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An Integrated Advanced Pattern Mining Framework for Strategic Retail Decision Intelligence

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Abstract: Retail businesses increasingly rely on data-driven intelligence to support strategic decision-making; however, existing approaches often focus on isolated pattern mining or predictive models, limiting their practical impact. This paper proposes an Integrated Advanced Pattern Mining Framework that unifies frequent, temporal, and utility-driven patterns extracted from large-scale transactional data. The mined patterns are consolidated and ranked using an Integrated Pattern Score, enabling the identification of actionable and business-relevant knowledge. To operationalize these insights, a hybrid recommendation mechanism combining interpretable rule-based reasoning and convolutional neural network–based predictive learning is introduced. Experiments conducted on a real-world retail dataset comprising one year of transactional records from a Bangladeshi supermarket demonstrate that the proposed hybrid approach achieves an F1-score of 0.84. Under offline evaluation, the framework achieved the highest projected revenue contribution (10.6%) compared with the classical association rule mining baseline (7.5%), while also outperforming standalone recommendation models. The results confirm that integrating advanced pattern mining with hybrid learning models provides an effective and scalable solution for strategic retail decision intelligence.

Keywords: pattern mining, business intelligence, association rules, retail strategies

1. Introduction

The rapid growth of retail transaction data has created unprecedented opportunities for data-driven strategic decision-making. Modern retail environments generate large volumes of transactional records capturing customer purchasing behavior across time, product categories, and promotional contexts. Extracting actionable knowledge from such data is essential for improving product recommendations, promotional strategies, inventory management, and overall business performance. However, transforming raw transactional data into reliable and economically meaningful decision intelligence remains a challenging research problem.

Association rule mining (ARM) and frequent pattern mining have long been employed to discover co-occurrence relationships among items in the retail transactional databases. While frequent itemsets mining provides significant insights into commonly purchased products, they often overlook the temporal regularities, profit-oriented considerations, and low-support yet strategically important patterns. As a result, decision-making based solely on the frequent patterns may be biased toward high-volume items. It also fails to capture the recurring temporal behaviors, seasonal effects, and high-utility associations. These limitations significantly reduce the practical value of conventional pattern mining approaches in real-world retail settings.

To address these challenges, recent studies have explored extensions such as regular and/or periodic pattern mining, relative regular frequent patterns, utility-based pattern mining, and rare association discovery. Regular and periodic patterns capture the temporal consistency and recurrence of itemsets over time. These are especially important when forecasting and promoting seasonal demand. Utility-driven patterns include economic factors like profit or revenue. It is useful to discover high-value itemsets other than frequency. Rare associations are low-support associations, but they could signify new trends or new niche products of high strategic importance. All of these pattern types provide useful information, but most of the literature approaches them individually. As a result, knowledge is too fragmented and difficult to be captured in a coherent business strategy.

One more significant weakness in the literature on retail analytics is a lack of actionable decision-making on the patterns discovered. Pattern mining indeed exploits multiple pattern types, but these patterns are typically reported in isolation, as there is no systematic mechanism to consolidate, prioritize, and translate them into concrete business actions. But retail managers are

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looking for ranked, interpretable insights that balance frequency, temporal stability, economic value (in terms of sales impact), and strategic relevance. In the absence of such types of integration, pattern mining outputs continue to be mostly descriptive and not prescriptive.

Motivated by these gaps, we introduce an Integrated Advanced Pattern Mining Framework (IAPMF) for improving strategic retail decision-making intelligence. We followed a common data analysis framework to implement frequent, temporal, and utility-based pattern mining within a single analytical workflow. Then, the extracted patterns are consolidated using redundancy reduction techniques. Finally, an Integrated Pattern Score (IPS) is calculated using the joint measure of support, temporal regularity, and utility. This type of scoring mechanism enables the prioritization of actionable knowledge patterns that are most relevant for retail decision-making.

To apply the IPS-ranked knowledge patterns in real applications, an additional hybrid recommendation layer is also included within the framework. This layer combines interpretable rule-based recommendation logic and a convolutional neural network (CNN)–based predictive learning model. This integration allows us to exploit both domain knowledge sensing and data-based learning from the retail dataset. The rule-based module provides explainability and transparency, and the CNN learns complex nonlinear relationships and time-based dynamics in the transactional data. This hybrid integration connects the gap between pattern mining and intelligent recommendation to make sure that discovered knowledge directly supports retail business decisions.

A real-world retail dataset is used to assess the effectiveness of our proposed framework that contains a year of transactional data in a large supermarket in Bangladesh. The dataset contains 100,000 transactional records and a total of 2382 unique items. The experimental results show that our proposed approach outperforms standalone pattern-based and learning-based methods in terms of predictive accuracy, decision confidence, coverage balance, and revenue uplift. These outcomes confirm that uniting advanced pattern mining with hybrid recommendation models provides a scalable and economically meaningful solution for strategic retail decision intelligence. The main contributions of this paper are briefly summarized as follows:

a. An integrated framework that unifies multiple advanced pattern mining techniques for complete retail knowledge discovery.
b. A novel IPS for consolidating and ranking heterogeneous patterns grounded on frequency, temporal behavior, utility, and strategic relevance.
c. A hybrid recommendation mechanism combining rule-based reasoning and CNN-based predictive learning to operationalize pattern intelligence.
d. An extensive experimental evaluation on real-world retail data demonstrating improved accuracy, coverage, and business impact.
e. A unified decision-oriented integration architecture that systematically connects multidimensional pattern consolidation, interpretable IPS-based evaluation, and hybrid predictive recommendation into a coherent retail decision intelligence pipeline.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 formalizes the problem definition and motivation. Section 4 presents the proposed integrated pattern mining framework with a hybrid recommendation strategy. Section 5 describes the dataset and experimental setup. Section 6 reports and analyzes the experimental results. Finally, Section 7 concludes the paper and presents future research directions.

2. Literature Review

The field of pattern mining originated with ARM introduced by Agrawal et al. [1]. Here, the authors set up a basis for discovering the frequent itemsets and association rules in transactional databases. The FP-Growth algorithm [2] improved computational efficiency over Apriori by eliminating candidate generation. In addition to frequency-based measures, utility-oriented mining was proposed to capture profit and quantitative importance in pattern discovery [3]. Subsequent research focused on rare itemset mining in transactional datasets [4]. A comprehensive survey of utility-oriented pattern mining [5] establishes the theoretical foundations for high-utility pattern extraction. These foundational works form the algorithmic backbone of modern utility, periodic, and hybrid pattern mining approaches.

Some recent studies deal with the integration of utility, periodicity, and efficiency constraints in pattern mining. The machine learning techniques for higher-dimensional pattern recognition have been studied to enhance scalability and predictive capability [6]. The regular high-utility sequential pattern mining was proposed by Ishita et al. for static, incremental, and sliding window databases [7]. They call attention to the need to link regularity and utility. The extraction of Top-K periodic high-utility patterns is even more efficient to provide more actionable knowledge due to choosing the most informative patterns [8]. IPHM is an incremental periodic high-utility mining in dynamic environments and is suitable for real-time adaptation [9]. Likewise, new measures, upper bounds, and pruning strategies are used to mine the high-utility periodic frequent patterns from multiple sequences in Mining High-Utility Periodic Frequent Patterns in Multiple Sequences (MHUPFPS) [10]. The closed high-utility periodic pattern mining has further reduced redundancy in extracted knowledge [11]. The stable periodic high-utility sequential pattern mining also guarantees robustness in the case of dynamically changing datasets [12]. In real-world scenarios of retail data, FP-Growth is more efficient and effective than Apriori and Eclat algorithms [13]. Collectively, these works demonstrate significant progress in scalable, utility-aware, and temporally constrained pattern mining.

Many challenges have been overcome in personalized recommendations, where recommender systems have been shifted from classical algorithm approaches to hybrid deep learning approaches [14]. A recent survey of comprehensive evaluation approaches for recommender systems is presented in [15]. Recent studies have further used machine learning–based approaches like FP-Growth association rules [16] and hybrid CNN collaborative filtering models [17] to improve personalized e-commerce recommendations. Similarly, deep learning–based business analytics often shows a gap between expectations and real-world performance [18]. These AI-based approaches focus on predictive accuracy but often lack interpretable pattern-level insights that motivate hybrid integration strategies.

Business intelligence (BI) and analytics platforms provide the strategic foundation for data-driven decision-making. Al-Okaily et al. [19] highlighted the effectiveness of BI and data analytics in improving organizational decision-making and performance. Advanced analytics and CNN-based predictive models have been used to optimize retail strategies and predict sales [20]. Data analytics and business intelligence also contribute to effective business decision-making and improved organizational performance [21]. Retail-specific analytics and seasonal pattern mining improve decision-support impacts by capturing recurring purchase behaviors and consumption trends [22]. The multilevel association-based approaches strengthen market basket analysis by capturing recurring purchasing patterns in retail supermarkets [23].

Hybrid architectures integrating temporal mining, rule-based reasoning, and deep learning represent the current frontier. DeepRule presents an integrated framework merging deep predictive modeling and hybrid search optimization for automated business rule generation [24]. Similarly, customer behavior analysis and predictive modeling have been applied in supermarket retail to support business expansion and customer satisfaction [25]. Dynamic ARM combined with deep learning enhances retail insights by detecting complex behavior patterns [26]. Furthermore, classification-based parallel frequent pattern discovery models support decision-making and tactical planning in retailing by competently identifying key patterns from large retail datasets [27]. However, existing pattern mining techniques remain largely fragmented, addressing isolated dimensions of customer behavior without considering their combined effect to directly support strategic management in real-world settings.

3. Problem Definition and Motivation

The environment in which retail supermarkets operate is highly dynamic. This is because such an environment is always influenced by changing customer demands, seasonality in purchases, different product assortments, and competitive pricing policies. The increased use of point-of-sale systems and online inventory management tools helped in creating very large databases of transactions over time. Such databases grant valuable opportunities to learn from them in order to make strategic decisions regarding inventory management, promotions, product bundling, and demand forecasting.

ARM is a method widely used for investigating transactions and finding out the combination of the most commonly purchased items by customers. Such associations are always stated as $X \Rightarrow Y$, while their performance is assessed through support and confidence. Although these techniques have proven effective for uncovering commonly purchased item combinations, their use on frequency-based thresholds limits their capacity to capture several important dimensions of retail behavior.

In real retail environments, decision-critical patterns are not always frequent. Products with high profit margins may be purchased less often, seasonal items may exhibit periodic demand, and certain product combinations may occur with regular time intervals rather than high overall frequency. Moreover, customer purchasing behavior often exhibits irregular yet meaningful structures influenced by promotions, cultural events, supply chain constraints, and local market characteristics. These complexities are particularly evident in emerging retail markets, where consumption patterns and operational practices differ significantly from those observed in developed economies.

Consequently, there is a growing need for analytical frameworks that move beyond traditional frequent pattern discovery and incorporate multiple behavioral dimensions, such as regularity, periodicity, and utility within a unified decision intelligence model. Without such integration, retail decision-makers risk relying on incomplete or misleading insights derived from fragmented analytical approaches.

3.1. Problem statement

Consider a large-scale retail transactional database $\mathscr{T}$ collected over time. The core problems addressed in this study can be expressed formally as:

How can diverse pattern dimensions including frequency, regularity, periodicity, and utility be successfully incorporated into a unified analytical framework that supports strategic retail decision intelligence?

More specifically, the objectives are to:

a. Extract multidimensional itemsets integrating support, utility, temporal regularity, and periodicity characteristics from transactional data.
b. Represent temporal scores explicitly using stability (regularity) and cyclic recurrence (periodicity) measures.
c. Integrate heterogeneous dimensions into a unified IPS to ensure balanced and interpretable evaluation.
d. Reduce redundancy while preserving high-value business intelligence.
e. Transform discovered multidimensional patterns into actionable intelligence for retail strategy formulation.

3.2. Motivation and significance

This work is motivated by methodological and applied perspectives. Research-wise, the existing pattern mining techniques are still quite fragmented. However, the majority of this work examines independent dimensions of customer behavior and does not assess their joint effect on decision quality. On the practical side, retail managers need interpretable and economically relevant insights. Therefore, they require insights that can directly aid strategic planning rather than large collections of abstract patterns.

In this study, we propose an IAPMF for bridging the transition from algorithmic pattern discovery to real-life retail decision intelligence. Moreover, the use of real transactional data from Bangladeshi supermarkets not only enhances the real-world applicability of our research but also helps provide empirical evidence in a relatively underdeveloped retail context.

4. Proposed Integrated Advanced Pattern Mining Framework

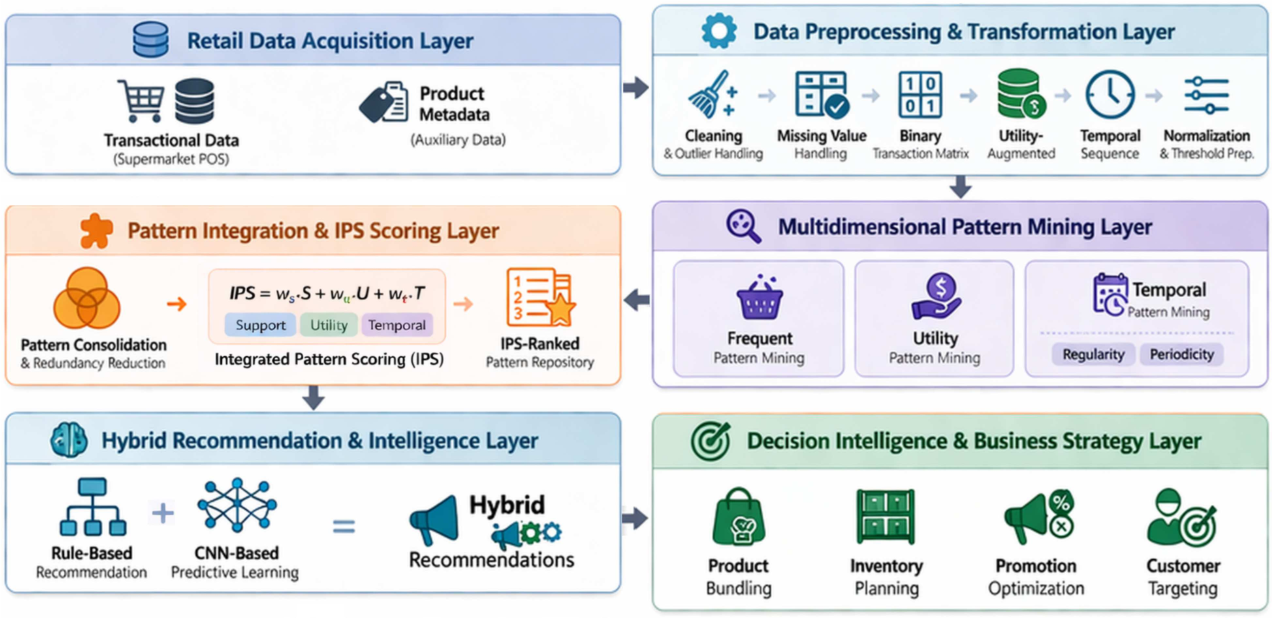
This section describes the proposed IAPMF to integrate heterogeneous types of patterns into one decision-oriented intelligence system. Unlike conventional approaches, our proposed framework fuses the pattern characteristics of multiple dimensions using a unified scoring mechanism (Integrated Pattern Scoring, IPS). The proposed architecture consolidates structural frequency, economic utility, and time dynamics into an integrated evaluation layer, ensuring analytical consistency and operational relevance.

4.1. Framework overview

The general architecture of the proposed framework is illustrated in Figure 1. Each functional layer is modular, interpretable, and analytically independent, but highly coupled together through a single stream of data flow.

Our proposed framework begins with the Retail Data Acquisition Layer. This layer collects the actual transactional data from a large retail supermarket in Bangladesh. The data come from diverse sources that reflect real-world retail operations. As a result, they are well suited for evaluating practical retail decision-making

Figure 1
Architecture of the proposed integrated pattern mining framework



scenarios. The collected raw data are fed into the next layer, which is known as the Data Preprocessing and Transformation Layer. Noise removal, missing value handling, normalization, and transactional restructuring are performed at this layer.

The backbone of our proposed framework is the Multidimensional Pattern Mining Layer. At this layer, we incorporate various complementary mining techniques. Unlike classic techniques that focus only on frequent itemsets, this layer systematically extracts frequent, utility-oriented, and temporal patterns from the transactional database. This complete mining approach confirms that both dominant and subtle behavioral patterns embedded in retail data are captured.

The extracted patterns are then fed into the Pattern Integration and IPS Scoring Layer, where integration is done through consolidation and redundancy reduction. In the IPS model, all the multidimensional patterns are consolidated to generate a single unified prioritization score based on the integration of support, utility, and temporal scores. Temporal score consists of two measures: regularity and periodicity scores.

The following stage is the Hybrid Recommendation and Intelligence Layer. This layer converts the extracted patterns into usable retail intelligence through the use of interpretative rule-based reasoning and a data-based predictive learning process. Here, the hybrid architecture provides both explainability and high predictive accuracy, which are necessary requirements for strategic retail operations. Both the rule-based layer and the CNN-based layer output values are integrated using the weight-based approach.

The last stage is the Decision Intelligence and Business Strategy Layer, which translates the analysis results into actionable retail intelligence. In light of historical transactional data, the framework allows for making strategically informed decisions through data analytics, which results in higher operational efficiency and better customer experiences.

Retail purchasing behavior is a multifaceted concept involving structural co-occurrence frequencies, economic value, temporal dynamics, and predictive relationships. The excessive focus on one particular aspect of analysis will likely result in a bias toward selecting patterns without accounting for complementary business intelligence knowledge. Motivated by this challenge, the presented framework offers a solution to the issue under discussion, providing a holistic decision-making-oriented approach to integrating heterogeneous analytical facets into one cohesive and understandable process. The methodological contribution of this study lies in its controlled multidimensional integration approach. The approach includes redundancy-aware pattern consolidation and an IPS mechanism that evaluates support, utility, and temporal reliability in a balanced manner. It also incorporates a hybrid recommendation strategy that combines interpretable rule-based reasoning with predictive learning. This integrated design transforms diverse analytical outputs into practical retail decision intelligence. At the same time, it preserves the transparency of the process and allows the contribution of each analytical dimension to be clearly understood.

4.2. Data representation and preprocessing

This subsection introduces the formal definitions of the retail data model, notation, and preprocessing steps used throughout the proposed framework.

4.2.1. Retail transaction data model

Let $\mathscr{I} = \{i_1, i_2, i_3, \ldots, i_n\}$ denote the finite set of all distinct items available in the retail system, where each item $i_j \in \mathscr{I}$ represents a unique product identified by a stock keeping unit. $\mathscr{T} = \{t_1, t_2, t_3, \ldots, t_m\}$ denotes the transactional database where each transaction $t_k \in \mathscr{T}$ is defined as $t_k = (X_k, \tau_k, U_k)$. $X_k \subseteq \mathscr{I}$ represents the set of items purchased in transaction t_k, τ_k denotes the temporal attribute associated with the transaction (date, time slot), and U_k denotes the utility information, such as quantity sold and revenue contribution. This enriched transactional representation enables the framework to support not only traditional ARM but also temporal, regular, and utility-oriented pattern discovery.

4.2.2. Data cleaning and transformation

Retail transaction data collected from supermarket environments often contain inconsistencies, such as missing values, duplicate transactions, and outliers. To address these issues, several preprocessing techniques are applied. Redundant transactions created due to synchronizations and billing attempts are eliminated to ensure unique transactions. Transactions that have missing critical attributes are deleted; however, non-critical missing values are filled in with domain-consistent methods. Abnormal transactions that have unrealistic quantities or utility values are carefully examined and eliminated to avoid any bias toward utility-based pattern measures.

After cleaning, the transactional data are converted into multiple analytical views to support diverse mining objectives. A binary transaction matrix $M \in \{0,1\}^{m\times n}$ is constructed for mining frequent patterns and association rules, where:

$$M_{k,j} = \begin{cases} 1, & if\ i_j \in t_k \\ 0, & otherwise \end{cases} \quad (1)$$

In addition, a utility-augmented representation is developed in which each transaction preserves item-level utility information, including quantity and revenue contribution. Furthermore, the transactions are organized into a temporal sequence based on their associated timestamps τ_k to facilitate the discovery of periodic, regular, and demand-driven patterns by capturing time-dependent purchasing behavior.

4.3. Multidimensional pattern mining layer

The Multidimensional Pattern Mining Layer constitutes the core analytical component of the proposed IAPMF. This layer is responsible for extracting diverse yet complementary behavioral patterns from retail transactional data by jointly analyzing structural frequency, economic utility, and temporal dynamics.

Formally, given a preprocessed transactional database $\mathscr{T}$, this layer discovers a set of candidate patterns $\mathscr{P}$, where each pattern $P \in \mathscr{P}$ is associated with multiple descriptive attributes, including support, utility, and temporal characteristics.

4.3.1. Frequent pattern mining

This module identifies itemsets that show strong co-occurrence relationships (co-occur frequently) in the transactional database. It captures dominant purchasing structures in retail environments. Unlike conventional approaches that rely solely on frequency as a measure of importance, our proposed framework treats support as a structural descriptor that contributes to subsequent multidimensional evaluation rather than a standalone decision criterion.

Let $P \subseteq \mathscr{I}$ denote an itemset. The support of P is defined as:

$$\mathrm{Sup}(P) = \frac{|\{t_k \in \mathscr{T} \mid P \subseteq X_k\}|}{|\mathscr{T}|} \quad (2)$$

where X_k represents the itemset associated with transaction t_k. A minimum support threshold θ_s is applied during this stage to restrict the candidate pattern space and ensure computational efficiency.

$$\mathrm{Sup}(P) \geq \theta_s \quad (3)$$

The role of θ_s is to eliminate extremely infrequent itemsets that would otherwise lead to a combinatorial explosion during pattern discovery.

4.3.2. Utility pattern mining

While frequency captures structural co-occurrence behavior, it does not reflect the economic significance of purchasing patterns. The utility pattern mining module addresses this limitation by prioritizing the business value of itemsets based on utility-related attributes including quantity sold and revenue contribution.

Let $q(i, t_k)$ denote the quantity of item i purchased in transaction t_k and $u(i)$ represent the external utility associated with item i (revenue weight). The utility of an itemset $P \subseteq \mathscr{I}$ within transaction t_k is defined as:

$$U(P, t_k) = \sum\nolimits_{i\in P} q(i, t_k) \cdot u(i) \quad (4)$$

The total utility of pattern P across the transactional database is computed as:

$$U(P) = \sum\nolimits_{t_k\in\mathscr{T},\, P\subseteq X_k} U(P, t_k) \quad (5)$$

Unlike conventional high-utility pattern mining approaches, which rely on fixed utility thresholds to determine pattern relevance, the proposed framework considers utility as a continuous evaluation criterion. Instead of filtering patterns using a predefined minimum utility threshold, utility values are normalized and incorporated directly into the IPS mechanism.

4.3.3. Temporal pattern mining

Temporal patterns play a critical role in understanding customer purchasing behavior in retail environments. In this study, temporal characteristics are modeled using two complementary components: regularity and periodicity, representing stability and cyclic recurrence, respectively. Let $P \subseteq \mathscr{I}$ denote a pattern, and let its ordered occurrence timestamps be represented as:

$$\mathscr{T}_{\mathscr{P}} = \{t_1, t_2, \ldots, t_n\}, \quad t_1 < t_2 < \ldots < t_n. \quad (6)$$

The sequence of inter-arrival gaps is defined as:

$$\Delta(P) = \{\Delta_1, \Delta_2, \ldots, \Delta_{n-1}\}, \text{ where } \Delta_i = t_{i+1} - t_i \quad (7)$$

1) Regularity Score (RS). The regularity score measures the consistency of pattern occurrences over time by capturing the variation in inter-arrival gaps. Patterns that occur at nearly uniform intervals exhibit high regularity, whereas those with highly fluctuating gaps are considered irregular.

Let μ_Δ and σ_Δ denote the mean and standard deviation of the gap sequence $\Delta(P)$, respectively. The regularity score is defined as:

$$RS(P) = 1 - \frac{\sigma_\Delta}{\mu_\Delta + \epsilon} \quad (8)$$

where ϵ is a small constant to prevent division by zero. This formulation ensures that $RS(P) \to 1$ when gaps are highly consistent ($\sigma_\Delta \approx 0$) and $RS(P) \to 0$ when variability in gaps increases.

2) Periodicity Score (PS). While regularity captures consistency, it does not explicitly reflect whether a pattern follows a recurring temporal cycle. The periodicity score addresses this by measuring the extent to which pattern occurrences conform to a dominant cycle. The cycle length τ is estimated in a data-driven manner as the median of inter-arrival gaps:

$$\tau = \mathrm{median}(\Delta(P)) \quad (9)$$

The periodicity score is then computed as:

$$PS(P) = 1 - \frac{1}{n-1} \sum_{i=1}^{n-1} \frac{|\Delta_i - \tau|}{\tau + \epsilon} \tag{10}$$

This formulation evaluates the relative deviation of each gap from the dominant cycle τ. Patterns that follow a repeating interval yield high periodicity scores, while irregular ones score lower.

3) Temporal Score Calculation. Since the raw regularity and periodicity scores may not be strictly bounded within a common scale across all patterns, normalization is required to ensure fair integration within the IPS framework. The min–max normalization is applied as follows:

$$\widehat{RS}(P) = \frac{RS(P) - RS_{min}}{RS_{max} - RS_{min}};\ \widehat{PS}(P) = \frac{PS(P) - PS_{min}}{PS_{max} - PS_{min}} \tag{11}$$

The final temporal score is defined as a weighted combination of normalized regularity and periodicity:

$$T(P) = \gamma \cdot \widehat{RS}(P) + (1-\gamma) \cdot \widehat{PS}(P) \tag{12}$$

where $\gamma \in [0, 1]$ controls the relative importance of stability versus cyclic behavior.

4.4. Pattern integration and IPS scoring layer

The Multidimensional Pattern Mining Layer generates several candidate pattern sets using different analytical perspectives, such as frequency-based co-occurrence patterns, utility-based economic patterns, and temporally consistent patterns. The Pattern Integration and IPS Scoring Layer eliminates redundancy of the overlapping patterns and consolidates them into a unified representation. After that, it computes the IPS for each pattern according to its normalized support, utility, and temporal values.

4.4.1. Pattern consolidation and redundancy reduction

To achieve effective pattern consolidation and reduce redundancy, patterns are evaluated using sub-pattern dominance and similarity overlap.

1) Sub-pattern dominance. For two patterns P_a and P_b, if $P_a \subset P_b$ and P_b achieve comparable or higher multidimensional strength (in terms of utility and temporal reliability), then P_a is considered dominated and removed to eliminate redundant representation.

2) Similarity overlap. Highly overlapping itemsets are identified using the Jaccard similarity measure:

$$J(P_a,\ P_b) = \frac{|P_a \cap P_b|}{|P_a \cup P_b|} \tag{13}$$

If $J(P_a,\ P_b) \geq \theta_J$, where θ_J is a high-overlap threshold, only the more informative pattern is retained.

This consolidation process produces a compact set $\mathscr{P}^* \subseteq \mathscr{P}$, improving interpretability and computational efficiency in subsequent stages.

4.4.2. Integrated Pattern Scoring (IPS)

After consolidation, the retained patterns are prioritized using an IPS mechanism. IPS provides a unified importance measure by jointly considering structural frequency, economic utility, and temporal reliability.

For each pattern P, we compute three key components: the normalized support score $S(P)$, the normalized utility score $U(P)$, and the normalized temporal value of $T(P)$. It should be noted that the temporal score $T(P)$ is inherently normalized as it is derived from normalized measures of regularity and periodicity. To ensure comparability across different dimensions, both support and utility are normalized through the min–max normalization technique.

$$S(P) = \frac{\mathrm{Sup}(P) - \mathrm{Sup}_{\min}}{\mathrm{Sup}_{\max} - \mathrm{Sup}_{\min}};\ U(P) = \frac{U(P) - U_{min}}{U_{max} - U_{min}} \tag{14}$$

The final IPS score of the pattern P is computed as:

$$\mathrm{IPS}(P) = w_s \cdot S(P) + w_u \cdot U(P) + w_t \cdot T(P) \tag{15}$$

subject to the constraint:

$$w_s + w_u + w_t = 1, \quad w_s, w_u, w_t \in [0, 1]. \tag{16}$$

The weighted IPS formulation was intentionally designed to preserve understandability and controllable contribution of different analytical dimensions. It also maintains flexibility to different retail decision priorities. This formulation ensures that patterns that are frequent but economically insignificant do not dominate the ranking. On the other hand, patterns with high business value receive appropriate priority. The formulation also guarantees that temporal stability and recurrence of patterns are effectively addressed. Through the inclusion of the dimensions in a single scoring system, it is ensured that all the modules contribute in a controlled, balanced, and understandable manner.

The outcome of this layer is the IPS-ranked list of consolidated patterns:

$$\mathscr{R} = \mathrm{Rank}(\mathscr{P}^*,\ \mathrm{IPS}) \tag{17}$$

This IPS-ranked pattern repository serves as the main knowledge base input for the next layer of the Hybrid Recommendation and Intelligence Layer.

4.5. Hybrid recommendation and intelligence layer

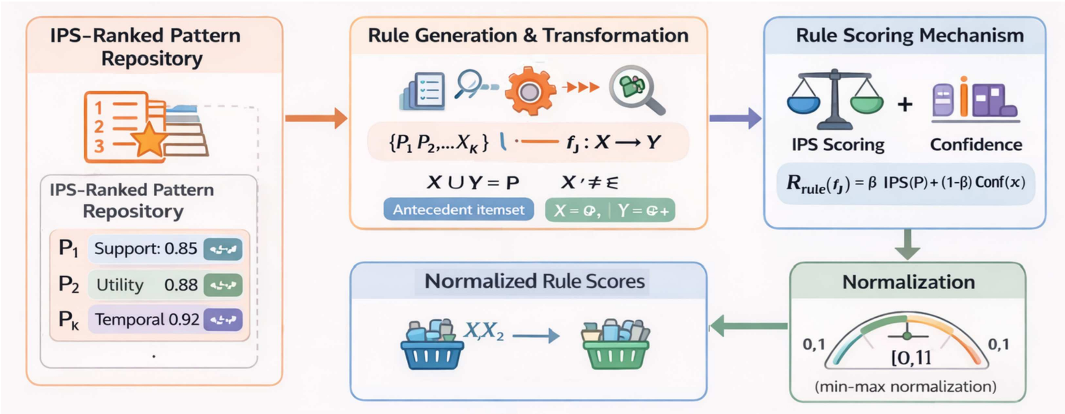
The Hybrid Recommendation and Intelligence Layer transforms IPS-ranked multidimensional patterns into actionable retail intelligence. This layer integrates interpretable rule-based reasoning with data-driven predictive learning. It is designed to balance explainability with predictive accuracy. Explainability is essential for managerial trust and decision transparency, and predictive accuracy is critical for effective recommendation and forecasting in dynamic retail environments.

Rather than relying on a single analytical paradigm, our proposed framework adopts a hybrid strategy that combines the complementary strengths of symbolic rule-based inference and deep learning–based prediction.

4.5.1. Rule-based recommendation module

The rule-based recommendation module is illustrated in Figure 2. This module generates interpretable association rules from IPS-ranked multidimensional patterns and assigns them meaningful importance scores suitable for hybrid recommendation and decision intelligence. Unlike classical ARM, which relies primarily on confidence-based filtering, our proposed framework adopts an IPS-guided rule generation and scoring strategy. Our IPS strategy ensures that rule importance reflects multidimensional pattern characteristics rather than frequency alone.

Figure 2
IPS-guided association rule mining



Let $\mathscr{R} = \{P_1, P_2, \ldots, P_k\}$ denote the set of consolidated patterns ranked by IPS. For a selected high-priority pattern $P \in \mathscr{R}$ with $|P| \geq 2$, association rules are constructed by partitioning P into antecedent and consequent itemsets. Formally, a rule r_j is defined as:

$$r_j : X \to Y \tag{18}$$

subject to:

$$X \cup Y = P, \quad X \cap Y = \emptyset, \quad X \neq \emptyset, \quad Y \neq \emptyset. \tag{19}$$

Here, X denotes the antecedent itemset, and Y denotes the consequent itemset.

To quantify the strength of a generated rule, the proposed framework integrates multidimensional pattern importance with directional association strength. This design avoids excessive penalization while preserving interpretability. The confidence of rule $r_j : X \to Y$ is computed as:

$$\text{Conf}(X \to Y) = \frac{\text{Sup}(X \cup Y)}{\text{Sup}(X)} \tag{20}$$

Finally, the rule-based recommendation score is then defined as:

$$R_{\text{rule}}(r_j) = \beta \cdot \text{IPS}(P) + (1 - \beta) \cdot \text{Conf}(X \to Y) \tag{21}$$

where $\beta \in [0, 1]$ controls the relative importance of multidimensional pattern strength and directional confidence.

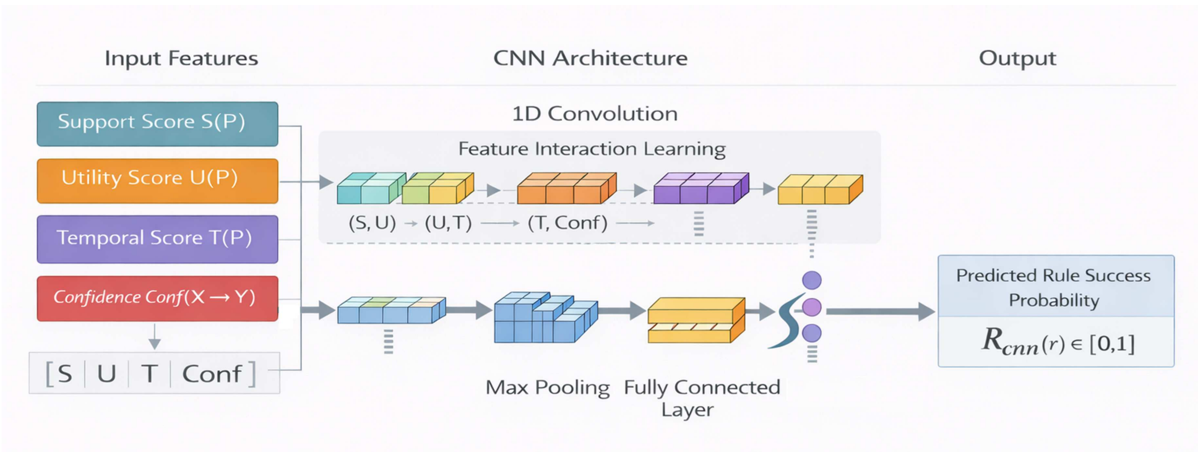
4.5.2. CNN-based predictive learning module

The CNN-based predictive learning module illustrated in Figure 3 captures nonlinear interactions among multidimensional rule characteristics and estimates the probability of rule success in future transactions. Unlike linear scoring mechanisms, this module captures higher-order interdependencies among structural frequency, economic utility, temporal reliability, and directional confidence.

Although CNNs are traditionally applied to spatial data, in the proposed framework, the CNN performs structured feature-level interaction learning over compact rule representations. This design enables nonlinear modeling while maintaining compatibility with interpretable IPS-based scoring.

The CNN architecture we propose is deliberately designed to be a lightweight one-dimensional convolutional network instead of being a deep spatial network. It is not large-scale representation learning but structure learning of interactions between adjacent multidimensional rule attributes. Although there are only a few dimensions of the input feature space, the convolution process employs interaction filters that enable learning of a localized nonlinear interaction between the features of support, utility, temporal reliability, and confidence. This lightweight design

Figure 3
CNN-based predictive learning module



preserves interpretability and computational efficiency and provides additional flexibility beyond purely linear scoring formulations.

1) Input Representation. For each generated rule $r: X \rightarrow Y$, a feature vector is constructed as:

$$x_r = [S(P),\ U(P),\ T(P),\ \mathrm{Conf}(X \rightarrow Y)] \tag{22}$$

where $S(P)$ and $U(P)$ are normalized support and utility scores, $T(P)$ is the temporal score obtained from regularity and periodicity integration, and $\mathrm{Conf}(X \rightarrow Y)$ is the directional confidence of the rule. All features are normalized to the interval $[0, 1]$ to ensure numerical stability and compatibility with the hybrid fusion mechanism. Thus, $x_r \in [0, 1]^4$.

2) 1D Convolution: Feature Interaction Learning. To capture localized nonlinear dependencies among adjacent pattern dimensions, a 1D convolution layer with kernel size $k = 2$ is applied. Let:

$$x_r = [x_1, x_2, x_3, x_4] \tag{23}$$

where $x_1 = S(P)$, $x_2 = U(P)$, $x_3 = T(P)$, and $x_4 = \mathrm{Conf}\ (X \rightarrow Y)$ The convolution operation computes interaction features:

$$z_j = \sigma\left(w_1 x_j + w_2 x_{j+1} + b\right), \quad j = 1, 2, 3 \tag{24}$$

producing:

$$(S, U), \quad (U, T), \quad (T, \mathrm{Conf}). \tag{25}$$

This sliding nonlinear interaction mechanism captures pairwise dependencies between consecutive pattern dimensions. The convolution here is not spatial; rather, it functions as a structured feature interaction detector.

3) Max-Pooling Layer. To reduce dimensionality and retain the more significant interaction signals, a max-pooling operation is applied over the convolutional feature map.

$$z^* = \max(z_1, z_2, z_3) \tag{26}$$

This improves robustness by preserving dominant nonlinear interactions while suppressing weak dependencies.

4) Fully Connected Layer. The pooled representation is passed through a fully connected layer:

$$h = \phi(Wz^* + b) \tag{27}$$

where

a. W = learnable weight matrix,
b. b = bias,
c. $\phi(\cdot)$ = nonlinear activation (ReLU).

This layer integrates interaction signals into a unified latent representation.

5) Sigmoid Output Layer. Finally, the rule success probability is estimated using a sigmoid activation:

$$R_{\mathrm{cnn}}(r) = \sigma\left(w^T h + b\right) \tag{28}$$

where $R_{\mathrm{cnn}}(r) \in (0, 1)$ represents the predicted probability that rule r will successfully occur in future transactions. Only a single probabilistic output is generated, ensuring interpretability and compatibility with the hybrid fusion strategy.

6) Rule Success Definition. To construct the binary target variable for CNN training, each association rule (r : X → Y) generated from the training partition was evaluated on future transactions contained in the validation and testing periods. A rule was considered successful ($y_r = 1$) if the consequent itemset Y appeared together with the antecedent itemset X in at least one future transaction, indicating that the association reoccurred after rule generation. Otherwise, the rule was labeled unsuccessful ($y_r = 0$). Multiple occurrences of the same rule during the evaluation period were treated as a single successful outcome. It ensures that the prediction task focuses on future rule recurrence rather than repeated occurrence frequency.

7) Training Objective. The training objective minimizes binary cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{r=1}^{N}\left[y_r \log(\hat{y}_r) + (1 - y_r)\log(1 - \hat{y}_r)\right] \tag{29}$$

where

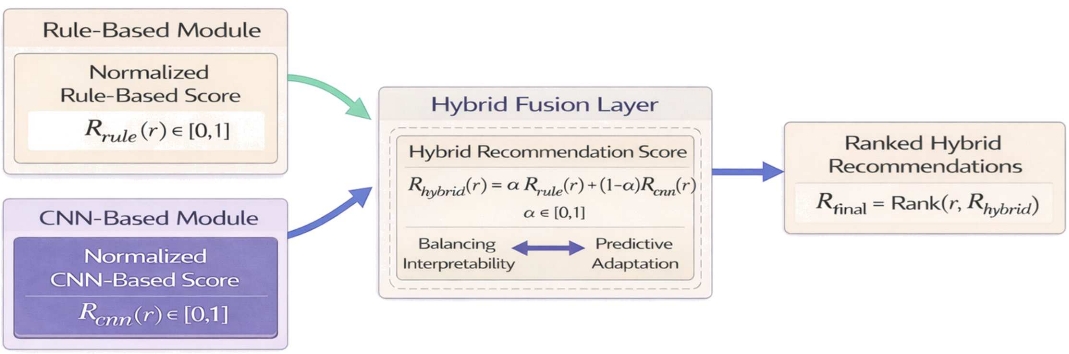
a. $y_r \in \{0, 1\}$ denotes observed rule success,

b. $\hat{y}_r = R_{\mathrm{cnn}}(r)$.

4.5.3. Hybrid fusion strategy

The hybrid fusion strategy is depicted in Figure 4. The purpose of this layer is to integrate interpretable rule-based scoring with predictive modeling to generate robust and decision-consistent recommendations. The main objective is to balance explainability (derived from IPS-ranked rule structures) with predictive adaptability (captured by the CNN module).

Figure 4
Hybrid fusion strategy combining rule-based interpretability and CNN-based predictive learning



The rule-based part guarantees that the model is clear and consistent with the multidimensional pattern importance. The CNN-based part helps to learn nonlinear feature interactions and latent behavior structures. Hybridization means the integration of the two approaches into one recommendation score.

The final hybrid recommendation score is computed as:

$$R_{\text{hybrid}}(r) = \alpha \cdot R_{\text{rule}}(r) + (1 - \alpha) \cdot R_{\text{cnn}}(r) \tag{30}$$

where

a. $R_{\text{rule}}(r) \in [0, 1]$ denotes the normalized rule-based recommendation score,
b. $R_{\text{cnn}}(r) \in [0, 1]$ denotes the predicted success probability from the CNN module,
c. $\alpha \in [0, 1]$ is a weighting parameter controlling the relative contribution of interpretability and predictive strength.

This convex combination ensures $R_{\text{hybrid}}(r) \in [0, 1]$, thus preserving probabilistic interpretability and numerical stability.

This recommended fusion does not rely heavily on symbolic reasoning or statistical learning. Instead, it suggests the creation of an appropriate interaction of multidimensional structural intelligence (support-utility-temporal), confidence (association strength), and nonlinear predictive modeling. In order to do that, it uses IPS-ranked features as the basis of the CNN module and controls the fusion parameter of it. This design mitigates overfitting and spurious recommendations while maintaining adaptability to the evolving retail landscape. The output of this layer is a ranked list of hybrid recommendation scores:

$$\mathcal{R}_{final} = Rank\left(r, R_{hybrid}\right) \tag{31}$$

4.6. Decision intelligence and business strategy mapping layer

The final layer of our proposed framework is shown in Figure 5. This layer converts the ranked hybrid recommendation rules into actionable retail decision intelligence. It is important to emphasize that the hybrid recommendation module does not directly generate business decisions. Rather, it produces a prioritized set of association rules, which are subsequently interpreted and mapped into strategic retail actions.

Let $\mathcal{R}_{final} = \{r_1, r_2, \ldots, r_n\}$ denote the ranked rule set obtained from the Hybrid Fusion Layer. Each rule r is associated with a hybrid recommendation score $R_{\text{hybrid}}(r)$. The ranking step serves as a prioritization mechanism. It allows the framework to identify the most reliable and economically meaningful rules from potentially large rule sets generated from transactional data. In practical decision-support scenarios, retailers typically focus on the Top-K ranked rules, where:

$$\mathcal{R}_{\text{topK}} = \{r_1, r_2, \ldots, r_K\}, \quad K \ll n. \tag{32}$$

These top-ranked rules represent the most actionable patterns, combining multidimensional pattern strength, directional association confidence, and predictive learning signals.

While hybrid ranking determines which rules are most important, the specific type of business decision supported by each rule is determined by analyzing its underlying pattern characteristics. To interpret these Top-K ranked rules for decision support, a decision mapping function is defined as:

$$D(r) = f(S(P), U(P), T(P), Conf(X \to Y)) \tag{33}$$

The mapping is performed by identifying the dominant pattern characteristic among the four attributes. Formally,

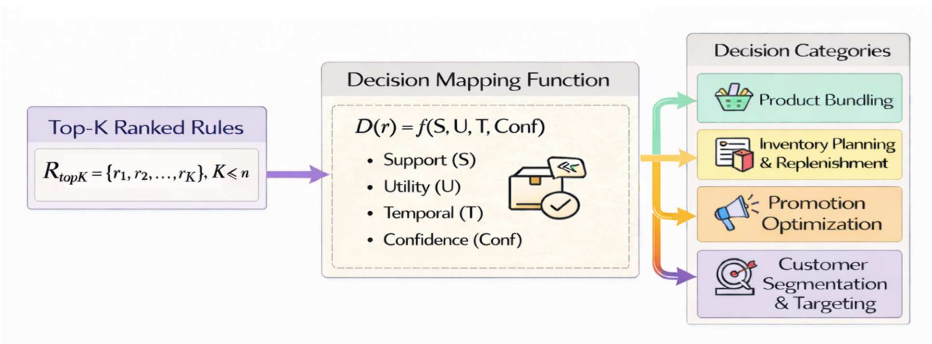
$$D(r) = \arg \max_{d \in \{\text{S,U,T,Conf}\}} (\text{Score}_d(r)) \tag{34}$$

where $\text{Score}_d(r)$ denotes the value of the corresponding rule attribute. Based on the dominant attribute, the rule is mapped to one of the four retail decision categories:

$$D(r) = \begin{cases} Product\ Bundling, & if\ S(P)\ is\ dominant \\ Inventory\ Planning, & if\ T(P)\ is\ dominant \\ Promotion\ Optimization, & if\ U(P)\ is\ dominant \\ Customer\ Targeting, & if\ Conf(X \to Y)\ is\ dominant \end{cases} \tag{35}$$

This deterministic interpretation mechanism allows the framework to translate hybrid-ranked association rules into decision-oriented insights while preserving interpretability.

Figure 5
Decision intelligence mapping for the Top-K ranked association rules



5. Experimental Setup

This section presents the experimental design used to evaluate the effectiveness of the proposed IAPMF. The experiments aim to assess the framework's ability to discover multidimensional retail patterns, generate hybrid recommendations, and support decision-oriented retail intelligence.

5.1. Dataset description

The experimental evaluation is conducted using a real-world retail transactional dataset collected from a large supermarket in Bangladesh. There are 100,000 transaction data entries in this dataset, which cover a period of one year continuously and include different kinds of purchase trends in different seasons and demands.

The dataset contains 2382 unique products. Transactions are taken directly from point-of-sale billing slips, meaning that the dataset reflects real-world retail buying behavior rather than synthetic or simulated data. The temporal span of one year enables the framework to capture both short-term purchasing correlations and long-term seasonal patterns.

Every transaction record contains some features required for multidimensional pattern analysis including items purchased, quantity, price, and the time stamps. Such properties allow the proposed framework to investigate structural co-occurrence relationships, contributions toward economic utility, and temporal purchasing behaviors. Table 1 summarizes the main attributes in the dataset.

Table 1
Dataset attributes

Attribute	Description
Transaction_ID	Unique identifier for each transaction
Item_List	Items purchased in the transaction
Price	Unit price of each item
Timestamp	Date and time of the transaction
Total	Total value of the transaction

The combination of item-level, economic, and temporal attributes makes the dataset particularly suitable for evaluating multidimensional pattern mining techniques and hybrid recommendation systems. To preserve customer privacy and comply with ethical data handling practices, all transactions were anonymized before analysis, and no personally identifiable information was included in the dataset.

5.2. Experimental protocol and parameter settings

The proposed IAPMF was evaluated by a systematic and sequential protocol following the pathway described in Section 4. We chronologically split the transactional dataset into three subsets, containing 70% for training, 15% for validation, and 15% for testing. This chronological partitioning preserves temporal consistency for predictive evaluation.

In order to avoid information leakage, we performed all multidimensional pattern discovery operations including frequent, utility, and temporal pattern extraction, IPS-based consolidation and ranking, rule generation, confidence estimation, and rule-based scoring only on the training subset. The validation subset was used only for the parameter tuning and model selection, while the testing subset was reserved strictly for the final predictive and recommendation assessment. Thus, no future transactional information from the validation or testing periods was used during the pattern construction, rule scoring, or CNN model training.

The predictive module based on CNN was subsequently trained to predict the rule success probabilities. Then, its outputs were integrated with rule-based scores through the hybrid fusion mechanism. Finally, it produces the final recommendation score $\mathrm{R}_{\mathrm{hybrid}}(\mathrm{r})$. The Top-K ranked rules were mapped into decision-support categories of product bundling, inventory planning, promotion optimization, and customer targeting.

Parameter settings were bounded around relevant characteristics of the datasets and a preliminary validation. To avoid prior bias in favor of any particular dimension and to enable an equal contribution from all dimensions of analysis, the IPS weights were initially set equal. This configuration gives equal value to structural frequency, economic utility, and temporal reliability when prioritizing patterns. Sensitivity analysis in varying weight combinations was also conducted to validate the effectiveness of the approach. It demonstrates stable performance of the recommendation regardless of moderate changes in parameters. The minimum support threshold was set to $\theta_s = 0.02$. Temporal scoring used $\gamma = 0.5$ to balance regularity and periodicity, while IPS weights were set to $w_s = w_u = w_t = \frac{1}{3}$. Rule scoring employed $\beta = 0.7$, and the hybrid fusion parameter was set to $\alpha = 0.6$.

The CNN architecture consists of a 1D convolution layer (kernel size$k = 2$), followed by max-pooling, a fully connected layer with ReLU activation, and a sigmoid output layer. The model was trained using the Adam optimizer with binary cross-entropy loss, a learning rate of 0.001, a batch size of 64, and 50 epochs.

To evaluate the effectiveness of the proposed framework, both recommendation accuracy metrics and business-oriented evaluation measures were considered.

6. Results and Discussion

This section presents the experimental results and analyzes the performance of the proposed framework. Comparative analysis with baseline approaches is conducted to demonstrate its effectiveness for retail decision support.

6.1. Pattern characteristics and IPS analysis

We extracted a total of 1142 candidate patterns from the training partition of the retail transactional dataset using a minimum support threshold of $\theta_s = 0.02$. For each discovered pattern P, three normalized evaluation measures were computed: the support score S(P) the utility score U(P), and the temporal score T(P). The score S(P) represents structural co-occurrence frequency, U(P) reflects economic contribution, and the T(P) represents stability and periodic recurrence of the pattern over time. These normalized scores enable consistent comparison across the multidimensional characteristics used in the proposed framework.

Descriptive statistics for the normalized scores of patterns in the candidate pattern set are shown in Table 2. The results indicate that the support score shows a relatively lower mean value (0.32), suggesting that many patterns occur with moderate structural frequency when the support threshold is applied. On the contrary, the utility score shows a higher mean value (0.58), meaning that many patterns bring significant economic value even when their occurrence frequency is moderate. The temporal score is intermediate in mean (0.49); it illustrates variation within the dataset with regard to the temporal stability and recurrence of customer purchasing behaviors.

Table 2
Descriptive statistics of normalized pattern scores (N= 1,142)

Statistic	Support $S(P)$	Utility $U(P)$	Temporal $T(P)$
Mean	0.32	0.58	0.49
Median	0.29	0.57	0.47
Standard deviation	0.18	0.16	0.18

The distribution plots of the normalized scores for support, utility, and temporal patterns (kernel density curve) are shown in Figure 6. Most support scores fall within the lower-to-moderate range. As a result, only a small number of item combinations are structurally dominant compared with moderately frequent associations. The distributions of utility scores are right-skewed, indicating that economically feasible combinations exist in the data. The temporal score shows a larger spread as some product combinations tend to occur regularly over time, while others are more random.

In the proposed framework, multidimensional retail patterns are prioritized for recommendation generation and strategic decision analysis through the IPS mechanism. The IPS metric combines structural frequency, economic usefulness, and temporal reliability in a single metric ranking. This helps to look for patterns that not only happen often but also are economically relevant and temporally consistent.

The Top-10 IPS-ranked patterns are shown in Table 3. These patterns represent the most valuable product associations discovered from the transactional dataset. The results reveal that the high-rank patterns are not only structurally frequent, but they also have high economic value and stable temporal behavior. For example, the pattern Chocolate + Biscuit achieves the highest IPS score (0.84) due to its extremely high support together with strong utility and temporal values. Similarly, patterns such as Rice + Cooking Oil and Beauty Soap + Shampoo also obtain

Figure 6
Kernel density distribution of normalized support, utility, and temporal scores

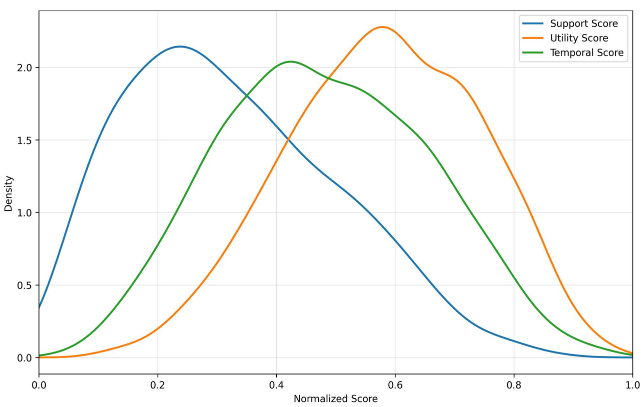


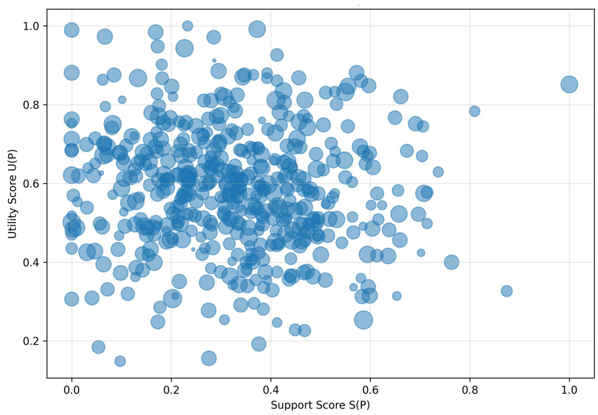
Table 3
Top-10 IPS-ranked retail patterns

Pattern (P)	$S(P)$	$U(P)$	$T(P)$	IPS
Chocolate + Biscuit	1.00	0.82	0.71	0.84
Rice + Cooking Oil	0.94	0.78	0.70	0.81
Beauty Soap + Shampoo	0.86	0.82	0.74	0.81
Body Lotion + Face Wash	0.77	0.84	0.76	0.79
Biscuit + Chanachur	0.87	0.74	0.74	0.78
Ice Cream + Soft Drink	0.58	0.82	0.91	0.77
Det. Powder + Dish Wash	0.81	0.73	0.75	0.76
Noodles + Egg	0.80	0.71	0.72	0.74
Baby Food + Baby Diapers	0.71	0.84	0.62	0.72
Potato + Egg	0.76	0.58	0.79	0.71

high IPS values, indicating their importance as core purchasing combinations in the retail environment.

Table 3 emphasizes the highlighted patterns, but Figure 7 offers a more global view of the multidimensional pattern space over the random subset of patterns. The bubble plot represents the support versus utility score, whereas the size of the bubble simply corresponds to the temporal score. The patterns are distributed across structural and economic dimensions, with an indicator of their temporal reliability. Patterns situated on the upper right section of the plot are product combinations that are both relatively supported and have a larger economic contribution, and bigger bubbles represent higher temporal stability.

Figure 7
Support–utility–temporal distribution of patterns

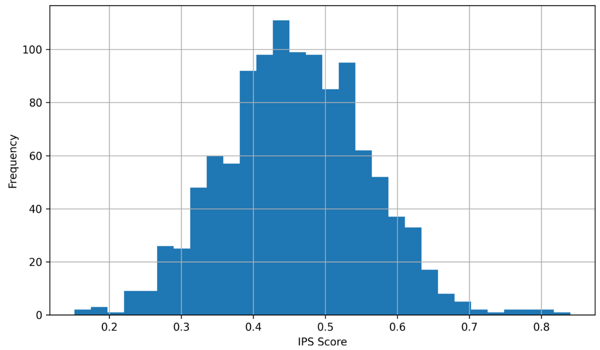


To further analyze the global ranking behavior of patterns, Figure 8 illustrates the distribution of IPS scores across all 1142 discovered patterns. The histogram shows that the majority of patterns exhibit moderate IPS values, indicating balanced but not dominant multidimensional importance. This distribution confirms that the IPS mechanism effectively differentiates highly influential retail patterns from the broader pattern population.

6.2. Rule-based and CNN-based model evaluation

In this stage, for each discovered pattern, directional rules are constructed by partitioning the itemset into antecedent and

Figure 8
Histogram of Integrated Pattern Scores (IPS) for the 1142 discovered patterns



consequent subsets. The strength of each rule is evaluated using the confidence metric together with the multidimensional importance captured by IPS. The rules are not filtered yet; instead, they are scored using the rule scoring formulation defined in Section 4.5.1.

Table 4 presents representative rule-based recommendation scores derived from the top-10 IPS-ranked patterns reported in Table 3.

The results illustrate that rules originating from the same pattern may still produce different recommendation strengths due to variations in directional confidence. For example, the rules Chocolate → Biscuit and Biscuit → Chocolate do not receive the same score due to differences in directional confidence, even though they originate from the same underlying pattern.

The CNN-based predictive module was evaluated to estimate the future reliability of association rules derived from IPS-ranked patterns by capturing nonlinear interactions among multidimensional features. From the 1142 discovered patterns, a total of 2926 association rules were generated and used as candidate rule instances for predictive learning. The CNN architecture described in Section 4.5.2 was trained, and the model outputs the predicted probability that a rule will successfully occur in future transactions, denoted as $R_{cnn}(r)$. The overall predictive performance is summarized in Table 5.

Table 5
Performance evaluation of the CNN-based rule success prediction model

Metric	Value
Accuracy	0.86
Precision	0.83
Recall	0.85
F1-Score	0.84
AUC	0.89

The results indicate that the CNN model effectively captures nonlinear dependencies among multidimensional rule features. To further evaluate the suitability of the proposed predictive module, the CNN model was compared with several alternative classifiers using the same multidimensional rule features and chronological evaluation protocol, as shown in Table 6.

The results indicate that all models benefit from the multidimensional IPS-guided feature representation. The proposed

Table 4
Representative rule-based recommendation scores derived from the top-10 IPS-ranked patterns

Rule r: $X \rightarrow Y$	Conf.	IPS	$R_{\text{rule}}(r)$
Chocolate → Biscuit	0.88	0.84	0.85
Biscuit → Chocolate	0.61	0.84	0.77
Rice → Cooking Oil	0.86	0.81	0.83
Cooking Oil → Rice	0.63	0.81	0.76
Beauty Soap → Shampoo	0.84	0.81	0.82
Shampoo → Beauty Soap	0.66	0.81	0.77
Body Lotion → Face Wash	0.82	0.79	0.80
Face Wash → Body Lotion	0.64	0.79	0.75
Biscuit → Chanachur	0.80	0.78	0.79
Chanachur → Biscuit	0.62	0.78	0.73
Ice Cream → Soft Drink	0.83	0.77	0.79
Soft Drink → Ice Cream	0.58	0.77	0.71
Det. Powder → Dish Wash	0.79	0.76	0.77
Dish Wash → Det. Powder	0.60	0.76	0.71
Noodles → Egg	0.77	0.74	0.75
Egg → Noodles	0.56	0.74	0.69
Baby Food → Baby Diapers	0.75	0.72	0.73
Baby Diapers → Baby Food	0.53	0.72	0.66
Potato → Egg	0.74	0.71	0.72
Egg → Potato	0.51	0.71	0.65

Table 6
Comparison with alternative predictive models

Model	F1-score	AUC
Logistic Regression	0.76	0.82
Random Forest	0.79	0.86
Multilayer Perceptron (MLP)	0.82	0.88
Proposed CNN	0.84	0.89

lightweight CNN achieves the highest overall performance, suggesting that localized nonlinear interaction modeling provides additional predictive capability beyond purely linear or shallow learning approaches.

Figure 9 illustrates the Receiver Operating Characteristic (ROC) curve of the CNN model on the test dataset. The curve plots the true positive rate against the false-positive rate across different classification thresholds. The resulting Area Under the Receiver Operating Characteristic Curve (AUC) value of 0.89 indicates strong predictive performance.

The confusion matrix in Figure 10 confirms that the CNN model correctly identifies the majority of successful rules while maintaining a relatively low false-positive rate. This indicates that multidimensional rule characteristics provide meaningful predictive signals for estimating rule reliability.

Figure 9
ROC curve of the CNN-based rule success prediction model

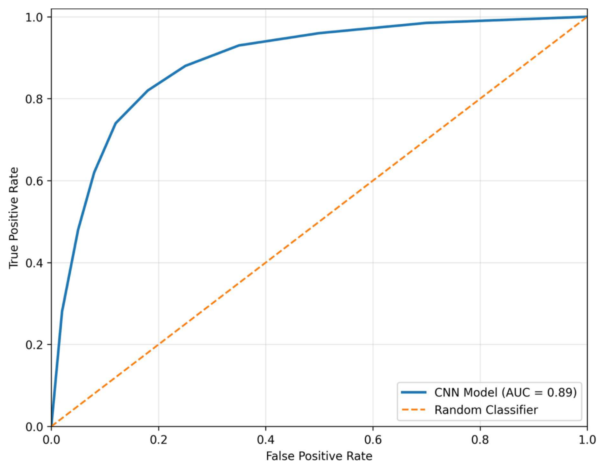
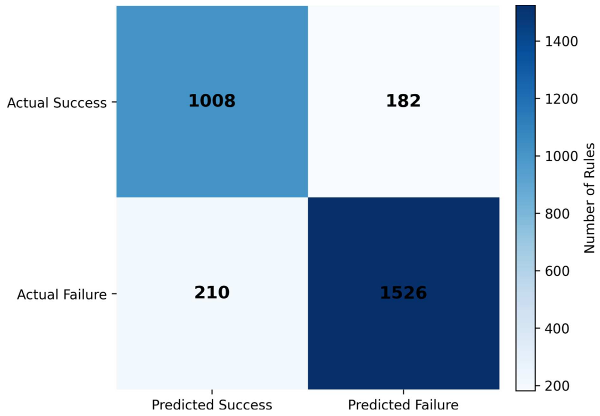


Figure 10
Confusion matrix of the CNN-based rule success prediction model



The predicted probabilities in Table 7 illustrate how the CNN model differentiates between stronger and weaker rules based on multidimensional characteristics. Rules with high support, utility, temporal stability, and confidence generally receive higher predicted success probabilities.

The CNN predictions are subsequently integrated with rule-based scores in the hybrid fusion strategy presented in the following subsection, enabling the framework to combine interpretable rule strength with predictive reliability for final rule ranking.

6.3. Hybrid recommendation performance and comparative analysis

In this subsection, we assess the performance of our proposed hybrid recommendation mechanism that integrates interpretable rule-based reasoning with CNN-based predictive learning. The objective of our hybrid model is not to artificially increase rule scores but to refine the ranking of candidate rules by incorporating predictive estimates of rule success probability.

To provide a comprehensive evaluation, we compared the proposed framework against three baseline approaches: classical ARM based on support and confidence, multidimensional integrated rule-based scoring (IPS) using support, utility, and temporal characteristics, and CNN-based predictive recommendation, which estimates rule success probability using learned feature interactions. We then selected the Top-100 rules from each ranking as candidate recommendations and validated each of these against the test dataset in order to evaluate recommendation

Table 7
Sample CNN-based predicted probabilities for representative association rules

Rule	S	U	T	Conf	CNN Prob.
Chocolate → Biscuit	1.00	0.82	0.71	0.88	0.93
Biscuit → Chocolate	1.00	0.82	0.71	0.61	0.72
Rice → Cooking Oil	0.94	0.78	0.70	0.86	0.91
Cooking Oil → Rice	0.94	0.78	0.70	0.63	0.84
Beauty Soap → Shampoo	0.86	0.82	0.74	0.84	0.89
Shampoo → Beauty Soap	0.86	0.82	0.74	0.66	0.77
Body Lotion → Face Wash	0.77	0.84	0.76	0.82	0.88
Face Wash → Body Lotion	0.77	0.84	0.76	0.64	0.74

Table 8
Recommendation performance comparison

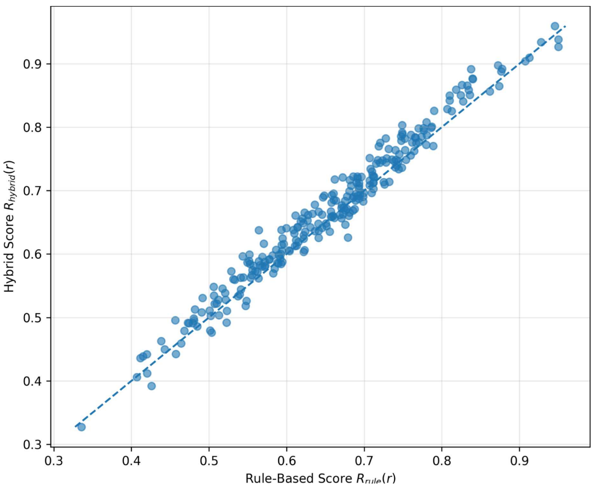
Model	Precision	Recall	F1-score
Classical ARM (Support + Confidence)	0.63	0.60	0.61
Rule-Based IPS Scoring	0.74	0.67	0.70
CNN-Based Prediction	0.78	0.80	0.79
Proposed Hybrid Model	0.86	0.83	0.84

quality. Finally, we assessed the recommendation performance using precision, recall, and F1-score, which measure how effectively each model prioritizes rules that actually occur in future transactions.

The results illustrated in Table 8 prove that the hybrid model consistently outperforms both of these management approaches individually. The classical ARM performs the worst since it uses only frequency-based co-occurrence relationships. The IPS-based model improves the precision through multidimensional characteristics of patterns including utility and temporal stability. The CNN model further enhances recall by learning nonlinear dependencies among rule features. The hybrid strategy produces the most reliable recommendation ranking by combining these complementary strengths.

Figure 11 shows the relationship between rule-based scores and hybrid scores for the generated rules. The diagonal reference line represents equal scores between the two models. Points above the line indicate rules whose ranking improves after incorporating CNN-based prediction, while points below the line correspond to rules whose importance is reduced by the predictive model. The strong alignment around the diagonal indicates that the hybrid model preserves the interpretability of rule-based scoring while selectively refining rule rankings based on predicted rule success probabilities.

Figure 11
Relationship between rule-based scores and hybrid scores for generated rules



Beyond the recommendation accuracy, we conducted an offline revenue-oriented evaluation to assess the economic significance of the recommended rules. For each recommendation model, we identified the Top-100 ranked rules and their associated item-level revenue contributions by aggregating transaction quantity and price information available in the dataset. The resulting values represent projected revenue contributions derived from historically observed purchasing patterns and are intended solely for comparative evaluation rather than as measures of actual business uplift.

Table 9 summarizes the projected revenue contributions of the evaluated recommendation strategies. The relative gain is computed with respect to the classical ARM baseline. The hybrid framework achieves the highest projected revenue contribution. The results indicate that the integration of multidimensional pattern knowledge with predictive learning improves the identification of item combinations that are both statistically reliable and economically valuable under historical transactional conditions.

The Decision Intelligence Layer maps the Top-K hybrid-ranked rules into strategic categories using their multidimensional characteristics, including support, utility, temporal stability, and confidence. Rather than treating all rules uniformly, the mapping process assigns decision roles based on dominant feature contributions. This enables the transformation of analytical outputs into structured business actions. Table 10 presents the representative rules and their corresponding strategy mappings.

The results of the mappings reveal that different rules' profiles are associated with unique strategic moves. Specifically, high-frequency and high-confidence rules are easily related to bundling and cross-selling approaches, whereas high-utility rules can be used for optimizing inventory and revenue. Finally,

Table 9
Projected revenue contribution of recommendation strategies

Model	Projected revenue contribution (%)	Relative gain vs ARM
Classical ARM	7.5	—
Rule-Based IPS Scoring	9.0	+20.0%
CNN-Based Prediction	10.2	+36.0%
Proposed Hybrid Model	10.6	+41.3%

Table 10
Representative rule-to-strategy mapping

Rule (X → Y)	Key characteristics	Mapped strategy
Rice → Dal	High support, high confidence	Product bundling
Milk → Bread	High support, moderate utility	Cross-selling
Cooking Oil → Flour	High utility, moderate support	Inventory optimization
Yogurt → Fruits	Strong temporal pattern	Seasonal promotion
Shampoo → Soap	Balanced IPS + confidence	Customer segmentation

Table 11
Sensitivity analysis under different IPS weight configurations

Weight configuration (w_s, w_u, w_t)	Precision	Recall	F1-score
Balanced (0.33, 0.33, 0.33)	0.86	0.83	0.84
Utility-Focused (0.20, 0.60, 0.20)	0.84	0.82	0.83
Temporal-Focused (0.20, 0.20, 0.60)	0.83	0.81	0.82
Support-Focused (0.60, 0.20, 0.20)	0.81	0.79	0.80

temporal patterns make possible the formulation of time-aware promotion campaigns.

Finally, the hybrid ranking allows only the most reliable and economically meaningful rules for decision mapping. This significantly improves the quality of actionable insights.

6.4. Sensitivity analysis

In order to assess the reliability of the proposed framework, sensitivity analyses have been performed for different IPS weightings and different settings for the hybrid fusion algorithm. The goal of such analysis is to test whether the performance of recommendations is stable in case of slight changes in key parameters.

First of all, we examined the robustness of the IPS mechanism by varying the relative importance of support, utility, and temporal dimensions. We evaluated four representative weighting configurations: a balanced configuration and three dimension-focused settings emphasizing support, utility, and temporal behavior, respectively. The hybrid recommendation framework was re-evaluated under each configuration using the same experimental protocol described in Section 5.2. The resulting recommendation performance is summarized in Table 11.

The findings suggest that the proposed framework is robust in terms of the IPS integration mechanism since it led to relatively stable recommendation performance fluctuation across different weighting configurations. The balanced weighting configuration achieves the best overall performance, suggesting that structural frequency, economic utility, and temporal reliability contribute complementary information for retail recommendation and decision intelligence.

In addition, we conducted a sensitivity analysis for the hybrid fusion parameter α, which controls the relative contribution of rule-based scoring and CNN-based prediction in the final recommendation score. Table 12 presents the recommendation performance obtained under different α values.

The results show that recommendation performance remains stable across moderate variations of α. The highest F1-score is obtained at $\alpha = 0.6$, indicating that an appropriate balance between rule-based intelligence and predictive learning yields the most effective recommendation performance.

Table 12
Sensitivity analysis under different hybrid fusion parameter settings

Weight configuration (α)	F1-score
0.3	0.81
0.4	0.82
0.5	0.83
0.6	0.84
0.7	0.83
0.8	0.82

7. Conclusion and Future Work

This paper proposed an integrated framework that unifies multidimensional pattern mining with hybrid predictive learning for strategic retail decision intelligence. By leveraging IPS-based pattern ranking alongside rule-based reasoning and CNN-based modeling, the framework effectively bridges the gap between pattern discovery and actionable recommendations. Experimental results on real-world retail data demonstrate that the hybrid approach achieves an F1-score of 0.84, outperforming the classical ARM baseline (0.61). It also achieves the highest projected revenue contribution (10.6%) compared with the evaluated baseline approaches under offline evaluation, supporting the practical effectiveness of the proposed hybrid recommendation strategy in prioritizing economically meaningful retail patterns alongside improved recommendation accuracy.

One limitation of the current framework is that a rule is considered successful when its antecedent and consequent co-occur at least once in future transactions. Although this definition provides a clear and reproducible target for predictive modeling, it may favor rules involving more common itemsets and does not fully capture recurrence frequency or antecedent-conditioned recommendation effectiveness.

Future research will investigate alternative definitions of rule success, including stricter or more graded definitions, to provide a more comprehensive evaluation of recommendation quality. Additional research will focus on adaptive fusion strategies, advanced deep learning architectures, and the integration of contextual information, including customer reviews and sentiment analysis, to further enhance recommendation relevance. Extending the framework to real-time and large-scale retail environments remains an important direction for practical deployment.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in SupershopBd1-Retail-Market-Dataset at https://github.com/Sohel-Rana-2/SupershopBd1-Retail-Market-Dataset.

Author Contribution Statement

Sohel Rana: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Md. Nazrul Islam Mondal:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision. **Md. Rabiul Islam:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision.

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