

# Scalable and Interpretable Agentic AI Recommendation Framework for Big Data Online Product Recommendation

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**Abstract**—Deep learning recommenders suffer from black-box opacity and struggle with heterogeneous, incomplete multi-criteria data. Current Agentic AI systems lack symbolic reasoning for verifiable decisions. We propose a Scalable Agentic Recommendation Framework (ARF) integrating Rough Set Theory (RST) with Analytic Hierarchy Process (AHP) and Association Rule Mining (ARM). Our event-driven agent architecture embeds symbolic rules for real-time reasoning and autonomous adaptation. A two-stage algorithm processes nominal, ordinal, and ratio data without forced discretization. Validated via consumer simulations, our approach reduces inference latency by 86% and rule-matching cost by 95% while maintaining interpretability. This bridges symbolic AI and agentic systems for big data e-commerce.

**Index Terms**—Rough set theory, association rules, multi-criteria data mining, agentic AI, scalable recommendation systems, e-commerce analytics.

## I. INTRODUCTION

THE paradigm of AI is shifting from passive models to Agentic AI – systems capable of autonomous perception, planning and execution in dynamic environments [1], [2]. In big-data e-commerce, recommendation systems must not only predict accurately but also explain why a recommendation is made, adapt in real time, and manage multi-step user journeys. However, state-of-the-art deep learning (Transformers, GNNs) acts as black boxes, lacking interpretability for high-stakes decisions [3]. Moreover, they struggle with data incompleteness and mixed scales (nominal, ordinal, ratio).

Research issues – current Agentic AI frameworks lack mathematically grounded mechanisms for handling uncertain multi-criteria data while remaining interpretable. Existing rule-based systems are static, cannot scale, or lack proactive planning.

Contributions – we propose a Scalable Agentic Recommendation Framework (ARF) with:

Architectural innovation: event-driven, microservices-based orchestrator that dynamically uses rough-set rules.

This work was supported by the National Science and Technology Council, Taiwan, Republic of China. (NSTC 115-2410-H-032-057)

Methodological rigor: two-stage mining integrating AHP, rough set reduction, and association rules for mixed-scale data.

Scalability & efficiency: 86% lower latency, 95% faster rule matching via caching and incremental learning.

Interpretability: verifiable reasoning trace for every agent's action.

## II. RELATED WORK

### A. Multi-criteria and multi-dimensional data

Recommendation systems increasingly use both multiple evaluation criteria (price, quality, convenience) and multiple dimensions (demographics, behavior, context) [7]–[10]. Their combination creates exponential complexity, which we address via rough set reduction.

### B. Rough set theory (RST)

Introduced by Pawlak [11], RST handles uncertainty without prior assumptions. It uses lower/upper approximations to deal with incomplete information. Recent works show RST's utility for feature selection (40-60% dimension reduction) [12,13] and rule extraction [14], and it directly processes mixed data types [15,16].

### C. Association rule mining (ARM)

Discovers co-occurrence patterns [17]. Quantitative ARM [19] and multi-level rules [20] exist, but standard methods struggle with ordinal/ratio scales where relative ordering matters – a limitation we overcome by integrating RST [21].

### D. Integration of RST with ARM

A promising but underexplored direction. Rough sets can pre-process (attribute reduction) or filter low-quality rules. Our two-stage framework uses RST indiscernibility to identify core attributes, then generates ARM rules from the reduced space [22].

### E. Online platform and product recommendations

Research focuses on consumer decision mechanisms, causality, explainability and fairness. Our work provides both interpretability and strategic insight of the first word.

### III. MATH

#### A. Rough set theory (RST) – Building multi-criteria data-pair comparison model.

The rough set theory originated from Z. Pawlak's [12]. This boundary region is defined as the difference set between the upper approximations of a set and the lower approximation of a set; in other words, the most important concept is a rough space. A rough space is a method of classification, grouping sets with similar characteristics or attributes into the same category. The fundamental assumption of RST is knowledge, which is considered a classification ability, this is the concept of rough space. The upper approximation set represents the set of descriptive values that definitively belong to the target group, while the lower approximation set represents the set of descriptive values that may belong to the target group. The information system in RST can be represented by a quadruple:  $S = \{U, P, V, f\}$ . Where  $U$  is a universe of discourse, also known as a non-empty set or universal set, representing all object records in the database;  $P$  represents all attributes in the database, a non-empty finite set;  $V$  represents the range of attribute  $p$ , the set of attribute values; and  $f$  is the information function between the object record and the attribute, where the value of  $f(x, p)$  determines the value of record  $p$  with respect to attribute  $x$ . Typically,  $S = \{U, P, V, f\}$  can be abbreviated as  $S = (U, P)$ . From  $S = \{U, P, V, f\}$ , the universe of discourse can be partitioned based on any attribute or set of attributes. Any attribute or set of attributes on  $P$  can be considered an equivalent relation on  $U$ . The set of all equivalence classes of attribute  $P$  is called basic knowledge, and the corresponding set of equivalence classes is called basic concepts.  $f$  specifies the attribute of each object in  $U$ . Each information system is viewed as a data table, with each column representing an object and each row displaying various attributes. An information system is often represented as a data table, where rows correspond to objects, columns to attributes, and table entries are attribute values.

Information system  $IS = (U, P)$ , where  $U$  represents a finite set of objects and  $P$  represents an attribute set;  $f_p : \{U \rightarrow V_p, \forall p \in P\}$ , where  $V_p$  represents attribute values.

Definition 2: Lower and upper approximations

The lower attribute set  $\underline{B}X$  and as  $\overline{B}X$  in the upper attribute set (Formula 1 and 2).

$$\underline{B}X = \{x_i \in U \mid [x_i]_{IND(B)} \subseteq X\} \quad (1)$$

$$\overline{B}X = \{x_i \in U \mid [x_i]_{IND(B)} \cap X \neq \emptyset\} \quad (2)$$

Definition 3: Accuracy of approximation

If there exists an  $X$  in  $B$  such that  $B$  is contained in or equal to the attribute set, then the exact value of  $X$  represents as Formula 3.

$$\mu_B(x) = card(\underline{B}X) / card(\overline{B}X) \quad (3)$$

Definition 5: Independence of attributes

If  $IND(P) = IND(P - p_i)$ , then  $p_i$  is unnecessary; we say that  $p_i$  is an independent property in  $P$ .

Definition 6: Core and reduct of attributes

If we remove the independent attribute from the information system, reducing it to the smallest possible subset of attributes, then this smallest possible subset is called the reduct attribute. Among multiple sets of reduct attributes, the attribute that is absolutely indispensable is called the core attribute.

Definition 7: Classification

Suppose that  $F = \{x_1, x_2, \dots, x_n\}$ ,  $x_i \subset U$  is a subset of the universal set  $U$ , and  $F$  satisfies the following conditions  $X_i \cap X_j = \emptyset$  and  $\cup X_i = U, i = 1, 2, \dots, n$ , then  $F$  is called a classification of  $U$ , and  $F$  is called a class (Formula 4 to 7).

$$\underline{B}(F) = \{\underline{B}(X_1), \underline{B}(X_2) \dots \underline{B}(X_n)\} \quad (4)$$

$$\overline{B}(F) = \{\overline{B}(X_1), \overline{B}(X_2) \dots \overline{B}(X_n)\} \quad (5)$$

$$\eta_B^F = \cup card(\underline{B}(X_i)) / card(U) \quad (6)$$

$$\beta_B^F = \cup card(\underline{B}(X_i)) / \cup card(U) \quad (7)$$

Definition 8: Decision table

When an information system (IS) table contains attribute  $A$  and decision variables  $D$ , we call it a decision table.

Definition 9: D-superfluous attributes

If attribute  $p_i \in B, B \subseteq P$  is D-redundant, and  $POS(B - a_i)(D)$ , then  $p_i$  is called D-redundant attribute.

Definition 10: Decision rules

Decision rules can be represented as:  $p_{k_i} \Rightarrow d_j$  means that attribute  $a_{k_i}$  has value  $i$ , and the symbol  $d$  means propositional implication, and  $d_j$  means decision variable  $d$  has value  $j$ .

#### B. Rough set association rules – Mining multi-criteria, multi-dimensional data association rules

First-stage algorithm: multi-criteria data processing

Step 1: Establish an information system

This study first transforms questionnaire data into an information system format that can be used based on rough set theory. Information function is corresponding value of the attribute.

Step 2: Explore similar association

Finding similarities between sorted data in an information system, that is, classifying data according to a specific domain, when describing the similarities between objects, it represents as, the set of attribute relationships can be represented as on Formula 8.

$$\frac{U}{A} = \{[x_i]_A \mid x_i \in U\} \quad (8)$$

Step 3: Explore core attributes

Because information system data is ordered data, there must be an order relationship between attributes. It represents the result of pairwise comparisons of the domain values of ordinal attributes, and the relevant definitions are as follows (Formula 9):

$$D_a^+ = \left\{ x_i \mid \frac{U}{a}, V_{a_i} > V_{a_j} \right\} \quad D_a^- = \left\{ x_i \mid \frac{U}{a}, V_{a_i} < V_{a_j} \right\} \quad (9)$$

Next, using the concept of unidentifiable relations in the foundation of rough set theory, the value ranges of ordered

data are compared one by one, two by two, and so on, and ordered data with related value ranges are represented by  $B$ . Where  $B$  is a subset of  $A$ . In unidentifiable relations, ordinal data with associations value ranges are the core attributes of the first stage (Formula 10).

$$ind(B) = [f_a]_{B \subseteq A} = \bigcap_{B \subseteq A} \left[ \frac{U}{a} \right] \quad (10)$$

Second-stage algorithm: Generation of rough set association rules (nominal, ordinal and ration scale data procession)

Step 1: Explore similar relationships

Finding similarities between data in a decision data table, that is, classifying according to a specific domain, the set of attribute relationships can be represented by the combination of all general attributes (Formula 11).

$$R(g_i) = \frac{U}{G} = \{[x_i]_G | x_i \in U\} \quad (11)$$

Step 2: Explore attribute reduction and core attributes

Based on the similar relationships found in step two, we then use these relationships to establish attribute reduction and core attributes. In other words, based on the set of similarity relationships, we can further discuss the core attribute (Formula 12).

$$ind(B) = [f_g]_{B \subseteq G} = \bigcap_{B \subseteq G} \left[ \frac{U}{g} \right] \quad (12)$$

Step 4: The relationship between the upper and lower bounds

We further utilize the approximation relationship between the upper and lower bounds to explore situations where the relationships are unidentifiable (Formula 13-15).

$$\underline{G}(X) = \bigcup \left\{ [x_i]_G \in \frac{U}{G} \mid [x_i]_G \subseteq X \right\} \quad (13)$$

$$\overline{G}(X) = \bigcup \left\{ [x_i]_G \subseteq \frac{U}{G} \mid [x_i]_G \cap X \neq \emptyset \right\} \quad (14)$$

$$Bn_G(X) = \overline{G}(X) - \underline{G}(X) \quad (15)$$

Step 5: Calculate support and confidence value

Finally, the concepts of support and confidence are calculated using the traditional association rule, replacing the accuracy rate commonly used in rough set theory. The relevant formulas are as follows (Formula 16 to 18):

Support:

$$Sup(ind(B)) = \left| \left\{ ind(B) \mid \underline{G}(X) \subseteq \overline{G}(X) \right\} \right| = \left| \frac{ind(B) \mid \underline{G}(X)}{\overline{G}(X)} \right| \quad (16)$$

Step Six: Decision rules (Formula 17-18)

$$\frac{\{x_1\}}{g_1 g_3} : g_{1_1} \cap g_{3_1} \Rightarrow d_{a_5}^1 = 3 \quad (17)$$

$$\frac{\{x_1\}}{g_1 g_2 g_3 g_4} : g_{1_1} \cap g_{2_1} \cap g_{3_1} \cap g_{4_1} \Rightarrow d_{a_5}^1 = 3 \quad (18)$$

#### IV. SCALABLE AGENTIC AI RECOMMENDATION FRAMEWORK

##### A. For system architecture development

This research adopts an event-driven, microservices architecture, with the Agentic Orchestrator as the core, dynamically scheduling specialized agents based on real-time context. Dynamic adaptability: Unlike static rule engines, this architecture dynamically assembles AI agent teams based on real-time context and user state. Explainability: Every recommendation decision traces back to specific rough set and association rules, enabling business personnel to understand and adjust strategies. Self-evolution: Real-time feedback loops continuously adjust rule weights and agent behavior strategies to adapt to rapidly changing social e-commerce trends. This architecture transforms static data mining insights into real-time, actionable intelligent agent systems, forming a foundation for next-generation agentic AI-powered social commerce.

##### B. Optimize the efficiency of Agentic AI recommendation system

Agentic AI recommendation systems deliver unprecedented personalized and proactive experiences by enabling autonomous perception, planning, action, and learning. However, this intelligence introduces performance challenges: high LLM inference latency, multi-agent collaboration complexity, and computational overhead from real-time data processing. Optimizing efficiency is essential for user experience, cost control, and system stability. Optimization addresses multiple dimensions: data processing, model inference, system architecture, caching strategies, and asynchronous mechanisms. Table 3 presents a complete optimization scheme based on our rough sets and association rule recommendation system.

#### V. EMPIRICAL VALIDATION

##### A. Online product recommendations

##### Rough set association rules for online product recommendations

In the numerical example, this study explores the ordinal and ratio scaling of product categories to establish a product recommendation system. That is, consumers' preferences for product categories are ranked on an ordinal and scale, meaning that the first category is ranked first, then the second, and so on. For that one of the questionnaire questions asks, "What is your preference ranking for product categories purchased through the 'PChome online shopping platform'?" and the five options are ranked as follows: (1) Office supplies, (2) Beauty and skincare, (3) Fashion clothing, (4) Daily necessities, and (5) 3C digital products, as shown in Table 1.

Table 1. PRODUCT CATEGORY RANKING PURCHAS ON THE PCHOME ONLINE PLATFOM

| Customer No. | First place                   | Second place                  | Third place                   | Fourth place                  | Fifth place                   |
|--------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| 001          | Office supplies<br>$it_1$     | Beauty and skincare<br>$it_2$ | Fashion clothing<br>$it_3$    | 3C digital products<br>$it_5$ | Daily necessities<br>$it_4$   |
| 002          | Office supplies<br>$it_1$     | Daily necessities<br>$it_4$   | Beauty and skincare<br>$it_2$ | Fashion clothing<br>$it_3$    | 3C digital products<br>$it_5$ |
| 003          | Beauty and skincare<br>$it_2$ | Daily necessities<br>$it_4$   | Office supplies<br>$it_1$     | 3C digital products<br>$it_5$ | Fashion clothing<br>$it_3$    |
| 004          | Beauty and skincare<br>$it_2$ | Office supplies<br>$it_1$     | Daily necessities<br>$it_4$   | 3C digital products<br>$it_5$ | Fashion clothing<br>$it_3$    |
| 005          | 3C digital products<br>$it_5$ | Beauty and skincare<br>$it_2$ | Fashion clothing<br>$it_3$    | Office supplies<br>$it_1$     | Daily necessities<br>$it_4$   |

Source: this study

#### Establish an average weighting model for product categories

Based on the core attributes obtained in step three, namely beauty and skincare and fashion apparel, to obtain subsequent product recommendations, we explore pairwise comparison relationships. Each product category is defined mathematically as follows:  $MC_i = \{mc_1, mc_2, \dots, mc_5\}$ ,  $i = 1, 2, \dots, 5$ , a non-empty set of product categories. Since the first stage of platform recommendations used the concept of AHP in the questionnaire to compare numerical importance scales pairwise, and due to the large number of product category combinations, the ranking of product categories in the questionnaire has been weighed as follows:

The ratios are allocated according to the numerical concept of AHP, converting the values 1, 3, 5, 7, 9 into 4%, 11%, 19%, 27%, and 39%, respectively. The first-ranked value is defined as 39% (9), because in absolute comparison, the ratio does not exceed 44%, so it is  $9 + 4.4 = 39\%$ . The second-ranked value is slightly lower than the first-ranked value, which is  $7 + 3.9 = 27\%$  (7). The ratio of the first-ranked value is reduced by 70%, resulting in a ratio of 27%. The ratio of the third-ranked value is  $5 + 3.9 = 19\%$  (5), and so on. Values less than 3 are rounded up or down because of their lower ranking. All other values are unconditionally discarded, and the total ratio is 100%. According to the AHP concept, a scale weighting table is established.

#### Generate the average weighting model for product categories

Since each consumer has a different weighting for each product category, these values are substituted into a regression model.  $MC_i = \{mc_1, mc_2, \dots, mc_5\}$ ,  $i = 1, 2, \dots, 5$  are estimates of  $\beta$ . Substituting these product category weight values from the model into the regression model yields  $\beta$  values, thus revealing the degree of consumer preference for certain product categories.

The estimated value is  $\beta^2 = 30.2$ , which means that the average weight of consumers in this product category is 30.2%. In other words, on PChome's online platform, consumers' preference for beauty and skincare products is the highest at 30.2%.

#### Patterns and rules for Agentic AI online product recommendations

The study used a total of 457 data samples from research subjects, which conformed to the decision-making rules of the Yahoo online platform. In order to comply with the algorithm based on rough set and association rules, the collected questionnaire data was first integrated into a general questionnaire database. Then, the data for the parts to be explored were converted into information system tables that the algorithm could use.

This ranking shows that consumer electronics is the top-ranked product category in consumers' minds, followed by electronics products, beauty products, luxury watches, apparel, clothing, and shoes and accessories. This phase focuses on consumer electronics ( $mc_1$ ) and luxury watches ( $mc_3$ ) as the main categories for subsequent research, because the above findings indicate that consumer electronics and watches have the largest number of consumers, totaling 228 and 229 respectively, adding up to 457 research participants.

The results show that consumers' average weight for consumer electronics and watches is 25% and 15.5% respectively, meaning that consumer electronics have a higher weight than watches. In other words, on the Yahoo online platform, consumers have the highest preference for consumer electronics at 25%. Following steps four and five, we learned that consumers generally prefer consumer electronics, with a preference rate of 25%. Since two of the criteria are consumer electronics and watches, we conducted a more detailed consumer behavior analysis on the factors influencing the purchases made by a total of 457 consumers through Yahoo online platform. We created a platform decision data table based on the multi-dimensional data regarding price, product, transaction mechanism, and quality. This study first converted the collected data into an information table that can be used by the algorithm.

In the sixth step of the second phase of this study, the recommendation system identified the 457 participants who ranked first and fourth in consumer electronics and second and fifth in watches through the previous five steps. We then created a decision data table for their consumer behavior and {price, product, transaction mechanism, quality} , after

screening, obtained a set of 22 rules. In other words, we considered all four factors that would lead to product purchase, as shown in Table 2 below.

TABLE 2. DECISION DATA TABLE FOR CONSUMER ELECTRONICS AND WATCH PRODUCTS

| No | Decision rules                                                                       | Consumer electronics $\beta_1$<br>Watches $\beta_3$ |
|----|--------------------------------------------------------------------------------------|-----------------------------------------------------|
| 1  | (product= diverse) & (transaction mechanism = convenient)                            | 25%<br>15.5%                                        |
| 2  | (price= comparable price) & (transaction mechanism = convenient) & (quality= stable) |                                                     |
| 3  | (price= comparable price) & (product= diverse) & (quality=good)                      |                                                     |

Source: This study

Using the AHP rough set association rules, taking consumers who rank consumer electronics as the first and fourth, and watches as the second and fifth, as an example, that is, consumers who rank consumer electronics as the first and fourth, and watches as the second and fifth, as the target customer group of interest, there are 4 sets including consumer electronics rankings. After the study, there are 5 sets in total, so the Rough Support ( $Sup(IND(B))$ ) is 1.07%. Among the ranking sets including consumer electronics, there are 3 sets of consumers who rank consumer electronics as the first and fourth, and watches as the second and fifth, so the Rough Confidence ( $Conf(IND(B) \rightarrow d_c)$ ) is 13.64%.

Based on the above, we found that the decision-making path is that if consumer electronics is ranked first, then watches are ranked second, or if consumer electronics are ranked fourth, then watches are ranked fifth. Then, we conducted a product recommendation. According to step five, consumer electronics  $\beta_1$  accounted for 25% and watches  $\beta_3$  accounted for 15.5%, which should be the most popular product on the Yahoo online platform. Based on the results of this decision-making rule, we can derive online product recommendations that can be used by online operators. Thus, using rough set association rules for multi-criteria and multi-dimensional data mining, this study proposes Figure 1 for agentic AI online product recommendations.

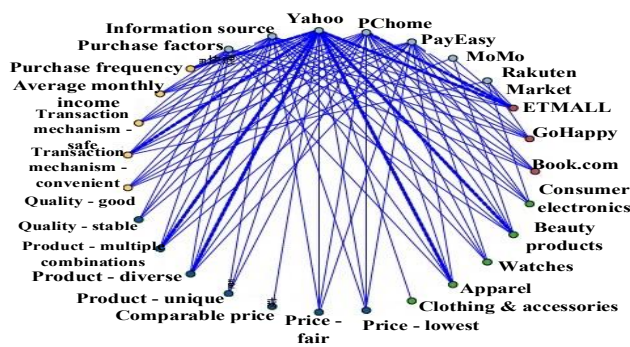


Fig 1. Association map of agentic AI online product recommendations

### Pattern 1: Strong online product recommendations

**Rule 1:** Consumers have a strong preference for product diversity on online platforms and recognize the convenience of their online shopping transaction mechanisms. Therefore, for popular consumer electronics and watch products on Yahoo, we can offer bundled sales to encourage consumers to make more purchases.

### Pattern 2: Weak online product recommendations

**Rule 4:** Consumers highly value online platforms that offer comparable prices, diverse products, convenient transaction mechanisms, and stable quality. Given that it's a relatively weak product, we can offer bundled sets of popular beauty and skincare products and group-buying food items to encourage diverse purchasing. Online operators can also refer to the consumer behavior of strong online platforms like Yahoo to understand why consumers prefer Yahoo and enhance our own platform's appeal.

### Agentic AI online product recommendations action

This numerical example explores consumer preference rankings for different product categories (such as consumer electronics, watches, and beauty products) on the Yahoo Shopping platform. Weights are calculated using the ratio scale and the AHP (Advanced Personalized Hierarchy Process) concept. Key findings and recommendation rules: Core attributes: Analysis shows that consumer electronics have the highest average preference weight (25%), followed by watches (15.5%). Decision path: If consumers rank electronics first, watches are usually second; if electronics are fourth, watches are fifth. The two show a strong correlation. Recommendation patterns: Pattern 1 (Strong Product Recommendation): For popular electronics and watches, offer bundled sales with diverse products and convenient transaction mechanisms to solidify loyalty. Pattern 2 (Weak Product Improvement): For relatively weak products (such as beauty products or food), refer to the successful attributes of the strong platform (Yahoo) (reasonable prices, stable quality) to launch bundled promotions.

### Agentic AI system architecture optimization

In this study, Event-Driven Architecture uses Kafka/Pulsar to capture consumer behavior events. Agentic AI acts as the consumer, updating the profile only when key events are triggered (rather than periodic polling). This architecture reduces system load and improves response time. Edge Computing (Edge Caching) caches recent recommendations on CDN. This reduces origin server requests, improving the experience, especially in areas with unstable networks. In addition, regarding Deployment and Operation Optimization, this study uses MLflow or SageMaker to manage rough set association rule base versions. Small-scale A/B testing is conducted on the new rule set, monitoring CTR (click-through rate), conversion rate, and retention rate. Inefficient global rule deployments are avoided.

## VI. IMPLICATIONS AND COMPARISON

### A. Theoretical implications

**Multi-criteria data mining integration:** This study bridges the gap between decision analysis (AHP) and data mining (association rules) by embedding pairwise comparison structures within rough set attribute reduction. This integration addresses the theoretical challenge of modeling complex preference structures in large-scale data.

### B. Practical implications

**For recommendation system designers:** The framework offers an interpretable alternative or complement to black-box models: Rules can provide explanations for recommendations ("because you have high income and seek discounts..."). Attribute reduction identifies the most discriminative features, potentially reducing data collection requirements. Support/confidence metrics quantify rule reliability for business decisions.

## VII. CONCLUSION, LIMITATIONS AND FUTURE WORK

### A. Concluding remarks

The exponential growth of e-commerce data demands analytical approaches that balance predictive power with interpretability, handle heterogeneous data types, and generate actionable business insights. The proposed multi-criteria, multi-dimensional rough set association rule framework addresses these needs by extracting transparent, verifiable patterns from complex consumer preference data. While limitations remain in scale, temporal dynamics, and predictive benchmarking, the framework provides a foundation for interpretable big data analytics in recommendation contexts. As e-commerce continues to evolve toward greater personalization and user-centric design, methods that illuminate rather than obscure the reasons behind recommendations will become increasingly valuable.

### B. Limitations

**Agentic AI integration.** The framing around "agentic AI" in the original submission was premature—the framework generates static rules rather than autonomous, adaptive agents. The revised framing appropriately focuses on data mining for interpretable patterns.

### C. Future work

**Large-Scale Distributed Implementation:** Deploying the framework on Spark/Hadoop clusters to validate scalability with millions of users.

## VIII. DECLARATIONS

### Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## ACKNOWLEDGMENT

Shu-Hisen Liao thanks for funding the National Science and Technology Council, Taiwan, Republic of China. (NSTC 115-2410-H-032-057)

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