Research Paper

Enhancing Retail Supermarket Financial Performance Through Market Basket Analytics Using Apriori Algorithm in Indonesia Market Case

Jerry Heikal[1]*, Ayu Gandhi[1]
[1] Bakrie University, Indonesia

Received : February 5, 2024	Revised : April 17, 2024	Accepted : April 18, 2024	Online : May 3, 2024

Abstract

Market Basket Analysis is a powerful technique in data mining and retail analytics that explores associations and patterns among items frequently purchased together by consumers. This technique reveals insights into consumer purchasing behaviour and facilitates the creation of compelling product bundles. This study identifies five distinct product bundling strategies tailored to diverse consumer personas prevalent in the Indonesian market, such as "Health enthusiast", "Exotic Flavor Explorer", "Food Enthusiast", "Fitness Freak", and "Budget-conscious Home Cook". These product bundling strategies leverage market basket analysis to enhance the shopping experience, meeting Indonesian consumers' diverse preferences and lifestyles in the retail supermarket landscape. The analysis provides a basis for effective promotional campaigns and personalized marketing efforts. By recognizing associations between products, supermarkets in Indonesia can design targeted promotions, encouraging customers to explore complementary items and potentially increase their overall spending.

Keywords *Market Basket Analysis, Product Bundling, Purchasing behaviour, Optimizing Financial Performance, Apriori Algorithm*

INTRODUCTION

The supermarket retail business is a cornerstone of the global economy, serving as a vital component in the supply chain that connects producers to consumers. Over the years, this sector has evolved significantly, adapting to changing consumer preferences, technological advancements, and market dynamics. As we celebrate the one-year milestone of our digital assistant, it is fitting to delve into a comprehensive analysis of the supermarket retail business, exploring its historical roots, current trends, and prospects (Rana & Mondal, 2021).

The roots of the modern supermarket can be traced back to the early 20th century when pioneers like Piggly Wiggly introduced the concept of self-service grocery stores. The idea of allowing customers to choose their products directly from the shelves marked a paradigm shift in the retail industry. Subsequent decades witnessed the rise of iconic supermarket chains, such as Kroger and Safeway, shaping the grocery retail landscape (Tatiana & Mikhail, 2018).

The supermarket retail business has embraced technology to enhance efficiency, customer experience, and overall operations. The implementation of barcode scanning, point-of-sale systems, and inventory management software has streamlined processes, reducing manual errors and improving inventory accuracy. Additionally, the integration of Artificial Intelligence (AI) and data analytics has empowered retailers to analyze consumer behaviour, optimize pricing strategies, and personalize marketing efforts (Ünvan, 2021).

The retail industry stands at the forefront of dynamic economic landscapes, serving as a barometer for consumer behaviour and economic trends. With the advent of advanced technologies and the proliferation of data-driven decision-making, retailers face unprecedented opportunities and challenges. In this milieu, understanding the intricacies of customer purchasing

Corresponding author's email: Jerry.heikal@bakrie.ac.id

patterns has become a paramount concern. Market Basket Analysis (MBA) emerges as a powerful tool for unravelling the complex dynamics inherent in retail transactions (Pillai & Jolhe, 2020). The retail landscape is profoundly transforming, shaped by shifting consumer preferences, technological advancements, and a globalized marketplace. Armed with smartphones and access to many online and offline channels, consumers wield immense power in shaping the retail narrative. The traditional linear path to purchase has given way to a complex, non-linear journey influenced by factors such as online reviews, social media, and personalized recommendations (Grau, 2017).

In this dynamic environment, retailers are tasked with adapting to rapid changes and predicting and influencing consumer behaviour. Market Basket Analysis, a technique rooted in association rule mining, serves as a beacon for retailers navigating the vast sea of transactional data. By uncovering hidden relationships between frequently purchased products, MBA provides insights beyond mere transactional data, offering a nuanced understanding of customer preferences and affinities (Patwary et al., 2021).

At its core, Market Basket Analysis delves into the 'co-occurrence' patterns within transactional data. For retailers, this translates into the ability to identify which products are often bought together and, consequently, make informed decisions about product placement, promotions, and inventory management. The insights derived from the MBA empower retailers to enhance the customer shopping experience, optimize pricing strategies, and ultimately bolster sales and profitability (Samboteng et al., 2022).

Moreover, MBA contributes to the evolution of personalized marketing strategies. In an era where consumers expect tailored experiences, understanding the associations between products enables retailers to create targeted promotions and cross-selling campaigns. By recommending complementary products based on historical purchasing patterns, retailers not only increase the value of each transaction but also foster customer loyalty.

The rise of big data technologies, coupled with advancements in machine learning and artificial intelligence, has paved the way for retailers to harness the full potential of Market Basket Analysis. Retailers now have the capability to process vast volumes of transactional data in real time, allowing for dynamic adjustments to strategies and tactics.

However, this technological prowess comes with its set of challenges. Retailers must grapple with issues related to data privacy, integration of disparate data sources, and the need for skilled personnel adept at interpreting complex analytical outputs. Additionally, the sheer volume of data generated by modern retail operations poses a challenge in extracting meaningful insights efficiently.

Market Basket Analysis and Market Basket Reporting are flashlights that shine a light on the business environment. Market basket analysis is the exploratory method to understand patterns and the nature of the business environment. This is to distinguish up from down, left from right, and forward from backward in a business environment. Market Basket Reporting is the monitoring method in the corner of the room. In that way, Market Basket Analysis is the dynamic and iterative creation of an expectation based on a set of observations; meanwhile, Market Basket Reporting is the static and repetitive validation of the business environment based on periodic (i.e., daily, weekly, or monthly) observations.

This journal research question explores Market Basket Analysis in the context of the ever-evolving retail supermarket industry in Indonesian market case. The subsequent sections delve into the methodology employed, the dataset utilized, and the findings gleaned from applying MBA techniques. Additionally, we discuss the implications of our findings on retail strategies and present avenues for future research in this dynamic field.

LITERATURE REVIEW

Market Basket Analysis (MBA) is a data mining technique that explores associations and patterns among items purchased together in a transaction. It plays a crucial role in retail, e-commerce, and various industries where understanding customer purchasing behaviour is essential. This literature review aims to explore the evolution, applications, challenges, and future directions of market basket analysis.

Market Basket Analysis, rooted in association rule mining, focuses on identifying relationships and patterns among products frequently purchased together. The foundation of MBA lies in the Apriori algorithm, allowing retailers to uncover hidden associations within transactional data. Association rules, expressed as "if-then" statements, reveal insights into customer preferences. Support, confidence, and lift are critical metrics in evaluating the strength and reliability of these rules.

The roots of market basket analysis can be traced back to the work of Agrawal, Imielinski, and Swami in the early 1990s, who introduced the Apriori algorithm. This algorithm efficiently identifies frequent itemsets in transaction data, forming the foundation for subsequent developments in association rule mining (Agrawal et al., 1993). One of the primary applications of market basket analysis is in the retail sector. Retailers leverage MBA to uncover relationships between products, optimize shelf layouts, and design targeted marketing strategies. Understanding which products are often purchased together enables retailers to enhance cross-selling opportunities (Srikant & Agrawal, 1996).

In the era of e-commerce, market basket analysis is instrumental in providing personalized recommendations to users. Recommender systems powered by MBA analyze user behaviour to suggest products based on the history of purchases and preferences (Linden et al., 2023). Despite its widespread adoption, market basket analysis faces certain challenges. One major challenge is the curse of dimensionality, especially when dealing with a large number of items. Scalability issues arise as the number of transactions and items increases, impacting the efficiency of algorithms (Han et al., 2000). As technology continues to advance, the integration of market basket analysis with machine learning and artificial intelligence opens new avenues. Incorporating predictive analytics and deep learning models enhances the accuracy of association rule mining and enables businesses to make more informed decisions (Wu & Kumar, 2009).

Traditional market basket analysis assumes static relationships between items. Future research may focus on dynamic market basket analysis, considering the temporal aspect of transactions and adapting to changing consumer preferences over time (Hahsler et al., 2011). Market basket analysis has evolved significantly since its inception, becoming a fundamental tool for businesses seeking to understand customer behaviour and optimize their operations. As technology progresses, the integration of advanced techniques and a focus on dynamic analyses will likely shape the future of market basket analysis.

Market basket analytics has found extensive applications in the retail sector, where understanding customer behaviour is paramount. By analyzing purchase patterns, retailers can optimize product placement, create personalized recommendations, and design targeted promotions. This not only boosts sales but also enhances the overall shopping experience for customers (Rana & Mondal, 2021).

One of the primary objectives of market basket analytics is to uncover opportunities for cross-selling and upselling. By identifying items frequently purchased together, businesses can strategically recommend complementary products to customers, thereby increasing the average transaction value. E-commerce giants like Amazon have successfully implemented this approach, showcasing the potential for significant revenue growth.

As datasets continue to grow in size and complexity, handling big data poses a significant challenge for market basket analytics. Traditional algorithms may struggle to scale efficiently. However, distributed computing and parallel processing advancements have paved the way for more robust solutions, allowing businesses to extract meaningful insights from vast datasets.

Markets are dynamic, and consumer preferences can shift rapidly. Adapting market basket analytics to account for changing trends and preferences is crucial. Machine learning algorithms and real-time analytics enable businesses to stay agile and responsive to evolving market conditions, ensuring that insights remain relevant and actionable.

The collection and analysis of customer transaction data raise ethical concerns regarding privacy. Striking a balance between extracting valuable insights and respecting customer privacy is imperative. Implementing anonymization techniques and robust data governance frameworks can help address these concerns, fostering trust between businesses and their customers.

The integration of machine learning algorithms into market basket analytics is a burgeoning trend. Predictive analytics can forecast future purchasing behaviour based on historical data, enabling businesses to proactively respond to emerging trends and customer preferences. This shift from retrospective analysis to predictive modelling opens new avenues for strategic decision-making.

Artificial Intelligence (AI) is revolutionizing the realm of personalization in market basket analytics. Businesses can tailor product recommendations with unprecedented accuracy by leveraging machine learning models. This not only enhances the customer experience but also fosters customer loyalty by delivering personalized and relevant offerings (Meftah et al., 2024).

Market basket analytics has emerged as a cornerstone in the realm of data analytics, providing businesses with valuable insights into consumer behaviour and purchasing patterns. From its foundational principles rooted in association rule mining to the latest trends integrating machine learning and AI, this analytical approach continues to evolve.

As businesses navigate the complexities of big data, dynamic market conditions, and privacy concerns, market basket analytics remains a potent tool for enhancing customer experience, optimizing sales strategies, and driving revenue growth. As we celebrate the one-year anniversary of this article, it is clear that the journey of market basket analytics is far from over, with continued innovation and advancements on the horizon.

RESEARCH METHOD

Market Basket Analysis (MBA) has emerged as a powerful analytical tool for understanding customer purchasing patterns and dynamics within the retail industry. This paper outlines a comprehensive methodology for conducting Market Basket Analysis to gain valuable insights into consumer behaviour, optimize product placement, and enhance overall retail strategy. The proposed methodology integrates data preprocessing, frequent itemset generation, rule extraction, and result interpretation, demonstrating its applicability in the dynamic landscape of the retail sector (Kaur & Kang, 2016).

Market Basket Analysis is deceptively simple. That simplicity is a function of the spartan list of elements in Market Basket Analysis. Market Basket Analysis does not involve a complex set of tools and syntax that require years of training to understand. Instead, Market Basket Analysis requires an understanding of the enterprise and its business. Knowledge of the business will guide the questions posed by the analyst during Market Basket Analysis and facilitate an analyst's cognitive understanding of the answers. Market Basket Analysis can pose an infinite array of questions with only four elements—Itemset, Object, affinity and Statistics. The simplicity and depth of these elements of Market Basket Analysis allow the flexibility inherent in Market Basket Analysis (Kurniawan et al., 2018).

The name Market Basket came from the retail environment. In a retail environment, an interaction with a customer is documented by the shopping cart in which the customer places the items selected for a transaction because all the items chosen by a customer are in that customer's shopping cart. All the items, and only the items chosen by a customer, are in that customer's shopping cart. It is very easy to identify the contents of a Market Basket—just look in that customer's shopping cart. This tangible and clear definition of a transaction, bounded by a shopping cart, led to a tangible and clear understanding of a transaction as a unit of work, known as a Market Basket. The analysis of the contents of all the shopping carts took the name Market Basket Analysis.

The items in an Itemset are Objects. The Objects of an Itemset can be the products in a shopping cart, the dinner selections in a restaurant, or the stocks and bonds purchased in a stock trade. In all these Itemsets, the Objects are clearly visible. They are in the shopping cart, on the dining room table, in the invoice line items, and so on, and clearly visible for both the enterprise and the customer to see. In its simplest form, Market Basket Analysis can be performed using these visible Objects. In that simplest Market Basket Analysis, the analyst seeks to find those permutations of Objects that occurred simultaneously in an Itemset. After finding those permutations of Objects that occurred simultaneously, an analyst can then calculate the frequency of occurrences of permutations of Objects. Some permutations of Objects occur very often. Other permutations of Objects occur very seldom. Some permutations of Objects never occur at all in an Itemset

Affinity is the probability that one Object will occur simultaneously in an Itemset with another Object. Affinity is calculated as a percentage or probability. When calculated as a percentage, that percentage is the proportion of past occurrences of two Objects occurring simultaneously in an Itemset. The probability that those two Objects will coincide in the future varies directly with the percentage of past Itemsets wherein the two Objects coincided. No set of two Objects will always occur in an Itemset. Regardless of the strength of the correlation between two Objects in an Itemset, they will not occur simultaneously every time.

Clearly, Market Basket Analysis draws heavily from statistics. Itemsets correspond to Sample Sets. Affinity, Correlation, and Probability are almost synonymous. So, it stands to reason that a strong background in statistics would serve a Market Basket Analyst well. An important distinction between Itemsets of Market Basket Analysis and Sample Sets of a Multiple Linear Regression is the flexibility of data. Market Basket Analysis found its first best application in retail marketing. Cash registers in the retail environment can capture transaction data in granular detail for every transaction. As such, transaction processing systems produce a volume and wealth of data that feed into Market Basket Analysis. Today, the software used in manufacturing, communications, supply chains, transportation, Web-based applications, and any other application that can capture and log activity produces large volumes of data used in Market Basket Analysis. The logged activity varies based on the activity in the Itemset. One Itemset may contain one object, and another may contain one thousand objects. This variability is not found in Multi Linear Regression, which has a predefined set of variables, each containing one and only one value at a time. Regardless, the statistical nature of Market Basket Analysis is still found in the calculations of Affinity between Objects in an Itemset.

Rapid changes in consumer preferences, technological advancements, and intense competition characterize the retail industry. To stay competitive, retailers need to leverage data-driven insights. Market Basket Analysis provides a robust methodology for extracting meaningful patterns from transactional data, offering retailers the ability to understand customer behaviour, enhance cross-selling strategies, and optimize inventory management.

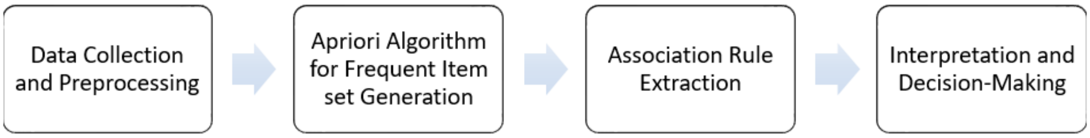

Figure 1. The flow

1. Data Collection and Preprocessing

The foundation of any successful MBA lies in the quality of the data. Retailers should gather transactional data, capturing details such as customer ID, transaction ID, and item purchased. Data preprocessing involves handling missing values, removing duplicates, and transforming the data into a suitable format for analysis.

2. Apriori Algorithm for Frequent Itemset Generation

The Apriori algorithm is a widely used technique for identifying frequent itemsets from transactional data. It employs an iterative approach to discover itemsets with support above a predefined threshold. Adjusting this threshold allows retailers to focus on the most relevant associations. The Apriori algorithm helps efficiently find frequent itemsets by avoiding exhaustive searches of all possible itemsets. It leverages the fact that if an itemset is infrequent, all its supersets will also be infrequent. The result of the Apriori algorithm is a list of frequent itemsets, which can then be used to generate association rules based on metrics such as support, confidence, and lift.

3. Association Rule Extraction

The generated frequent itemsets derive association rules by evaluating metrics such as support, confidence, and lift. Support measures the frequency of occurrence of a rule, confidence quantifies the reliability of a rule, and lift indicates the strength of the association between items. Association rules are composed of three main components such as Antecendent (X), consequent (Y) and Support, Confidence and Lift. Antecedent (X) is the item or set of items found in the transactions and acts as the basis or condition for the rule. Consequent (Y) is the item or set of items that are likely to be found in the same transactions as the antecedent based on observed patterns. Support, Confidence, and Lift: These metrics are used to evaluate association rules' strength and significance. Support (A) measures the frequency of occurrence of the itemset in the dataset. Confidence (B) measures the likelihood that the rule is true, given the presence of the antecedent. Lift (C) indicates how much more likely the consequent is, given the presence of the antecedent than its standalone likelihood.

$$Support = \frac{Freq\ (X,Y)}{N} \qquad \text{(A)}$$

$$Confidence = \frac{Freq\ (X,Y)}{Freq\ (X)} \qquad \text{(B)}$$

$$Lift = \frac{Support}{Support\ (X) * Support\ (Y)} \qquad \text{(C)}$$

These rules help retailers and businesses make informed decisions regarding product placement, promotions, and inventory management, ultimately enhancing the customer shopping experience and maximizing sales.

4. Interpretation and Decision-Making

Interpreting the extracted rules is crucial for informed decision-making. Retailers should consider the context of their business, industry trends, and customer demographics. For instance, rules with high confidence but low lift may indicate commonly purchased items but not necessarily items that drive each other's sales.

Market Basket Analysis discovers patterns. The logic of those patterns isolates the actions of the enterprise, the response to those actions, and the probability of that response occurring. If the enterprise desires a specific response (e.g., increased sales, increased productivity, increased product quality), the logic of Market Basket Analysis identifies the actions that lead to that response and the probability that the response will occur. The enterprise can use that information to consider its options.

The logic of Market Basket Analysis is a pattern. The three parts of that pattern are a Driver Object, a Correlation Object, and their Affinity (i.e., the probability to occur simultaneously). The purpose of the Market Basket Analysis pattern is to provide the enterprise with actionable information.

The goal of Market Basket Analysis is to produce actionable information. Significant fluctuations in the correlation between two objects indicate a pattern of randomness that can be neither leveraged nor avoided. If the enterprise cannot forecast the correlation between two objects, then the enterprise is left to the whims of chance. For this reason, randomness is an indicator of a future area of investigation. Only when the overlaying patterns of correlation are each identified can they become actionable information for the enterprise.

Market basket analysis cannot replace the enterprise's decision-making process. Instead, market basket analysis can identify the probable response of others in the business environment to each option available to the enterprise. The decision-making process is not replaced; Market Basket Analysis enhances it.

FINDINGS AND DISCUSSION

The dataset used in this analysis captures secondary data of retail transactions in Indonesian supermarkets from January to March 2023, encompassing diverse products and customer interactions. Each row corresponds to a unique transaction, while columns represent individual products. The dataset provides a rich source of information for understanding customer preferences, cross-selling opportunities, and the dynamics of product associations.

In a retail store, that unit of business activity is the sales transaction documented on a receipt. The customer presents products for purchase. The cashier records the products in a cash register. Once all the products have been entered into the cash register, the cash register prints a receipt. The cashier presents the receipt to the customer, who then pays for the products listed on the receipt for the price listed on the receipt. That receipt is the lowest-level, most granular transaction in the enterprise. Let the receipts be the Itemset.

In market basket analysis, a product itemset refers to a collection of items frequently purchased together in a transaction. The analysis aims to identify associations or relationships between items based on their co-occurrence in these transactions.

Table 1. Product Itemset

Support	Itemsets
0.59	({' beverages '})
0.55	({' snack, biscuit, confectionery '})
0.54	({' chilled/dairy '})
0.53	({' home meal '})

Support	Itemsets
0.53	({' spices '})
0.41	({' health & beauty, personal care '})
0.39	({' fruit local '})
0.39	({' snack, biscuit, confectionery ', ' home meal '})
0.38	({' beverages ', ' snack, biscuit, confectionery '})
0.38	({' beverages ', ' home meal '})

At this point, the Itemset has been defined. The Driver Object and Correlation Object have been defined. Thus far, all these definitions have been business definitions within the source systems that hold these objects. To facilitate the analysis of the Itemsets and Objects, they must have keys compatible with the Market Basket Analysis application.

Association rules in market basket analysis express relationships between different items based on their co-occurrence in transactions. These rules are used to uncover patterns and insights into customer purchasing behaviour. The typical form of an association rule is "if X, then Y," indicating that the presence of items X in a transaction is associated with the presence of items Y.

Table 2. Association Rules

Antecedents	Consequents	Antecedent support	Consequent support	Support	Confidence	Lift
home meal, cleaning/home care	health & beauty, personal care	0.25	0.41	0.20	0.81	1.96
fruit import	fruit local	0.30	0.39	0.22	0.73	1.85
beverages, frozen food	home meal	0.25	0.53	0.21	0.87	1.64
fresh meat, beverages	spices	0.24	0.53	0.21	0.85	1.62
fresh meat, home meal	chilled/dairy	0.24	0.54	0.21	0.85	1.58

In light of the insights gained from the association rules, we present the top 5 segments for product bundling strategies for retail optimization:

1. Health enthusiast

This profile buys products of home meals, cleaning/home care, health and beauty, and personal care. Description Purchase Motivation Nutrient-rich meals, organic cleaning products, and a focus on health and wellness.

2. The Exotic Flavor Explorer

This profile buys products of fruit import, fruit local. They enjoy trying unique and exotic fruits worldwide, seeking new and unusual flavours.

3. Food Enthusiast

This profile buys products of beverages, frozen food, and home meals. This segment prefers gourmet ingredients for home-cooked meals, unique beverages, and high-quality frozen foods.

4. Fitness Freak

This profile buys products of fresh meat, beverages, and spices. They are dedicated to fitness and muscle building, prioritize high-protein meat choices, and look for beverages that support hydration and recovery.

5. Budget-conscious Home Cook

This profile buys products like fresh meat, home meals, and chilled/dairy. They strive to create delicious and nutritious meals while being mindful of the budget. Shops for economical cuts of fresh meat and seeks affordable dairy options. Focuses on meal planning to minimize food waste.

Market basket analysis helps businesses understand customer behaviour and preferences, enabling them to optimize product placement, design targeted promotions, and enhance the overall shopping experience. The impacts of market basket analytics result on the retail supermarket are,

a. Enhancing Customer Experience

One of the immediate impacts of market basket analytics is its ability to enhance the overall customer experience. By identifying products commonly purchased together (Product Bundling), businesses can optimize their store layouts, creating a more intuitive and convenient shopping experience for customers. For instance, placing complementary items in close proximity can encourage additional purchases, leading to increased customer satisfaction and loyalty.

Moreover, businesses can leverage these insights to personalize recommendations for individual customers. Recommender systems, powered by market basket analytics, enable businesses to suggest relevant products based on a customer's past purchase history, preferences, and the behaviour of similar customers. This personalized approach not only boosts sales but also fosters a deeper connection between the business and its customers.

b. Inventory Management and Optimization

Effective inventory management is crucial for businesses to maintain a balance between meeting customer demand and minimizing carrying costs. Market basket analytics plays a pivotal role in optimizing inventory by identifying fast-moving items and predicting demand patterns. Businesses can use these insights to streamline their inventory, ensuring that popular products are adequately stocked while minimizing the risk of overstocking less popular items.

Additionally, market basket analytics can help businesses identify product bundling opportunities. By understanding which products are frequently bought together, businesses can create bundled offerings, providing customers with added value while increasing the average transaction value. This not only optimizes inventory but also serves as a strategic pricing and marketing tactic.

c. Pricing Strategies

Market basket analytics offers valuable insights into pricing strategies and the effectiveness of promotions. Businesses can identify price-sensitive products by analysing transaction data and adjust pricing strategies accordingly. Furthermore, understanding the relationships between products allows businesses to design effective promotional campaigns, such as "buy one, get one free" or "bundle discounts," enticing customers to make additional purchases.

These insights enable businesses to implement dynamic pricing strategies, responding to changes in demand and market conditions. By aligning pricing with customer behaviour, businesses can maximize revenue and profitability while maintaining a competitive edge in the market.

d. Campaign Optimization

Marketing is a critical aspect of any business strategy, and market basket analytics can significantly impact the effectiveness of marketing campaigns. Businesses can tailor their marketing messages to resonate with specific customer segments by identifying product affinities and customer preferences. Targeted advertising and promotions based on market basket insights can result in higher conversion rates and improved return on investment for marketing expenditures.

Moreover, businesses can identify cross-selling and upselling opportunities through market basket analytics. Recommending complementary products in marketing materials or online platforms can drive additional sales and contribute to the overall success of marketing campaigns.

e. Strategic Decision-Making

Market basket analytics results provide information that empowers businesses to make strategic decisions aligned with customer preferences and market trends. Whether entering new markets, expanding product lines, or refining business processes, the insights derived from market basket analytics guide decision-makers in making informed and data-driven choices.

Furthermore, businesses can use market basket analytics to stay agile and responsive to changing consumer behaviour. As market trends evolve, businesses can adapt their strategies in real time, ensuring continued relevance and competitiveness in the market.

Prior research on improving retail supermarket financial performance through market basket analytics using the Apriori algorithm has primarily focused on Western markets. However, in contrast, our study delves into the Indonesian market, employing machine learning techniques with a Python-based approach tailored to Indonesian-specific consumer behaviours and market dynamics. By doing so, we aim to provide insights unique to the Indonesian retail landscape, offering valuable contributions to both academia and industry in this region.

CONCLUSIONS

Market Basket Analysis has proven to be an invaluable tool for retailers seeking to optimize their operations. Identifying frequent item sets and association rules provides a roadmap for strategic decision-making, enabling retailers to enhance customer satisfaction, drive sales, and stay ahead in a competitive market. The presented top 5 segments for product bundling strategies serve as actionable insights, offering a concrete path for retailers to implement innovative approaches that align with customer preferences and market trends. As the retail landscape continues to evolve, the integration of advanced analytics and data-driven strategies becomes increasingly essential for sustained success.

The other impact of market basket analytics results extends beyond transaction data analysis. Businesses can leverage these insights to enhance customer experiences to optimise inventory, pricing strategies, and marketing campaigns to drive strategic growth. As businesses continue to embrace data-driven decision-making, market basket analytics stands out as a powerful tool that not only uncovers hidden patterns in customer behaviour but also guides businesses toward a more informed and successful future. In the ever-evolving landscape of commerce, market basket analytics remains a crucial driver of innovation and competitive advantage, enabling businesses to stay ahead of the curve and meet the dynamic needs of their customers

LIMITATION & FURTHER RESEARCH

While market basket analysis provides valuable insights, it does have limitations. One challenge lies in the assumption that associations identified in historical transaction data will remain consistent over time. External factors, such as changing consumer preferences or economic conditions, can influence purchasing patterns. Additionally, the analysis might struggle with infrequent or one-time purchases, leading to sparse data and less reliable associations. Privacy concerns also arise, as the technique involves scrutinizing individual purchasing behaviour. Ensuring data accuracy and mitigating biases is crucial, as inaccurate or biased data can result in flawed insights. Despite these limitations, businesses can still harness market basket analysis effectively by considering these constraints in their decision-making processes.

REFERENCES

Agrawal, R., Imielinski, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *ACM SIGMOD Record, 22*(2), 207-216. https://doi.org/10.1145/170036.170072.

Grau, G. R. (2017). Market basket analysis in retail [Master's thesis, Universitat Politècnica de Catalunya]. https://upcommons.upc.edu/handle/2117/100880?locale-attribute=en.

Hahsler, M., & Chelluboina, S. (2011). Visualizing association rules in hierarchical groups. *Journal of Computational and Graphical Statistics, 87,* 317–335 (2017). https://doi.org/10.1007/s11573-016-0822-8.

Han, J., Pei, J., & Yin, Y. (2000). Mining frequent patterns without candidate generation. *ACM SIGMOD Record, 29*(2), 1-12. https://doi.org/10.1145/335191.335372.

Kaur, M., & Kang, S. (2016). Market Basket Analysis: Identify the changing trends of market data using association rule mining. *Procedia computer science, 85,* 78-85. https://doi.org/10.1016/j.procs.2016.05.180,

Kurniawan, F., Umayah, B., Hammad, J., Nugroho, S. M. S., & Hariadi, M. (2018). Market Basket Analysis to identify customer behaviours by way of transaction data. *Knowledge Engineering and Data Science, 1*(1), 20. https://doi.org/10.17977/um018v1i12018p20-25.

Linden, G., Smith, B., & York, J. (2003). Amazon.com recommendations: Item-to-item collaborative filtering. *IEEE Internet Computing, 7*(1), 76-80. https://doi.org/10.1109/MIC.2003.1167344.

Meftah, M., Ounacer, S., & Azzouazi, M. (2024). Enhancing Customer Engagement in Loyalty Programs Through AI-Powered Market Basket Prediction Using Machine Learning Algorithms. In *Engineering Applications of Artificial Intelligence* (pp. 319-338). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-50300-9_18.

Patwary, A. H., Eshan, M. T., Debnath, P., & Sattar, A. (2021, July). *Market Basket Analysis Approach to Machine Learning*. In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-9). IEEE.

Pillai, A. R., & Jolhe, D. A. (2020). Market basket analysis: Case study of a supermarket. In *Advances in Mechanical Engineering: Select Proceedings of ICAME 2020* (pp. 727-734).

Rana, S., & Mondal, M. N. I. (2021). A Seasonal and Multilevel Association Based Approach for Market Basket Analysis in Retail Supermarket. *European Journal of Information Technologies and Computer Science, 1*(4), 9-15. https://doi.org/10.24018/compute.2021.1.4.31.

Samboteng, L., Rulinawaty, R., Kasmad, M. R., Basit, M., & Rahim, R. (2022). Market basket analysis of administrative patterns data of consumer purchases using data mining technology. *Journal of Applied Engineering Science, 20*(2), 339-345.

Srikant, R., & Agrawal, R. (1996). Mining quantitative association rules in large relational tables. *ACM SIGMOD Record, 25*(2), 1-12. https://doi.org/10.1145/235968.233311.

Tatiana, K., & Mikhail, M. (2018). Market basket analysis of heterogeneous data sources for recommendation system improvement. *Procedia Computer Science, 136*, 246-254. https://doi.org/10.1016/j.procs.2018.08.263.

Ünvan, Y. A. (2021). Market basket analysis with association rules. *Communications in Statistics - Theory and Methods*, *50*(7), 1615–1628. https://doi.org/10.1080/03610926.2020.1716255

Wu, X., & Kumar, V. (2009). *The Top Ten Algorithms in Data Mining*. Chapman and Hall/CRC.