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A Review of Knowledge Management in Extracting Association Rules for Marketing Decision-Making

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ABSTRACT

Recently, intensive applications of data-driven methods emerged in marketing decision-making and customer behavior analysis. Although conventional approaches produced Association Rules (ARs) from transaction trends, these rules were frequently overlooked since they were extracted statically and isolated from lifecycle management systems. Therefore, this study integrated the association rule extraction technique with a knowledge management framework to enhance rule quality and ensure long-term utility. The proposed approach segmented customers based on purchasing behavior using recency, frequency, and monetary (RFM) parameters. Following the extraction of these behavioral features, the K-Means algorithm clustered customers into distinct segments, including high-volume, new, and moderate purchasers. To enhance decision-making accuracy and eliminate irrelevant patterns concealed within transactions, machine learning models, specifically XGBoost and Isolation Forest, were deployed to filter out redundant rules. This integration of knowledge management enabled continuous system learning and optimization. Ultimately, the outcomes demonstrated a substantial positive impact on marketing decision support, delivering higher-quality, actionable insights for strategic planning.

1. Introduction

In today's data-driven business environment, organizations increasingly rely on data analysis techniques to understand customer behavior and support marketing decision-making. Customer behavior analysis plays an essential role in identifying recurring purchasing patterns and relationships among products, which can be utilized in marketing strategies, pricing

optimization, and personalized recommendation systems. Association Rule Mining (ARM) is one of the most widely used techniques for discovering hidden relationships in transactional databases. Several algorithms have been developed for ARM, including Apriori, FP-Growth, and Eclat. Among these, FP-Growth has gained significant attention due to its efficiency in extracting frequent itemsets without generating candidate sets. Unlike Apriori, which repeatedly scans the database to generate candidate itemsets, FP-Growth constructs a

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compact FP-tree structure that reduces computational complexity and improves mining performance [1], [2]. These techniques have been successfully applied in various marketing applications. For example, Yanti et al. (2024) utilized FP-Growth on retail transaction data to generate purchasing rules that improved promotional planning and product placement strategies [3]. Similarly, Kajornkasirat et al. (2025) applied ARM techniques to customer datasets and derived association rules that enhanced customer experience and increased sales performance [4]. Despite the effectiveness of ARM techniques, the extracted rules are often large, complex, and difficult to interpret directly for practical decision-making. Most existing studies focus mainly on rule extraction as a standalone analytical process while neglecting the role of Knowledge Management (KM) in organizing, maintaining, and utilizing the generated knowledge. In many cases, association rules become outdated or less valuable when they are not systematically managed, updated, and integrated into organizational knowledge processes [5]. Knowledge Management provides mechanisms for capturing, organizing, sharing, and maintaining knowledge generated from analytical systems. Integrating KM with ARM can significantly improve the practical value of extracted association rules by transforming raw analytical outputs into structured and reusable organizational knowledge. Several recent studies highlight the importance of this integration. For instance, Yanti et al. (2024) demonstrated how ARM-based customer relationship insights can support marketing strategies, while Kajornkasirat et al. (2025) showed that customer segmentation rules managed through knowledge-oriented processes contribute to business growth and customer satisfaction [4]. However, there is still a lack of comprehensive review studies that systematically examine the integration of Knowledge Management and Association Rule Mining within marketing decision support systems. Therefore, this paper aims to review and analyze the current state of research on KM-ARM integration in marketing applications. The study seeks to identify existing research trends, challenges, and opportunities, as well as to clarify how KM practices can enhance the effectiveness and sustainability of ARM-based marketing decisions.

2. Theoretical Background

As marketing becomes more and more data-driven and intelligent, it is more important than ever to comprehend the theoretical frameworks that guide marketing decisions. People don't just make decisions based on gut feelings or past experiences anymore. They also use advanced analytics to find patterns in massive data and turn them into useful information. So, it is becoming more and more important to combine knowledge management approaches with association rule mining techniques. This is because this combination gives firms a knowledge base that helps them make better and longer-lasting marketing decisions

2.1 Knowledge Management (KM)

In 2023, Idris and a group of individuals presented a specific definition of knowledge management, stating, "Knowledge management is the ability to manage information, which includes obtaining knowledge from multiple sources, both external and internal, and then transforming it into new strategies and innovative ideas, then applying and storing them." In other words, they obtain data sources, whether external or internal, and then transform this data into knowledge, applying it, and then storing it. Knowledge management enables organizations to collect, organize, and efficiently store knowledge assets. [6]. It is the primary way in which companies and organizations produce knowledge. They acquire, organize, store, disseminate, and use it effectively to support strategies, enhance decision-making, and improve organizational performance. Knowledge management is concerned with making the tacit knowledge of individuals explicit, so that it can be shared and used throughout the organization to stimulate innovation, prevent the repetition of previous mistakes, and increase responsiveness to market changes [7]. Knowledge management consists of three main components: people, processes, and technology. People are the creators and users of knowledge [45]. Processes are the activities that capture, store, update, and apply knowledge in decision-making [46]. Technology provides the tools and platforms that enable us to store, share, and access knowledge [47]. Together, these three transform knowledge into a sustainable asset for the organization.

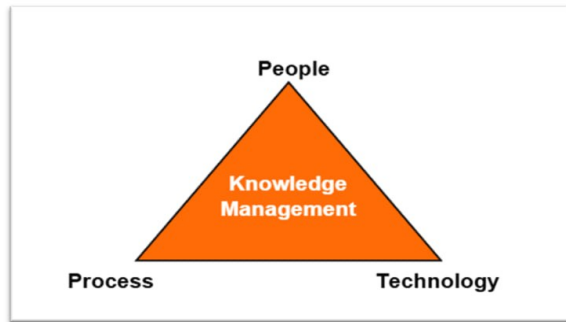


Figure 1. Components of Knowledge Management [8].

The above triangular diagram illustrates the three fundamental components of knowledge management: people, process, and technology. The model proposes that successful knowledge management is attained by the balance of these components: people generate and share knowledge, processes structure it, and technologies provide access to it. This equilibrium is the key to sustainable and successful knowledge flow in organizations [8].

The types of knowledge that are essential to knowledge management include tacit, procedural, and explicit knowledge. These types are particularly important in marketing decisions, and each plays a significant and distinct role in capturing, organizing, and applying information. The following is an overview of these three basic types of knowledge.

A – Explicate Knowledge

Knowledge that can be effectively documented and stored (e.g., policies, manuals, and documents), and easy to share and transfer. It is also known as discernible knowledge and is widely used in content management systems and enterprise portals [9].

B - Implicit / Procedural Knowledge

Also known as "practical knowledge" or "know-how." It is not documented knowledge but can be acquired and applied through training or observation. It is often used as the basis of employee training and the development of skills based on their acquired experience [10].

C – Tacit Knowledge

Deeper and more complicated than tacit knowledge; personal knowledge that is based on experience and context, and cannot be easily formulated or directly transferred. Said by Nasab to

account for over 90% of knowledge in organizations and usually transferred through practice and informal coordination [11].

2.2 Knowledge Management Processes

The figure illustrates the basic processes of knowledge management within an integrated cycle. It begins with knowledge creation and acquisition, then moves through the stages of capture, sharing, storage, and application, concluding with the evaluation stage to ensure continuous improvement. This representation reflects the circular nature of knowledge flow within organizations to support learning, innovation, and decision-making [12].

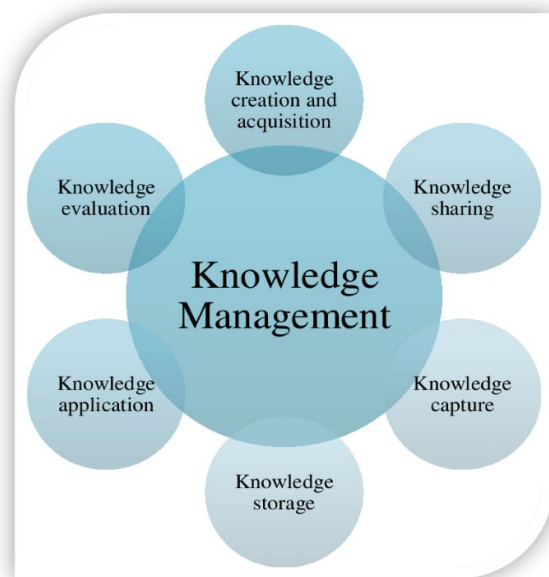


Figure 2. The Knowledge Management Process Cycle [12].

A-Knowledge creation and acquisition

It involves training as many people as possible who already possess the same profession through practical training, so that the knowledge stored in one person is transformed into distributed expertise for those who have been trained [12].

B-Knowledge sharing

is the learning process that occurs through people collaborating with and helping each other to develop themselves and acquire new knowledge [12].

C – Knowledge Capture

means converting tacit knowledge in individuals' minds into explicit knowledge that can be written down or documented [12].

D – Knowledge Store

refers to knowledge repositories such as databases, documents, or reports that store knowledge for future use [12].

E – Knowledge Application

Using the knowledge created and captured in various educational or practical situations [12].

F – Knowledge Evaluation

The process of examining and evaluating existing knowledge to ensure it is accurate and relevant to the topic or need [12].

2.3 Association Rule Mining (ARM)

Association Rule Mining (ARM) is a pattern discovery technique used in large databases to extract correlations between items within a set of transactions. It aims to identify rules of the type "if X happens, then Y is likely to happen," which helps analyze consumer behavior or uncover hidden correlations in data. It is a cornerstone of shopping cart analysis and data-driven marketing [13].

2.3.1 Common Algorithm using in ARM

These three algorithms are important algorithms in association rules, as they differ in their form and structure for analyzing customer behavior, which makes choosing one of them an important matter for extracting useful rules and applying them. Among the most important of these three algorithms are Apriori, FP-Growth, and ECLAT, as each of them relies on different search and processing mechanisms.

A – Apriori

This algorithm is based on the idea that if a set of elements is rare, then all individual branches are also rare. The algorithm starts by searching and finding duplicate individual elements, then gradually builds with a larger set of elements, where it scans the data elements repeatedly, which makes it slow on large data. Therefore, it is suitable for medium and small data due to its simplicity.[14].

B – FP-Growth

FP-Growth outperforms Apriori by avoiding candidate generation. It builds a compact structure called an FP-Tree to store data efficiently. Frequent patterns are then extracted using a divide-and-conquer strategy. As a result, it is much faster and more memory-efficient, especially with large datasets [14].

C – Eclat

Eclat takes a different approach by storing a list of transactions for each item (TID list). It calculates support using set intersections instead of scanning the dataset repeatedly. It applies depth-first search and works well with dense datasets. However, it may become slow or memory-heavy with very large or sparse data [14].

2.4 KM and ARM Integration

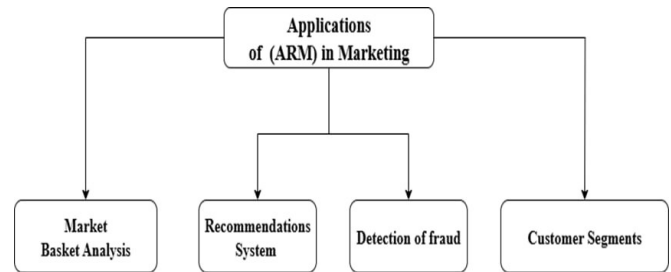
Knowledge management (KM) involves processes for creating, sharing, and using an organization's knowledge assets to achieve strategic goals [16]. Data mining – including association rule mining (ARM) – discovers patterns and correlations hidden in large data repositories, effectively turning raw data into actionable knowledge. For example, Shettigar et al. note that data mining "enabling organizations to discover hidden knowledge and relationships in their data" is crucial for supporting effective KM and decision-making [17]. In practice, many organizations "lack the ability to learn from historical data" and thus miss opportunities to reuse existing knowledge [16]. Integrating ARM with KM addresses this gap by capturing discovered patterns (association rules) as explicit knowledge in KM systems, ensuring that insights (e.g. co-purchase rules or usage patterns) are recorded, managed, and applied rather than lost. In this way, ARM becomes a component of the knowledge discovery process: data mining is "a process leading to the analysis and use of large datasets to extract valuable insights and the resulting knowledge" [18], and KM provides the framework to store and exploit these insights in decision support.

Table 1. Comparative Analysis of Apriori, FP-Growth, and Eclat Algorithms [15]

Aspect	Apriori	FP-Growth	Eclat
Data Representation	horizontal layout	Also uses horizontal layout but transforms into a compressed tree (FP-Tree).	Employs vertical format using transaction ID (TID) lists for each item.
Candidate Handling	Generates all possible candidate itemsets level by level.	Avoids candidate generation through tree-based pattern extraction.	No candidate generation; relies on intersection of TID lists.
Database Scans	Requires multiple full database scans—one per iteration level.	Only two full scans: one to build the FP-tree.	Requires fewer scans; works with in-memory TID list intersections.
Execution Efficiency	Slower on large or dense datasets due to candidate explosion.	Highly efficient and scalable, especially with dense or large datasets.	Performs well on dense data; less efficient on sparse or huge datasets.
Memory Consumption	Can be high due to candidate generation and support counting.	Optimized memory use via FP-tree structure.	Memory usage depends on size of TID lists and dataset density.
Application	Best used for closed item sets.	Used in cases of large data	Best used for free item sets

2.5 Applications of Association Rule Mining (ARM) in Marketing

ARM is used in fraud detection, retail studies, and recommendation systems. It is a data mining method for extracting rules from big data and is also important for decision support systems due to its ability to identify important rules [19].

**Figure 3.** Application of ARM in Marketing [19]

The above diagram shows the main and important applications of Association Rule Mining (ARM) in marketing. ARM is widely used to analyze customer purchasing behavior (market basket analysis), detect suspicious patterns (fraud detection), improve customer recommendations (recommender systems), and segment customers based on their purchasing habits (customer segmentation). These applications help companies make informed, data-driven marketing decisions. The application in Marketing is:

1 - Market Basket Analysis

It is widely used to know what items customers buy most frequently. For example, if a customer buys milk, he often buys bread with it. This method helps us to know several things, including understanding how to arrange products inside the store. We can also know how to display cross-selling offers. For example, we make an offer that says buy a calculator and get a certain mouse at half price. We also control inventory management so that a product that is related to other products does not run out. [20].

2 - Recommendations System

Retailers leverage association rules (ARM) to build a profile for each customer based on their past purchase characteristics and preferences. If a customer purchases the first product, the system suggests a second product based on their previous preferences. These recommendations enhance

customer satisfaction and contribute to increased sales [21].

3 – Detection of fraud

ARM is also used to detect fraud and identify abnormal patterns, enabling organizations to monitor any abnormal or anomalous cases and issue a warning by examining transaction data [22].

4 – Customer Segments

The ARM system also segments customers based on the nature of their purchases, enabling businesses to manage their plans accordingly. For example, customers with high incomes are offered discounts or better offers [23].

3. Literature Review

In recent years, there has been increased interest in integrating knowledge management and association rules extraction in the field of marketing. Many studies have addressed how relying on data and the knowledge management process can improve the effectiveness of marketing decision-making [24].

In 2023, Zhao [31] developed a decision support system (DSS) based on knowledge extracted from data mining techniques. This system helped improve sales forecasting accuracy, but it did not directly utilize association rule extraction algorithms and did not address structured customer knowledge, which justifies a gap in rule-based knowledge.

Saura (2021) [32]. conducted a broad survey on machine learning and data science applications in digital marketing, identifying ARM as a core technique for market basket analysis and consumer behavior understanding. However, his review emphasized technical tools and lacked integration with KM frameworks or knowledge reuse strategies.

In 2025, Gupta [33]. used the fuzzy rules model. The model's objective was to understand customer preferences and also improve system accuracy. This study did not focus on knowledge storage from a knowledge management perspective and focused only on algorithmic and technical aspects.

In 2023, Saeed and others [34]. presented a conceptual model for the knowledge management lifecycle in financial institutions. Despite the comprehensiveness of their proposed framework, it has not been tested in marketing fields. In 2025,

Hunyadi [35] compared the Apriori and FP-Growth algorithms using real data from e-commerce websites. Their study found that FP-Growth was more efficient at extracting rules. While their study provided valuable insights and ideas, it hasn't organized and stored these rules as usable knowledge for the long term. These studies have shown that knowledge management is a crucial component of marketing, but some focus on integrating knowledge management with the extraction of correlational rules and the proper reuse of that extracted knowledge. Currently, there is a lack of integration between knowledge management and correlational rule extraction, leading to gaps in this area.

3.1 Literature Analysis

Previous studies conducted between 2020 and 2025 reveal a growing interest in integrating knowledge management and association rule mining to improve marketing decision-making. While association rule mining techniques have been used for a long time, their synergy with knowledge management systems remains limited and often superficial.

Association Rule Mining (ARM) algorithms are frequently used in studies to uncover patterns that can be practically exploited, such as purchasing behavior or product bundling strategies. For example, Gupta et al. (2025) used the Fuzzy ARM algorithm to improve recommendation systems in e-commerce platforms, while Hunyadi et al. (2025) demonstrated the effectiveness of the FP-Growth algorithm in analyzing large transaction databases. These studies emphasize the pivotal role of ARM in extracting marketing knowledge.

The integration and reuse of knowledge management remains incomplete. While Saura and Chauhan (2023) described systems that generate valuable insights, they did not link these to knowledge management. In 2023, Saeed proposed a knowledge management framework that also incorporates correlation rule extraction. While tested in the financial sector, its effectiveness in marketing has not been proven.

Many previous studies extract data only once and use static data, limiting the extraction of strategic insights. None of these studies included mechanisms for updating, maintaining, storing, or reusing the discovered rules.

In general, recent studies show promising potential for integrating correlation rule extraction (ARM) with knowledge management (KM). However, this integration has been limited. Therefore, rules

should not only be extracted but also organized, stored, updated, and reused. This will ensure the sustainability of this knowledge and its ability to adapt to rapid market changes.

4. Result and Discussion

This section provides an overview of the findings from other research regarding the combination of knowledge management and the extraction of correlation rules. Recent literature shows that the extraction of correlation rules has become an utmost necessary task, especially regarding the understanding of customers' behavior and purchasing patterns. The findings from other studies, such as those by Gupta (2025) and Hunyadi (2025), have shown that correlation rules extraction algorithms and fuzzy rules have a great role to play in the success of e-commerce. However, the findings from Said (2023) have shown that though the application of the frameworks, such as the framework by Said (2023), may seem limited to other sectors rather than the marketing sector, the findings from other studies, such as Saura (2021) and Schole (2023), have shown the importance of deriving insights from the data. Nonetheless, the findings have not shown the importance of the use or transfer of the data within the boundaries of knowledge management. This failed amalgamation of the two concepts regarding the use of the findings from the research will limit the importance of the findings from the research. The data analyzed from the research provides findings only once without going into cycles such as storage or repeated use. This will provide an indication that though the extraction from the databases provides great powers of analysis. Therefore, the results collectively suggest that future marketing decision support systems should move beyond rule extraction and focus on managing ARM outputs as evolving knowledge assets, enabling sustainable, adaptive, and knowledge-driven marketing strategies.

5. Gaps Identified

Despite the growing interest in integrating association rule mining (ARM) with knowledge management (KM) in the fields of marketing and business intelligence, studies still reveal clear shortcomings. Shaw et al. (2025) point out that most research treats knowledge management and data analytics as two separate fields, emphasizing the weak integration between knowledge

management practices and big data analytics initiatives [25]. In other words, the extracted association rules are rarely linked to a coherent knowledge management framework as the knowledge acquired is often isolated from organizational knowledge repositories.

In general, association rule mining is typically applied once to a historical dataset, resulting in a static set of rules. This approach results in these rules quickly becoming outdated as new data arrives (early studies noted that mining is performed "once and only once" on a static database). Few studies address the flow of rules or their real-time updating, and thus the extracted knowledge cannot adapt to changes in the market or ever-changing customer behavior [5].

On the other hand, many of the results of ARM are not organized or linked within formal knowledge management (KM) frameworks. For example, Selamat et al. (2020) demonstrated that organizations do not effectively leverage tacit knowledge (the accumulated expertise of individuals) and often rely on traditional IT systems for KM. This means that most ARM applications focus on explicit and visible data, such as customer profiles, while neglecting the deeper expertise within the organization. Consequently, the discovered rules remain isolated from the broader knowledge assets within the organization, limiting their usefulness in supporting decision-making [26].

There are also conceptual models without application. One recurring gap is that many proposals for integrating knowledge management and association rule mining remain at the conceptual level, lacking empirical validation. This essentially calls for "an innovative assessment plan for knowledge management and knowledge governance" to ensure the usability of the generated knowledge, as stated by Selmat et al. [26]. In other words, although many frameworks and structures have been proposed, only a few have been applied or tested in real-world settings. Shaw et al. (2025) point out that knowledge management and business models are often presented without case studies or prototypes, meaning that the practical synergy between knowledge management processes and ARM algorithms remains unproven [25]. In summary, recent studies consistently point out that KM-ARM integrations are hampered by static, one-off rule extraction; insufficient structuring of knowledge (especially tacit knowledge); lack of real-time updates; and the prevalence of unvalidated conceptual models.

Addressing these gaps – for example by developing adaptive, knowledge-driven ARM systems with live feedback loops – is a clear direction for future research.

6. Future Research Opportunities

Based on the gaps in current research we have examined, this study proposes a conceptual framework that integrates knowledge management and association rule extraction into the context of marketing decision-making. This framework aims to address the major limitations of previous studies, particularly the lack of knowledge structuring, the extraction of consistent rules, and the limited integration of organizational knowledge repositories.

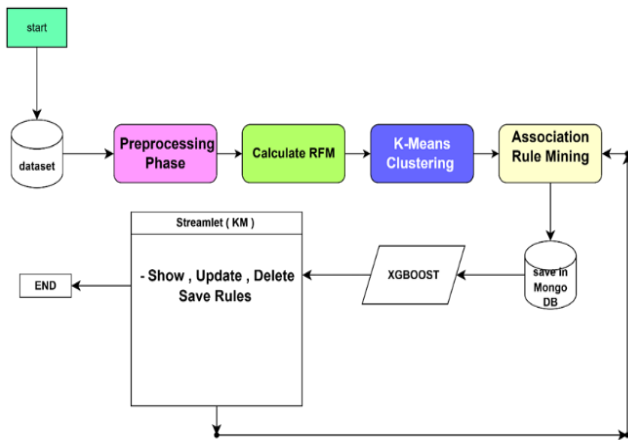


Figure 4. A Proposed Framework for Integrating Knowledge Management with Association Rule Mining Using RFM and Machine Learning Techniques

The proposed framework (Figure 4) starts from the preprocessed dataset, which involves removing duplicates and entails many other details. Next comes the second phase, which involves calculating RFM features: recency, frequency, and monetary value. Then, the features undergo clustering based on K-Means to segregate customers and further involves the application of ARM to identify patterns based on the behavior of the customers. However, to aid better accuracy in predictions, the proposed framework involves the use of XGBoost as an additive predictive model. Based on all details that emerge from all phases, the structured, interpreted, and organized knowledge acquisition and handling is facilitated by the Streamlit knowledge management module. Finally, all output results are included in the NoSQL database (MongoDB), and all outputs can be accessed in the future and remain

prospective. But another phase has been introduced, and that involves feedback. The proposed framework involves an incorporated feedback mechanism that aims to re-enter updated details about knowledge and insights derived from the ARM and XGBoost module to the Streamlit KM module.

7. Equations

This section presents the mathematical formulas used in the proposed framework. The model integrates the Recency, Frequency, and Monetary Value (RFM) scoring system to describe customer behavior, followed by K-MEANS clustering techniques and the extraction of association rules from them. Equations are presented to determine how to calculate RFM scores, along with other analytical steps that support customer segmentation and rule extraction. These formulas form the basis for building marketing knowledge and guiding decision-making processes.

First, we calculate the recency, frequency, and monetary value of each customer.

Support is a way to find out how often an item or group of objects shows up in a data set. In other words, support is the number of transactions that have a certain set of items divided by the total number of transactions. The rule is more important and can be used in more situations if it has greater backing [27].

$$Support(X \Rightarrow Y)$$

$$\frac{\text{Number of transactions containing both } X \text{ and } Y}{\text{Total number of transactions}} \quad (1)$$

Then we calculate confidence, which is the probability that product Y will be purchased by customers who previously purchased product X, and it expresses the strength and value of the association rule [27].

$$Confidence(X \Rightarrow Y) = \frac{\sigma(X \cup Y)}{\sigma(X)} \quad (2)$$

σ here is Represents the number of occurrences or Support Count of a particular element in association rules.

Then (Lift) measures the strength of the relationship between X and Y compared to the random probability. If it is greater than 1, it indicates a positive relationship, and if it is less than 1, it indicates a negative relationship.

$$Lift(X \Rightarrow Y) = \frac{Confidence(X \Rightarrow Y)}{Support(Y)} \quad (3)$$

These equations are used to calculate recency, frequency, and monetary value, then apply the k-means algorithm, extract the association rules, and store them in a special database.

8. Illustrative Case Study of the Proposed Framework

To illustrate the practical applicability of the proposed Knowledge Management–Association Rule Mining (KM–ARM) framework, an illustrative case study based on a retail marketing scenario is presented. In this scenario, customer transactional data are first preprocessed to compute Recency, Frequency, and Monetary (RFM) metrics, which are then used to segment customers into homogeneous groups using K-Means clustering. This segmentation step ensures that customer behavioral differences are captured before the rule mining process.

Subsequently, the FP-Growth algorithm is applied within each customer cluster to extract cluster-specific association rules that reflect purchasing patterns more accurately than global rule extraction. The discovered rules are then stored within a structured knowledge base, enabling knowledge organization, reuse, and continuous refinement over time. Marketing decision makers can utilize this stored knowledge to support actions such as product bundling, personalized promotions, and customer retention strategies.

9. Enhancing the Proposed Framework with Intelligent Models

Integrating machine learning into the following application enhances the marketing decision-making process. For example, the XGBOOST classifier can be used to determine which group a new user belongs to upon entering the system, based on their behavior. It can be trained by taking user behavior as its input and then classifying these users into which group they belong. For example, if a person makes frequent purchases, they will be classified as a frequent purchaser and will be shown special offers. In addition, an algorithm like Isolate Forest can be used to isolate outliers. For example, if a customer buys sugar and then buys tea, this is not considered an outlier because the criteria, such as trust, support, and boost, are equal

in magnitude and are also strong. However, if they buy tea and then, by chance, buy clothes, the correlation between these criteria is not strong, and this is considered an outlier because the criteria are not equal. This particular purchase is random over a whole year, for example, unlike purchases like tea and sugar within the same year.

10. Research Contributions

This research is dedicated to realizing a long-term process where rules mined from data are converted into reusable knowledge. The major contributions can be listed below:

1. A method incorporating the extraction of correlation rules with the management of knowledge for more intelligent decision-making in marketing, ensuring rules are relevant for more than the point of their creation.
2. Segmentation of the customers is done through an analysis of the monetary value for every customer, frequency of purchase, and recency, thereafter clustering the profiles using K-Means before the rules are generated from the framework.
3. For every identified cluster, the FP-GROWTH algorithm is utilized to find the rules specific to that particular cluster, unlike finding all the rules simultaneously. This prevents fragmentation and undistinguishable rules, and the phenomenon of “rule explosion,” which has existed in the previous studies.
4. The use of a special database is specifically geared toward the capacity to store these extracted rules, as opposed to extracting rules for a single use.
5. Develop a control panel using Python, similar to Streamlet, to support marketing decisions.

11. Conclusion

This study emphasizes the need for the integration of knowledge management and the extraction of correlation rules for informed marketing decisions. This comes with the realisation that this attempt will be more successful compared to the earlier extraction that took place for a limited period of time without the integration of the information within the knowledge lifecycle. The findings from the study will be summarized below.

1. According to the studies analyzed in this research, it has been evident that most studies undertook the extraction of correlation rules for short-term durations without taking into consideration the integration of knowledge management.

2. The proposed method integrates correlation rule extraction by using FP growth, the k-means clustering algorithm, and customer behavior study. The method also retains, reuses, and adjusts these rules in order to present a complete model for making long-term marketing strategies.
3. The integration of knowledge management with correlation rules extraction, storage, and efficient management helps to make accurate marketing decisions.
4. Association rules management in a knowledge base improves recommendation quality and facilitates creating better strategies for marketing.
5. Future studies should emphasize the creation of dynamic systems that can continuously update and verify knowledge bases to keep up with the developing consumer behavior and market trends.

In some previous studies where correlation rules were extracted, Liao et al. (2015) used the Apriori algorithm with user clustering to extract knowledge from social network data and online purchases. They showed that user behavior improves marketing decisions, although the reuse of knowledge was limited to analytical interpretation only [28]. Zekic-Soshak and Haas (2015) used the FP-Growth model within an online marketing system and showed that extracting sets of recurring elements can support marketing strategy formulation when combined with the underlying knowledge management layer, but without dynamic feedback or rule evolution [29]. Esteratt and Lalich (2017) applied Apriori ARM to sales transaction data to support decision-making in the automotive retail sector, where the extracted rules were treated as fixed organizational knowledge rather than as part of the ongoing knowledge management lifecycle [30].

12. Summary of Techniques and Findings in Related Work

Table 2. Summary of Reviewed Studies Integrating KM and ARM in Marketing

Author(s)	Year	Method Used	Dataset	Key Finding	Gap Identified
Zhao, X. & Li, C. [31]	2023	Data-mining DSS (BP neural net)	Simulated sales data (Chinese company)	Data-driven marketing system combining data mining with neural networks (BP) achieving 85% accuracy in sales forecasting.	Relies on historical structured data; does not integrate association-rule analysis or unstructured customer knowledge.
Saura, J. R [32].	2021	Data-science in Digital Marketing (Survey of ML/ARM techniques)	Literature (digital marketing cases)	A review of the use of data science in marketing identified ARM as an essential tool for market basket analysis and marketing analytics methods.	Focus is on methods, not on managing organizational “knowledge”; does not propose combining ARM with a KM framework for marketing.
Gupta, N. et al [33].	2025	Fuzzy Association-Rule Mining	E-commerce live-streaming data (public dataset)	Proposed a fuzzy ARM framework for live-stream e-commerce. Fuzzy logic refines association patterns, improving recommendation relevance and consumer engagement. Extracted knowledge (e.g. consumer preferences) is more nuanced with fuzzy rules.	Tested on static datasets; lacks dynamic/real-time integration. Did not evaluate integration with a knowledge base or experts’ input.
Saeed, T. et al.[34]	2023	KM + Data Analysis Framework (incl. ARM)	Financial services (FinTech) data	Outlined a KM–data-science lifecycle for FinTech firms. In the “discovery” phase, association-rule mining is used to uncover interdependencies among features. Demonstrated how ARM can reveal hidden patterns in transactional data for customer insights.	Focused on finance domain; the framework is conceptual and has not been validated on marketing data. KM processes are generic (e.g. codification) but specific marketing applications are not addressed.
Hunyadi, I. D. et al.[35]	2025	Comparative ARM (Apriori vs. FP-Growth)	Real e-commerce transaction logs	Empirical comparison: FP-Growth outperforms Apriori for large-scale shopping data. This yields faster and more memory-efficient rule mining in marketing contexts. Provides practical guidelines (tooling in RapidMiner) for selecting ARM techniques in e-commerce.	Study focuses on algorithm efficiency, not on capturing or using domain knowledge. Does not address how discovered rules are managed as “marketing knowledge” or integrated into decision processes.

Nomenclature

Column A	Column B
X ,Y	Two related items appear together in a single purchase.
σ	here is Represents the number of occurrences or Support Count of a particular element in association rules.
ARM	Association rules mining
KM	Knowledge management
FP-Growth	Frequent Pattern Growth
Apriori	A Priori Algorithm
Eclat	Equivalence Class Transformation
RFM	Recency, Frequency, Monetary
ML	Machine Learning
AI	Artificial inelegant

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Conflicts of Interest

The authors declare no conflict

Appendix

Appendixes appear after acknowledgments.

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