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Scenario-Based Association Rule Mining in Veterinary Services Using FP-Growth: Differentiating Clinical and Customer-Driven Patterns

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ABSTRACT

Veterinary clinics routinely generate transactional data that contain valuable information about both operational workflows and customer preferences. This study aims to differentiate between procedural and customer-driven service patterns by applying the FP-Growth association rule mining algorithm to 1,000 anonymized transactions comprising 94 unique items, collected from a veterinary clinic in West Java, Indonesia, during 2023. Two distinct analytical scenarios were constructed: Scenario 1 includes all services (procedural and customer-driven), while Scenario 2 excludes procedural items such as “Vet” and “Visit Dokter” to focus solely on client-initiated behaviors. Data preprocessing involved aggregating transaction items into a market basket format suitable for frequent pattern mining. The FP-Growth algorithm was employed to extract association rules, evaluated using support, confidence, and lift metrics. Results from Scenario 1 revealed rule patterns reflective of standard clinical protocols and operational dependencies, informing bundled service packages and inventory management. In contrast, Scenario 2 uncovered customer-driven associations, highlighting opportunities for personalized promotions and service innovation. The comparative analysis demonstrates the utility of scenario-based association rule mining for both operational optimization and customer engagement. While the findings provide actionable insights for clinic management, further validation with practitioners and implementation in multi-clinic settings are recommended to confirm real-world applicability and enhance generalizability.

I. INTRODUCTION

In the current digital era, the utilization of data mining has become crucial for uncovering hidden patterns within transactional data, particularly in the retail sector. Veterinary Clinics, as part of the animal healthcare and retail industry, face challenges in understanding consumer behavior to enhance marketing strategies and service quality.

In recent years, the animal healthcare industry has experienced significant growth, driven by increasing public awareness of the importance of animal health and welfare. This growth is reflected not only in the rising number of veterinary clinics but also in the expanding diversity of products and services offered, which include food, accessories, medical services, and animal health consultations [1].

The transactional data collected by pet shops contains valuable information about consumer purchasing patterns. However, the volume and complexity of such data often render manual analysis impractical. One effective approach to address this challenge is the application of data mining techniques to analyze customer transaction data and uncover meaningful patterns and insights. Among the most widely used data mining techniques for analyzing transactional data is association rule mining (ARM) [2]. Most foundational work in ARM was pioneered by Agrawal, and ARM is considered one of the most critical and comprehensive functions in data mining. Association rule mining offers a systematic framework for pattern discovery and model identification. It also facilitates the validation of domain-driven hypotheses by quantifying item co-occurrence relationships, ultimately contributing to the generation of new, valuable association rules [3].

Other field areas where association rule mining can be applied are market basket analysis. Market basket analysis provides a powerful solution for uncovering hidden patterns within large datasets and is capable of identifying unintended transactional relationships, where the purchase of certain products influences the purchase of others [3][4].

One of the popular algorithms in association rule mining (ARM) is the Frequent Pattern Growth (FP-Growth) algorithm. This algorithm is well-known for its efficiency in handling large datasets without the need to generate candidate itemsets, unlike the Apriori algorithm. The FP-Growth algorithm constructs a compressed structure known as the FP-Tree to efficiently represent frequent itemsets without generating candidates. As demonstrated in [5], this structure significantly improves memory efficiency compared to Apriori, particularly when analyzing medium to large datasets, making it a superior choice for large-scale data analysis. Likewise, [6] demonstrated the effectiveness of FP-Growth in distributed systems such as Hadoop MapReduce, enabling efficient processing of massive retail and clinical datasets. These advancements strengthen the algorithm's utility in rea-world service environments. A study in [7] demonstrated that FP-Growth effectively identifies co-purchase patterns in retail environments through market basket analysis (MBA), making it suitable for uncovering complementary product relationships., such as customers' tendencies to buy certain products together, which can be leveraged to enhance revenue through more targeted marketing strategies [8].

The application of ARM in veterinary contexts remains underexplored compared to its widespread adoption in retail and e-commerce. Studies shown in [9] suggest that pattern mining can support medical diagnosis and service bundling in pet clinics. Another relevant study was conducted in [10], which applied market basket analysis in a beauty clinic setting to identify product and service combinations that influence customers' purchasing decisions [11].

Despite this growing body of work, few studies have addressed the methodological challenge of distinguishing between rules driven by clinical protocols and those emerging from customer preferences. This research introduces a dual-scenario analysis approach using the FP-Growth algorithm on veterinary clinic data. By comparing results across two conditions—one including procedural items (e.g., "Vet", "Visit Dokter") and one excluding them—this study aims to identify both operational dependencies and organic behavioral trends [12].

The objective of this research is to contribute a deeper understanding of item associations in veterinary services, provide actionable insights for service design, and expand the application of FP-Growth in the broader landscape of service-oriented healthcare analytics [13] [14]. [15] explored the integration of association rule mining with genetic algorithms to identify factors influencing air quality, showing the method's adaptability to diverse analytical domains. Several international studies support the use of FP-Growth in a wide range of domains. In the context of veterinary informatics, [9] applied clustering and association rule mining to analyze medical records in an animal hospital. The combination of HTCA clustering with ARM enabled the identification of frequent co-occurring symptoms and diagnoses, providing decision support for clinical procedures. Similarly, [16] implemented FP-Growth to analyze drug usage patterns in a veterinary clinic. The study found strong associations between commonly co-administered medications, which supported more effective inventory management [17] [18].

In the retail sector, FP-Growth has been widely adopted to extract customer purchasing patterns for strategic purposes. As shown in [10] this algorithm was applied to analyze product-to-product purchases and to model the relationships between products. In [19] compared the Apriori and FP-Growth algorithms in analyzing association rules on wholesale transaction data. The results indicated that FP-Growth is more efficient in execution time compared to Apriori, especially on large datasets. These findings align with the proposal put forward in [20] who stated that traditional Association Rule Mining (ARM) methods, such as the Apriori algorithm, are less efficient and less practical for large-scale transactional databases due to generating numerous candidate itemsets and requiring multiple scans [21]. To address this issue, a more efficient and scalable algorithm, namely FP-Growth, was introduced, proposed in [22][23]. The FP-Growth algorithm utilizes a compressed data structure called the frequent pattern tree (FP-tree) to store frequent itemsets along with their support counts, and mines association rules directly from the FP-tree without generating candidate itemsets [24] [25].

Moreover, [26] explored the integration of the FP-Growth algorithm with clustering methods such as K-Medoids to provide more accurate product recommendations to customers. Their findings indicated that, compared to sales data without prior clustering, no association rules could be discovered. This aligns with the opinion expressed by [27] that a common issue in recommendation techniques is that datasets with large volumes tend to be neglected by association rules. Therefore, the implementation of the K-Medoids algorithm on large datasets in this case study can assist in the process of mining association rules to generate more accurate product recommendations, as the dataset subjected to association becomes smaller [28] [29].

In addition to external studies, this research also builds upon the author's previous investigations on the application of Association Rule Mining with FP-Growth. Earlier studies explored its use in different service contexts, including a beauty clinic and a retail environment, each highlighting the algorithm's ability to uncover co-occurrence patterns relevant to customer service optimization. The current study differentiates itself by focusing on transactional data from a veterinary clinic. This setting introduces a new dimension—clinical service co-occurrence—where both procedural and consumer-driven patterns coexist. By comparing two scenarios that include and exclude procedural items, this study builds on previous work while extending the application of FP-Growth into the domain of animal healthcare services.

II. METHODOLOGY

This study applied the FP-Growth algorithm to extract association rules from transactional data collected from a veterinary clinic located in West Java, Indonesia. The methodology was designed to identify both procedural and customer-driven item associations by constructing two analytical scenarios. Figure 1 presents an overview of the analytical workflow adopted in this study.

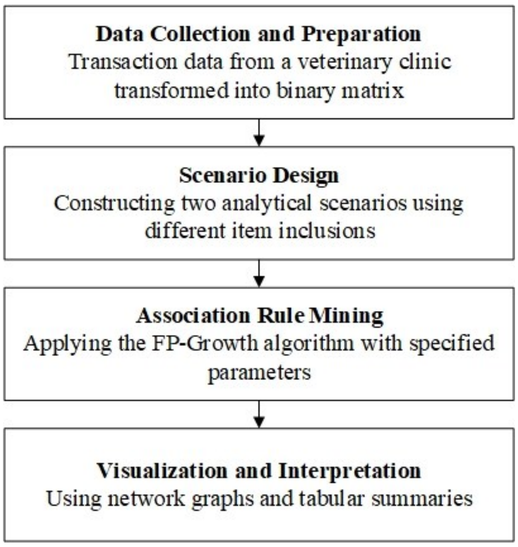

Figure 1. Analytical Workflow

Figure 1 illustrates the analytical workflow, beginning with transaction data cleaning and encoding, followed by scenario partitioning and association rule extraction using FP-Growth. The process concludes with rule visualization and interpretation for managerial use.

A. Data Source and Collection

This research is based on transactional records sourced from a veterinary clinic situated in West Java, Indonesia. The dataset encompasses the period from January to December 2023, comprising 1,000 anonymized transactions. Each transaction corresponds to a unique invoice and may include one or more services or product items rendered to a client. In total, the dataset covers 94 distinct items, reflecting the diversity of clinical and ancillary services offered within the facility. On average, each transaction contains approximately 3.6 items, indicative of prevalent service bundling practices in veterinary care. All sensitive client and clinic identifiers were removed to uphold ethical standards and maintain confidentiality.

B. Item Classification and Scenario Framework

A core methodological contribution of this study lies in the differentiation between procedural (clinic-driven) and customer-driven service patterns. The classification of items was conducted through manual coding, informed by expert consultation and a thorough review of the clinic's standard operating procedures (SOPs):

- Procedural Items are those inherently mandated by clinical workflow or standard veterinary protocols, such as "Vet", "Visit Dokter", "Rawat Inap", and routine vaccination services.
- Customer-Driven Items represent services and products requested at the discretion of the pet owner, including grooming, transportation ("Antar Jemput"), dietary supplements, and retail offerings.

TABLE 1.
SUMMARIZES REPRESENTATIVE EXAMPLES OF EACH ITEM CATEGORY

Category	Example Items
Procedural	Vet, Visit Dokter, Vaksinasi, Rawat Inap
Customer-Driven	Grooming Kucing, Antar Jemput, Suplemen, RC Recovery Can

This dual categorization forms the basis for a scenario-based analytical framework:

- Scenario 1 includes the entirety of recorded items (procedural and customer-driven), capturing association patterns reflective of both clinical protocols and organic customer behavior.
- Scenario 2 explicitly excludes procedural items, thereby isolating association patterns driven primarily by customer preferences.

This framework facilitates comparative analysis, enabling the discernment of operational dependencies vis-à-vis client-initiated service patterns.

C. Data Preprocessing

Prior to analysis, the transactional dataset underwent a preprocessing stage to ensure compatibility with market basket analysis requirements. Rather than generating an explicit binary matrix, the original data where each row represented a single item within a transaction was systematically transformed through an aggregation process. Utilizing the Aggregate operator in Altair AI Studio, all items sharing the same transaction identifier were concatenated into a single row, thereby restructuring the dataset so that each record represented the complete set of items purchased in a given transaction. This approach produced a market basket format in which each transaction was expressed as a delimited string of co-occurring items, directly aligning with the input specifications of the FP-Growth algorithm. The adoption of this aggregation and concatenation method streamlined the data preparation process, minimized potential misclassification, and maintained analytical rigor for subsequent association rule mining.

D. Association Rule Mining Algorithm and Parameterization

The study employs the Frequent Pattern Growth (FP-Growth) algorithm to extract frequent itemsets and generate association rules, owing to its computational efficiency and capacity to process large transactional datasets without candidate itemset generation. Analysis was conducted using Altair AI Studio 2024, a data mining platform equipped with native support for pattern mining workflows.

The FP-Growth algorithm was parameterized as follows:

- Minimum Support: 0.015 (rules must appear in at least 1.5% of all transactions)
- Minimum Confidence: 0.30
- Minimum Lift: 1.00

For enhanced interpretability in network visualizations, additional support thresholds were imposed: a minimum support of 0.05 for Scenario 1 and 0.02 for Scenario 2.

E. Visualization and Interpretations

The extracted rules were visualized using network graphs to enhance interpretability. Each node represented an item, while the directed edges depicted rules with arrowheads pointing to consequent items. The weight of each edge was proportional to the rule's confidence.

In addition, tabular summaries were created to highlight the most relevant high-confidence rules in each scenario. These tables were used to derive managerial implications, such as opportunities for service bundling, inventory forecasting, and personalized promotions.

III. RESULT AND DISCUSSION

This section presents the findings from both analytical scenarios and discusses their practical implications. Scenario 1 includes procedural elements ("Vet", "Visit Dokter"), representing clinic workflow patterns, while Scenario 2 excludes them to focus on customer-driven behaviors.

A. Scenario 1: Procedural Pattern Analysis

Scenario 1 reveals strong associations involving "Vet", "Visit Dokter", and "Rawat Inap Kucing", reflecting standardized clinical procedures. For instance, the co-occurrence of "RC Recovery Can", "Infus Set – GEA", and "Rawat Inap Kucing" indicates a typical post-operative care cluster.

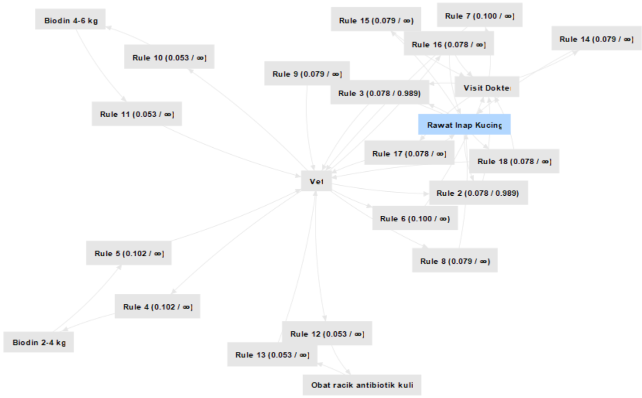

Figure 2. Network Graph of Association Rules – Scenario 1 (Only rules with support ≥ 0.05 are shown for clarity)

Figure 2 illustrates the network structure of association rules identified under Scenario 1, which incorporates both procedural and customer-driven items, with only rules exceeding the minimum support threshold of 0.05 displayed for clarity. In this diagram, "Vet" emerges as a highly central node, directly connected to a range of consequential services and products, such as "Rawat Inap Kucing," "Visit Dokter," "Biodin 2-4 kg," and "Obat racik antibiotik kulit." The dense concentration of edges surrounding procedural items reflects the standardized and protocol-driven nature of clinical workflows in veterinary practice.

The visualization reveals several important insights for clinic operations and service design. The prominence of associations between "Vet," "Rawat Inap Kucing," and "Visit Dokter" signifies their fundamental roles in typical treatment pathways. For example, frequent co-occurrence of these items suggests opportunities to develop bundled service packages for inpatient care or post-treatment monitoring, thereby streamlining processes and improving patient outcomes. Similarly, the repeated linkage between "Vet" and specific medications, such as "Biodin 2-4 kg" and "Obat racik antibiotik kulit," highlights commonly prescribed combinations that could inform inventory planning, facilitate rapid service delivery, and reduce waiting times for clients.

From a managerial perspective, the network's structure supports the identification of core clinical services that serve as decision anchors for resource allocation, workload management, and staff training. By leveraging these association rules, clinic management can optimize scheduling for high-demand services, design targeted promotional campaigns, and implement standardized care pathways that enhance both operational efficiency and client satisfaction.

Overall, the network diagram not only visualizes statistical relationships but also provides a practical framework for data-driven service innovation within the clinic. Future validation of these patterns through expert review and integration into clinical practice guidelines is recommended to maximize their real-world impact.

B. Scenario 2: Customer-Driven Association Patterns

This subsection explores the dynamics of customer preferences when procedural anchors are removed from the transaction data. By eliminating dominant items such as "Vet" and "Visit Dokter", the resulting rules and associations are more reflective of individualized purchasing behaviors.

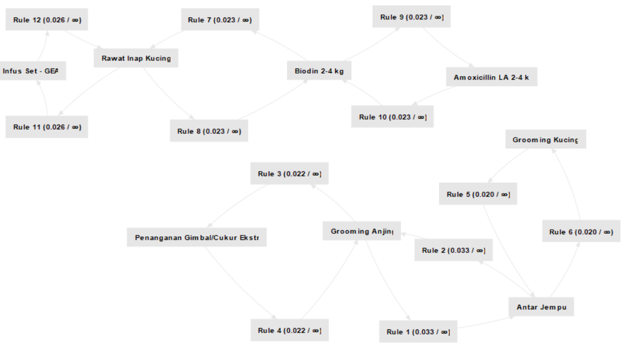

Figure 3. Network Graph of Association Rules – Scenario 2 (Only rules with support ≥ 0.02 are shown for clarity)

Figure 3 presents the association network derived from Scenario 2, in which procedural items such as "Vet" and "Visit Dokter" have been excluded to isolate patterns that are predominantly shaped by customer preferences. Unlike the dense and centrally anchored configuration observed in Scenario 1, this network exhibits a more dispersed structure, characterized by several independent hubs including "Grooming Anjing," "Antar Jemput," and "Biodin 2–4 kg." This pattern reflects a greater heterogeneity in purchasing behaviors, emphasizing the varied and individualized nature of customer-driven service utilization.

The emergence of strong rules, such as [Grooming Anjing] → [Antar Jemput], highlights a clear customer demand for bundled convenience services. This insight can directly inform the design of integrated promotional packages, such as offering grooming combined with pick-up and drop-off services, particularly during peak demand periods like holidays or inclement weather. Similarly, the association between [Biodin 2–4 kg] and [RC Recovery Can] indicates a recurring pattern of clients combining nutritional supplements or specialized diets with medical products. This finding provides actionable guidance for merchandising layout, cross-selling strategies at the point of sale, and the development of algorithmic recommendation systems to drive ancillary sales.

From a managerial standpoint, the sparser and less predictable network structure signifies the need for a more adaptive and personalized approach to marketing and service design. The decentralization of item relationships suggests that clinics should consider segmenting clients based on their unique behavioral patterns and tailoring offerings to meet distinct needs, thereby improving client retention and satisfaction.

While these findings offer valuable analytical and practical insights, it should be noted that their real-world applicability would be further enhanced by direct validation with clinic practitioners and clients. Future research may incorporate qualitative feedback or A/B testing of recommended bundles to ensure the operational effectiveness of data-driven service innovations.

C. Comparison Between Scenarios

This subsection compares the structural and managerial implications of the two analytical approaches. The inclusion or exclusion of procedural elements leads to significantly different rule structures and strategic interpretations.

TABLE 2.
COMPARISON OF SCENARIO-BASED RULE MINING OUTCOMES

Criteria	**Scenario 1 (Procedural)**	**Scenario 2 (Customer-Driven)**
Central Items	Vet, Visit Dokter, Rawat Inap	Grooming, Pickup, Supplements
Confidence Range	0.15 – 1.00	∞ (Deterministic Co-occurrence)
Lift Interpretation	SOP-driven clusters	Organic behavior and preferences
Network Structure	Dense, centralized	Sparse, diverse
Business Implication	SOP optimization	Cross-selling, personalization

Table 1 outlines key differences between the scenarios, focusing on central items, confidence ranges, lift interpretations, and resulting business applications. The comparative format enables a clear understanding of how scenario design affects both data interpretation and actionable outcomes. This highlights the importance of aligning data preprocessing choices with the specific decision-making goals of veterinary clinic management.

The key takeaway from this comparison is that analytical framing significantly affects the patterns uncovered and their managerial value. Scenario 1 is better suited for internal resource planning, whereas Scenario 2 supports innovation in client service offerings.

D. Summary of High-Confidence Rules by Scenario

This section synthesizes key association rules extracted from both analytical scenarios and highlights their potential managerial and operational applications. The extracted rules reveal distinct structural characteristics: Scenario 1 presents highly centralized procedural patterns, while Scenario 2 uncovers deterministic and organically emerging behaviors.

TABLE 3.
TOP ASSOCIATION RULES – SCENARIO 1

Antecedent	Consequent	Confidence
Vet, Visit Dokter	Rawat Inap Kucing	0.783
Vet, Rawat Inap Kucing	Visit Dokter	0.989
Visit Dokter, Rawat Inap Kucing	Vet	0.989
Vet	Biodin 2–4 kg	∞
Biodin 2–4 kg	Vet	∞
Vet	Visit Dokter	∞
Visit Dokter	Vet	∞
Vet	Rawat Inap Kucing	∞
Rawat Inap Kucing	Vet	∞
Vet	Biodin 4–6 kg	∞
Biodin 4–6 kg	Vet	∞

Table 3 presents the most prominent rules extracted under Scenario 1, including both high-confidence and deterministic associations. The patterns reveal structured procedural sequences within clinical workflows, such as diagnostic-to-treatment transitions and repeated co-prescriptions.

TABLE 4.
TOP ASSOCIATION RULES – SCENARIO 2

Antecedent	Consequent	Confidence
Grooming Anjing	Antar Jemput	∞
Antar Jemput	Grooming Anjing	∞
Grooming Anjing	Penanganan Gimbal/Cukur Ekstra	∞
Penanganan Gimbal/Cukur Ekstra	Grooming Anjing	∞
Grooming Kucing	Antar Jemput	∞
Antar Jemput	Grooming Kucing	∞
Biodin 2–4 kg	Rawat Inap Kucing	∞
Rawat Inap Kucing	Biodin 2–4 kg	∞
Biodin 2–4 kg	Amoxicillin LA 2–4 kg	∞
Amoxicillin LA 2–4 kg	Biodin 2–4 kg	∞

Table 4 highlights the strongest deterministic co-occurrence patterns in Scenario 2, all with a confidence of ∞ (i.e., perfect conditional occurrence). These rules suggest strong and consistent preferences or treatment patterns among customers when procedural anchors are removed.

Building on the technical insights of the previous tables, Table 4 links selected high-confidence rules to operational and marketing applications, demonstrating how rule-based knowledge can inform real-world clinical and business decisions. These rules can serve as the foundation for bundled services, predictive stocking, or targeted promotions.

Table 5 summarizes high-confidence association rules with direct relevance to veterinary clinic operations. Each rule is linked to a proposed application, ranging from service bundling and inventory management to targeted promotions. This illustrates the dual utility of association rule analysis in streamlining internal workflows and enhancing client engagement strategies.

TABLE 5.
SELECTED HIGH-CONFIDENCE RULES AND APPLICATIONS

Scenario	Rule	Confidence	Application
1	[Rawat Inap Kucing, Infus Set] → RC Recovery Can	0.72	Develop bundled post-operative packages
1	[Vet, Biodin 2–4 kg] → Amoxicillin LA 2–4 kg	0.56	Prepare treatment kits in advance
2	[Grooming Anjing] → [Antar Jemput]	∞	Promote grooming + pickup bundles
2	[Biodin 2–4 kg] → [RC Recovery Can]	∞	Suggest combo purchases at checkout
2	[Penanganan Gimbal] → [Grooming Kucing]	∞	Offer premium grooming upgrades

Note: Rules selected based on confidence ≥ 0.50 or deterministic behavior.

These association rules offer strategic guidance for the development of proactive service models. For instance, grooming customers may be offered bundled transport options, while loyal clients may benefit from automated replenishment systems or personalized loyalty incentives. Such applications contribute to service continuity, inventory efficiency, and increased customer retention.

E. Rule Evaluation and Methodological Considerations

The scenario-based approach highlights the influence of pre-processing decisions in association rule mining. Inclusion or exclusion of dominant service items reshapes not only the analytical output but also the strategic interpretations available to decision-makers. Hence, scenario selection should align with specific managerial objectives—whether operational efficiency or market responsiveness.

Although the derived rules demonstrate clear patterns, no domain expert validation or post-analysis testing was conducted to assess their practical utility in real-world settings. Future research should consider incorporating expert reviews, survey-based rule relevance ratings, or implementation feedback to strengthen the credibility of rule applications.

This study is also limited by its scope, drawing from a single clinic within a defined operational period. Therefore, while the rules extracted are meaningful, they should be validated across different clinic settings and with larger datasets. Future studies could integrate longitudinal data, multi-clinic comparisons, or behavioral segmentation to generalize findings.

In addition, the repetition of high-confidence rule clusters such as "Infus Set – GEA", "RC Recovery Can", and "Rawat Inap Kucing" reinforces the potential for data-driven clinical workflow standardization. Conversely, the emergence of discretionary item pairs in Scenario 2 supports innovation in customer engagement and micro-targeting.

In summary, association rule mining—when carefully scoped and interpreted—serves not only as a pattern recognition tool but also as a strategic asset for optimizing both internal workflows and external client services in veterinary care environments.

IV. CONCLUSION

This study employed the FP-Growth algorithm to analyze transactional data from a veterinary clinic, aiming to uncover association patterns among services and products. By constructing two distinct analytical scenarios—one inclusive of procedural elements (such as "Vet" and "Visit Dokter") and another excluding these items—the research was able to differentiate between rule patterns driven by clinical protocols and those shaped by customer preferences.

The findings from Scenario 1 elucidate the operational and clinical structures that underpin standardized diagnostic and treatment workflows. These insights are particularly valuable for the development of bundled service packages, enhancement of inventory management, and the promotion of procedural consistency across clinical visits. In contrast, Scenario 2 highlights consumer-driven associations, revealing unique client preferences and combinations that can inform the design of personalized service offerings, targeted promotional strategies, and customer segmentation initiatives.

The comparative analysis underscores the utility of scenario-based association rule mining as both an analytical framework and a practical decision support tool within healthcare service environments. The use of network visualizations further facilitates the interpretation of rule strength and item centrality, enhancing the ability of clinic managers to make data-driven decisions that align operational practices with evolving customer expectations.

Despite the practical and analytical contributions of this study, several limitations must be acknowledged. Notably, the identified association rules and network structures have not yet undergone direct validation with clinical practitioners or operational management. Consequently, while the patterns discovered provide a robust foundation for managerial innovation, their real-world applicability and sustainability remain to be confirmed through stakeholder engagement and practical implementation.

Future research should address these limitations by integrating qualitative validation methods, such as expert reviews, practitioner interviews, or pilot testing, to ensure that the association rules are both actionable and contextually relevant. Additionally, further studies could expand the analytical scope by incorporating time-series analysis, clustering based on pet profiles or customer segments, and conducting multi-clinic comparisons to enhance the generalizability and operational value of the findings.

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REFERENCES

[1] J. Wang and Z. Cheng, "FP-Growth based Regular Behaviors Auditing in Electric Management Information System," *Procedia Comput. Sci.*, vol. 139, pp. 275–279, 2018, doi: 10.1016/j.procs.2018.10.268.

[2] S. M. Shah, M. Lütjen, and M. Freitag, "Text mining for supply chain risk management in the apparel industry," *Appl. Sci.*, vol. 11, no. 5, pp. 1–20, 2021, doi: 10.3390/app11052323.

[3] K. Shaukat, S. Zaheer, and I. Nawaz, "Association Rule Mining: An Application Perspective," *Int. J. Comput. Sci. Innov.*, no. November 2015, pp. 29–38, 2015.

[4] A. Lawi, A. Agung, D. Ely, and I. Muhammad, "Exploring the Landscape of Deep Learning Techniques for IoT Data : A Systematic Literature Review," vol. 15, no. 2, pp. 578–588, 2025.

[5] A. E. Widjaja, "Analysis of Apriori and FP-Growth Algorithms for Market Basket Insights: A Case Study of The Bread Basket Bakery Sales," *J. Digit. Mark. Digit. Curr.*, vol. 1, no. 1, pp. 44–59, 2024, doi: 10.47738/jdmdc.v1i1.2.

[6] A. Senthilkumar, "An efficient FP-Growth based association rule mining algorithm using Hadoop MapReduce," *Indian J. Sci. Technol.*, vol. 13, no. 34, pp. 3561–3571, 2020, doi: 10.17485/ijst/v13i34.1078.

[7] Iyad S. Alkronz and Samy S. Abu-Naser, "Association Rule Mining using FP-Growth Algorithm in Market Basket Analysis," *Int. J. Acad. Eng. Res.*, vol. 5, no. 11, pp. 5–13, 2021.

[8] A. A. Dermawan, A. Lawi, D. A. Putera, and D. E. Kurniawan, "Optimizing Inventory Management : Data-Driven Insights from K- Means Clustering Analysis of Prescription Patterns," vol. 11, no. 3, pp. 811–820, 2024, doi: 10.15294/sji.v11i3.8690.

[9] T. C. Hsiao, S. L. Shieh, T. L. Chen, C. H. Liu, and Y. C. Yeh, "Data analysis of medical records in veterinary hospital using clustering method and association rule," *Appl. Math. Inf. Sci.*, vol. 9, no. 6, pp. 3319–3326, 2015, doi: 10.12785/amis/090659.

[10] R. Dio, A. A. Dermawan, and D. A. Putera, "Application of Market Basket Analysis on Beauty Clinic to Increasing Customer's Buying Decision," *Sinkron*, vol. 8, no. 3, pp. 1348–1356, 2023, doi: 10.33395/sinkron.v8i3.12421.

[11] G. Schuh *et al.*, "Data mining definitions and applications for the management of production complexity," *Procedia CIRP*, vol. 81, no. March, pp. 874–879, 2019, doi: 10.1016/j.procir.2019.03.217.

[12] S. C. Gamoura, D. Damand, Y. Lahrichi, and T. Saikouk, "Jo ur na l P re r f," *Int. J. Prod. Econ.*, p. 109672, 2025, doi: 10.1016/j.ijpe.2025.109672.

[13] S. Bagui, K. Devulapalli, and J. Coffey, "A heuristic approach for load balancing the FP-growth algorithm on MapReduce," *Array*, vol. 7, no. May, p. 100035, 2020, doi: 10.1016/j.array.2020.100035.

[14] C. W. Lin, T. P. Hong, and W. H. Lu, "Linguistic data mining with fuzzy FP-trees," *Expert Syst. Appl.*, vol. 37, no. 6, pp. 4560–4567, 2010, doi: 10.1016/j.eswa.2009.12.052.

[15] X. Wu, Q. Wen, and J. Zhu, "Association rule mining with a special rule coding and dynamic genetic algorithm for air quality impact factors in Beijing, China," *PLoS One*, vol. 19, no. 3 March, pp. 1–23, 2024, doi: 10.1371/journal.pone.0299865.

[16] N. Salsabila, N. Sulistiyowati, and T. N. Padilah, "Pencarian Pola Pemakaian Obat Menggunakan Algoritma FP-Growth," *J. Appl. Informatics Comput.*, vol. 6, no. 2, pp. 120–128, 2022, doi: 10.30871/jaic.v6i2.4187.

[17] A. Srivastava and D. Sinha, "FP-growth-based signature extraction and unknown variants of DoS/DDoS attack detection on real-time data stream," *J. Inf. Secur. Appl.*, vol. 89, no. February, p. 103996, 2025, doi: 10.1016/j.jisa.2025.103996.

[18] A. A. Dermawan and M. Muqimuddin, "Strengthening the Competitiveness of SMEs after the Covid 19 Pandemic (Case Study: Producers of Luti Gendang)," *... J. Sains, Teknol. dan ...*, vol. 20, no. 1, pp. 355–364, 2022.

[19] Mitha Rosadi and Muhammad Siddik Hasibuan, "Comparison of Apriori and FP-Growth Algorithms in Analyzing Association Rules," *PIKSEL Penelit. Ilmu Komput. Sist. Embed. Log.*, vol. 12, no. 2, pp. 399–408, Sep. 2024, doi: 10.33558/piksel.v12i2.9965.

[20] W. NG, R. Sukma, and C. Juliane, "Optimizing Marketing Strategies Using FP-Growth and Association Rule Mining Algorithms in the Textile Industry," *J. World Sci.*, vol. 3, no. 5, pp. 557–566, 2024, doi: 10.58344/jws.v3i5.599.

[21] B. C. Hidayanto, R. F. Muhammad, R. P. Kusumawardani, and A. Syafaat, "Network Intrusion Detection Systems Analysis using Frequent Item Set Mining Algorithm FP-Max and Apriori," *Procedia Comput. Sci.*, vol. 124, pp. 751–758, 2017, doi: 10.1016/j.procs.2017.12.214.

[22] M. Yin, W. Wang, Y. Liu, and D. Jiang, "An improvement of FP-Growth association rule mining algorithm based on adjacency table," *MATEC Web Conf.*, vol. 189, pp. 0–6, 2018, doi: 10.1051/matecconf/201818910012.

[23] K. Gadia and K. Bhowmick, "Parallel text mining in multicore systems using FP-tree algorithm," *Procedia Comput. Sci.*, vol. 45, no. C, pp. 111–117, 2015, doi: 10.1016/j.procs.2015.03.100.

[24] S. A. Ahmed and B. Nath, *Modified FP-Growth: An Efficient Frequent Pattern Mining Approach from FP-Tree*, vol. 11941 LNCS. Springer International Publishing, 2019. doi: 10.1007/978-3-030-34869-4_6.

[25] L. Shabtay, P. Fournier-Viger, R. Yaari, and I. Dattner, "A guided FP-Growth algorithm for mining multitude-targeted item-sets and class association rules in imbalanced data," *Inf. Sci. (Ny).*, vol. 553, pp. 353–375, 2021, doi: 10.1016/j.ins.2020.10.020.

[26] I. Syukra, A. Hidayat, and M. Z. Fauzi, "Implementation of K-Medoids and FP-Growth Algorithms for Grouping and Product Offering Recommendations," *Indones. J. Artif. Intell. Data Min.*, vol. 2, no. 2, p. 107, 2019, doi: 10.24014/ijaidm.v2i2.8326.

[27] K. Christidis, D. Apostolou, and G. Mentzas, "Exploring Customer Preferences with Probabilistic Topics Models," *Ke.Tu-Darmstadt.De*, pp. 1–13, 2010.

[28] R. Qi and X. Guo, "Analysis of Intelligent Energy Saving Strategy of 4G/5G Network Based on FP-Tree," *Procedia Comput. Sci.*, vol. 198, no. 2021, pp. 486–492, 2021, doi: 10.1016/j.procs.2021.12.274.

[29] M. Narvekar and S. F. Syed, "An optimized algorithm for association rule mining using FP tree," *Procedia Comput. Sci.*, vol. 45, no. C, pp. 101–110, 2015, doi: 10.1016/j.procs.2015.03.097.