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# LEVERAGING MARKET BASKET ANALYSIS TO DEVELOP SALES STRATEGIES FOR MSMEs: A CASE STUDY OF LOS IN BETWEEN

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**Abstract**

**Background:** Micro, Small, and Medium Enterprises (MSMEs) a cornerstone of Indonesia's economic, contributing approximately 61% to the national GDP (Haryo Limanseto, 2022). However, MSMEs, particularly in the competitive Food and Beverage (F&B) sector, face persistent challenges including limited access to capital, technological adoption gaps, and volatile consumer preferences (Badan Pusat Statistik, 2023). These factors make revenue stability a critical issue.
**Purpose:** Through a case study of LOS In Between, this research aims to: (1) demonstrate the application of MBA in a resource-constrained, offline MSME setting; (2) identify product associations to inform bundling and upselling strategies for the business; and (3) propose a replicable analytical approach that can be adapted by other small-scale F&B businesses to enhance sales performance. This study aims to analyze consumer purchasing patterns through Market Basket Analysis (MBA) and to provide actionable data-driven strategies to improve sales performance and competitiveness in MSMEs.
**Design/methodology/approach:** This study applies Market Basket Analysis using the Apriori algorithm to transactional data from LOS In Between (January–June 2025). Association rules derived from support, confidence, and lift metrics were translated into practical sales strategies—including bundling, upselling, and cross selling.
**Findings/Result:** The analysis revealed that STM functions as an anchor product frequently purchased with items such as SJ and WF, making it ideal for strategic bundling. Products with weaker associations, such as CMM, were considered more suitable for upselling promotions. The findings show that even MSMEs with modest transaction volumes can leverage simple data analytics to uncover purchasing patterns, optimize sales, and enhance customer experience.
**Conclusion:** MBA provides a practical and scalable analytical tool for MSMEs to design evidence-based sales strategies. By leveraging transaction data, MSMEs can increase revenue, strengthen customer engagement, and sustain competitiveness in dynamic market environments.
**Originality/value (State of the art):** This study addresses the gap by adapting Market Basket Analysis to a micro-scale F&B, LOS In Between. Its novelty lies not only in applying MBA to this constrained setting but also in proposing a practical methodology that converts association rules into actionable strategies like bundling and upselling, designed for periodic re-mining to track preference shifts. The research also outlines how MBA can be integrated with lightweight decision frameworks suitable for MSMEs, providing localized evidence from Indonesia's F&B sector.

**Keywords:** market basket analysis, sales strategies, MSMEs, apriori, purchase patterns

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## INTRODUCTION

MSMEs play a crucial role in Indonesia's economic structure. They contribute approximately 61% to the national GDP, supported by around 66 million business units and equivalent to IDR 9,580 trillion (Haryo Limanseto, 2022; Indonesian Chamber of Commerce and Industry, 2024). According to Badan Pusat Statistik (2024), micro and small industries remain the backbone of the national economy, sustaining growth and fostering regional development. Despite their strategic role, MSMEs operate within a context of persistent structural challenges, such as limited capital, technological constraints, uneven infrastructure and restricted market access (Badan Pusat Statistik, 2023). These limitations make them particularly vulnerable to dynamic consumer preferences and intense competition. Consequently, data-driven strategies have become essential for MSMEs to maintain competitiveness and ensure sustainable growth.

Within this MSME landscape, Indonesia's Food and Beverage (F&B) sector has demonstrated robust growth, contributing 7.15% to national GDP in the first half of 2024 and maintaining a growth trajectory projected at 4.53% for 2024 (CRIF, 2024). According to Badan Pusat Statistik (2025), the F&B service activities sector reached approximately IDR 405 trillion in 2023, representing substantial economic contribution. However, this growth has intensified competition within the food service industry, creating challenging conditions particularly for newly established MSMEs. Industry analysis reveals that Indonesian food service operators face persistent pricing pressure and thin profit margins, with full-service restaurants typically achieving profit margins between 3-6%, while casual dining establishments operate within even narrower margins of 3-5% (Markwide, 2026; Global Data, 2025). In Tasikmalaya specifically, with a per capita GDP of IDR 36.95 million as of 2023 (Agus Dwi Darmawan, 2024), price sensitivity among consumers further constrains profitability. This competitive pressure creates acute vulnerability to revenue fluctuations, where even modest declines can threaten operational viability and long-term sustainability for resource-constrained F&B MSMEs.

LOS In Between exemplifies this challenge. Established in 2022 as an affordable, youth-oriented noodle bar in Tasikmalaya (Cari Kuliner Indonesia, 2023; Nidiapraja, 2024), the business operates with approximately 50-70 daily transactions and a menu featuring core noodles and rice bowls. Its revenue model depends heavily on high-margin add-ons (beverages, side dishes, protein upgrades) to achieve profitability, making average order value optimization is critical for sustainability. This business model, which relies on increasing the average order value through complementary items, makes it an ideal candidate for MBA-driven sales optimization strategies. Recent operational data underscores the urgent need for such analytical intervention. LOS In Between experienced a significant revenue decline in the second quarter of 2025, as illustrated in Figure 1.


Figure 1. Monthly revenue trend of LOS in between

As shown in Figure 1, the business suffered a substantial revenue contraction in Q2 2025. Sales fell from IDR 56.8 million in April to IDR 38.7 million in May, representing a 32% decline, followed by only a partial recovery in June (IDR 42.4 million). This trend signals a clear risk to revenue sustainability and highlights the necessity for data-driven strategies to reverse the trend.

Market Basket Analysis (MBA) is a well-established data mining technique, pioneered by (Agrawal et al. 1993) for uncovering product associations in large retail datasets. Extensively applied in the retail and service sectors, MBA enables businesses to optimize product placement, design targeted promotions, and implement effective upselling and cross-selling strategies (Fageeri et al. 2023; Kurniawan et al. 2017). Rather than focusing solely on algorithmic complexity, MBA provides practical insights for managerial decision-making, making it particularly suitable for MSMEs with limited analytical resources (Chatterjee & Poovathingal, 2020). Prior applications in the food and beverage sector show MBA's value in improving menu design and sales through data-driven recommendations (Zhao et al. 2019).

Recent studies also highlight its versatility beyond large-scale retail, extending to healthcare, hospitality, and lifestyle sectors, for predicting consumer behavior and enhancing marketing strategies (Rao et al. 2021). Methodologically, research has demonstrated enhanced decision-making when MBA is integrated with complementary analytical frameworks. Studies have combined MBA with multi-criteria decision methods such as Analytical Hierarchy Process (AHP) for systematic prioritization of identified product associations based on profitability, operational feasibility, and customer value criteria (Govindan et al. 2020). Additionally, integration with competitive strategy frameworks enables contextualization of product bundling strategies within industry dynamics, addressing competitive rivalry, buyer power, and barriers to entry through data-driven differentiation (Islami et al. 2020; Spender et al. 2017).

However, most research emphasizes large enterprises or e-commerce platforms, leaving a significant gap in applying this analytical technique to the specific context MSMEs in the casual dining sector. Furthermore, few studies translate association rules into implementable strategies or propose adaptive protocols for resource-constrained environments or demonstrate practical pathways for integrating MBA with strategic decision frameworks in MSME contexts.

This study addresses these gaps through three distinct contributions that advance both theory and methodology. Theoretically, it extends Data-Driven Decision Making (DDDM) theory to resource- constrained MSME contexts by demonstrating that analytical capabilities can generate strategic value without sophisticated infrastructure (Bianchini & Michalkova, 2019). This challenges the implicit assumption in MBA literature that effective analytics requires extensive technical resources, revealing that strategic value emerges from actionable insight generation tailored to organizational capacity rather than analytical complexity. The study further contributes to entrepreneurial orientation theory by illustrating how MSMEs can operationalize innovativeness, proactiveness, and risk-taking dimensions through accessible data practices, showing that entrepreneurial behaviors can be systematically enhanced beyond intuition-based approaches (Covin & Wales, 2019).

Methodologically, this research develops a simplified MBA implementation framework specifically designed for micro-scale F&B businesses. Unlike existing MBA studies requiring 10,000+ transactions in large retail contexts (Agrawal et al. 1993; Fageeri et al. 2023), this framework adapts to low-volume environments (1,000-2,000 annual transactions).

Empirically, this study provides the first documented application of MBA to a micro-scale F&B industry in Indonesia, demonstrating that businesses with <100 daily transactions can derive meaningful strategic insights. By applying this framework to LOS In Between, the research generates localized evidence from Tasikmalaya's F&B sector and develops replicable procedures other MSMEs can adapt, directly supporting Indonesia's national MSMEs digitalization agenda through practical, low-cost analytical solutions.

This study employs a practical, data-driven approach to problem-solving by leveraging existing transactional data. Beyond identifying associations, this study translates analytical insights into actionable strategies, including upselling, cross-selling, and bundling. Prior research demonstrates that these strategies effectively increase transaction size and customer lifetime value when properly timed (Pandya & Dholakia, 2021). Industry evidence shows 72% of F&B businesses actively employ such approaches to boost revenue (Ono Suite, 2024). Building on successful applications in the hospitality industry (Meliarini et al. 2021), this research integrates MBA findings with practical sales tactics, enabling MSMEs to enhance profitability while maintaining revenue stability (Saura et al. 2023).

This research aims to: (1) analyze customer purchasing patterns at LOS In Between using MBA; (2) identify product associations that can inform upselling, cross-selling, and promotional strategies; (3) develop actionable recommendations for increasing sales in MSMEs; and (4) provide insights for MSMEs to adopt sustainable and scalable sales strategies. This study addresses an urgent need for practical, low-cost analytical solutions. By bridging the gap between data analytics and strategic execution, this study contributes to both academic discourse and practical solutions for MSME competitiveness in Indonesia's dynamic market environment.

## METHODS

This study employed traditional MBA metrics including support, confidence, and lift to identify product associations. In line with recent innovations, it also considered predictive rule strength as an extension of these traditional metrics by referencing hybrid models like FSA-Red and M5P, which enhance decision-making based on rule stability and forecast accuracy (Sulianta & Laksana, 2024).

The study employed transactional data with both cross-sectional and time-series dimensions derived from the sales records of a food and beverage business, which is LOS In Between, covering the period from April to June 2025. The cross-sectional component captured transaction IDs, item codes, and purchase frequency at specific points, while the time-series component enabled analysis of purchasing pattern evolution over time. This type of data was chosen because it provides detailed insights into purchasing behavior, enabling the identification of co-occurring items suitable for bundle or package recommendations (Hartinah & Sugiyono, 2024; Kaban et al. 2024).

Data were collected through secondary sources, specifically the company's point-of-sale (POS) system, which systematically records each transaction in real-time (Grahitama et al. 2025; Sikibi, 2022). This technique was considered reliable since it minimizes human error and ensures objectivity (Marques et al. 2023; Purwasih et al. 2023). The dataset requirements for Market Basket Analysis do not specify a fixed minimum number of transactions, as effectiveness depends more on the analytical parameters used than on dataset size (Rahayu, 2023). However, studies commonly utilize datasets ranging from 100 to over 300 transactions to identify statistically significant association rules (Rahayu, 2023; Mustakim et al. 2018).

The dataset requirements included: (1) complete transactional records containing transaction IDs, item codes, and timestamps on a per-transaction basis; (2) data spanning at least one full business quarter to capture representative purchasing patterns; and (3) a data quality threshold of 95% completeness with no critical missing values (Agrawal et al. 1993;Rahayu, 2023). The effectiveness of Market Basket Analysis depends primarily on setting appropriate minimum support thresholds (e.g., 50%) and minimum confidence thresholds (e.g., ≥0.75) to identify meaningful product associations (Rahayu, 2023; Valle et al. 2018). The dataset was then cleaned and pre-processed to remove missing or inconsistent entries before conducting further analysis. The dataset used in this study covers transaction data from January 2025 to June 2025, focusing on Q2 (April-June 2025) for detailed analysis, comprising 1,384 transactions that met all specified requirements.

The study applied the Market Basket Analysis (MBA) method using the Apriori algorithm to identify association rules between items (Das, 2025; Hermawan et al. 2024; Wijaya et al. 2024). In a business context, Market Basket Analysis provides information on products that are likely to be purchased simultaneously and determines the most appropriate product to promote (Rahayu, 2023). The application of the association rule method in market basket analysis has two stages to find and generate information and knowledge from a database (Rahayu, 2023). The steps undertaken are as follows:

Identifying for frequent itemsets

In the first stage, frequent itemset discovery, the process involves identifying combinations of items that meet the minimum support requirements in the transaction database (Rahayu, 2023). Support is calculated using the formula:

Support (A=>B=P (A U B) (1)

Generating associtation rules

In the second stage, forming association rules, after all frequent itemsets have been identified, the next step is to form an association rule that can fulfill a confidence value (Rahayu, 2023). To find out the confidence value, the confidence value can be calculated using the following formula:

Confidence: P (A∩B)= Σ Transaction containing A and B x 100% (2)

According to Rahayu (2023), the support value of itemset or product variation group A against itemset B is equal to the probability of itemsets A and B combined, while the confidence percentage of itemset A against itemset B is equal to the probability of the combination of itemsets A and B divided by the probability of itemset A.

The complete MBA implementation followed a structured methodology (Saputra et al. 2023). First, data preprocessing involved cleaning transaction data and converting it into a suitable format for mining. Second, frequent itemset discovery identified item combinations meeting the minimum support threshold through iterative scanning of the transaction database. Third, association rule generation created rules from frequent itemsets that satisfied minimum confidence thresholds. Fourth, rule evaluation assessed pattern strength using measures such as support, confidence, and lift ratio, which measure itemset frequency, rule strength, and the degree of association between items, respectively (degree of independence between items) to evaluate the strength of associations between items (Nugraha et al. 2023; Rahayu, 2023; Valle et al. 2018). All data preprocessing, algorithm implementation, and evaluation processes were carried out using Google Colab as the computational platform, ensuring efficient and reproducible analysis. These rules then served as the basis for designing potential package combinations and making managerial recommendations.

This study hypothesizes that customer transactions at LOS In Between exhibit recurring patterns of co-purchased items, and that these patterns, when analyzed using the Market Basket Analysis (MBA) technique, can reveal strong product associations. Such associations are expected to form the basis for effective upselling and cross-selling strategies, thereby contributing to more targeted and efficient sales interventions. Support for this hypothesis can be found in the study by Alifah (2025), who applied the Apriori algorithm to retail transaction data and found that item pairs with high support and lift values were effective indicators of consumer preference. These association patterns enabled businesses to develop bundle-based promotions that closely aligned with natural customer purchasing behavior.

Further evidence is provided by Ridwan & Lubis (2025), who implemented MBA in a minimarket setting and demonstrated that frequent co-purchase itemsets can be leveraged to optimize product placement and increase transaction value. Their findings suggest that even simple transactional data, when analyzed systematically, can yield significant operational improvements. Based on this body of evidence, the hypothesis rests on a strong theoretical and empirical foundation, suggesting that co-purchase patterns in transactional data can be analyzed to uncover strategic opportunities, thereby empowering MSMEs to increase sales revenue and design relevant menu offerings.

This study employs a systematic framework that integrates the identified business problem with Market Basket Analysis methodology to develop actionable sales strategies for LOS In Between. The framework addresses the 32% revenue decline through a structured analytical process encompassing data collection, MBA processing, and strategic recommendation development.

The framework begins by establishing the Research Background, which identifies LOS In Between as a youth-oriented F&B MSME with an add-on dependent revenue model operating in a context where limited MBA research exists for offline MSMEs. This contextual foundation leads to Problem Identification, which highlights the critical revenue decline from April to June 2025, necessitating data-driven sales optimization and improved add-on and bundling strategies. The literature review stage reveals the research gap: while MBA has been extensively applied to large retailers and e-commerce platforms, limited research addresses its implementation in resource-constrained offline F&B MSMEs (Agrawal et al. 1993;Rahayu, 2023;Valle et al. 2018;Mustakim et al. 2018).

Following the conceptual foundation, the framework proceeds to Input Transaction Data stage, where transactional data from the POS system of LOS In between covering April to June 2025 with Q2 focus is collected. The Pre-Processing and Process stage follows a systematic eight-step procedure (Rahayu, 2023): (1) Data Cleaning to remove missing or inconsistent entries; (2) Data Merger to consolidate transaction records; (3) Data Selection to identify relevant variables; (4) Data Transformation for Mining to convert data into suitable format for analysis; (5) Mining Process Using the Apriori Algorithm to identify frequent itemsets; (6) Calculation of Confidence and Support to evaluate association rule strength; (7) Determination of Association Rule based on minimum support and confidence thresholds; and (8) Outcome Evaluation to assess the validity and actionability of detected patterns. These rules are evaluated through support, confidence, and lift values to determine item relevance and purchasing patterns (Pratama & Dewi, 2025).

The framework culminates in the Result and Strategic Recommendations stage, which produces actionable insights including: (1) Association Rules identifying product combinations with high support-confidence-lift values; (2) Menu Package Bundling Recommendations based on frequently co-purchased items; (3) Add-on Upselling Strategies to increase average order value; (4) Cross-selling Optimization techniques. The expected outcome is to reverse the revenue decline and increase average order value (AOV) through data-driven complementary item recommendations that align with consumer purchasing patterns and business sustainability objectives.

## RESULTS

This study employs transactional data from LOS In Between as the primary source. The dataset comprises 1,384 sales records with bill numbers grouped to represent individual transactions. Each transaction details purchased menu items under the "Food" category. Variables include bill identifier, menu code, and menu category, collected retrospectively from the point-of-sale (POS) system to ensure accuracy and reliability.

The dataset was structured in a transactional format, where each record is identified by a unique Bill Number that represents a single customer transaction and links all purchased items within that transaction. For example, a transaction such as TRS_1 may include multiple menu codes, including CMM (Creamy Miso Mian) and CJ (Creamy Jiaozi), indicating that these items were purchased simultaneously in one order. This structure effectively captures co-purchase behavior, which is essential for Market Basket Analysis, as it maintains the relationships among items purchased together and enables the identification of product associations and purchasing patterns across the entire dataset comprising 1,384 transactions.

To support the implementation of Market Basket Analysis, the transactional data were transformed using One-Hot Encoding, converting the original purchase records into a binary matrix suitable for association rule mining. In this representation, a value of "1" indicates the presence of a specific menu item in a transaction, while a value of "0" indicates its absence. This transformation allows the Apriori algorithm to systematically process all transactions, identify frequent itemsets, calculate support and confidence values, and generate association rules that reveal meaningful purchasing patterns. The resulting patterns provide an analytical basis for developing data-driven bundling and upselling strategies aimed at increasing the average order value and addressing the revenue decline experienced by LOS In Between.

As shown in Table 1, the binary transformation includes 1,384 transactions, where "1" indicates the presence of an item and "0" indicates its absence. This encoding enables efficient identification of co-occurring items for association rule mining. For example, TRS_1 shows CJ and CMM purchased together, while TRS_2 shows CBM02 and CMM. This representation simplifies identifying co-occurring items for MBA-based marketing strategies.

Following the representation of transactional data in Table 1, the data were subjected to one-hot encoding. The resulting encoded dataset is used for subsequent analysis using the Apriori algorithm. The algorithm attempts to find itemsets that are purchased together in transactions at a specified frequency. In essence, the algorithm identifies underlying purchasing patterns. Table 3 presents results categorized by support thresholds, revealing underlying purchasing patterns.

Table 2 shows CMM (38.4%) and STM (32.7%) exhibit high support values, appearing in a substantial proportion of transactions. Item combinations like (STM, CMM) at 11.3% support reveal co-purchasing behavior, which is useful for designing bundling strategies, promotions, and upselling approaches based on empirical customer tendencies. The high support of STM (32.7%) confirms its role as an anchor product, attracting customers and anchoring bundles. Although explicit F&B anchoring studies are limited, the concept aligns with menu engineering findings. Table 2's frequent itemsets provide preliminary co-occurrence understanding but lack directional association insights. Extending Apriori generates association rules capturing conditional purchase probability based on support, confidence, and lift metrics. Table 3 summarizes the most relevant discovered associations.

Table 3 summarizes the association rules derived from the frequent itemsets using the Apriori algorithm. Each rule consists of an antecedent, representing the if-condition, and a consequent, representing the then-outcome, accompanied by the corresponding support, confidence, and lift measures. The findings indicate that most of the generated rules exhibit relatively low confidence and lift values. This suggests that although certain items frequently appear together, the conditional dependence between them is generally weak. For example, the rule (CJ) → (CMM) records a support value of 0.169 and a confidence level of 0.084, with a lift of 0.496, reflecting limited predictive capability. Comparable patterns are observed in the rules (STM) → (SJ) and (RMN) → (WF), where frequent co-occurrence does not translate into strong associative influence. Overall, these results indicate that the extracted rules primarily capture natural co-purchase behavior rather than strong causal or predictive relationships. Consequently, further refinement—such as adjusting minimum threshold parameters or prioritizing rules with higher lift values—may be necessary to derive more actionable insights. Nevertheless, even associations with modest strength can uncover meaningful complementary consumption patterns. For MSMEs, such insights remain strategically valuable for menu structuring, promotional planning, and upselling strategies, reinforcing the notion that small-scale datasets can still generate significant business value (Bianchini & Michálková, 2019).

Table 1. One-hot encoded transformation of transactional data for market basket analysis

| | Menu Code | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CBM01 | CBM02 | CJ | CK | CMM | DOGA | DOGM | EDON | HDON | KDON | LCCN | LCN | OBM01 | OBM02 | RMN | RW | SBM01 | SBM02 | SJ | SM01 | SM02 | STDON | STM | WF | WS |
| TRS_1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TRS_2 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TRS_3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TRS_4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| ….. | | | | | | | | | | | | | | | | | | | | | | | | | |
| TRS_1384 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |

Table 2. Frequent menu item sets and their support values from LOS in between transactions

| Index | Support | Item Sets |
|---|---|---|
| 3 | 0.383671 | (CMM) |
| 20 | 0.327312 | (STM) |
| 2 | 0.169075 | (CJ) |
| 16 | 0.132948 | (SJ) |
| 12 | 0.130780 | (RMN) |
| 21 | 0.124277 | (WF) |
| 8 | 0.118497 | (LCCN) |
| 30 | 0.112717 | (STM, CMM) |
| 22 | 0.109104 | (WS) |
| 23 | 0.083815 | (CJ, CMM) |

Table 3. Association rules with support, confidence, and lift metrics from market basket analysis

| antecedents | consequents | antecedent support | consequent support | support | confidence | lift |
|---|---|---|---|---|---|---|
| 0 | (CJ) | (CMM) | 0.169 | 0.384 | 0.084 | 0.496 |
| 3 | (SJ) | (STM) | 0.133 | 0.327 | 0.057 | 0.429 |
| 11 | (STM, CMM) | (CJ) | 0.113 | 0.169 | 0.027 | 0.237 |
| 1 | (CMM) | (CJ) | 0.384 | 0.169 | 0.084 | 0.218 |
| 8 | (RMN) | (CJ) | 0.131 | 0.169 | 0.027 | 0.210 |
| 2 | (STM) | (SJ) | 0.327 | 0.133 | 0.057 | 0.174 |
| 17 | (WF) | (RMN) | 0.124 | 0.131 | 0.021 | 0.169 |
| 9 | (CJ) | (RMN) | 0.169 | 0.131 | 0.027 | 0.162 |
| 16 | (RMN) | (WF) | 0.131 | 0.124 | 0.021 | 0.160 |
| 12 | (CJ) | (STM, CMM) | 0.169 | 0.113 | 0.027 | 0.158 |

While Table 3 provides detailed numerical results, Figure 2 complements this information through a network visualization of association rules, in which nodes represent individual items and edges denote the strength of associations based on support, confidence, or lift metrics. This visual approach enhances intuitive interpretation of inter-item relationships and facilitates the identification of product clusters that can be leveraged for bundling strategies, recommendation systems, and cross-selling optimization.

The Market Basket Analysis revealed distinct purchase patterns within the transactional data, with the association network (Figure 2) providing a clear visualization of these relationships. The network identified STM as a central anchor node, exhibiting strong directional associations with SJ (confidence = 0.43) and WF (confidence = 0.37), while weaker links exist between other items like STM-CMM. These findings align with service-sector MBA literature, where moderate confidence levels often indicate complementary purchase tendencies rather than deterministic predictions, underscoring the need to interpret rules within their operational context (Rao et al. 2021; Zhao et al. 2019). However, while this diagnostic insight is valuable, the translation of these associative patterns into a concrete, prioritized strategy for a single business remains a critical challenge.

To bridge this applicability gap, this study integrates these analytical findings with established strategic frameworks, demonstrating a direct pathway from insight to action. The network-derived associations serve as primary inputs for the Analytic Hierarchy Process (AHP). For instance, the strong rule (STM) → (SJ) becomes a candidate "Premium Bundle", while the weaker but strategically important link between high-support items STM and CMM suggests an "Anchor Duo" opportunity. AHP enables the manager to systematically prioritize these options against weighted criteria such as profit margin, operational feasibility, and strategic fit, moving the business from a list of potential actions to a ranked, resource-efficient implementation plan.

Concurrently, Porter's Five Forces provides the competitive lens, leveraging STM as the core of a bundle can reduce buyer power through increased perceived value, while unique, data-informed combinations (e.g., STM, SJ, WF) create a differentiated offering that mitigates competitive rivalry. This dual integration, using AHP for internal prioritization and Porter's Five Forces for external validation, ensures that the MBA findings are contextualized within both the business capabilities and its market position.

This integrated approach directly addresses the unique position of MSMEs, for whom low-volume, transactional data is often the most accessible digital asset (Sulianta & Laksana, 2024). It extends the value of basic analytics by embedding them within a structured decision-making cascade, diagnose with MBA, prioritize with AHP, and validation with competitive analysis. Consequently, the study moves beyond merely demonstrating that patterns exist to providing a replicable methodology for converting these patterns into a defensible, customized strategy. This supports the broader imperative for MSME digitalization, showing how basic records can be transformed into strategic resources that foster competitive resilience and data-driven growth (Alifah, 2025).

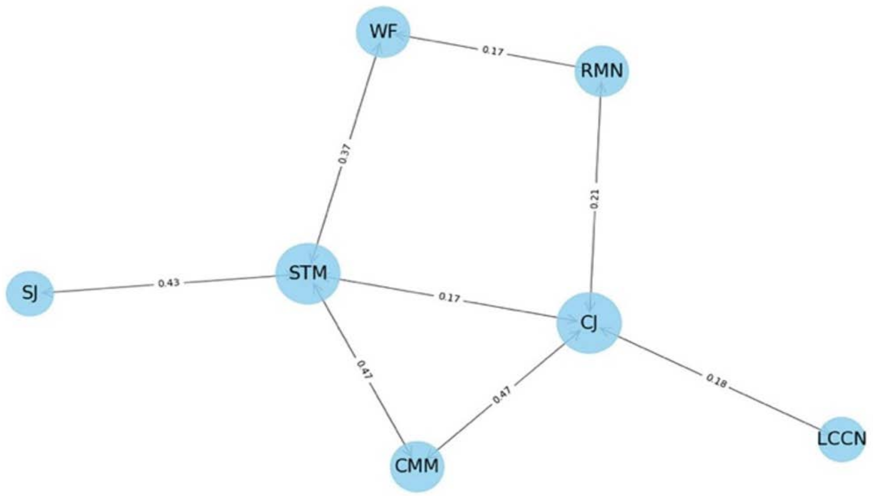


Figure 2. Network graph of product associations derived from market basket analysis at los in between

**Managerial Implications**

The findings reveal that MSMEs can craft strategies from simple daily transactions. For instance, STM can serve as the anchor product for combo packages; SJ and WF can be positioned as upselling add-ons. Customer behavior-based bundling increases transaction value and satisfaction through ease-of-purchase. This demonstrates entrepreneurial orientation dimensions: innovativeness (new bundles), proactiveness (anticipating demands), and risk-taking (leveraging weak items), deepening MSME competitiveness. (Covin & Wales, 2019), conversely, products such as CMM, which show weaker associations, can be offered discounts to trigger impulse purchases. Data-driven strategies boost revenue across sectors (Meliarini et al. 2021). MSMEs adopting this approach may gain a competitive edge in an increasingly crowded market (Saura et al. 2023), aligning with national SME digitalization agendas where basic records become strategic resources. Embedding analytics supports business growth and digital competitiveness policy objectives (Marczewska & Weresa, 2021).

Translating these analytical findings into actionable strategies bridges data insights and business decisions. The results indicate that STM serves as an effective anchor in promotional bundles due to its higher support rate, attracting complementary sales. Designing tiered bundles such as STM-only (basic), STM+SJ (favorite), and STM+SJ+WF (complete) enables MSMEs to address different customer segments while increasing average transaction value without forcing upselling. Products with weaker associations, such as CMM, should be tactically marketed as impulse-buy items or loyalty rewards rather than through independent promotions to optimize inventory turnover and maintain profit margins. Menu layout also plays a strategic role: placing STM centrally with visual links to SJ and WF can subtly guide purchase behavior and boost cross-selling potential.

While Market Basket Analysis effectively identifies product associations, its integration with complementary analytical methods enhances strategic decision-making comprehensiveness. Combining MBA with Analytical Hierarchy Process (AHP) enables managers to prioritize bundling strategies by weighing multiple criteria such as profit margin, customer preference strength, and operational feasibility (Govindan et al. 2020). For instance, while MBA reveals that STM+SJ has a strong association, AHP can determine whether this bundle should be prioritized over STM+WF based on ingredient costs and profit contribution. Integrating MBA with competitive strategy analysis provides strategic context within market dynamics, enabling MSMEs to create differentiated bundles that reduce buyer bargaining power and mitigate competitive threats through proprietary customer preference knowledge (Kitsios & Kamariotou, 2021;Islami et al. 2020).

The application of Porter's Five Forces framework to MBA-derived insights allows businesses to address competitive rivalry through unique product combinations, strengthen supplier relationships for high-demand anchor products, and create switching costs that reduce customer price sensitivity (Spender et al. 2017). Further enhancement through Customer Segmentation Analysis (RFM) tailors MBA-derived bundles to specific segments, high-value customers could receive premium bundles (STM+SJ+WF) while occasional customers get entry-level combinations. This multi-method integration transforms MBA from a descriptive tool into a comprehensive strategic framework for contextualized, prioritized decision-making aligned with digital business transformation objectives (Kitsios & Kamariotou, 2021).

From a policy perspective, the findings carry significant implications for government agencies, business development services, and entrepreneurship support organizations. Policy makers should invest in accessible digital infrastructure such as cloud-based POS systems with built-in MBA modules or government-sponsored analytics portals that require minimal technical expertise, addressing the digital divide for resource-constrained businesses. Capacity-building programs should emphasize practical, hands-on data analytics training through workshops demonstrating actionable insights extraction using free tools like Google Colab or Excel, combined with real-world case studies, peer-learning sessions, and mentoring programs. Regional digitalization policies should recognize transaction data as a strategic asset requiring protection and structured utilization, incentivizing MSMEs through tax benefits, grants, or preferential access to business development services. Industry associations should facilitate knowledge-sharing platforms where MSMEs can exchange successful implementation practices, while integrating data literacy into entrepreneurship education curricula prepares future business owners with foundational analytical capabilities. These multi-level interventions create an enabling ecosystem for MSME digital transformation and competitive capacity building, supporting broader economic resilience and innovation-driven growth (Kitsios & Kamariotou, 2021).

Beyond firm-level strategies, regular data re-mining, ideally on a quarterly basis, helps MSMEs identify shifting consumer preferences and refine bundle combinations, ensuring adaptive and evidence-based decisions rather than static assumptions. Supporting this process, accessible analytical tools such as Google Colab, Excel add-ins, or open-source dashboards can empower MSMEs to adopt data-driven management with minimal cost and technical barriers. Training programs focused on simple, hands-on data analytics, combined with peer-sharing platforms showcasing successful cases, can further strengthen adoption. Progressive digital transformation starting from transaction data utilization allows small businesses to gradually build analytical capabilities and competitiveness.

From an implementation perspective, Market Basket Analysis itself requires minimal investment, using existing POS data and free software. Prior studies in the retail sector have shown that data-driven bundling and targeted promotions improve transaction efficiency and inventory control. Within this study's context, such approaches demonstrate that even basic analytics can deliver meaningful strategic and financial benefits for MSMEs, aligning with national goals of digital and sustainable business growth.

## CONCLUSIONS AND RECOMMENDATIONS

### Conclusions

This study applied Market Basket Analysis (MBA) to LOS In Between and identified STM as an anchor product frequently paired with SJ, WF, and CJ, revealing significant bundling and upselling opportunities. The findings demonstrate that MSMEs with limited data can derive strategic insights to enhance efficiency, customer experience, and competitiveness. MBA enables differentiation through anchor-based packages that align with consumer behavior, reflecting a shift toward evidence-based decision-making that strengthens market resilience. The results suggest positioning STM as the bundle core, designing tiered packages for diverse segments, and promoting low-confidence items like CMM as upsell options. In conclusion, MBA illustrates how basic transactional data can be transformed into practical sales strategies, empowering MSMEs to build sustainable competitive advantages in dynamic markets.

From a theoretical perspective, this study makes several contributions to business theory. First, it extends Data-Driven Decision Making (DDDM) theory to resource-constrained MSMEs contexts, demonstrating that analytical capabilities do not necessarily require sophisticated infrastructure to generate strategic value. This challenges the implicit assumption in existing literature that effective data analytics is primarily accessible only to large organizations with extensive technical resources. Second, the study contributes to entrepreneurial orientation theory by illustrating how MSMEs can operationalize innovativeness, proactiveness, and risk-taking dimensions through simple analytical techniques, revealing that entrepreneurial behaviors can be systematically enhanced through accessible data practices rather than solely through intuition or experience. Third, by demonstrating MBA's effectiveness in offline F&B MSMEs, the research extends the applicability of association rule mining theory beyond its traditional domains of large retail and e-commerce, showing that purchasing pattern analysis remains valid and actionable across different business scales and operational contexts.

Finally, the study contributes to digital transformation theory by proposing a progressive, capability-building approach where MSMEs can incrementally develop analytical competencies starting from existing transactional data, thereby offering a more realistic and accessible pathway to digitalization than transformation frameworks designed for resource-rich organizations. These theoretical contributions collectively advance understanding of how small businesses can leverage data analytics for competitive advantage within their resource realities.

**Recommendations**

Based on these findings, several recommendations are proposed for key stakeholders. For LOS In Between managers, the priority should be implementing tiered promotional bundles centered on STM (basic, favourite, complete packages), strategically marketing products with weaker associations like CMM as impulse items or loyalty rewards, redesigning menu layout to position STM centrally with visual links to SJ and WF, and establishing quarterly data re-mining schedules to adapt strategies to evolving preferences.

For policymakers, efforts should focus on facilitating MSME access to free analytics tools (Google Colab, Excel add-ins), organizing practical training workshops combined with peer-sharing platforms showcasing successful cases, and developing progressive digital transformation roadmaps that start from basic transaction data utilization and gradually build analytical capabilities without overwhelming initial investments.

For future research, longitudinal studies should validate the findings over extended periods and across seasonal patterns, predictive modelling techniques should be incorporated for demand forecasting, comparative studies across multiple MSMEs and sectors should test generalizability, and experimental designs with control groups should measure actual revenue impact of MBA-based strategies compared to traditional methods.

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