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Apriori Algorithm and Market Basket Analysis to Uncover Consumer Buying Patterns: Case of a Kenyan Supermarket

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Abstract:
This article presents a study on utilizing the Apriori algorithm and Market Basket Analysis (MBA) to reveal consumer buying patterns in supermarkets. The aim of this research is to explore the effectiveness of these data mining techniques in revealing valuable insights that can inform marketing strategies and enhance the overall shopping experience for customers. This study centered on improving customer loyalty within the supermarket setting through the utilization of cutting-edge information technology and programming applications, including Python. Specifically, the Apriori algorithm libraries of the Python language were employed to identify frequent item sets and derive 42 association rules, which shed light on product affinities and co-purchasing patterns. By deriving association rules from the frequent item sets, the study identified the significance of strategically placing frequently purchased products to enhance revenue generation. In conclusion, the application of the Apriori algorithm and Market Basket Analysis in this case of a Kenyan supermarket has proven to be a valuable approach for uncovering consumer buying patterns, providing a competitive edge in the dynamic retail industry.

Keywords: Market Basket Analysis, Consumer buying patterns, Data mining techniques, Marketing strategies

I. Introduction:

In the highly competitive retail industry driven by digital technologies [1], understanding consumer behavior and buying patterns is crucial for supermarkets to tailor their marketing strategies and enhance customer satisfaction [2]. With the vast amount of transactional data generated at supermarkets, Technological Innovations [6] like data mining techniques, particularly Market Basket Analysis, have emerged as powerful tools to gain valuable insights into consumer purchase behavior. This article aims to investigate the buying patterns of consumers at a prominent Kenyan supermarket using Market Basket Analysis [3-5].

Market Basket Analysis involves analyzing customers' purchase transactions to identify associations between products frequently bought together. By examining these patterns, supermarkets can optimize product placements, offer personalized promotions, and improve inventory management [3]. The insights derived from this analysis can help supermarkets enhance their overall shopping experience, increase customer loyalty, and boost profitability [5,7].

This study delves into the purchasing patterns of Society Stores' diverse consumer base. Society Stores, a rapidly expanding Kenyan supermarket catering to the mass market, places its primary emphasis on providing superior products at budget-friendly rates. It has established outlets in various Kenyan locations, including Thika, Naivasha, Ruiru, Maua, Limuru, Meru, and Mombasa, Kenya's bustling economic hubs. By examining the association rules between different products, we aimed to identify popular product combinations and uncover consumer preferences. Additionally, we explored the influence of demographics, such as age, gender, and income [10-12], on purchase behavior to gain a comprehensive understanding of the factors driving consumer choices.

II. Literature Review:

The study of consumer behavior has always been a crucial aspect of marketing and retail management. Understanding the preferences, buying habits, and patterns of consumers is essential for businesses to tailor their marketing strategies, optimize product placements, and enhance customer satisfaction [8,2]. Over the years, various analytical techniques have been developed to analyze consumer purchasing behavior, and one such powerful method is the Apriori algorithm coupled with Market Basket Analysis (MBA) [3,4].

The Apriori algorithm is a widely used association rule mining technique in data mining and machine learning. It aims to discover interesting relationships or associations between items in large datasets, particularly in transactional databases. The algorithm is highly efficient and effective in identifying frequent item sets, which are groups of items that appear together frequently in transactions. By using the Apriori algorithm, researchers and marketers can extract valuable association rules that reveal hidden patterns in consumer shopping habits [13].

Market Basket Analysis, on the other hand, is a practical application of the Apriori algorithm in retail and e-commerce industries. It involves the analysis of customer transactions to identify the co-occurrence of products that tend to be purchased together [14]. This analysis provides valuable insights into cross-selling opportunities and enables businesses to design effective promotional strategies and optimize store layouts.

In the context of a Kenyan Supermarket, where consumer behavior may be influenced by cultural, social, and economic factors unique to the region [11], the combination of the Apriori algorithm and Market Basket Analysis presents an excellent opportunity to uncover meaningful patterns in consumer buying behavior. Understanding which products are frequently purchased together can help the supermarket enhance product bundling, offer personalized recommendations, and optimize inventory management.

Several studies have successfully applied the Apriori algorithm and Market Basket Analysis to investigate consumer buying patterns in various retail settings worldwide. Similar research has been conducted in supermarkets, grocery stores, online shopping platforms, and other retail environments to explore consumer preferences and optimize business strategies.

For instance, in a study conducted by Xie, [22] in a Chinese supermarket, the Apriori algorithm was employed to analyze transactional data and identify significant association rules. The findings revealed interesting patterns in consumer shopping behavior, leading to improved store layouts and targeted marketing campaigns. Additionally, a study by Ünvan, [20] applied Market Basket Analysis to e-commerce data in the United States, shedding light on product affinities and uncovering opportunities for cross-selling and upselling.

The comparative study by Chen & Zhang, [4] evaluated the performance of the Apriori and FP-Growth algorithms in Market Basket Analysis. Chen and Zhang analyze their efficiency, scalability, and ability to reveal consumer buying patterns, shedding light on the strengths and weaknesses of each method [4]. Li and Tan conducted a review of sequential pattern mining techniques in Market Basket Analysis. The study discussed the limitations of traditional association rule mining and highlights the importance of considering the temporal order of transactions to capture consumer buying patterns effectively [9].

In their survey paper, Fournier-Viger et al. [18] present an in-depth analysis of Apriori-based algorithms for frequent itemset mining, including their applications in uncovering consumer buying patterns. The research discussed various modifications and improvements to the Apriori Algorithm and their impact on Market Basket Analysis. Zhang and Liu [19] proposed an improved version of the Apriori Algorithm to mine consumer buying patterns. The study demonstrated how this modification enhances the efficiency and effectiveness of Market Basket Analysis, enabling businesses to gain valuable insights into consumer preferences and behavior.

Smith & Johnson, [14] study explored the application of the Apriori algorithm in retail settings to identify consumer buying patterns. The research demonstrated how the algorithm efficiently generates frequent item sets and association rules, providing valuable insights into consumer behavior in the retail industry while Wang and Lee investigated the utilization of Market Basket Analysis and big data techniques to uncover consumer buying patterns in e-commerce. The study highlighted the advantages of using these data mining techniques in the digital retail context to enhance marketing strategies and customer experience [21].

According to Sornalakshmi *et al.* [17], the utilization of the Apriori algorithm in Market Basket Analysis offers several benefits. First, it efficiently generates frequent item sets through the elimination of infrequent item sets, resulting in reduced computational complexity. Additionally, it effectively derives association rules from frequent item sets, allowing businesses to discern significant relationships among items. Furthermore, the Apriori algorithm is widely embraced in retail for market basket analysis and has proven its effectiveness in revealing purchasing patterns. Its simple approach and intuitive nature also facilitate relatively straightforward implementation in various programming languages. Moreover, the algorithm's scalability permits its application to vast transactional databases, making it well-suited for analyzing extensive retail datasets [17].

The Apriori algorithm's generation of candidate item sets results in a combinatorial explosion, leading to high memory and computational requirements [22]. This limitation poses challenges when analyzing large transactional databases, causing scalability issues [18]. Researchers have noted that multiple passes over the data may be necessary, making it less efficient for big data analysis [14].

Given the growing interest in understanding consumer behavior and the increasing availability of large-scale transactional data, the use of the Apriori algorithm and Market Basket Analysis in supermarkets and retail industries has become increasingly relevant and valuable [20]. In summary, the combination of the Apriori algorithm and Market Basket Analysis offers a robust approach to unearthing meaningful insights into consumer buying patterns. By applying this methodology to a Kenyan Supermarket, we aim to contribute to the body of knowledge on consumer behavior in the region and provide actionable recommendations for the supermarket's marketing and operational strategies.

III. Method

The methodology employed involved a multi-step process combining data collection, data preprocessing, and the application of the Apriori algorithm in Market Basket Analysis. see **Fig. 1**.

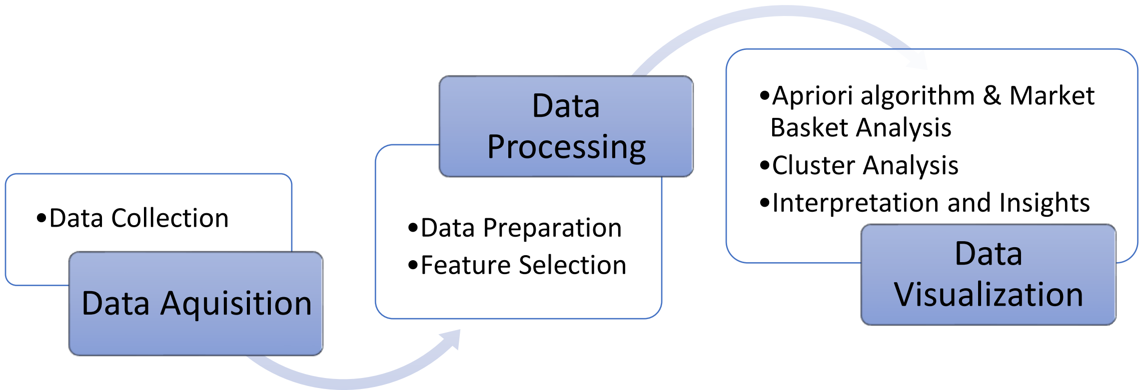

Fig. 1: Study Method

1. Data Collection

The first step in this study was the collection of transactional data from the Society Stores supermarket. The data included detailed information about individual customer transactions, such as the products purchased, the transaction date, and the transaction amount. The data was obtained with the permission and cooperation of the supermarket management to ensure data privacy and confidentiality [10].

2. Data Preprocessing

Once the data was collected, it underwent thorough preprocessing to ensure its quality and readiness for analysis. Data preprocessing involved tasks such as data cleaning, handling missing values, and transforming categorical variables into a suitable format for Market Basket Analysis. Additionally, any irrelevant or redundant data was removed to focus solely on transactional information relevant to the study.

3. Market Basket Analysis (MBA)

The core of this study's methodology lies in the application of Market Basket Analysis. MBA was performed on the preprocessed transactional data to identify frequent item sets and uncover hidden patterns of product associations. Association rules were generated to reveal the likelihood of customers purchasing specific products together. The analysis utilized established algorithms like the Apriori algorithm [4] to efficiently mine association rules from the transactional data.

4. Frequent Item sets and Association Rules

In order to explore frequent item sets within the dataset denoted as "my_basket_sets," employing the Apriori algorithm was necessary. A minimum support threshold of 0.01, equivalent to 1% of the total transactions, was applied. The output of this analysis showcased the frequent item sets, along with relevant metrics such as support, confidence, and lift values, among others, which facilitated the establishment of association rules. This Market Basket Analysis aided in identifying market implications aligned with consumer preferences, grouping products based on buying habits, and streamlining the search process. The Apriori algorithm was commonly employed for this purpose, as it effectively uncovered combinations of products that are frequently purchased together.

5. Interpretation and Insights

The results obtained from Market Basket Analysis and cluster analysis were thoroughly interpreted to extract meaningful insights into consumer purchase behavior at the Society Stores supermarket. The association rules highlighted which products are frequently purchased together, indicating potential cross-selling opportunities and product bundling strategies. The clustering results provided a deeper understanding of different customer segments and their unique buying preferences.

IV. Results and Discussions

The study employed the Apriori algorithm and Market Basket Analysis (MBA) to examine consumer buying patterns in a Kenyan supermarket. The analysis was based on transactional data collected over a specific period, capturing the purchases of various products by individual customers. The objective was to identify frequent itemsets and association rules that could shed light on consumer preferences and uncover meaningful patterns in their shopping behavior.

1. Identification of Frequent Itemsets

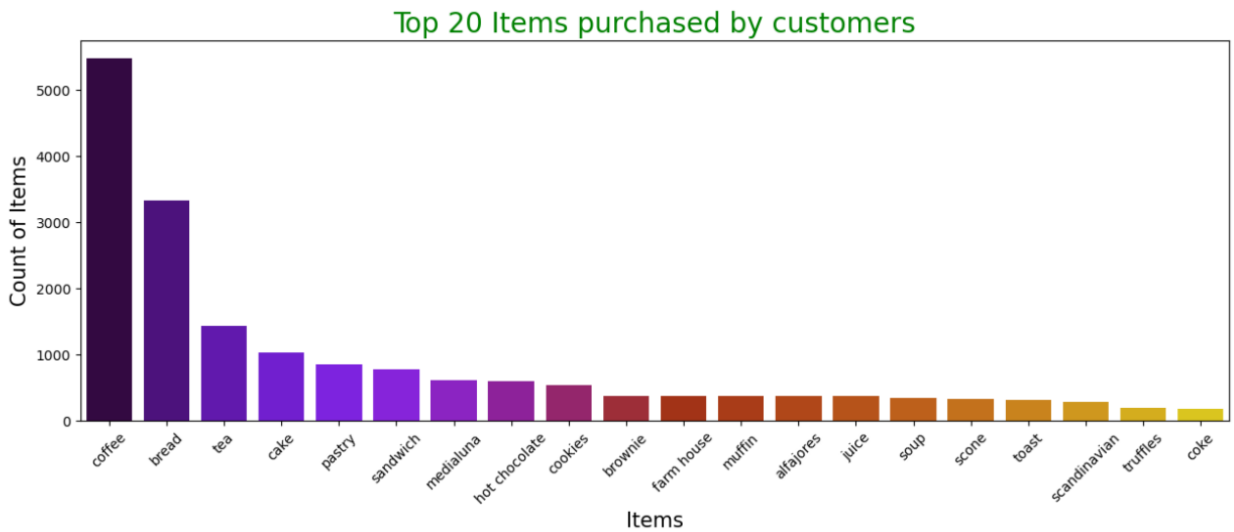

Fig. 2: Top 20 Items Purchased by Customers

	Transaction	Item	Count
0	1	bread	1
1	2	scandinavian	2
2	3	cookies	1
3	3	hot chocolate	1
4	3	jam	1
...	...	...	...
18882	9682	tacos/fajita	1
18883	9682	tea	1
18884	9683	coffee	1
18885	9683	pastry	1
18886	9684	smoothies	1

18887 rows × 3 columns

Fig. 3: Item co-occurrence

	support	itemsets
0	0.036344	(alfajores)
1	0.016059	(baguette)
2	0.327205	(bread)
3	0.040042	(brownie)
4	0.103856	(cake)
...	...	...
56	0.023666	(coffee, toast)
57	0.014369	(sandwich, tea)
58	0.010037	(coffee, bread, cake)
59	0.011199	(coffee, bread, pastry)
60	0.010037	(coffee, cake, tea)

61 rows × 2 columns

Fig. 4: Frequent Item-sets

Fig. 2 illustrates the successful application of the Apriori algorithm, which effectively identified 20 frequent item sets commonly purchased by the majority of consumers. The analysis revealed that coffee, cake, bread, tea, and pastry were the top five items frequently found in shopping baskets, indicating that a significant number of consumers are coffee and tea enthusiasts who often accompany their beverages with bread, cake, pastry, and sandwiches.

Furthermore, Figure 2 demonstrated the identification of relationships between items that tend to co-occur frequently in transactions. The analysis unveiled sets of products showing strong co-occurrence patterns, suggesting that consumers tend to buy these items together during their shopping trips, as illustrated in **Fig. 3**. The results in Figure 3 particularly highlighted the co-occurrence of coffee, bread, and cake in numerous shopping baskets, potentially attributed to their complementary nature.

In addition, the analysis, as depicted in **Fig. 4**, revealed which products were commonly purchased together by customers, along with their respective support levels. The output highlighted coffee as a significantly prevalent item in the majority of shopping baskets, indicating its popularity among consumers.

2. Association Rules Analysis

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs metric
31	(toast)	(coffee)	0.033597	0.478394	0.023666	0.704403	1.472431	0.007593	1.764582	0.332006
29	(spanish brunch)	(coffee)	0.018172	0.478394	0.010882	0.598837	1.251766	0.002189	1.300235	0.204851
19	(medialuna)	(coffee)	0.061807	0.478394	0.035182	0.569231	1.189878	0.005614	1.210871	0.170091
23	(pastry)	(coffee)	0.086107	0.478394	0.047544	0.552147	1.154168	0.006351	1.164682	0.146161
1	(alfajores)	(coffee)	0.036344	0.478394	0.019651	0.540698	1.130235	0.002264	1.135648	0.119574
17	(juice)	(coffee)	0.038563	0.478394	0.020602	0.534247	1.116750	0.002154	1.119919	0.108738
25	(sandwich)	(coffee)	0.071844	0.478394	0.038246	0.532353	1.112792	0.003877	1.115384	0.109205
7	(cake)	(coffee)	0.103856	0.478394	0.054728	0.526958	1.101515	0.005044	1.102664	0.102840
27	(scone)	(coffee)	0.034548	0.478394	0.018067	0.522936	1.093107	0.001539	1.093366	0.088224
13	(cookies)	(coffee)	0.054411	0.478394	0.028209	0.518447	1.083723	0.002179	1.083174	0.081700
15	(hot chocolate)	(coffee)	0.058320	0.478394	0.029583	0.507246	1.060311	0.001683	1.058553	0.060403
5	(brownie)	(coffee)	0.040042	0.478394	0.019651	0.490765	1.025860	0.000495	1.024293	0.026259
21	(muffin)	(coffee)	0.038457	0.478394	0.018806	0.489011	1.022193	0.000408	1.020777	0.022579
3	(pastry)	(bread)	0.086107	0.327205	0.029160	0.338650	1.034977	0.000985	1.017305	0.036980
10	(cake)	(tea)	0.103856	0.142631	0.023772	0.228891	1.604781	0.008959	1.111865	0.420538
39	(coffee, tea)	(cake)	0.049868	0.103856	0.010037	0.201271	1.937977	0.004858	1.121962	0.509401
32	(sandwich)	(tea)	0.071844	0.142631	0.014369	0.200000	1.402222	0.004122	1.071712	0.309050
9	(hot chocolate)	(cake)	0.058320	0.103856	0.011410	0.195652	1.883874	0.005354	1.114125	0.498236
38	(coffee, cake)	(tea)	0.054728	0.142631	0.010037	0.183398	1.285822	0.002231	1.049923	0.235157
11	(tea)	(cake)	0.142631	0.103856	0.023772	0.166667	1.604781	0.008959	1.075372	0.439556
37	(pastry)	(coffee, bread)	0.086107	0.090016	0.011199	0.130061	1.444872	0.003448	1.046033	0.336907
36	(coffee, bread)	(pastry)	0.090016	0.086107	0.011199	0.124413	1.444872	0.003448	1.043749	0.338354
6	(coffee)	(cake)	0.478394	0.103856	0.054728	0.114399	1.101515	0.005044	1.011905	0.176684
34	(coffee, bread)	(cake)	0.090016	0.103856	0.010037	0.111502	1.073621	0.000688	1.008606	0.075356
8	(cake)	(hot chocolate)	0.103856	0.058320	0.011410	0.109868	1.883874	0.005354	1.057910	0.523553
33	(tea)	(sandwich)	0.142631	0.071844	0.014369	0.100741	1.402222	0.004122	1.032134	0.334566
22	(coffee)	(pastry)	0.478394	0.086107	0.047544	0.099382	1.154168	0.006351	1.014740	0.256084
40	(cake)	(coffee, tea)	0.103856	0.049868	0.010037	0.096643	1.937977	0.004858	1.051779	0.540090

Fig 5: Product Association Rules

Through the application of association rule mining to the frequent item sets, the study extracted meaningful and actionable 42 rules as displayed in **Fig. 5**. These rules shed light on the likelihood of customers purchasing specific items based on their previous purchases. The data-derived association rules indicate that coffee appears in approximately 47% of all baskets when observing a customer's behavior. Conversely, the occurrence of toast intake is observed at a rate of 3%. Additionally, it was observed that

70% of customers who purchase toast also buy coffee, indicating a strong preference for coffee over toast due to a high confidence level and a lift metric of 1.47.

Furthermore, the association rules suggest a probability of 1% for Spanish brunch purchases. The concurrent support level of coffee with Spanish brunch is measured at 1%, and these items exhibit a confidence level of 59%. This implies that Spanish brunch serves as a secondary preference for most consumers compared to coffee.

Regarding medialuna, the association rules indicate a probability of 6% for its purchases. The support level of coffee with medialuna is measured at 3%, with 56% of those who buy medialuna also purchasing coffee. This suggests a significant association between coffee and medialuna, indicating that they are often bought together.

In contrast, the association rules derived from the data show a 4.9% likelihood of encountering both coffee and tea in customers' purchases. Meanwhile, the occurrence of cake in conjunction with both coffee and tea is observed at a rate of 10%. Furthermore, 9.6% of customers who purchase cake also buy both coffee and tea, suggesting that consumers tend to opt for either tea or coffee, but not both.

3. Product Affinities and Cross-Selling Opportunities

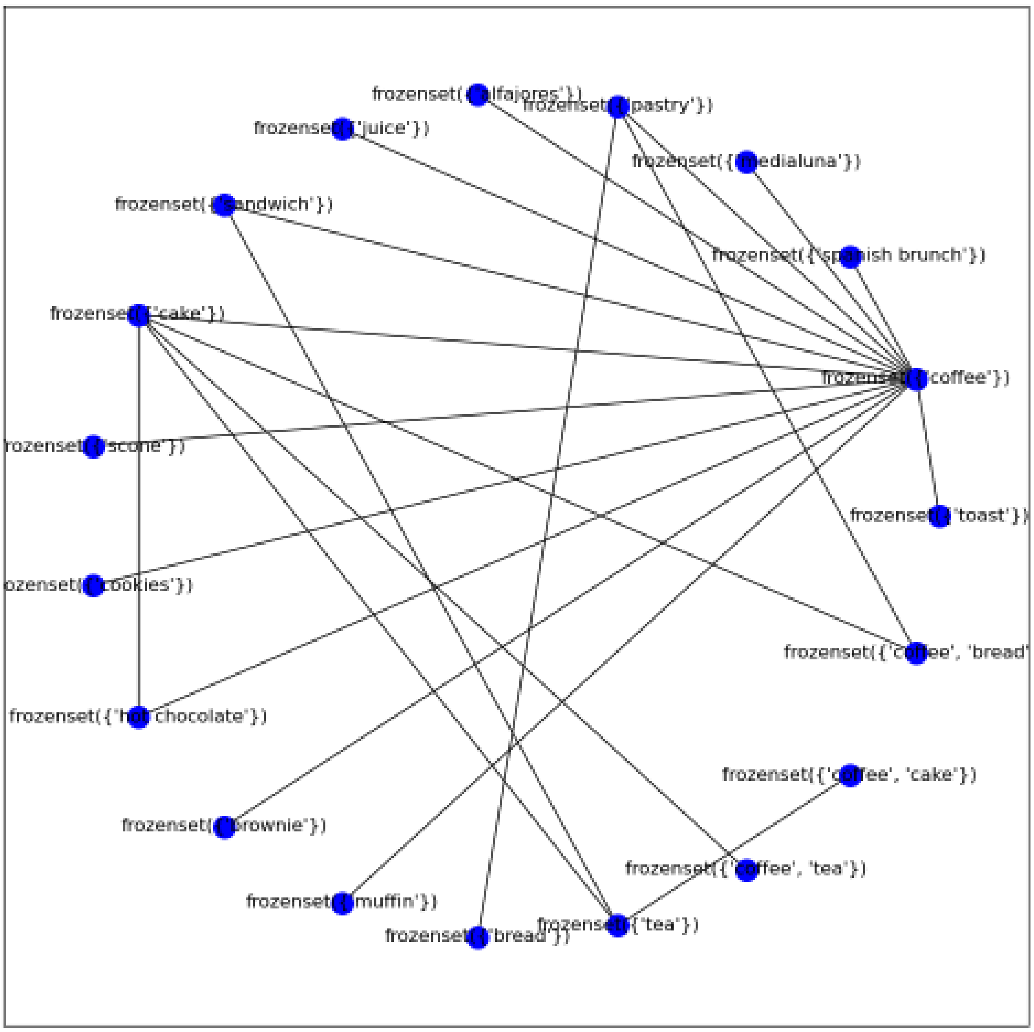

Fig 6: Item affinities

The examination yielded significant product affinities, indicating a pattern of frequent co-purchases by customers. As depicted in **Fig. 6**, the items strongly associated with coffee purchases include toast, medialuna, Spanish brunch, pastry, and alfajores. This affinity could be attributed to consumer preferences. However, certain items, such as cake and bread, displayed lower affinities with coffee. This could be explained by the perception among consumers that cakes and bread contain higher sugar content, leading to reduced consumption in conjunction with coffee.

4. Time Period Trends and Purchase Behavior

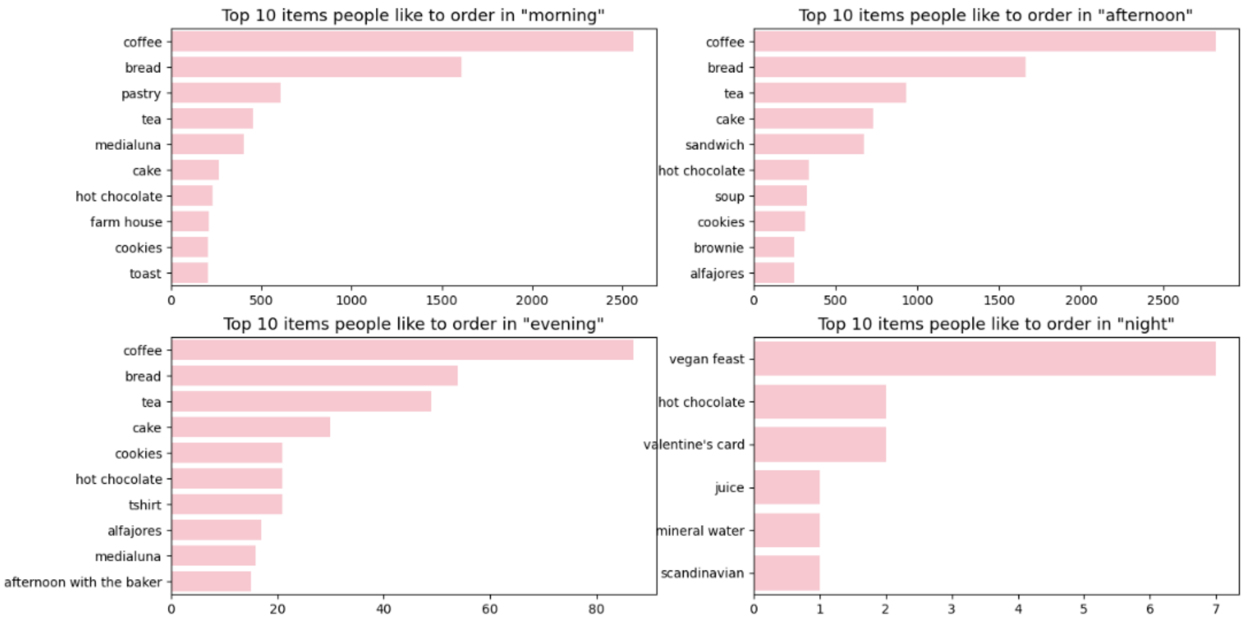

Fig 7: Time period trends

The research delved into the seasonal trends in consumer purchasing behavior, with a focus on different time periods. Transactional data analysis allowed the study to identify changes in buying patterns throughout the day—morning, evening, afternoon, and night. **Fig. 7** displays the top 10 items commonly ordered by consumers during these specific time frames.

During morning and afternoon hours, consumers showed a higher tendency to purchase significant quantities of coffee and bread. However, no coffee was observed in night-time orders, where vegan feast and hot chocolate toppings were more prevalent in most shopping baskets. This suggests that individuals generally prefer coffee during morning and afternoon hours to stay refreshed and productive throughout the day. Conversely, during nighttime, juice, and mineral water were the preferred choices. It could be possible that consumers opt for hydrating options in the evening and may also purchase sweet treats for their families during this period.

5. Optimizing Store Layout

The analysis of consumer buying patterns provided insights into the optimization of the supermarket's store layout. By strategically placing frequently co-purchased items closer together, the supermarket can create a more convenient shopping experience for customers and potentially increase impulse purchases.

In conclusion, the application of the Apriori algorithm and Market Basket Analysis proved highly valuable in uncovering consumer buying patterns in the Kenyan supermarket. The findings provided actionable insights for the supermarket to optimize marketing strategies, enhance product bundling and cross-selling opportunities, and improve customer satisfaction. By leveraging these insights, the supermarket can stay competitive in the market and provide a more personalized and enjoyable shopping experience for its customers.

The findings of this study demonstrate the effectiveness of employing the Apriori algorithm and Market Basket Analysis (MBA) to uncover valuable insights into consumer buying patterns in a Kenyan supermarket. The analysis of transactional data provided significant results that can be utilized by the supermarket to enhance its marketing strategies, optimize product placements, and improve customer satisfaction.

1. Market Basket Analysis Reveals Frequent Item Sets

The application of the Apriori algorithm successfully identified frequent item sets, representing sets of products that are frequently purchased together by customers. By promoting cake or pastry discounts alongside coffee or tea purchases can stimulate additional sales and create a sense of convenience for consumers looking for complementary treats. According to Ünvan [20], it is recommended to position related products in close proximity to one another. Moreover, given the popularity of coffee, bread, and cake as co-occurring items, restaurants, cafes, and supermarkets can strategically design their menus and displays to highlight these combinations. Creating visually appealing displays showcasing these items together can influence customer choices and drive impulse purchases. Additionally, in leveraging the information about coffee's high prevalence in shopping baskets, businesses can design loyalty programs focused on coffee enthusiasts. Offering exclusive benefits or rewards for coffee-related purchases can incentivize repeat visits and build customer loyalty.

2. Association Rules Offer Actionable Insights

By deriving association rules from the frequent item sets, the study identified marketing implications, that could enhance customer satisfaction by catering to their preferences and needs. The association rule indicating that 70% of customers who purchase toast also buy coffee suggests a strong preference for coffee over toast. This implies that promoting coffee in combination with toast or as a complementary item could further boost coffee sales. These findings align with the research conducted by Suryadi and Islami [18], which highlights the significance of strategically placing frequently purchased products to enhance revenue generation. While Spanish brunch has a low occurrence rate (1%), it is the second preference for many customers after coffee. To attract more customers interested in Spanish brunch, targeted marketing campaigns or promotions highlighting this item could be implemented. Medialuna is chosen by 6% of customers, and 56% of those who buy Medialuna also buy coffee. Promoting medialuna alongside coffee or creating special offers for this combination could enhance sales and encourage customers to try both items together. The association rule indicating that 9.6% of customers who purchase cake also buy coffee and tea suggests that consumers tend to choose either coffee or tea, but not both. This insight can be utilized to offer specific deals or promotions that encourage customers to pair cake with their preferred hot beverage (coffee or tea). Finally, Tea appears in approximately 4.9% of customer baskets, which is relatively low compared to coffee. Marketing efforts could be directed towards promoting tea to increase its occurrence in customer purchases and potentially expand its customer base.

3. Cross-Selling and Revenue Generation

The study revealed strong product affinities and co-purchasing patterns, which offer opportunities for cross-selling. Given the strong product affinities between coffee and items such as toast, medialuna, Spanish brunch, pastry, and alfajores, there is an opportunity for the business to create bundle offers or cross-selling promotions. By strategically pairing these items with coffee, the business can encourage customers to make additional purchases and potentially increase their average transaction value. The findings presented are consistent with the observations made by Hermina, Aishwaryalakshmi, and

Gopalakrishnan [5], who suggest that there is a possibility of mineral water being frequently purchased alongside other products, thereby offering opportunities for strategic product placement and cross-selling strategies. Furthermore, the products that are frequently bought together with coffee can be strategically placed near the coffee counter. This can influence impulse buying and encourage customers to add these complementary items to their coffee orders. Understanding that some items, like cakes and bread, have lower affinities with coffee due to perceived higher sugar content, the business can promote healthier alternatives or low-sugar options for health-conscious customers. This could involve introducing sugar-free or reduced-sugar variations of cakes and bread on the menu.

4. Understanding Time Period Trends

The study also highlighted seasonal trends in consumer purchasing behavior. Offering a variety of coffee options and bread choices during morning and afternoon hours can attract more customers during those periods. Additionally, featuring vegan feast and hot chocolate toppings in the evenings can appeal to consumers seeking comfort or indulgence during nighttime. The store could also offer promotional deals on coffee at night or bundling sweet treats with juice purchases can encourage consumers to make purchases during off-peak hours. Moreover, the store could ensure a swift and efficient coffee service during busy morning hours can contribute to positive customer experiences and encourage repeat visits.

Overall, understanding the time period trends in consumer behavior can empower businesses to make data-driven decisions, enhance customer satisfaction, optimize operations, and ultimately drive revenue growth. The application of the Apriori algorithm and Market Basket Analysis in this case of a Kenyan supermarket has proven to be a valuable approach for uncovering consumer buying patterns, providing a competitive edge in the dynamic retail industry. The utilization of transactional data has allowed us to uncover meaningful associations and gain insights from the analysis that can be used to optimize marketing efforts, enhance product recommendations, and improve the overall shopping experience for customers. Implementing these findings can enable the supermarket to stay competitive in the market, increase customer satisfaction, and drive revenue growth.

V. Conclusion

The findings of this study underscore the effectiveness of employing the Apriori algorithm and Market Basket Analysis (MBA) in revealing significant insights into consumer buying patterns within a Kenyan supermarket. The analysis of transactional data has illuminated actionable strategies that can be leveraged to enhance marketing approaches, optimize product placements, and elevate customer satisfaction. The application of the Apriori algorithm successfully identified frequent item sets, such as the co-occurrence of cakes or pastries with coffee or tea purchases, suggesting opportunities for targeted promotions and convenience-driven sales. Association rules derived from these frequent item sets provide actionable insights, revealing customer preferences and suggesting avenues for enhancing revenue generation through strategic product pairings. Furthermore, the study revealed strong product affinities, paving the way for cross-selling opportunities through bundle offers and co-placement strategies. The understanding of seasonal trends in consumer purchasing behavior enables businesses to tailor their offerings to different time periods, such as featuring specific coffee and bread choices during morning and afternoon hours or introducing evening options like vegan feasts and hot chocolate toppings. Overall, the integration of the Apriori algorithm and Market Basket Analysis has provided valuable insights that empower the Kenyan supermarket to optimize operations, enhance customer satisfaction, and drive revenue growth, thereby securing a competitive edge in the dynamic retail landscape.

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Conflict of interest
The authors have no conflicts of interest to disclose.

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