https://doi.org/10.34074/rere.00608

Research Article

From Intuition to Insight: A Business Intelligence Case Study of Daily Sales and Food-Waste Performance in a Sri Lankan Café

Senumi Amaya Rajasundara Waidyalankara,[1], Gamalathge Amasha Malindi Premarathne[1], Sellapperumage Asheni Subhangi Fernando[1], Dasanayake Mudiyanselage Yenuli Dulansa[1], Gilmini Dantanarayana[2], Dilki Shihara Muthumala Jayasooriya[3]

[1] Faculty of Computing, University of Sri Jayewardenepura

[2] Department of Information Systems Engineering and Informatics, Faculty of Computing, University of Sri Jayewardenepura

[3] Department of Scientific Computing, Faculty of Computing, University of Sri Jayewardenepura.

ABSTRACT

In Sri Lanka, small family-owned cafes and bakeries typically make decisions on production,staffing and menus on a day to day basis without having data on hand to assist in decision making. Such judgements are often sound, but they are off-the-record, unverifiable, unauditable and can represent unnoticed losses due to overproduction and mismatched staffing. This paper is an applied case-study of one month of operational data (1,890 records across 63 items over 30 days) collected from an operational cafe and analysed through a four page interactive Microsoft Power BI (MS-PB) dashboard that reports on sales overview, item analysis, day-wise sales pattern and wastage analysis. All references to ”profit” are to gross contribution (sales revenue minus cost of goods sold and value of wastage) and not accounting net profit as this does not include business overheads, including rent, wages and utilities. It was observed that cake was the largest revenue category (40% of total revenue) and the largest source of food wastage (Rs. 363, 045 of Rs. 806,133), making it the most financially impactful category to manage. Sales volume and contribution did not consistently align. Highest selling items were the low margin savoury snacks while the highest-margin items were moderately sold items like cake, this would not have been seen as important from a volume-based perspective. The revenue per day generated during weekend days was approximately 36% higher than during weekdays, and served as an evidence base to test weekend staffing. Overall wastage was 15.7% of production (almost one-third of monthly gross contribution), and the single best-selling product, Chicken Patty, was the most wasted, suggesting an overproduction pattern. This study demonstrates that just a small, structured, one-month dataset can reveal operational insight and that accessible BI tools makes the analysis possible for enterprises without a dedicated analytics team. The results are given as insights and testable proposals rather than demonstrated operational improvements, since the data are from one month.

Keywords: Business Intelligence, Small and Medium Enterprises, Data Visualisation, Food Waste, Power BI, Foodservice Operations.

INTRODUCTION

Small independent and family-run cafes and bakeries in the food-service industry are making day-to-day operational decisions based on their knowledge and the owner's experience with the business, including whether to produce a baked good, how to staff the kitchen, and whether a menu item is worth keeping. This is acceptable and sometimes correct, but it is not explicitly recorded for future analysis and exists only in the owner's mind . It cannot be checked by staff against evidence at the end of a trading month, and cannot be transferred if the owner is not present. This can be an organisational blind spot. For example, an owner may think that cakes are his most successful product line, but never look at sales figures to confirm this. These little things can compound over time, from a lack of staffing for a weekend shift to a slightly over-baked tray from time to time (Krishnapriya & Ajith Kumar, 2026; Llave, 2017).

Business Intelligence (BI)directly tackles this issue. A BI approach enables the daily activities to be recorded in a structured method. What was produced, sold and disposed of, with the monetary amount, are transformed into interactive,visual dashboards that even a non-technical manager can read and understand at a single glance. For smaller organisations with limited resources and no dedicated analytics team, having the ability to make decisions in a proactive rather than a reactive way is perfect, as they can make decisions based on a readable visual summary of the raw operational data. Although SMEs face challenges like low in-house knowledge and high implementation costs, the benefits of BI for SMEs have been shown in the literature, such as improving the quality of decision making, the efficiency of operations, and financial performance (Krishnapriya & Ajith Kumar, 2026; Llave, 2017).

For this project, the analytical tool used is Microsoft Power BI. Easy to use, widely taught and designed to allow managers/staff with no query-writing knowledge to easily navigate data via simple visual controls. This study was carried out for Rodrigo's, a cafe in Colombo,Sri Lanka, where the data for one month of sales, production, and wastage of items was collected directly at the premise and fed into a 4 page interactive dashboard which includes the sales performance, item analysis, daily/weekly sales trends, and food wastage. The aim wasn't just to draw up charts, it was to find out something the cafe could act on the following month, such as reevaluating an underperforming menu line, the amount of a menu item being produced, or even adjusting weekend hours.

Throughout this paper, the word 'profit' is defined in the sense that the cafe itself uses it, where profit equals to sales revenue minus cost of goods sold minus the value of wastage. Technically in accounting terms this would be known as gross contribution as opposed to net profit since business overheads (rents, wages, utilities etc.) are not included. This reflects how the business actually measures performance and all monetary amounts thereafter are based on this. The structure of this paper is as follows. The problem statement and specific operational research questions are introduced, followed by a discussion on background information on BI in small businesses, design of visualisation, and measurement of food-waste. The Methodology part discusses the process used for collecting data, the data set, data tools, and data analysis. Findings are then shared and discussed on the four themes of the dashboard, followed by suggestions for the cafe and reflections on the limitations of the study.

PROBLEM STATEMENT

Data is generated in the daily operations of the cafe in many dimensions such as quantity produced, quantity sold, quantity wasted, and the revenue and cost of each item. In most cases, however, this information is not collected, aggregated or analysed. As a result, there are a number of basic but important questions that are not answered and the management cycle is poorly organised.

This gap appears in five distinct blind spots that are all linked to each other, such as, uncontrolled overproduc-

tion and wastage, unrecorded stockouts during peak demand, unknown relationship between sales volume and true profitability, no evidence of whether the staffing should be more or less on weekdays compared to weekends, and no evidence whether monthly revenues are increasing, decreasing, or level. These decisions are all made from memory, not through a formal checkable record, and each has a significant consequence when the decision is not well made. They all have a common cause: Decisions regarding production and staffing are made without access to past sales data in a structured and usable format at Rodrigo's.

RESEARCH QUESTIONS

To resolve this problem, the following five research questions are used:

1. **Overproduction and wastage:** *What are the items that are always over-produced and what is the monetary amount lost due to that?* If you don't have wastage tracking, you cannot rectify the overproduction amount.
2. **Stockout vs revenue loss:** *Which items sell out during peak hours and how much is the cafe's loss due to that?* The busiest days could be losing customers that don't even show up in sales figures, as sales figures only reflect completed transactions.
3. **Popularity vs profitability:** *How do the top selling items compare if cost price is taken into account, not just selling price?* If the product is a high volume, low margin product, then management may be tempted to focus on the wrong products.
4. **Demand Scheduling:** *Which days of the week are busier or quieter, based on definite evidence rather than a best guess?* Important for better implementation of the staff rosters
5. **Revenue trend visibility:** *Does the cafe have an increasing, level or declining trend and whether it is visible across the month and which days should be explored in greater detail?*

The aim of this research is to develop a multi-page interactive dashboard to address the five questions with evidence, determine the best and worst performing products based on sales volume and financial contribution, quantify the demand and food waste by day of the week and transform each finding into a concrete,testable operational proposal.

BACKGROUND AND RELATED WORK

This study covers the context of four strands of previous research. The first relates to the use of BI by smaller businesses. BI systems are seen as an indispensable tool to support the process of business decision making and systematic reviews on BI in the context of SMEs always show that the adoption of BI improves decision quality, operational efficiency and financial performance (Llave, 2017). The same literature is sparse in its expression of the challenges that still exist in uptake for micro and small firms: financial constraints, lack of skilled staff and infrastructure are the more common issues (Krishnapriya & Ajith Kumar, 2026), which makes a no-barrier desktop tool like Power BI appealing. In this study, it can be considered a miniature of the observations made in the literature on the whole.

The second strand is related to the design of visualisations. This is because the value of a dashboard is dependent on the type of visualisation used and the question being asked. If the data are not sequential, e.g. non-sequential categorical, using a line chart can mislead, as it implies a trend that is not present in the data. So, when used appropriately, line charts are used when the values change over time, bar or column charts are used when the values are

being ranked and compared, and a part-to-whole chart (donut) should be used only when the total is 100% (Microsoft, 2024). The dashboard of this study was constructed following these principles not based on visual preference.

The third thread is related to food-waste measurement in the food-service context, which is one of the key findings of the study. Structured quantification of waste is a critical first step to reducing waste; the majority of all catering units that quantified waste also reduced waste and the units with the highest waste recorded the greatest cost-effective opportunities for reducing waste (Eriksson et al., 2019). This directly validates the premise underlying the study that there can be no action without a cost, and that ranking waste by item is the first step towards targeting it.

In the first strand, there is not much evidence available on the local level related to BI in Sri Lanka, and it is related to adoption, not use. In Kandy district, a sample of 100 SME entrepreneurs were selected for technology-organisation-environment survey, and the study results of the sample indicated that the relative advantage, complexity, organisational resources and competitive pressure are the significant factors affecting the adoption of BI, and the IT knowledge of the managers are the moderating factors to the effect of the relative advantage (Herath, 2024). This study does not document any lessons a small business learned from their own operational data, instead it focuses on what a SME does with BI.

The fourth strand relates to the assessment of the product performance in food businesses and to minimising overproduction. The products are evaluated using two parameters: popularity and contribution margin, which will influence pricing decisions, allocation of resources and prioritisation (Noone & Cachia, 2020). An Indonesian tourism oriented cafe determined that of 39 items tested, 16 items (41%) were high demand with low margin ”plowhorse” items, indicating that good customer demand may not always lead to profitability (Viano et al., 2026). This is similar to the ”high volume savoury snacks” versus ”moderate volume, high margin gateaux” split that is reflected in the item analysis below. On its own, a life-cycle analysis of a machine-learning forecasting application for bakeries demonstrated that machine-learning-based demand forecasting can significantly minimise overproduction, and that demand changes from day-to-day, season-to-season, holiday-to-holiday, and event-to-event (Hubner et al., 2024).

Forecasting can be a very potent tool if there is sufficient data and technical expertise in the small cafe, or a descriptive dashboard is a worthwhile starting point, and the item level waste ranking that comes below is the input to be fed into a forecasting model.

METHODOLOGY

Data collection

The data used in this study were realistic data collected directly from the café and bakery of Rodrigo’s in Colombo, not simulated or hypothetical figures. The data were collected on site, using the own daily records of the café for the reporting period June 2026. The number of items produced, sold and wasted for each menu item for each of the 30 days, as well as the unit selling price or cost price are recorded in the café for each menu item, and the rest of the monetary fields are calculated as follows. The data was collected over one month of visits, and thus only covers the month at a time; this means that the data was a result of the café’s own historical record for this month, as the researchers were not continuously observing the café. This approach introduces a limitation in the study as the quantities are based on the café’s day-to-day record keeping and the results are not automatically audited against physical stock. This method was selected for its ability to provide a whole month of a business’s trading activity, at an item level, which would be difficult to recreate by observing the trading activity for a few days or weeks only.

Table 1: Positioning of this study against related work.

	Study: focus & approach	Contribution	Gap	How this study addresses it
1	SME BI impacts, literature review (Llave, 2017).	Links BI adoption to better decisions, efficiency and financial performance.	No operation data for a real business, only aggregates of evidence.	Provides a specific one month instance of these benefits, in a café.
2	BI adoption in MSMEs, systematic review (Krishnapriya & Ajith Kumar, 2026).	Identifies barriers: cost, skills and infrastructure.	States problems but does not attempt to identify a low cost solution to avoid them.	Leverages a low cost desktop application, Power BI, without an analytics team.
3	Visualisation types (Microsoft, 2024).	Chart-selection principles.	Documentation from the vendor rather than empirical evaluation.	Applies the principles and shows the resulting findings.
4	Waste quantification, 735 EU catering units (Eriksson et al., 2019).	Measuring waste is linked to reducing it.	No ranking of items, and no link to sales and contribution; no Sri Lankan setting.	Sorts items and categories of waste and correlates them with revenue and contribution
5	Sri Lankan SME BI adoption, Kandy (Herath, 2024).	Adoption factors for BI in Sri Lanka.	Studies are meant to be adopted, not what they predict through data inputs from BI; not food service.	Shares the insights that BI provides from actual café data.
6	Menu engineering re-engineered, steakhouse chain (Noone & Cachia, 2020)	Better pricing and placement decisions	Pricing/Placement in a large chain; no waste no small-café setting	Combines waste and day-of-week demand into the volume vs margin view, in a small café
7	Menu engineering, Indonesian tourism café (Viano et al., 2026).	Shows how many popular items have low margins	Popularity and margin based; no waste or day of week analysis; no dashboard	Data for waste, weekday demand and revenue concentration is added to an interactive dashboard
8	Bakery ML forecasting LCA (Hubner et al., 2024)	Forecasting cuts bakery overproduction.	Does not have the historical information or technical expertise of a micro-café; does not identify items that are wasting the most.	Provides descriptive baseline (15.7% wastage, top waste item: Chicken Patty) for forecasting to be based on.

Dataset description

There are 1,890 observations of 63 menu items during the 30 days that correspond to June 2026; each menu item is classified into one of four categories: Cake, Savory, Sweet, and Beverages. Each record is one item for each day, rather than a summary of that item's performance over the month, so there are 63 x 30 = 1890 rows. Table 2 provides

a list of the fields. The level of detail needed for the profitability and wastage analysis that this study is based upon can be found in the cost, wastage, and contribution fields.

Table 2: Dataset field descriptions.

Date	Description
Date	Calendar date of the record (1-30 June 2026)
Item ID	Unique alphanumeric identifier for each menu item.
Category	One of: Cake, Savory, Sweet, Beverages.
Item	Menu item name
Produced Qty	Units produced/baked that day.
Unit Price	Selling price per unit (Rs.)
Cost Price	Production cost per unit (Rs.).
Sold Qty	Units actually sold that day.
Wasted Qty	Units unsold and discarded.
Wastage Value	Monetary value of wasted units (Rs.).
Sale Revenue	Total revenue from sold units (Rs.).
Cost of Sold Item	Total production cost of units sold that day (Rs.).
Gross Contribution (labelled ”Profit” in the dataset)	Sale Revenue less Cost of Sold Item and Wastage Value, per item per day (Rs.). Excludes overheads such as rent, wages and utilities, so it is a contribution figure, not accounting net profit.

Tools

All data from the one month period was organized in a table format in Microsoft Excel. Data modelling, creating DAX-measures, and creating a dashboard was performed in Microsoft Power BI Desktop. Within Power BI, data cleaning and data-type corrections were performed using Power Query and two new columns were added for day-of-week analysis.

Data cleaning, validation and preparation

All cleaning was done before analysis by importing the raw Excel file into Power BI Desktop and opening it in the Power Query Editor before loading it to the report canvas. There were three preparation steps performed.

First, data typing. Each of the columns’ data types were verified and corrected: the Date column was set as Date; the nine numeric columns (Produced Qty, Unit Price, Cost Price, Sold Qty, Wasted Qty, Wastage Value, Sale Revenue, Cost of Sold Item, and Gross Contribution) were set as Whole Number or Decimal Number as appropriate; and Item ID, Category, and Item were set as Text.

Second, completeness and validation. The data was screened for missing and blank records. All the 1,890 item-day records were complete, no missing data in any field, except for trailing empty rows beyond the data region which were eliminated with Remove Blank Rows. Since each menu item was recorded on each of the 30 days, the total number of data items recorded is exactly 63 x 30 = 1,890, and this was used as an integrity check to ensure that no item-days were lost or repeated. The internal consistency of the monetary fields obtained was also checked: for each record, Cost of Sold Item = Cost Price x Sold Qty and Gross Contribution = Sale Revenue - Cost of Sold Item - Wastage Value. No records were found that needed adjustment or deletion. There were no missing values, so no imputation or deletion of rows was required; if there had been missing quantities, the missing item-days would have been reported and excluded from these results instead of estimated.

Third, columns derived for day-of-week analysis. Two columns were added, because the source only had a calendar date. Day of Week was calculated using Date.DayOfWeekName([Date]) which returns the weekly name for each record. Is Weekend calculated as if Date.DayOfWeek([Date], Day.Monday) ¿= 5 then ”Weekend” else ”Weekday” which groups Saturday and Sunday as ”Weekend” and the other five days as ”Weekday”.

The eight DAX measures used in the visuals were based on these prepared data: Total Revenue = SUM([Sale Revenue]), Total Gross Contribution = SUM([Gross Contribution]), Total Wastage Cost = SUM([Wastage Value]), Total Sold Qty = SUM([Sold Qty]), Total Produced Qty = SUM([Produced Qty]), Total Wasted Qty = SUM([Wasted Qty]), Wastage % = DIVIDE([Total Wasted Qty], [Total Produced Qty]), and Contribution Margin % = DIVIDE([Total Gross Contribution], [Total Revenue]). The two percentage measures were intentionally reported using DIVIDE() to avoid a division error if the denominator is zero (e.g., no production for an item on a filtered day, it will return a blank rather than a division error on the dashboard).

Visualisation approach

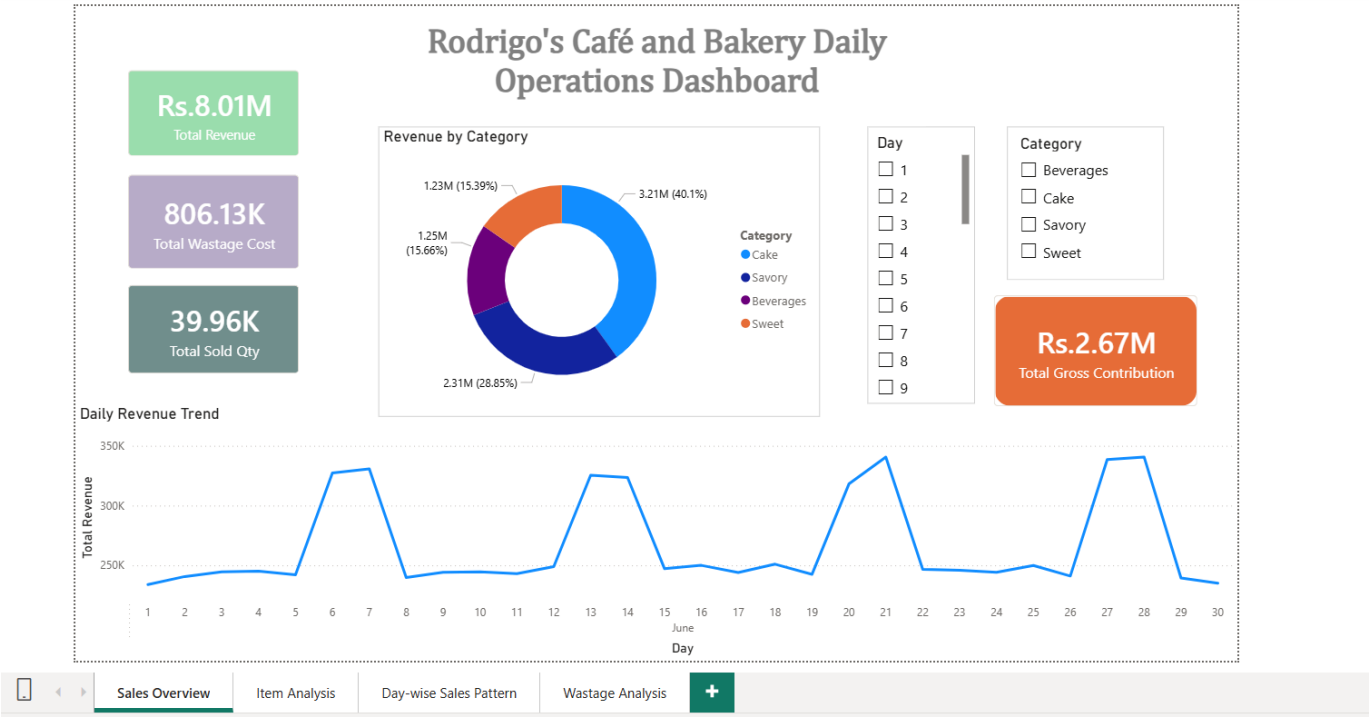
The dashboard was split into four report pages, each focusing on a specific operational question: Sales Overview (overall performance), Item Analysis (item-level contribution and ranking), Day-wise Sales Pattern (weekday/weekend and daily demand), and Wastage Analysis (food waste by item and category). The visualisation principle was used to decide on chart types, rather than appearance: line charts were used for time series (daily revenue, daily wastage cost); bar and column charts were used for ranking and comparison (items, days of the week); and donut charts were only used where the total is meaningful as 100% (revenue and wastage value by category). The official Microsoft Power BI documentation (Microsoft, 2024) was used to create Measures, slicers, formatting and colour themes. The gross-contribution measure is called ”Profit” on the dashboard; it is contribution before overheads.

RESULTS AND DISCUSSION

Sales overview

The total revenue of the cafe in June 2026 was Rs. 8,008,045 and the total gross contribution of was Rs. 2,667,544 which is an overall contribution margin of about 33.3% (after cost of goods and wastage, but before overheads like rent and wages). A total of 39,963 units were sold, representing an 84.3% sell-through of 47,413 units produced.
The sales data collected indicated that a large proportion of the revenue was received from one category. As shown in Figure 1, Cake alone accounted for nearly 40% of monthly revenue (Rs. 3,211,390) compared with the Beverages and Sweets category combined (Rs. 2,486,230) and was just over 1.4 times the next best category, savoury grab-and-go at Rs. 2,310,425 (about 29%). This was followed by Beverages and Sweets contributing Rs. 1,253,780 and Rs.

Figure 1: Sales Overview dashboard page.



1,232,450 respectively (15–16% of monthly revenue). This concentration is important: the sales of cakes are a major factor that affects the financial health of the café as this means that the café is dependent on the sale of cakes. With two-fifths of the income distributed to one category, any failure in the operation of cake production would have a larger impact on overall income than any other category. Thus, the café's biggest revenue contributor and the most significant source of revenue exposure is cake. The daily revenue trend (1, lower panel) revealed no sustained day-to-day movement and reached peaks at roughly seven-day intervals around a fairly flat mean. The peaks occur on weekends, as discussed below in the day-wise pattern, indicating a structural weekly pattern and not random noise.

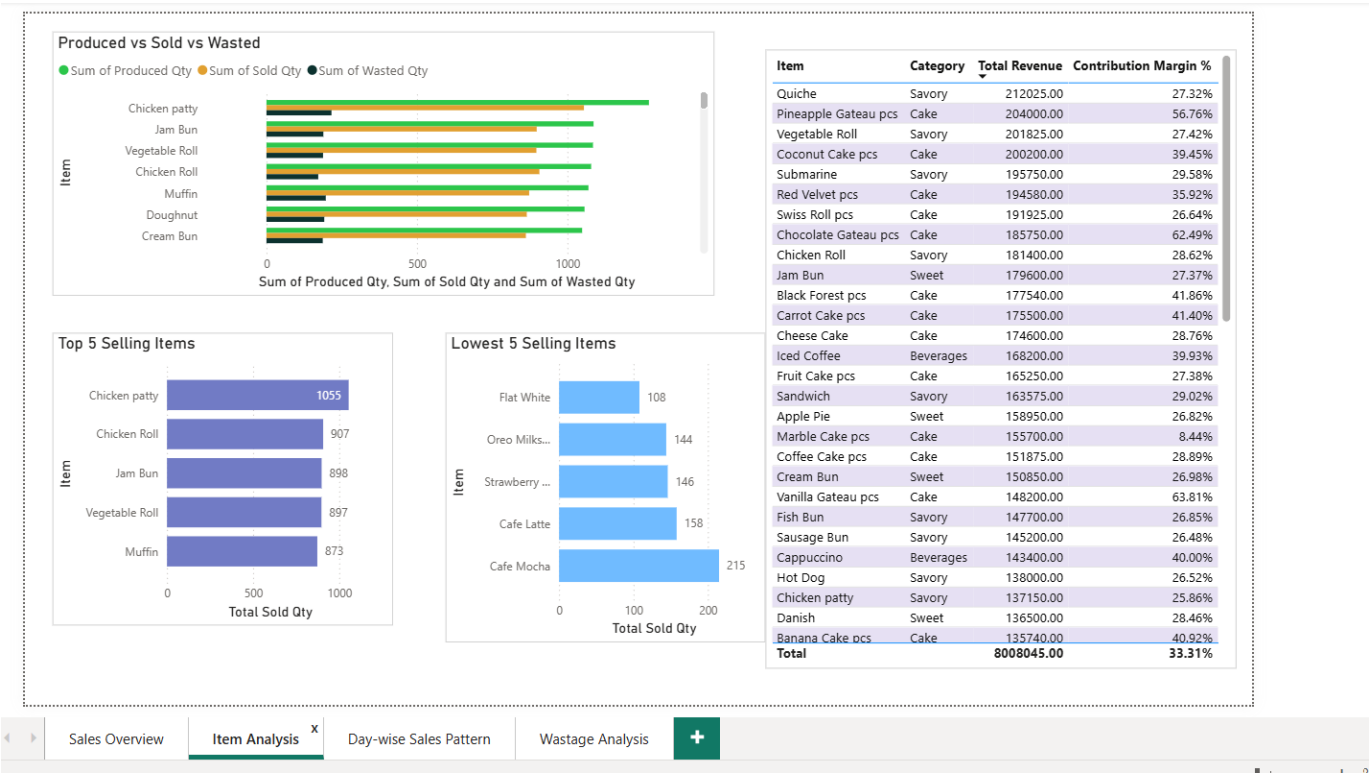
Item analysis

The top five items ranked by units sold were Chicken Patty (1,055), Chicken Roll (907), Jam Bun (898), Vegetable Roll (897), and Muffin (873). None is a cake or beverage; while cake is the revenue driver, on a daily basis the focus will be on quick and inexpensive grab-and-go products. To sum up, cakes make the most money per sale and savoury snacks generate the most transactions.

On the other hand, the five least popular products were all beverages: Flat White (108 units, less than four a day), Oreo Milkshake (144), Strawberry Milkshake (146), Cafe Latte (158), and Cafe Mocha (215). This implies that at present the beverage menu may be larger than customers demand, and there is a management question to test: would dropping the least popular drinks significantly impact profit or would it free ingredients and time from preparing beverages for customers with minimal loss of profit.

When comparing the revenue-ranked table of items with the table of contribution margins, it can be seen that the sale volume of an item does not always correspond to the contribution margin. Generally, Chocolate Gateau (62.5%) and Pineapple Gateau (56.8%) had the highest margins, whereas the highest volume items were the savoury snacks,

Figure 2: Item Analysis dashboard page.



which had lower margins. It is a descriptive observation of the data for the month and not a formal statistical test of correlation because that 63 items for one month would not be strong enough to support. Even as a descriptive pattern, however, it is directly actionable: an owner who adopts "what sells most" as a guiding principle for "what is most valuable" will undervalue these high-margin items. Their margins indicate it might be worth experimenting with more noticeable menu positioning or promotion and seeing how sales are affected, an experiment that the dashboard can enable, but cannot prove. It is consistent with the literature of menu engineering, in which popular items tend to be low-margin "plowhorses" while the highest profit items tend to be "moderate" sellers (Noone & Cachia, 2020; Viano et al., 2026).

Day-wise sales pattern

There was a definite trend in revenue for days of the week. Sunday (Rs. 1,335,480) and Saturday (Rs. 1,309,285) were the two peak days, with a distinct mid-week trough across Wednesday (Rs. 977,155), Thursday (Rs. 988,985), and Friday (Rs. 974,575), each about a quarter lower than the peaks. The levels on Monday (Rs. 1,206,860) and Tuesday (Rs. 1,215,705) were near weekend levels, perhaps a carry-over from the weekend demand.

The influence increases when the split is made between a weekday and a weekend. The 22 weekdays produced Rs. 5,363,280 and the 8 weekend days produced Rs. 2,644,765, averaging Rs. 243,785 per weekday against Rs. 330,596 per weekend day. The average weekend day generates approximately 36% more revenue than the average weekday, even though weekends only account for about one-quarter of the month. This lift occurred in all four categories, not just one, indicating that any adjustment like an increase in staffing on the weekend can be made across all categories

Table 3: Total revenue by day of week.

Day	Total Revenue (Rs.)
Monday	1,206,860
Tuesday	1,215,705
Wednesday	977,155
Thursday	988,985
Friday	974,575
Saturday	1,309,285
Sunday	1,335,480

Figure 3: Day-wise Sales Pattern dashboard page.

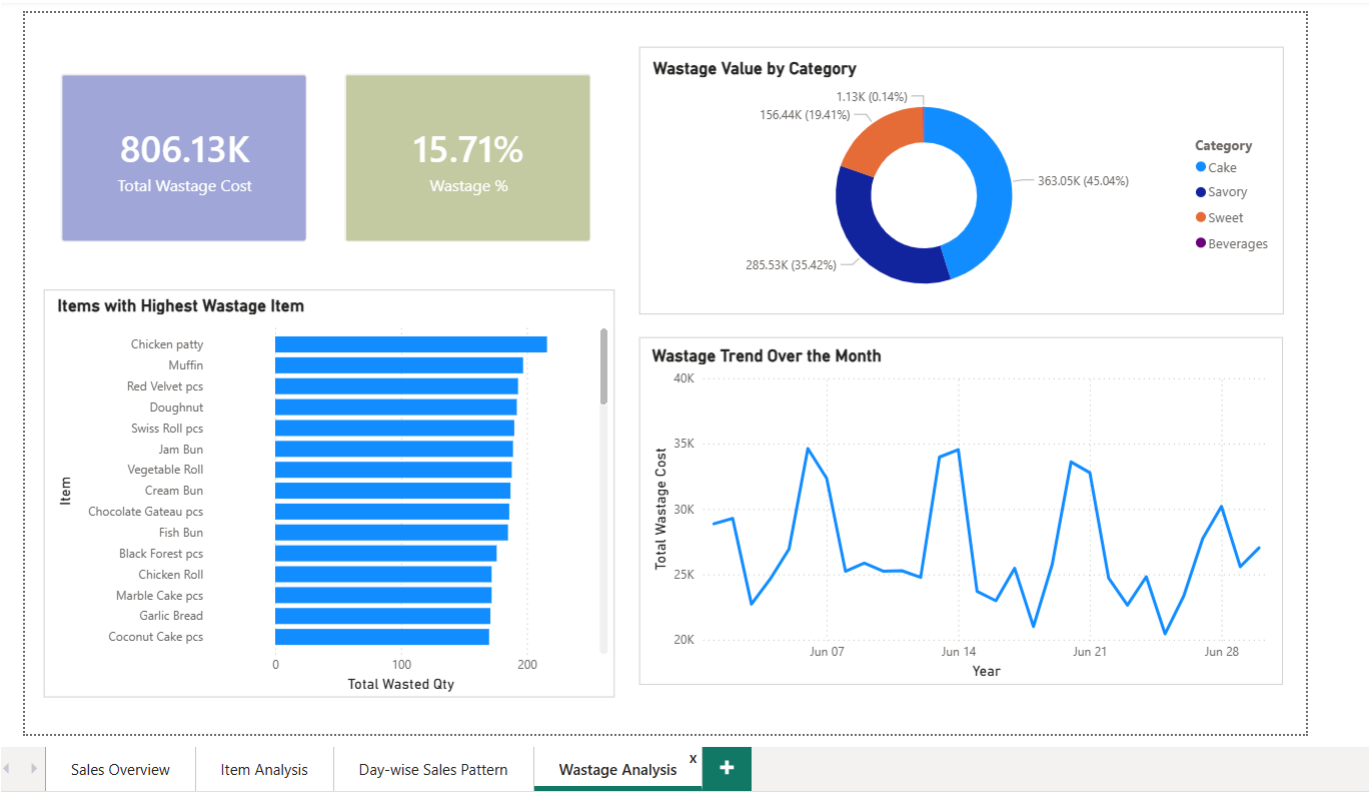


rather than just one category. This is provided as a proposition for testing in relation to service quality and labour cost but does not constitute a proven result.

Wastage analysis

The café wasted 7,450 of 47,413 units made, costing Rs. 806,133 or approximately 15.7%, which is roughly one in every 6 units made that goes unsold. Wastage is one of the largest areas for improvement in terms of the percentage of

Figure 4: Wastage Analysis dashboard page.



the café's monthly gross contribution, accounting for almost a third of the contribution.

Wastage was concentrated in solid foods rather than drinks. Cake led at Rs. 363,045, with Savory (Rs. 285,525) and Sweets (Rs. 156,435) following behind; Beverages were negligible at Rs. 1,128, with drinks being made to order rather than batch produced. This verifies the sales-overview results that Cake is the top revenue item and top waste item and therefore is the most important to be managed.

The most wasted items at item-level were Chicken Patty (216 units), Muffin (197), Red Velvet Cake (193), Doughnut (192), and Swiss Roll (190). Most importantly, Chicken Patty is the top-selling item (as per Item Analysis) and the most-wasted, suggesting that the demand for Chicken Patty is not weak, but it is overproduced. This indicates a low-risk proposal to test: a modest decrease in the number of patties produced per day would be unlikely to result in stockouts, given the amount currently being discarded, and would be expected to reduce the wastage cost directly. Since this is based on one month of aggregate daily figures, it is advisable to use it incrementally and monitor it, so that any impact on stockouts and sales can be measured before significant changes are made. The daily wastage cost was highest on the 6th of June with Rs. 34,615 and lowest on the 25th of June with Rs. 20,450, with the average being Rs. 26,871 over the month; although the modest spread is worth monitoring, one month of data is not enough to draw a conclusion, consistent with the fact that structured measurement is the first step to meaningful reduction of wastage (Eriksson et al., 2019).

Discussion

The four views combined superseded intuition on production, menu composition, and staffing for this café and month. It is important to point out what the study does and doesn't establish. Each finding is an insight that was

identified from the dashboard, not an improvement shown after implementing change based on the insight. No operational changes were made or observed during the timeframe of the study, and thus the recommendations below are only recommendations, the impacts of which will need to be tested. The single month scope also precludes the ability to distinguish fine day-to-day variation (early- versus late-June wastage), or ordinary fluctuation or calendar effects; and the figures are gross contribution, not net profitability. The contribution of the work within these boundaries is that an affordable BI tool, applied to one structured month of real item-level data can bring up specific questions that can be tested at the operation that a small café could not otherwise see – and only the first step towards doing so is starting to take them – before they can be acted on and verified.

CONCLUSIONS

The aim of this project was to identify if this process could be improved by taking one month of the small café's operational data and structuring and visualising this information on an interactive Power BI dashboard. It could: within the constraints mentioned below, it could identify patterns that would not have appeared on paper. There are four findings that stand out. First of all, Cake is the biggest revenue stream, and the biggest source of wastage, which is why it's the most financially relevant management category. Secondly, sales volume/count and contribution are not always correlated – high margin items like Chocolate Gateau and Pineapple Gateau are only moderate sellers and a menu focussed on units sold alone would be missing these items. Third, for all four categories, weekend revenue per day is consistently on average 36% higher. Fourth, Chicken Patty is the most-wasted item and best seller, which suggests a likely and correctable over-production pattern.

The results lead to four suggestions for Rodrigo's management to test and monitor, not necessarily to implement outright. First, reducing the batch sizes of high volume of high wastage items (Chicken Patty, Muffin, Red Velvet Cake) could reduce wastage cost if it is implemented gradually to allow for any impact on stockouts to be identified. Second, review the beverage range and consider the possibility of removing one or two of the lowest sellers and track revenue to monitor and determine whether there's little downside. Third, providing high margin, lower volume products to the menu could increase the contribution margin, if change in sales is measured. Fourth, if weighed against labour cost, there is the potential to raise the number of staff members on the weekends to match the impact of the 36% in revenue. When reviewing these situations, the dashboard will tell you where the opportunity lies, and the next step takes you to the benefit, which can be proven by making the change and measuring the outcome.

The main limitation of the study is its single month and single business scope. The month-level observations (early/late-June wastage) are hypotheses to be followed up rather than conclusions and a longer time series would be required to disentangle the long-term trend from calendar effects. The data used are based on the café's own records and have not undergone a physical audit, and the totals are gross contributions, not net profits as overheads are not taken into account. Most importantly, each reported result is an insight that has been identified via the dashboard rather than a demonstrated improvement that was observed following an operational change: no operational change was made and no measurement was taken as part of the study so the effect of the recommendations cannot be said as yet. The paper's role, with a month's worth of real item-level data, is to illustrate how a low-cost BI tool can transform an ordinary day at the small cafés that lack a business analyst into a series of specific, measurable questions about production, pricing, demand and waste that the business might not otherwise be able to ask. The natural next step is to determine if there are tangible benefits to taking action on them and the dashboard created here offers a way to measure these benefits.

REFERENCES

Eriksson, M., Malefors, C., Bergstrom, P., Eriksson, E., & Persson Osowski, C. (2019). What gets measured gets managed-Or does it? Connection between food waste quantification and food waste reduction in the hospitality sector. Resources. *Conservation & Recycling: X*, *4*, 100021. https://doi.org/10.1016/j.rcrx.2019.100021

Herath, H. M. K. G. S. S. (2024). Factors influencing the adoption of business intelligence systems among small and medium-sized enterprises (SMEs) in the Sri Lankan context. *Journal of Business Studies*, *11*(2), 57–72. https://doi.org/10.4038/jbs.v11i2.108

Hubner, N., Caspers, J., Coroama, V. C., & Finkbeiner, M. (2024). Machine-learning-based demand forecasting against food waste: Life cycle environmental impacts and benefits of a bakery case study. *Journal of Industrial Ecology*, *28*(5), 1122–1136. https://doi.org/10.1111/jiec.13528

Krishnapriya, G., & Ajith Kumar, N. (2026). Business intelligence adoption in MSMEs: A systematic review of challenges, benefits, and emerging trends. In A. K. Tripathi, A. K. Saha, & V. Shrivastava (Eds.), *Proceedings of world conference on artificial intelligence: Advances and applications* (pp. 331–351). Springer. https://doi.org/10.1007/978-3-032-22289-3_27

Llave, M. R. (2017). Business intelligence and analytics in small and medium-sized enterprises: A systematic literature review. *Procedia Computer Science*, *121*, 194–205. https://doi.org/10.1016/j.procs.2017.11.027

Microsoft. (2024). *Visualization types in Power BI*. https://learn.microsoft.com/en-us/power-bi/visuals/power-bi-visualization-types-for-reports-and-q-and-a

Noone, B. M., & Cachia, G. (2020). Menu engineering re-engineered: Accounting for menu item substitutes in pricing and menu placement decisions. *International Journal of Hospitality Management*, *87*, 102504. https://doi.org/10.1016/j.ijhm.2020.102504

Viano, M. R. O., Purnamasari, R. P., Wibowo, B., & Affandi, D. (2026). Menu engineering for restaurant performance: Evidence from a tourism-oriented cafe in Indonesia. *Journal of Tourism Sustainability*, *6*(2), 241–258. https://doi.org/10.35313/jtospolban.v6i2.217