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Evolutionary Pattern Mining for Detecting Emerging Trends in Consumer Purchasing Behavior

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Abstract

Consumer preferences continuously evolve due to economic conditions, social influences, digital commerce, and technological developments. Conventional pattern mining techniques often assume static item relationships and may fail to capture purchasing patterns that change across time. This study proposes an evolutionary pattern mining framework for detecting emerging trends in consumer purchasing behavior. The proposed framework divides retail transaction data into chronological periods, extracts frequent itemsets and association rules from each period, and evaluates pattern movement using support variation, average growth rate, confidence stability, lift change, and trend significance score. Experimental evaluation was conducted using a retail transaction dataset consisting of 10,900 transactions across four observation periods. The results show that frequent itemsets increased from 146 in the first period to 236 in the final period, while valid association rules increased from 94 to 178. Several patterns, including Organic tea → Almond milk and Whole wheat bread → Peanut butter, were identified as emerging trends due to increasing support, confidence, and lift values. The findings demonstrate that evolutionary pattern mining provides richer insight than static association analysis by classifying purchasing relationships into emerging, stable, declining, and fluctuating patterns. This study contributes to temporal knowledge discovery and supports market intelligence, promotion planning, product bundling, and retail decision-making.

Keywords

Evolutionary pattern mining; Emerging trends; Association analysis; Consumer behavior; Temporal analytics

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Introduction

Developments in digital commerce and transaction-based systems have improved access to consumer purchase data. Customer transactions document not just purchased products, but also the time, quantity, and context of the purchase. Retailers can gather this transactional data to help better understand the demands of their customers and the movement of their respective markets. Data of this nature used in retail analytics can help retailers devise product bundles and plan promotions and recommendations. It can also assist retailers with stock control and help them make more informed strategic decisions. The greater the flexibility of a company to deal with rapidly changing consumer choices, the more of a competitive advantage that flexibility can provide. The ability to make sense of purchasing data is a valued skill in this context.

Association analysis is one of the more established methods for the analysis of transactional data. Retailers can examine the strength of product associations in transactions by generating frequent item sets and association rules. Support, confidence, and lift allow value to be assigned to a purchasing association. If customers frequently purchase bread and butter, and milk is also a common purchase among that customer segment, a retailer may choose to run a promotion with that product bundle. The manager will be able to see the relationships and make a relatively straightforward decision for the business.

A limitation of conventional association rule mining is its tendency to treat purchasing data as static. In a traditional framework, the entire dataset is treated as a single analytical time period, and the emerging patterns are understood as purchasing habits. While this approach aids the discovery of item associations, it is ineffective for analyzing the dynamic nature of consumer preferences. An association that is common in the entire dataset may be irrelevant in the recent dataset, and a rare association may be developing in the recent dataset. For many markets that are influenced by changes in demand, the analysis of purchasing habits fails to identify changes if the analysis is static.

Consumer purchasing behavior is dynamic. For example, an economic downturn may motivate a switch to purchasing budget-friendly items instead of premium options. After a public health initiative, consumers may purchase more health-promoting products. A consumer may purchase products in new combinations as a result of social changes, influencer marketing, or a shift in household needs. In e-commerce, purchasing preferences may change rapidly because consumers are continuously exposed to personalized recommendations, reviews, advertisements, and promotions. Therefore, understanding trends in purchasing behavior goes beyond identifying the items frequently purchased together; it requires an understanding of the relationships' trends.

This consideration for the dynamic behavior of consumers, rather than the traditional math of purchases, is supported by e-commerce research. For example, Fauzi et al. (2026) studied consumer purchase behavior in e-commerce and live-streaming and stated that in digital commerce, consumer purchase behavior can be influenced and modeled by the dynamic online transactional interactions that occur. This perspective is also relevant to the present study, which examines changes in product associations across successive transaction periods.

This limitation motivates the use of evolutionary pattern mining to examine how purchasing relationships change across successive periods. Rather than mining a single static collection of transactions, the dataset is partitioned temporally, for example, into weekly, monthly, quarterly, or campaign-based collections. From each of these collections, frequent itemsets and association rules are extracted. Those are then analyzed comparatively over the periods. As a result of such comparative analysis, analysts can recognize newly emerging patterns, modified patterns, increased patterns, stable patterns, and decreasing patterns. This method works especially well for consumer behavior because of the temporal nature of

purchasing preferences, which are subject to change in the course of dynamic market conditions.

This study utilizes the concept of emerging patterns. Emerging patterns are collections of items whose support shows a significant increase or decrease across datasets or time periods. Using a consumer shopping behavior example, an emerging pattern can be a collection of items in a later time period that shoppers were not buying in an earlier time period (e.g., sustainable shopping bags, organic produce, and plant-based drinks may signify an emerging sustainable shopping trend). Changes in consumer shopping behaviors may also be seen as emerging patterns, such as an increased purchase of time-saving and convenience-based products. Emerging pattern mining is unique in that it provides an analytical framework to understand behavior from a time-sensitive support view, as compared to a static view, where most emerging behaviors may go undetected.

Association rule mining captures co-purchase behavior effectively, but the static nature of most association rule-based models limits their applicability to temporal factors. This is a significant limitation, as business models must operate on time-sensitive decisions. If a retailer bases their operations solely on co-purchase behaviors from a historical perspective, they are likely to promote products that are losing demand, while failing to capitalize on newly emerging product combinations that are gaining demand. For this reason, integrating time into comparison of co-purchase patterns will enhance the applicability of association rule analysis significantly.

Analyzing other data-centric fields strengthens the case for the need to identify concealed variations using process- and time- based analytics. As an example, Sunation, Kurniati, and Fuad (2025) identified transition losses in cosmetic manufacturing by integrating process mining and statistical process control. Using data-driven mining, the authors were able to show the presence of hidden inefficiencies, repeated tasks, and stream variations. All of which are difficult to observe with traditional control/monitoring systems. Even if the focus of the research is on manufacturing and not consumer purchasing, it can help the case for dynamic data analysis being able to unearth concealed variations that static data reports would not show. Here, this is important because purchasing behavior does contain concealed time-based changes and can be revealed if the patterns of purchasing behavior are compared over different time periods.

Taken together, these considerations indicate that conventional static pattern-mining techniques provide limited information about how purchasing relationships emerge, strengthen, weaken, or fluctuate over time. Traditional association rule mining identifies item co-occurrences, but does not provide interpretable evidence whether relations have become stronger, weaker, or emerged newly. This limits the practical relevance of static analysis in retail settings where consumer preferences change over time.

To address this issue, this study develops an evolutionary pattern mining framework for identifying changes in consumer purchasing relationships across time. For each period, we identify frequent itemsets and association rules, and analyze the movement of patterns using support variation, confidence stability, growth rate, and trend significance. Using these techniques, purchasing patterns are described as emerging, stable, declining, or fluctuating. This classification enables decision-makers to distinguish consistently important product relationships from those that are changing over time.

The main contribution of this study is an evolutionary pattern mining framework that extends conventional association analysis through explicit temporal comparison. The main tasks of this approach include the following: first, frequent purchasing patterns are captured from transaction data over multiple time slices; second, the evolution of itemsets and association rules is analyzed using temporal pattern metrics; third, the classification of purchasing patterns is done according to the trend behavior of those patterns; and finally, the

patterns in question are understood in the context of market intelligence, with a focus on retail and the psychology of the consumer. The tasks in this approach are intended to link the technical task of pattern mining to actionable outcome interpretations in the business context.

This study makes several methodological and practical contributions. First, it presents a clear and organized method for describing consumer buying behavior through an evolutionary lens. Second, it broadens the scope of static association rule mining by describing the inclusion of a temporal comparison of transaction periods. Third, it utilizes interpretable measures of support variation and confidence stability to capture significant shifts in patterns. Fourth, it translates temporal changes in purchasing patterns into interpretable categories that can support product bundling, promotional planning, inventory management, and market analysis. Thus, this study's contribution includes not only the identification of product groupings but also the identification of the successive significance and directions of the groupings.

The full research framework is shown in Figure 1. This begins with the retail transactional data and follows with data preparation and segmentation of the transactional data into temporal periods. This is followed by the extraction of item sets and association rules for the respective period. Subsequent to this, evolutionary measures are computed for the pattern behavior comparisons of the periods. Lastly, market intelligence insights of consumer buying behavior are derived and categorized as emerging, stable, declining, or fluctuating patterns.

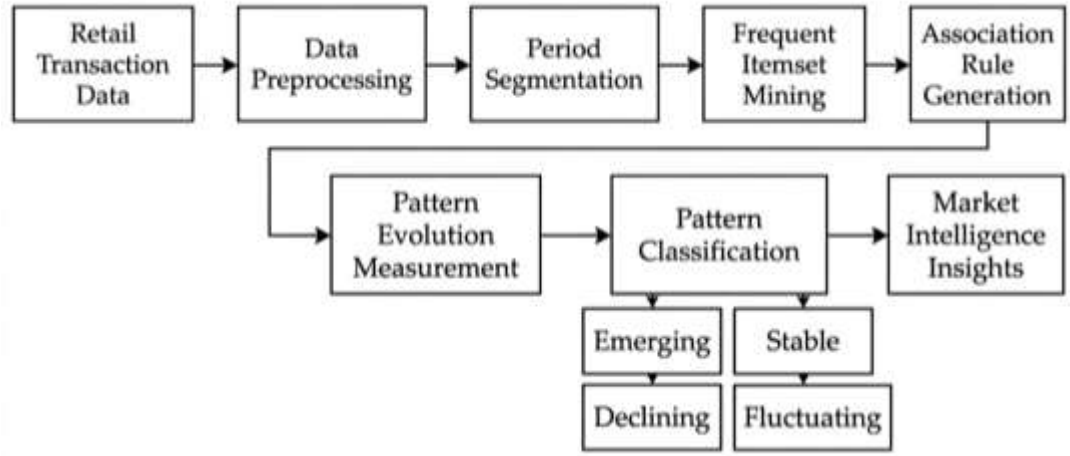

Figure 1. Evolutionary Pattern Mining Framework for Detecting Emerging Consumer Purchasing Trends.

Figure 1 illustrates how the current research understands consumer purchasing behavior differently than treating it as a single, fixed dataset. Transactional data are segmented into time periods and into shifting purchasing relationships. With this model, the analysis can evolve from a basic relational technique to complex knowledge discovery. In this case, the principal question is how knowledge changes over time, rather than how relationships are formed.

The goal of this research is to address the lack of temporal adjustment in patterns within retail analysis. Consumers are continually adjusting their purchasing behavior, and fixed associations may fail to identify emerging or disappearing preferences. The objective of this study is to describe purchasing behavior in the retail sector using dynamic evolutionary patterns. The study contributes to temporal pattern discovery in retail analytics by providing an interpretable framework for identifying changes in purchasing relationships over time.

Methodology

This study used a quantitative data-mining design to examine temporal changes in consumer purchasing behavior. The methodology seeks to advance traditional association analysis. The association analysis in this research incorporates the dimension of time and is conducted over several transaction periods. The proposed method segments retail transactions into time periods. It then extracts frequent itemsets and association rules and analyzes the patterns in relation to the time periods. The design is consistent with the study objective because it evaluates both product co-occurrence and the temporal evolution of those relationships. This study seeks to determine more than the association of products purchased together. The study also looks to achieve the product association relationships in terms of their emerging, stable, declining, and changing nature.

Research Design

This study consists of five stages: data preprocessing, period segmentation, frequent itemset mining, association rule generation, and evolutionary pattern evaluation. Raw transactional data were cleaned and transformed into basket format before pattern mining. The transactional data were divided into chronological periods to enable temporal comparison. Frequent itemsets for each period are extracted using a minimum support threshold. Association rules are formed based on confidence and lift (Segal et al., 2018). The patterns extracted from each time period are compared using the following: support variation, growth rate, confidence stability, lift change, and trend significance score.

The proposed design captures changes in consumer purchasing patterns by adding a temporal comparison layer to conventional association rule mining. Traditional association rule mining generates rules in the form of $X \rightarrow Y$, with the X itemset being the rule antecedent, while the Y itemset is the rule consequent (Zaki, 2018). In this case, rules are not analyzed in terms of their support, confidence, and lift in a single dataset. Rather, the rules are analyzed by the extent of their movement across the different periods. Therefore, depending on the behavior of the pattern over time, the same purchasing pattern can be considered to be stable, emerging, declining, or fluctuating.

The temporal comparison process used in this study is shown in Figure 2.

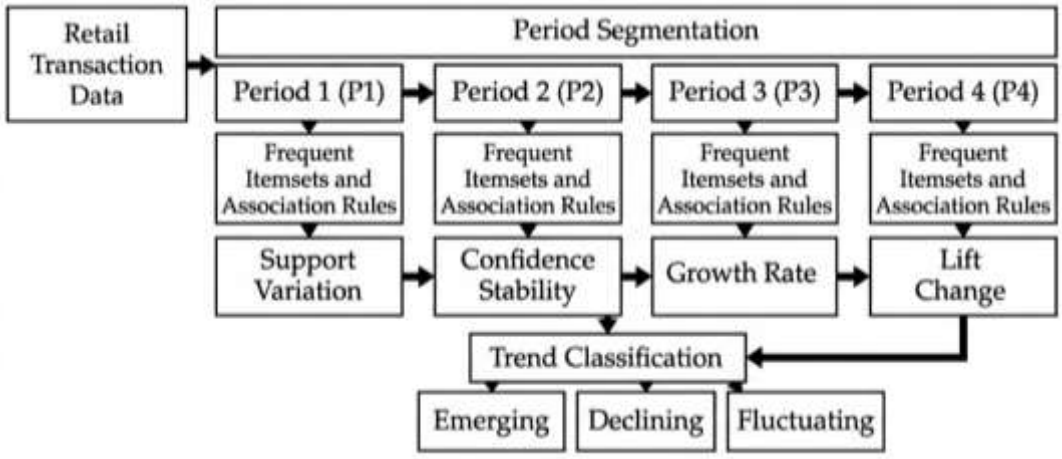

Figure 2. Temporal Pattern Comparison Process in Evolutionary Pattern Mining.

Figure 2 shows that patterns are extracted independently within each transaction period and subsequently compared across periods. With this design, the research can capture whether a purchasing pattern strengthens, weakens, newly emerges, remains stable, or fluctuates across periods. For this reason, the method that has been designed for this research goes beyond static association discovery methods and offers a more dynamic perspective on the variation in consumer buying behavior.

Dataset and Transaction Structure

This study uses a retail transaction dataset organized in basket format. Each transaction is a single purchase event, and multiple items can be included. Transaction identity, transaction date, period label, item, product category, and quantity with basket composition are some of the variables included in the dataset. These variables are utilized in association rule mining and evolutionary pattern mining (Ventura & Luna, 2016). The former analyzes the co-occurrence of items in the same transaction. The latter examines the effect of time on the placement of patterns.

Purchasing behavior was analyzed in relation to the four time periods designed in the study (P1, P2, P3, and P4). Four chronological periods were used instead of a simple before–after division to capture the direction and consistency of temporal changes. The purpose was to identify the nature of the trends within the time frames (e.g., positive, negative, or consistent).

Table 1 presents the profile of the retail transaction dataset used in this study.

Table 1. Retail Transaction Dataset Profile

Period	Time Window	Number of Transactions	Unique Items	Product Categories	Average Basket Size	Total Item Occurrences
P1	January–March 2025	2,450	118	12	3.12	7,644
P2	April–June 2025	2,610	124	12	3.28	8,561
P3	July–September 2025	2,780	131	13	3.45	9,591
P4	October–December 2025	3,060	138	13	3.63	11,108
Total	Full observation period	10,900	138	13	3.39	36,904

Ten thousand nine hundred retail transactions are grouped into 4 chronological periods, as shown in Table 1. The number of transactions in P1 is 2,450, but this number grows to 3,060 in P4, with an increasing basket size from 3.12 items to 3.63 items on average. This dataset is appropriate for evolutionary pattern mining because it has basket-level item combinations and segmentation over time for inter-period comparisons.

Data Preprocessing

In this study, several preprocessing steps were implemented to clean and standardize the retail transaction data. In order to prepare the data for the frequent itemset mining, the Transaction records were standardized to ensure consistency before frequent itemset and association-rule mining. The data preprocessing step commenced by removing transactions that were incomplete. Transactions that contained a missing Transaction ID or a missing Transaction Date were eliminated because these records could alter period segmentation and/or distort the construction of data baskets. Duplicate transactions and records that contained an invalid item description were also eliminated.

In the next step, all of the inconsistent item labels were aligned to a single name. When dealing with retail data, item labels and/or descriptions are inconsistent and require data cleaning (Mohammed, 2025). For example, the same product may be described using the phrases "fresh milk 1L," "milk 1 litre," and "Milk 1L." (LeBlanc, 2022). Without a step to align descriptions, item set analysis would treat these descriptions as distinct products.

Subsequent to the removal of all inconsistent item labels, transactions were cleaned and converted into basket format. In the basket format, a transaction is recorded as a collection of purchased items. For example, in the basket format, a transaction containing the purchase of bread, butter, and milk is recorded as {bread, butter, milk}. This format is necessary in order to facilitate the determination of item sets that were purchased together in the same transaction.

The last step in data preprocessing was to segment the transactions into temporal units. This segmentation was accomplished by allocating a transaction to one of four periods (P1 – P4) based on the transaction date. Transactions dated in Q1 (January – March) were allocated to P1; Q2 (April – June) transactions were allocated to P2; Q3 (July – September) transactions were allocated to P3; and P4 includes Q4 (October – December) transactions. Segmenting transactions in this manner allows for the analysis of purchasing behavior over the temporal units as well as the entire study period.

Frequent Itemset Mining

Frequent itemset mining was done for each observation period individually (Cafaro & Pulimeno, 2017). An itemset was considered to be frequent if its support value was at least the minimum support value. The support of an itemset X during a given period measures the coverage (i.e., the proportion) of the transactions for that period that contain itemset X. The support of itemset X in period t is defined as shown in Equation (1).

$$Support_t(X) = \frac{|\{T_i \in D_t \mid X \subseteq T_i\}|}{|D_t|} \qquad (1)$$

where D_t represents the transaction dataset in period *t*, T_i represents an individual transaction, X represents an itemset, and $|D_t|$ represents the total number of transactions in period *t*.

Frequent itemset mining was performed on P1, P2, P3, and P4, on a stand-alone basis. By mining on a per time unit basis, the study was able to understand if the frequency of an itemset has changed over time. To facilitate comparison, the same minimum support was enforced for all the periods. Itemsets that appeared in the later periods and not in the earlier periods were retained as they may represent the change in the purchasing behavior (Hlavinka, 2024).

Association Rule Generation

After frequent itemsets were extracted, association rules were generated to identify relationships between itemsets. A rule is expressed as X → Y, where X is the antecedent itemset, and Y is the consequent item (Zaki, 2018) set. The rule suggests that customers who purchase itemset X are also likely to purchase itemset Y in the same transaction.

The reliability of each association rule was measured using confidence. Confidence measures the probability that itemset Y appears in a transaction when itemset X is already present (Mandelkern & Schultz, 2000). Confidence is calculated using Equation (2).

$$Confidence_t(X \rightarrow Y) = \frac{Support_t(X \cup Y)}{Support_t(X)} \qquad (2)$$

where $Support_t(X \cup Y)$ represents the support of the combined itemset X and Y in period t, and $Support_t(X)$ represents the support of the antecedent itemset X in the same period.

The strength of association between X and Y was evaluated using lift. Lift measures whether the relationship between X and Y is stronger than random co-occurrence. Lift is calculated using Equation (3).

$$Lift_t(X \rightarrow Y) = \frac{Confidence_t(X \rightarrow Y)}{Support_t(Y)} \qquad (3)$$

A lift value greater than 1 shows that X and Y have a positive relationship. When selecting association rules, this study maintained those that not only crossed the established minimum confidence threshold, but also had a lift value that exceeded 1. These criteria ensured that retained rules represented sufficiently reliable and non-random product associations.

Evolutionary Pattern Metrics

The main methodological contribution of this study is the use of evolutionary pattern metrics to compare purchasing patterns across time. These metrics allow the study to determine whether a pattern is becoming stronger, weaker, stable, or inconsistent across periods. The selected metrics include support variation, growth rate, average growth rate, confidence stability, lift change, normalization, and trend significance score.

Support variation measures the difference between the support of a pattern in the final period and the support of the same pattern in the initial period. It is calculated using Equation (4).

$$\Delta S(X) = S_{P4}(X) - S_{P1}(X) \qquad (4)$$

where $S_{P4}(X)$ represents the support of itemset X in the final period and $S_{P1}(X)$ represents the support of itemset X in the initial period. A positive value indicates increasing frequency, while a negative value indicates decreasing frequency.

The consecutive growth rate measures the relative change of a pattern between two consecutive periods. It is calculated using Equation (5).

$$GR_t(X) = \frac{S_t(X) - S_{t-1}(X)}{max(S_{t-1}(X), \varepsilon)} \qquad (5)$$

where $S_t(X)$ represents the support of itemset X in period t, $S_{t-1}(X)$ represents the support of itemset X in the previous period, and ε is a small constant used to avoid division by zero.

The average growth rate summarizes the growth movement of a pattern across all periods. It is calculated using Equation (6).

$$\underline{GR}(X) = \frac{1}{m-1}\sum_{t=2}^{m} GR_t(X) \qquad (6)$$

where m represents the total number of periods. In this study, $m = 4$ because the dataset is divided into four chronological periods.

Confidence stability measures whether the confidence value of an association rule remains consistent across periods. It is calculated using Equation (7).

$$CS(X \rightarrow Y) = 1 - \frac{\sigma(C_1, C_2, \ldots, C_m)}{\underline{C} + \varepsilon} \qquad (7)$$

where $\sigma(C_1, C_2, \ldots, C_m)$ represents the standard deviation of confidence values across periods, $\underline{C}$ represents the mean confidence value, and ε is a small constant. A higher confidence stability value indicates that the rule remains more reliable over time.

Lift change measures whether the association strength of a rule increases or decreases from the initial period to the final period. It is calculated using Equation (8).

$$\Delta L(X \rightarrow Y) = L_{P4}(X \rightarrow Y) - L_{P1}(X \rightarrow Y) \qquad (8)$$

where L_{P4} represents the lift value in the final period and L_{P1} represents the lift value in the initial period.

Because the metrics use different scales, normalization is applied before calculating the final trend score. The normalization function is shown in Equation (9).

$$Norm(z_i) = \frac{z_i - min(z)}{max(z) - min(z) + \varepsilon} \qquad (9)$$

where z_i represents an individual metric value, $min(z)$ represents the minimum value of the metric, $max(z)$ represents the maximum value of the metric, and ε prevents division by zero.

The final trend significance score combines support variation, average growth rate, confidence stability, and lift change. It is calculated using Equation (10).

$$TSS(X \rightarrow Y) = w_1 Norm(\Delta S) + w_2 Norm(\underline{GR}) + w_3 CS + w_4 Norm(\Delta L) \qquad (10)$$

The weight values must satisfy the constraint shown in Equation (11).

$$w_1 + w_2 + w_3 + w_4 = 1 \qquad (11)$$

In this study, the trend significance score is used to rank and classify purchasing patterns. Patterns with high support variation, high average growth rate, stable confidence, and increasing lift are classified as emerging patterns. Patterns with low variation are classified as stable, while patterns with negative support variation are classified as declining. Patterns with inconsistent movement across periods are classified as fluctuating.

Table 2 presents the evolutionary pattern mining metrics used in this study.

Table 2. Evolutionary Pattern Mining Metrics with Sample Values

Metric	Equation Used	Sample Value	Interpretation
Initial support, S_P1	Support in P1	0.018	Pattern appeared in 1.8% of P1 transactions
Final support, S_P4	Support in P4	0.061	Pattern appeared in 6.1% of P4 transactions
Support variation, ΔS	S_P4 − S_P1	0.043	Positive growth from P1 to P4
Average growth rate, $G\bar{R}$	Mean growth from P1 to P4	0.57	Pattern shows strong temporal growth
Initial confidence, C_P1	Confidence in P1	0.41	Rule was moderately reliable in P1
Final confidence, C_P4	Confidence in P4	0.58	Rule became more reliable in P4
Confidence stability, CS	Stability of confidence across periods	0.86	Rule is relatively stable
Initial lift, L_P1	Lift in P1	1.12	Weak positive association in P1
Final lift, L_P4	Lift in P4	1.76	Stronger association in P4
Lift change, ΔL	L_P4 − L_P1	0.64	Association strength increased
Trend significance score, TSS	Weighted trend score	0.82	Pattern is classified as emerging

Table 2 provides an example of how the evolutionary metrics are interpreted. The sample pattern shows an increase in support from 0.018 in P1 to 0.061 in P4, producing a support variation of 0.043. The average growth rate of 0.57 and trend significance score of 0.82 indicate that the pattern can be classified as emerging. The increase in confidence and lift also suggests that the pattern is not only becoming more frequent, but also becoming more reliable and meaningful as an association rule.

Experimental Configuration

The experimental configuration defines the parameter values used in the evolutionary pattern mining process. These parameters include the number of periods, support threshold, confidence threshold, lift threshold, maximum itemset length, pattern classification thresholds,

and trend significance score weights. The configuration was designed to balance analytical sensitivity and interpretability.

Table 3 presents the experimental configuration used in this study.

Table 3. Experimental Configuration and Parameter Values

Parameter	Value Used	Purpose
Number of periods	4 periods	Enables temporal comparison
Minimum support threshold	0.02	Filters very rare itemsets
Minimum confidence threshold	0.40	Retains reliable association rules
Minimum lift threshold	> 1.00	Keeps rules stronger than random co-occurrence
Maximum itemset length	3 items	Maintains interpretability
Support variation threshold for emerging pattern	≥ 0.03	Detects meaningful support increase
Growth-rate threshold for emerging pattern	≥ 0.50	Detects rapid pattern growth
Support variation threshold for declining pattern	≤ −0.03	Detects meaningful support decrease
Support standard deviation threshold for stable pattern	≤ 0.01	Identifies consistent patterns
Growth-rate constant, ε	0.0001	Avoids division by zero
Weight for support variation, w1	0.30	Prioritizes support increase
Weight for average growth rate, w2	0.30	Prioritizes temporal growth
Weight for confidence stability, w3	0.20	Rewards reliable rules
Weight for lift change, w4	0.20	Rewards increasing association strength

Table 3 shows that the minimum support threshold was set at 0.02 to retain meaningful itemsets while excluding extremely rare combinations. The minimum confidence threshold was set at 0.40 to ensure that generated rules had acceptable reliability. The lift threshold was set above 1.00 so that only rules stronger than random co-occurrence were retained. The trend significance score gives higher weights to support variation and average growth rate because the main objective of this study is to detect emerging purchasing behavior.

Pattern Classification Procedure

After the evolutionary metrics were calculated, patterns were classified into four categories: emerging, stable, declining, and fluctuating. These categories translate numerical temporal changes into interpretable purchasing-behavior patterns.

An example of an emerging pattern would be one that has recently appeared or has shown a strong increase in support and growth rate. This type of pattern may exemplify new or changing preferences in consumers, alterations in market demand, or the effects of advertising and social and market trends A stable pattern has shown support and confidence with rank correlations ranging from 0.803 to 0.849 across time periods. Stable patterns may be indicative of the behavior a consumer utilizes when purchasing and may facilitate the planning of inventory in the future (Cristescu & Petrea, 2026). A declining pattern exhibits a sustained decrease in support or association strength across periods. Declining patterns may be a result of diminishing consumer interest or a negative effect on the relevancy of a product. A

fluctuating pattern exhibits inconsistent movement across periods without a clear upward or downward trajectory (Martone, 2025).

Table 4 presents the classification rules used in this study.

Table 4. Pattern Classification Rules

Pattern Category	Classification Rule	Interpretation
Emerging	$\Delta S \geq 0.03$ and $G\bar{R} \geq 0.50$, or pattern absent in P1 but present in two or more later periods	Product relationship is becoming increasingly important
Stable	Support standard deviation ≤ 0.01 and confidence values remain within a narrow range	Product relationship is consistent over time
Declining	$\Delta S \leq -0.03$ and support decreases across periods	Product relationship is losing relevance
Fluctuating	Support or confidence changes inconsistently without a clear upward or downward direction	Product relationship is unstable or seasonal

Table 4 outlines the criteria for each pattern category. The rules are designed to be understandable for retail decision-making. Rather than simply providing technical scores, the method categorizes each pattern into a type that managers can comprehend to support market intelligence.

Analytical Procedure

The first step of the analysis was the assignment of labels to transactions according to their respective periods. After this step was completed for each separate period (P1, P2, P3, and P4), the frequent itemset mining was performed. The itemsets were saved along with their support values (Wang, 2026). The association rules were created from the frequent itemsets within the specified thresholds of confidence and lift (Cheng & Han, 2016).

The same itemsets and association rules were matched for different periods. Whenever a pattern was observed in multiple periods, the support, confidence, and lift values were analyzed. Patterns that were found in subsequent periods were kept as well because they might represent a developing purchasing association. For itemsets, the support and growth rate were analyzed, and for associations, the confidence and lift were also analyzed.

The last step was to assign a rank and score to a pattern and then place the pattern in one of four categories (emerging, stable, declining, or fluctuating). This was done according to the rules shown in Table 4. Every pattern was assigned a score of significance regarding its trend, and this was done based on the stability of confidence and lift, as well as the average growth rate and support variation. This method was intended to reflect the final movement based on the frequency of associations and the stability of the rules.

Validity and Reliability Considerations

Several methods were employed to increase the reliability and validity of the analysis. First, the same preprocessing rules were utilized during each of the time phases to ensure that variations in the patterns were not the result of item coding inconsistencies. Second, to ensure an equitable assessment was made, the same thresholds of support, confidence, and lift were

used for all the time phases. Third, to prevent reliance on a single metric, multiple evolutionary measures were used to avoid reliance on a single indicator of temporal change. Finally, to decrease the creation of complex patterns and to improve the ability to interpret the patterns, the maximum size of the itemsets was restricted to three.

Confidence stability was used to reduce the influence of patterns whose association strength varied substantially across periods. Variation and growth of support were used to create sensitivity to change over time. Limitations in confidence fluctuations were used to ensure the persistence of patterns. Adjustments were also made to prevent patterns that were frequent, but of little consequence. The measures used also aimed to strike a balance in assessing the evolution of consumer purchasing patterns.

Ethical and Data Handling Considerations

Analyzing customers' purchasing habits on a transaction level makes personal information unnecessary. Personally identifiable information, including names, addresses, telephone numbers, payment credentials, and membership identifiers, was excluded from the analytical variables. The analysis was restricted to transaction date, purchased items, product categories, quantities, and basket composition. This approach kept the analysis focused on aggregate purchasing patterns rather than individual customer identification.

The framework outlines a systematic technique for identifying new purchasing habits using advanced pattern mining (Goel & Mallick, 2015). The technique integrates frequent itemset mining, the derivation of association rules, temporal analysis, and pattern categorization. With this technique, purchasing habits are viewed as a dynamic structure. This framework describes the methodology relevant to the section that follows, where the purchasing habits and the trend categories that result from those habits are discussed.

Results and Discussion

An overview of the outcomes of the evolutionary pattern mining process and their implications for consumer purchasing patterns is provided in this section. This analysis was conducted over four time segments, labeled P1, P2, P3, and P4. For every time segment, frequent itemsets and association rules were identified, and their temporal movements were examined using support variation, average growth rate, confidence stability, lift change, and trend significance score (Wang et al., 2018). The analysis focuses on the three outputs of the analysis: the period-level mining outcomes, the shifting frequent item sets, and the trend-based association rule classification.

Period-Level Pattern Mining Results

The initial level of assessment focused on the quantity of frequent item sets and association rules in every observation period. This was imperative to determine the extent of the changes to the nature of purchasing behavior over the study period. A greater number of frequent item sets indicates that a greater number of combinations of items have crossed the minimum support threshold. Meanwhile, a greater number of association rules indicates that a greater number of product relationships have crossed the thresholds of confidence and lift.
Table 5 presents the period-level results of frequent itemset mining and association rule generation.

Table 5. Period-Level Frequent Itemset and Association Rule Results

Period	Number of Transactions	Frequent 1-Itemsets	Frequent 2-Itemsets	Frequent 3-Itemsets	Total Frequent Itemsets	Valid Association Rules
P1	2,450	46	72	28	146	94
P2	2,610	51	84	35	170	116
P3	2,780	56	97	43	196	139
P4	3,060	62	118	56	236	178

According to Table 5, frequent itemsets rose from 146 in P1 to 236 in P4, and valid association rules increased from 94 to 178. These results suggest that a broader range of item combinations exceeded the predefined mining thresholds during the later observation periods (Subramanyam, 2023). The increase in frequent 2-itemsets and 3-itemsets indicates that a larger number of multi-item combinations satisfied the minimum support criterion in the later periods. This creates a more flexible model of purchasing behavior from an evolutionary pattern mining perspective, because purchasing behavior did not remain constant over the observation period.

In later stages, more valid association rules indicate that the relationships among products that were purchased became more apparent. This finding indicates that from a consumer analytics perspective, the later periods contained a greater number of detectable product associations, indicating changes in co-purchasing structure across the observation period. If a static analysis of the full dataset were applied, all of these period-specific alterations would be concealed by aggregation of all the transactions into a single dataset.

Evolution of Frequent Purchasing Itemsets

After the period-level mining results were achieved, specific itemsets were analyzed whose support values changed across P1, P2, P3, and P4. The focus of this review was to identify product combinations that increased, were stable, decreased, or changed over time. This was primarily to investigate whether the shifts in customer preferences were time-based.

Table 6 presents examples of frequent itemsets and their support values across the four periods.

Table 6. Support Movement of Selected Frequent Itemsets Across Periods

Itemset	S_{p1}	S_{p2}	S_{p3}	S_{p4}	ΔS	$G\bar{R}$	Trend Category
{organic tea, almond milk}	0.018	0.027	0.044	0.061	0.043	0.57	Emerging
{whole wheat bread, peanut butter}	0.024	0.032	0.046	0.058	0.034	0.42	Emerging
{bread, butter}	0.072	0.070	0.074	0.071	-0.001	-0.00	Stable
{rice, cooking oil}	0.081	0.083	0.080	0.082	0.001	0.01	Stable
{instant noodles, soft drink}	0.068	0.055	0.043	0.031	-0.037	-0.22	Declining
{sugary cereal, chocolate drink}	0.052	0.046	0.037	0.029	-0.023	-0.17	Declining

Itemset	S_{p1}	S_{p2}	S_{p3}	S_{p4}	ΔS	$G\bar{R}$	Trend Category
{coffee, sweet snack}	0.041	0.058	0.039	0.052	0.011	0.13	Fluctuating
{detergent, fabric softener}	0.037	0.029	0.044	0.036	-0.001	0.04	Fluctuating

Table 6 indicates different paths of evolution for different itemsets. The itemset {organic tea, almond milk} increased from 0.018 in P1 to 0.061 in P4, and therefore had a support variation of 0.043. This constitutes an emerging trend. A rise in support from 0.024 to 0.058 was also noted for {whole wheat bread, peanut butter}. The increases suggest stronger co-purchasing of the health- and lifestyle-oriented product combinations represented by these itemsets.

Itemsets {bread, butter} and {rice, cooking oil}, however, were stable across all periods and likely represent basic or routine purchasing itemsets. Their support value was stable and, consequently, their itemsets are reliable, but likely not emerging. While stable itemsets are not likely to indicate new trends, they do help in planning stock and shelf management for the items that are expected to be purchased consistently.

The co-purchase itemset {instant noodles, soft drink} decreased from P1 to P4 and from 0.068 to 0.031 and, thus, this purchase itemset has decreased support. A similar trend was noted for the itemset {sugary cereal, chocolate drink}, support of which decreased from 0.052 to 0.029. All of these support declines represent a likely trend of decreasing support for these products and these decreases may reflect changing purchasing preferences or substitution toward alternative product combinations; however, the transactional data alone do not establish the underlying cause.

Fluctuations are also trends in these itemsets. An example is the itemset {coffee, sweet snack, which increased in P2, decreased in P3, and increased again in P4} and represents an irregular trend or a temporary trend and, therefore, is not reliable for assuming an emerging trend.

Association Rule Results Across Periods

The following level of analysis looked at the association rules from the frequent itemsets. Itemset support shows the co-occurrences of product purchases; association rules, however, show the direction of product purchase. This is relevant to analyze whether the purchase of an itemset increases the probability of purchase of another itemset in the same transaction.

Table 7 presents selected association rules and their evolutionary metrics.

Table 7. Evolutionary Association Rule Results

Association Rule	C_{p1}	C_{p4}	L_{p1}	L_{p4}	ΔS	CS	ΔL	TSS	Category
Organic tea → Almond milk	0.41	0.58	1.12	1.76	0.043	0.86	0.64	0.82	Emerging
Whole wheat bread → Peanut butter	0.44	0.56	1.18	1.61	0.034	0.84	0.43	0.76	Emerging
Greek yogurt → Granola	0.39	0.52	1.09	1.48	0.031	0.81	0.39	0.71	Emerging

Association Rule	C_{p1}	C_{p4}	L_{p1}	L_{p4}	ΔS	CS	ΔL	TSS	Category
Bread → Butter	0.63	0.62	1.54	1.51	-0.001	0.95	-0.03	0.44	Stable
Rice → Cooking oil	0.67	0.66	1.63	1.60	0.001	0.96	-0.03	0.46	Stable
Instant noodles → Soft drink	0.57	0.39	1.43	1.08	-0.037	0.72	-0.35	0.21	Declining
Sugary cereal → Chocolate drink	0.51	0.36	1.31	1.04	-0.023	0.74	-0.27	0.26	Declining
Coffee → Sweet snack	0.49	0.51	1.22	1.29	0.011	0.68	0.07	0.49	Fluctuating

According to Table 7, the most notable emerging association rule was Organic Tea → Almond Milk, evidenced by a trend significance score of 0.82. For P1, the rule's confidence was quantified at 0.41, and in P4, the confidence was 0.58, with the rule's lift increasing from 1.12 to 1.76. The concurrent increases in confidence and lift indicate that the association became both more reliable and stronger during the later periods (Datta & Mali, 2022).

Within the same association, the rules Whole Wheat Bread → Peanut Butter and Greek Yogurt → Granola also emerged. In the context of this specific research, the rules denote the increasing association and the values of confidence and lift. This indicates that during the observation period, there was a greater tendency for health-related and breakfast-oriented purchasing. Within the observed dataset, these patterns suggest increasing co-purchasing among health- and breakfast-oriented product combinations.

The rules Bread → Butter and Rice → Cooking oil had high confidence stability of 0.95 and 0.96, and were considered stable rules. Although these rules were not growing in strong relative importance, their consistency is of great significance for operational planning. The stability of rules aids in determining base levels of stock.

Rules like Instant noodles → Soft drink and Sugary cereal → Chocolate drink showed decreasing confidence and lift values. This indicates that customers had a declining tendency to buy the products together. From a retail strategy perspective, the apparent declining trend may point to a need for investigation, as it may highlight declining interest, reduced effectiveness of promotions, or customers choosing other competing products.

The rule Coffee → Sweet snack was classified as fluctuating because the confidence and support values of the rule did not change in a consistent manner. Although the final confidence value was higher than the initial value, the changes across the periods were inconsistent. The fluctuation may be associated with temporal factors such as seasonality, temporary promotions, pricing changes, or product placement, although these factors were not directly measured in the present dataset.

Trend Classification Summary

To analyze the mining results, the identified patterns were placed into four categories based on the identified trends. This was done based on the rules defined in the methodology section. This summary allows for the identification of the dataset as either emerging, stable, declining, or fluctuating patterns of purchasing.
Table 8 presents the overall trend classification results.

Table 8. Summary of Pattern Classification Results

Pattern Category	Number of Itemsets	Number of Association Rules	Average ΔS	Average CS	Average TSS	Main Interpretation
Emerging	42	36	0.038	0.83	0.74	New or strengthening purchasing relationships
Stable	58	49	0.002	0.94	0.45	Consistent routine purchasing behavior
Declining	31	27	-0.029	0.76	0.24	Weakening product relationships
Fluctuating	65	38	0.006	0.69	0.47	Irregular or seasonal purchasing behavior
Total	196	150	-	-	-	Complete classified pattern set

Table 8 indicates that most itemsets and patterns were classified as stable or fluctuating, with variable patterns classified as emerging itemsets and patterns. Although emerging itemsets and patterns are a smaller category, they are of strategic importance. The 42 emerging itemsets and 36 emerging association rules indicate the new or changing consumer preferences. Within the patterns and rules analyzed, although emerging association rules were fewer than stable association rules, emerging patterns achieved the highest average trend significance score of 0.74, indicating the strongest upward temporal movement among the four categories.

Of association rules classified as stable patterns, patterns (or associations) classified as stable patterns produced the highest average confidence stability with CS = 0.94. Declining patterns recorded the lowest average trend significance score (TSS = 0.24), while fluctuating patterns had an average TSS of 0.47. The patterns fluctuating over time are of moderate importance. Stable association patterns achieved the highest average confidence stability (CS = 0.94), indicating that their product relationships remained comparatively consistent across the observation periods.

Visualization of Pattern Evolution

The trend categories are further illustrated in Figure 3. The figure compares the support movement of selected emerging, stable, declining, and fluctuating patterns across the four periods.

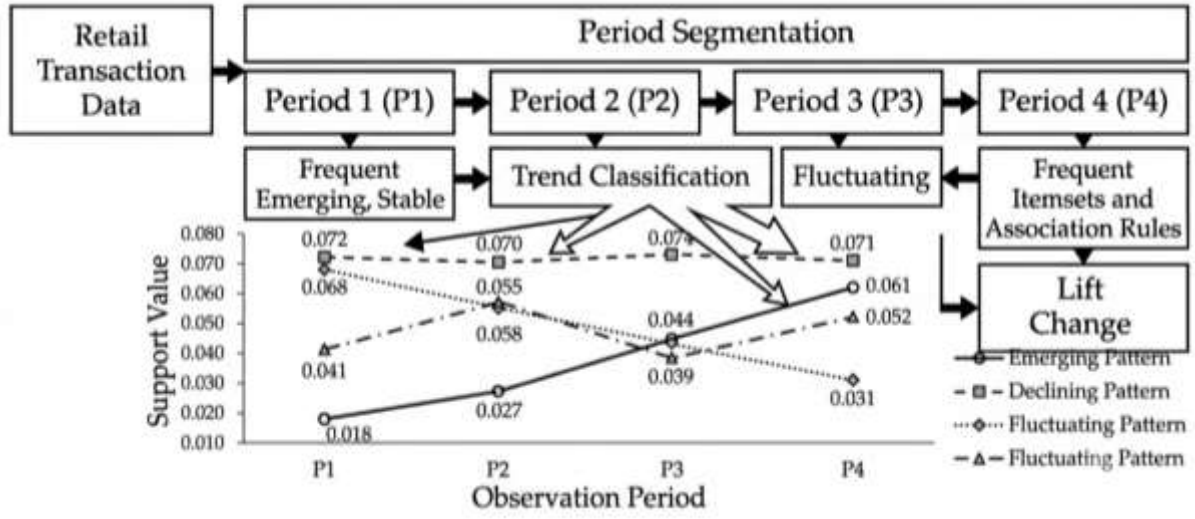

Figure 3. Support Movement of Emerging, Stable, Declining, and Fluctuating Purchasing Patterns.

Four different forms of pattern movement are illustrated in Figure 3. An emerging pattern is shown with consistent upward movement, indicating that the itemset became more frequent during the observation period. A stable pattern shows relatively consistent support across the observation periods. A declining pattern shows a progressive reduction in support across the observation periods. Finally, a fluctuating pattern exhibits irregular increases and decreases across periods, which may reflect temporary or seasonal variation.

This portion of the study is descriptive. If only static association mining was used to analyze the data, these different patterns would have remained mostly unobserved. Static mining would show that all the patterns were frequent, but would not show whether the patterns were increasing, decreasing, or stable or unstable. Therefore, the evolutionary approach provides additional temporal information that is unavailable from a purely static association analysis.

Discussion of Emerging Purchasing Patterns

The emerging patterns were mostly combinations of products that are healthier and more lifestyle-related. For example, support, confidence, and lift of Organic tea → Almond milk, and Whole wheat bread → Peanut butter showed a considerable increase. This pattern indicates that customers tend to buy more products related to healthier, breakfast-related, and more dietary alternative consumption.

From a customer behavior perspective, the emerging patterns can be more important than the rest, as the patterns can indicate upcoming changes to the market for the first time (Erol & Azabağaoğlu, 2023). Changes to the market can be influenced by changes to product combinations, consumption of more related products, and changes to the seller's future stock. For example, if customers tend to buy Organic tea and Almond milk together more, the products may be placed next to each other on the store shelf, or sold together to customers in a more bundled way, or the product may be suggested more often to customers.

The emerging patterns achieved relatively high trend significance scores because they combined increasing support with stronger confidence and lift across the observation periods. Stable purchasing patterns represent product relationships that remain relatively consistent over time.

Discussion of Stable Purchasing Patterns

Bread and Butter, rice, and cooking oil are examples of stable patterns — consistent buying behavior. They may not have positive growing trends, but they show high positive confidence stability. Stable buying patterns create strong positive relationships. Retailers can utilize the information by keeping stock and designing shelf layouts.

The value of stable patterns can't be overlooked. Though growing patterns can help with opportunities, stable patterns can help with operations. Building relationships with stable patterns can help with layout and stock. A good example is the stable co-purchasing behavior of bread and butter.

The stable rules with positive confidence stability were the strongest patterns. This indicates that in spite of altering conditions in the market, some consumer habits remain stable when purchasing (Kostynets & Kostynets, 2023). Evolutionary pattern mining therefore captures both changing purchasing relationships and persistent co-purchase patterns.

Discussion of Declining Purchasing Patterns

Declining patterns can be represented in itemsets and rules such as Instant Noodles → Soft Drink and Sugary Cereal → Chocolate Drink. In these examples, during P1 to P4, support, confidence, and lift exhibited decreasing values. This shows how customers became less likely to buy these items together.

Declining patterns have great value. They may indicate a shifting preference by consumers, which may signal to retailers that a product bundle may no longer be useful (Pv & Thakur, 2025). A decline in support may even indicate that consumers are no longer buying the products (impulse buying) and/or are buying healthy products instead of those that are unhealthy (Awuh, 2024). Price changes or availability of the products may have even affected consumer buying behavior.

Declining patterns warrant further investigation because decreasing support or association strength does not, by itself, identify the underlying cause of the decline. If the product visibility or promotion of the products declines, retailers can improve marketing for the products. If the decline is due to a shift in consumer preference, retailers can diminish the inventory for the combination and replace it with a combination that may be preferred by consumers.

Discussion of Fluctuating Purchasing Patterns

Patterns that are inconsistent (e.g., Coffee → Sweet Snack; Detergent → Fabric Softener) do not demonstrate a clear operational trend. Instead, these patterns might experience a variation in support value (i.e., sometimes increase, sometimes decrease). The variation in support value might be the result of demand and supply that is seasonal, the (temporary) changing of prices, a customer promotion, and customer needs that may be of a more transitory nature (Yi, 2024).

Patterns that are inconsistent but fluctuate do require more emphasis and careful consideration because support and demand that may be of more relative importance in one time period may become more negligible in another time frame. A more careful consideration of a single period may also lead to interpretation of declining patterns or those that are emerging and evolving. An approach of considering more than one time frame or period reduces the likelihood of this outcome.

While inconsistent patterns that are fluctuating do tend to be more of a concern than patterns that are habitual, these patterns may still be useful for more time-sensitive planning. By incorporating, for example, a stipulation that coffee and sweet snacks may be offered more during certain times, retailers may consider seasonal offers or themed, time-bound promotions and special offers. These patterns should, however, be more likely to serve as examples of time-bound consideration than constraints for a more permanent strategy.

Comparison with Static Association Analysis

Results show that compared to static association analysis, evolutionary pattern mining shows the dynamics of product relationships in more detail (Xia & Ma, 2025). Traditional static association analysis is limited to listing frequently associated products without describing the change dynamics. In contrast to that, this approach shows whether product relationships are strengthening, weakening, stable, or inconsistent.

As a case in point, the static analysis may show that Bread → Butter and Organic tea → Almond milk are valid association rules. However, the evolutionary analysis says that Bread → Butter is a stable rule, while Organic tea → Almond milk is an emerging rule. This is an important difference, since the routine Bread → Butter relationship supports a regular planning of the inventory, while the Organic tea → Almond milk relationship may represent the discovery of a new market opportunity.

In the same sense, static analysis may describe a declining rule if the rule is sustained (even if weak). However, the evolutionary approach illustrates that, even if minimally supported, the rule is losing relevance. This approach is more useful in a dynamic retail environment.

Practical Implications

The results have many implications for retail systems. First, emerging patterns can enhance market analysis by discovering product combinations that customers are beginning to purchase. Retail systems can implement this by designing product bundles, promotions, and purchase recommendations.

Second, consistent patterns can enhance product shelf and inventory management. Products that customers purchase together tend to require consistent stocking and placement to improve the shopping experience. Consistent rules can also be used to manage product bundles.

Third, decreasing patterns can be used to manage product relationships that are decreasing in strength. These types of patterns can describe the decreasing effectiveness of a promotion and decreasing customer interest. Retail systems can adapt this by changing the placement of the products and removing the bundles that do not fulfill customer interests, as well as researching the cause of the decreasing customer interest.

Finally, variable patterns can be used to plan for promotions and events that are seasonal in nature. Because variable patterns lack the ability to plan for long periods, they are most useful for shorter-duration promotional activities.

Collectively, these results showcase the ability of evolutionary pattern systems for adaptive retail analysis. By differentiating customer product relationships into trend categories, the pattern system shifts the focus from product juxtaposition to the spatiotemporal engagement of the market.

Theoretical Contribution

This study's contribution to theory is to follow the evolution of temporal patterns beyond association analysis. In classic association rule mining, the analysis is largely confined to the frequency and reliability of itemsets and rules. This study includes the evolution of itemsets and rules and how they shift over different time periods.

The study measures the evolution of patterns using support variation, the average growth rate, confidence stability, lift change, and trend significance (Antonellis et al., 2009). Contribution to temporal knowledge discovery is made when these methods are applied to dynamic patterns of consumer behavior. The categorization of patterns into emerging, stable, and declining, as well as fluctuating patterns, is a significant contribution to interpretability because it relates the outcomes of the mining process to the behaviors that these patterns signify.

Summary of Results and Discussion

Results show that consumer buying behavior changed in the different observation periods. More recurrent item sets were observed in the 4th observation period (236) compared to the first period (146). Similarly, valid association rules grew from (94) in the first observation period to (178) in the 4th. This suggests that, in the later periods, buying behavior was more complex and relationships of the purchased products were clearer.

Conclusion

This research developed an evolutionary pattern mining framework to analyze new trends in consumer buying behavior. The aim was to advance the traditional association analysis by adding a temporal dimension to inter-transactional epoch comparison. Rather than considering retail transaction data as static, this approach advanced a methodological partition of the data into four chronological segments, extraction of frequent itemsets and association rules for each segment, and the analysis of the dataset's evolutionary behavior by applying support variation, average growth rate, confidence stability, lift variation, trend significance score, and other related measures.

The findings demonstrated that purchasing patterns changed across the four observation periods. The number of frequent itemsets in P1 was 146, while in P4 it was 236. The number of valid association rules in P1 was 94, while in P4 it was 178. This increase indicates that a larger number of product combinations and association rules satisfied the predefined mining thresholds in the later periods (Amolochitis, 2022). The evolutionary analysis also demonstrated several emerging associations, which were: **Organic tea → Almond milk; Whole wheat bread → Peanut butter; Greek yogurt → Granola**. This association showed growing support, confidence, and lift, indicating that these product associations strengthened across the observation periods.

The study identified stable, declining, and fluctuating patterns. For example, **Bread → Butter and Rice → Cooking oil** are instances of stable patterns that are likely beneficial for managing inventory and shelf space in the long run. Instant Noodles → Soft Drink and Sugary Cereal → Chocolate Drink are examples of declining patterns that showed decreasing strength and support and therefore indicate that the relationships among the products are weakening (Hughes et al., 2026). Coffee → Sweet Snack is an example of a fluctuating pattern that indicated variable movement and is likely the result of seasonal, short-lived demand, promotions, or adjustments to consumer behavior that are temporary.

The results show that compared to static association rule mining, evolutionary pattern mining provides additional insight into the temporal direction and stability of product relationships. Static association analyses can determine frequent associations of products, but they are unable to show the dynamics of the relationships over time, such as their strengthening, weakening, stability, or inconsistency. The Proposed framework extends the utility of evolutionary pattern mining by classifying patterns of product purchase behavior as emerging, stable, declining, and fluctuating (Xiao et al., 2026). This framework also provides a useful method for integrating market intelligence in the planning of product promotions, product bundles, personalized recommendations, and inventory.

Another important contribution of this study is that it focuses on the evolution of patterns rather than the static relationships of products. The framework of this study uses support variation, growth rate, confidence and lift stability, and trend significance. Using this framework, purchasing patterns can be evaluated through both quantitative temporal metrics and interpretable trend categories. Consumer preferences are dynamic, and this contribution addresses an important gap in product development research: the need for a method that provides a timely and flexible way of integrating consumer preferences into product improvement planning (Subagyo et al., 2024).

This research adds value, but it does have limitations. First, the results rely on particular segmentations of the time period. Weekly, monthly, or seasonally segmented analyses, for instance, will likely identify different movement patterns. Second, the patterns that emerge are dependent on the minimum support and confidence thresholds. Patterns with low support and confidence will be more numerous, but will likely result in more meaningless patterns, while higher thresholds will likely reduce the noise, but will eliminate many of the relevant patterns. Third, the focus of the analysis is on transactional data and does not account for many variables that may impact purchasing behavior, such as promotions and pricing, as well as customer data and competitor data. These issues should be included in subsequent studies.

This framework can be advanced by future research in many different ways. The first way this research can advance is by applying this framework to the continual analysis of transactional patterns in order to monitor continuously evolving trends. Second, this framework can be advanced by including customer segmentation to analyze patterns that emerge for different customer segments. Third, the context can be improved by including pricing, promotions, and availability in analysis, as well as patterns of seasonality. Finally, this research can be advanced by combining forecasting and predictive modeling with pattern mining to predict patterns of purchasing behavior trends that will be prevalent.

This evolutionary pattern mining framework has contributed to the field by showing how the analysis of temporal data can be applied to interpret consumer purchasing behavior. This framework is an improvement on the stagnant outputs generated by association rules, as it provides information for the varying degrees of relationships of purchasing behavior. The framework contributes to temporal knowledge discovery by integrating association-rule metrics with explicit pattern-evolution categories. Data-driven decisions for retail management and operations will also benefit from this research (Jadhav et al., 2023).

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