by bundling them with top performing items, which increases the perceived value of the good and increases the profitability. Examples such as, **Biryani special combo**, **Butter chicken meal**, **breakfast delight** and **Mutton jumbo pack** pair popular and mediocre dishes to optimize sales growth.
- **Inventory Optimization Findings**: The development of Advanced Inventory management dataset improved overall stock efficiency by optimizing reorder levels, reducing wastage, and adjusting procurement cycles. Key findings within the Inventory management dataset include:
    - Essential ingredients like **Garlic**, **Wheat Flour**, and **Mutton** had the highest stock usage efficiency (~97-98%), ensuring optimal utilization.
    - An excess stocking of perishable goods which includes **Eggs**, **Butter** and **Rice**, more suitable purchase frequency adjustments were applied.
    - Spices and seasonings had the lowest stock usage efficiency (~90%), underscoring the misalignment perceived demand and actual demand.

(2) Recommendations for business operations:

Firstly, discussing essential recommendations with respect to Menu strategy:

- **Increase prices for inelastic items** (e.g., Tandoori Chicken, Butter Chicken, Mutton Rogan Josh) by 5-10% to maximize the revenue.

- **Decrease prices for elastic items** (e.g., Fish Fry, Vegetable Biryani, Chicken Biryani) by 5-15% to enhance demand and overall sales volume.
- **Remove low-performing items** (e.g., Pav Bhaji, Chole Bhature, Mysore Bonda) from the menu as they will incur more losses and fewer monetary gains.
- **Rebrand different low-tier items** by establishing more exciting dishes (e.g., Momos → Tandoori Momos, Tea → Masala Tea, Falooda → Chocolate sundae Falooda) to develop a new customer base and to optimize the revenue.
- **Low and Mediocre-performing dishes should be sold as a combo with a successful item.** Combos such as, Breakfast delight, Biryani special combo, Butter chicken meal should be introduced to ensure weaker items gain traction while driving the overall sales forward.
- **Charm pricing** (e.g., Masala dosa priced at 90 rupees instead of 100) should be implemented to enhance customer perception of value.
- **Decoy pricing** (e.g., Chicken Biryani at 250 rupees Vs. Hyderabadi Biryani at 280 rupees) makes mid-tier options more attractive by leveraging consumer psychology.
- **Conduct customer feedback surveys post-implementation** to assess the reception of the new menu by the customer base, fine-tune the menu accordingly once in every 4 months.
- **Implement 80-20 rule,** retain the majority say 80% of items in the menu, but do keep experimenting 20% of the items for every 4 months by introducing them under the category of, "seasonal dishes", "Summer specials", "winter specials" and etc., this will ensure the restaurant always has an active customer base and active sales throughout the year.

Lastly, discussing about the essential recommendations with respect to Inventory Management:

- **Optimize Purchase Frequency,** adjusting restocking schedules to prevent overstocking and minimize waste.
- **Reduce overstocking of spices & beverages,** lower procurement for slow-moving ingredients to cut storage costs.
- **Align order quantities with demand trends,** use sales data to dynamically adjust stock levels based on actual consumption.
- **Setting precise reorder levels,** implement threshold-based ordering (generally threshold levels are kept at 5-8%) to ensure stock availability without excess accumulation.
- **Minimize perishable goods wastage,** improve tracking for high-waste items (e.g., eggs, dairy, vegetables) to reduce spoilage.
- **Implement Digital Inventory tracking,** use automated tools to monitor stock values in real-time and to enhance overall efficiency of inventory.