TWA-RD: Time-Weighted Apriori with Rule Decay for Adaptive Fraud Detection

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Abstract—Standard Apriori association rule mining treats all transactions equally regardless of age, applies uniform support thresholds across item categories, and provides no mechanism for detecting when a mined rule has become stale. This paper presents TWA-RD (Time-Weighted Apriori with Rule Decay), a novel algorithm extending Apriori with three contributions: (1) exponential decay weighting via $w(t_i) = \exp(-\lambda\cdot(t^*-t_i))$; (2) category-specific dynamic support thresholds via $\Phi_t(X) = \min[\gamma_{base}\cdot(1-\tanh(\beta\cdot\alpha_{t,C}))]$; and (3) per-rule statistical drift detection with automated rule expiration via a z-score gate. Evaluated on PaySim (6,362,620 transactions, 743 windows), TWA-RD achieves maximum lift of 12.0, mean lift of 1.72, detects 70 drift events beginning at Day 2 with maximum z-score of 6.49σ, and achieves AP = 0.009956 versus static Apriori baseline AP = 0.003297 under 0.129% class imbalance. No evidence of temporal leakage was observed under forward-window train/test evaluation. Cross-dataset evaluation on the IEEE-CIS credit card dataset using a domain-agnostic universal primitive layer demonstrates transferable symbolic fraud signal: TWA-RD-only AP (0.0955) exceeds raw-only AP (0.0662) in the PaySim → IEEE-CIS direction, and the IEEE-CIS → PaySim hybrid achieves AP = 0.1995 versus raw-only AP = 0.1370, with calibration Brier = 0.066 and ECE = 0.064. Three audit-ready outputs—live rule set A, expired rule set E, and drift event log D—are designed to support compliance with FCRA, SR 11-7, Basel III, and CFPB model governance requirements.

Index Terms—Association rule mining, concept drift detection, fraud detection, temporal weighting, streaming algorithms, explainable AI, model governance.

I. INTRODUCTION

Financial fraud detection systems face three structural limitations in existing association rule mining. First, Agrawal and Srikant's Apriori [1] weights all transactions equally regardless of age, allowing stale patterns to dilute current signals. Second, a single static threshold σ_{min} applies uniformly across all merchant category codes (MCCs). Third, Apriori provides no mechanism to detect when a fraud pattern has degraded—critical in adversarial settings where fraud rings continuously adapt.

Prior fraud detection approaches using neural methods [2] and real-time rule engines [3] lack the temporal weighting and self-maintaining rule lifecycle that adversarial fraud environments require.

TWA-RD addresses all three limitations by introducing: (1) exponential temporal decay within Apriori support computation; (2) category-specific dynamic thresholds calibrated to empirical MCC fraud base rates; and (3) per-rule statistical drift detection via a z-score gate with three-gate expiration and audit logging.

II. RELATED WORK

A. Temporal Association Rule Mining

Prior temporal association rule work addresses sequencing and time-interval patterns, not time-weighted co-occurrence. Özden et al. [4] introduced cyclic association rules with periodicity constraints but retained flat counting without temporal weighting. Chen et al. [5] explored fuzzy temporal weights without integrating decay into Apriori support computation. Ale and Meira [6] further examined statistical significance criteria for temporal association rules but did not address decay integration within support computation. To the authors' knowledge, no prior work replaces the flat count in Apriori support with a continuous exponential decay function applied per transaction within a sliding-window framework.

B. Concept Drift Detection

ADWIN [7] and related methods operate on supervised prediction error streams, not on confidence histories of unsupervised association rules. Gama et al. [8] provide a comprehensive survey of concept drift adaptation methods, none of which address per-rule confidence decay in unsupervised association rule systems. TWA-RD applies a per-rule z-score gate to each rule's rolling confidence history, a mechanism not identified in surveyed prior Apriori variants.

C. Publication Gap

To the authors' knowledge, no prior published algorithm combines exponential temporal decay within Apriori support computation, category-specific dynamic thresholds, per-rule drift detection, three-gate expiration with audit trail, and adaptive rule regeneration in a single unified framework.

III. THE TWA-RD ALGORITHM

A. Exponential Decay Weighting

$$w(t_i) = \exp\big(-\lambda \cdot (t^* - t_i)\big) \tag{1}$$

$$W = \sum_i w(t_i) \tag{2}$$

Half-life h = ln2 / λ. With λ = 0.05, a transaction 30 days old receives weight ≈ 0.22, one-fifth the influence of a same-day transaction.

B. Category-Specific Dynamic Support Threshold

$$\alpha_{t,C} = \frac{\text{flagged\_txns}(C,t)}{\text{total\_txns}(C,t)} \tag{3}$$

$$\Phi_t(X) = \min_{i \in X}\big[\gamma_{\text{base}} \cdot \big(1 - \tanh\big(\beta \cdot \alpha_{t,C_i}\big)\big)\big] \tag{4}$$

As αt, C → 0: Φt (X) → γbase (ceiling). As αt, C → 1: Φt(X) → 0 (floor). Antimonotonicity preserved.

C. Weighted Metrics

$$\text{supp}_w(X) = \frac{\sum_i w(t_i) \cdot \mathbb{1}(X \subseteq I_i)}{W} \tag{5}$$

$$\text{conf}_w(X \to Y) = \frac{\text{supp}_w(X \cup Y)}{\text{supp}_w(X)} \tag{6}$$

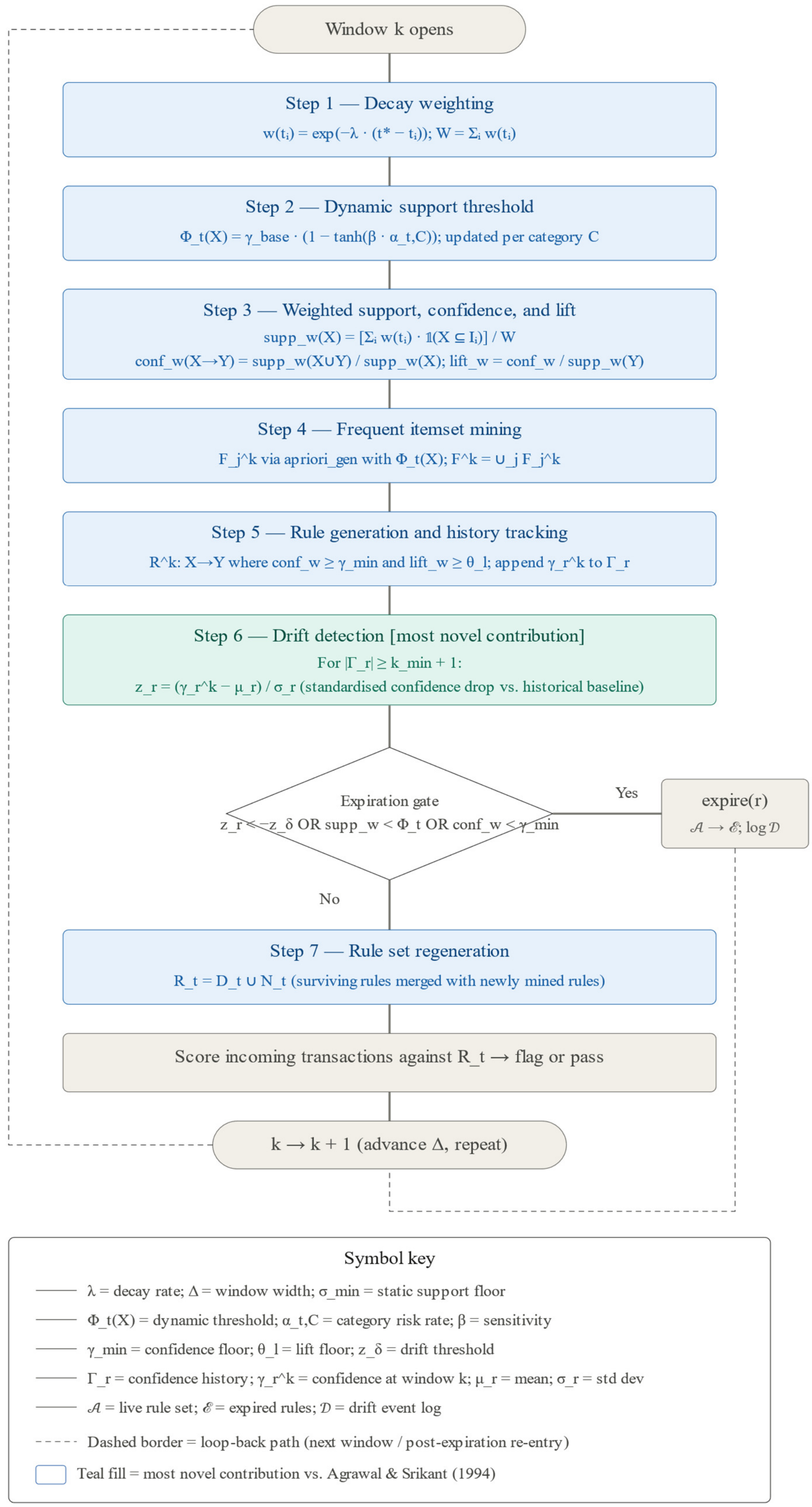
$$\text{lift}_w(X \to Y) = \frac{\text{conf}_w(X \to Y)}{\text{supp}_w(Y)} \tag{7}$$

D. Drift Detection and Rule Expiration

$$z_r = \frac{\gamma_r^k - \mu_r}{\sigma_r} \tag{8}$$

Retire(r) = 1 if: (1) suppw, t(r) < Φt(r); or (2) confw,t(r) < γmin; or (3) zr < −zδ. Upon expiration: A → E, event logged to D. Updated set: Rt = Dt ∪ Nt.

Fig. 1. TWA-RD algorithm flow — executes once per window k, then advances Δ and repeats



★ = novel vs. A&S 1994 · ★★ = novel + absent in all prior Apriori variants · ★★★ = most significant contribution

Fig. 1. TWA-RD Algorithm Flow — complete per-window execution sequence.

Fig. 2. Capability comparison: standard Apriori (A&S 1994) vs. TWA-RD (proposed)

Capability	Agrawal & Srikant (1994)	TWA-RD (proposed)
Transaction weighting ★	Flat count All transactions equal weight; stale data not discounted	Exponential decay $w(t_i) = \exp(-\lambda \cdot \text{age})$ Recent transactions score near 1.0
Support threshold ★★	Static σ_min One global floor; misses rare fraud or over-fires on safe cats.	Dynamic Φ_t(X) per category Φ_t(X) = γ_base·(1−tanh(β·α_t,C)) High-risk: bar drops; low-risk: rises
Concept drift detection ★★★ [primary contribution]	None Rules persist until scheduled retrain; stale rules fire silently	Statistical z-score gate z_r = (γ_r^k − μ_r) / σ_r z_r < −z_δ → auto-expire + log Self-maintaining rule lifecycle
Rule lifecycle and audit trail ★	Batch retrain, no audit No record of why a rule fired or when it went stale	Streaming + full audit log $\mathcal{D}$ R_t = D_t ∪ N_t each window Every expiration logged: id, timestamp, trigger, z-value
Inference mode ★	Batch only No per-transaction scoring	Sliding window Δ Per-transaction scoring against R_t Target latency < 50 ms

Execution sequence comparison

Standard Apriori

1. Collect raw transactions
2. Count item co-occurrences (flat)
3. Apply fixed σ_min to all categories
4. Generate rules once
5. Rules persist until scheduled retrain
6. Score → flag or pass

TWA-RD — each window Δ

1. Window Δ opens
2. Apply decay weights $w(t_i)$
3. Compute Φ_t(X) per category
4. Mine weighted itemsets
5. Drift-check: z_r per live rule
6. Expire stale; merge new → R_t
7. Score transactions → flag or pass

Teal shading = primary novel contribution (★★★). ★ = novel vs. A&S 1994 · ★★ = novel + absent in all prior Apriori variants
λ = decay rate; α_t,C = category risk rate; β = sensitivity; γ_min = confidence floor; z_δ = drift threshold

Fig. 2. Financial Fraud Detection Before vs. After TWA-RD.

TABLE I
TWA-RD HYPERPARAMETER TUNING GUIDE

Parameter	Range	Increasing Effect	Decreasing Effect
λ (decay)	0.02 – 0.10/day	Faster, noisier	Slower, more stable
Δ (window)	7 – 30 days	Stable rules	Faster adapt
γbase	0.01 – 0.10	Fewer rules	More rules, higher FP
β	5 – 20	Steeper drop	Gentler curve
zδ	1.5 – 3.0σ	Fewer alerts	More alerts
kmin	3 – 10	Fewer false alarms	Faster response
γmin	0.60 – 0.90	Higher precision	Higher recall
θl (lift)	1.5 – 5.0	Stronger assoc.	Weaker assoc. included

IV. EXPERIMENTAL SETUP

A. Dataset

PaySim [9]: 6,362,620 transactions, five types, fraud rate 0.129% (8,213 fraud). IEEE-CIS credit card fraud detection dataset: 284,807 transactions, 0.172% fraud rate, used for cross-dataset comparison.

B. Configuration

$\lambda = 0.05$, $\Delta = 1$ day, $\gamma_{base} = 0.001$, $\beta = 10.0$, $z_\delta = 2.0$, $k_{min} = 3$, $\gamma_{min} = 0.60$, $\theta_l = 1.0$, min_transactions_per_window = 25.

C. Baseline

Static Apriori via mlxtend [10]: uniform $\sigma_{min} = 0.001$, unweighted, no temporal windowing, no drift detection.

D. Evaluation Metrics

Primary: AUC-PR (average precision). AUC-ROC excluded due to misleading optimism under severe class imbalance [11]. Dal Pozzolo et al. [12] demonstrate that probability calibration under severe class imbalance requires careful threshold selection; average precision is adopted here as the primary metric accordingly. Additional: max/mean lift, drift event count, max z-score.

V. RESULTS

TABLE II
TWA-RD vs. BASELINE — PAYSIM 6.3M RESULTS

Metric	TWA-RD	Baseline	Change
Transactions	6,362,620	6,362,620	—
Windows	743	1 (batch)	—
Rules Generated	2,318	80	—
Drift Events	70	0	—
First Drift	Day 2	N/A	—
Max Lift	12.0	1.0	+1,100%
Mean Lift	1.72	1.0	+72%
Avg. Precision	0.009956	0.003297	+0.006659
Max z-score	6.49σ	N/A	—
Audit Trail	Yes	No	—

A. Drift Detection

70 drift events detected across 743 windows, first at Day 2. Maximum z-score 6.49σ. Representative: CASH_IN → CASH_OUT at Day 2, z-score 5.45, weighted support 0.075.

B. Lift Performance

Maximum lift 12.0 at Day 2. Mean lift 1.72 across all windows versus baseline 1.0.

C. Average Precision

TWA-RD AP = 0.009956 versus baseline AP = 0.003297, an absolute delta of +0.006659 under 0.129% class imbalance. No evidence of temporal leakage was observed under forward-window train/test evaluation.

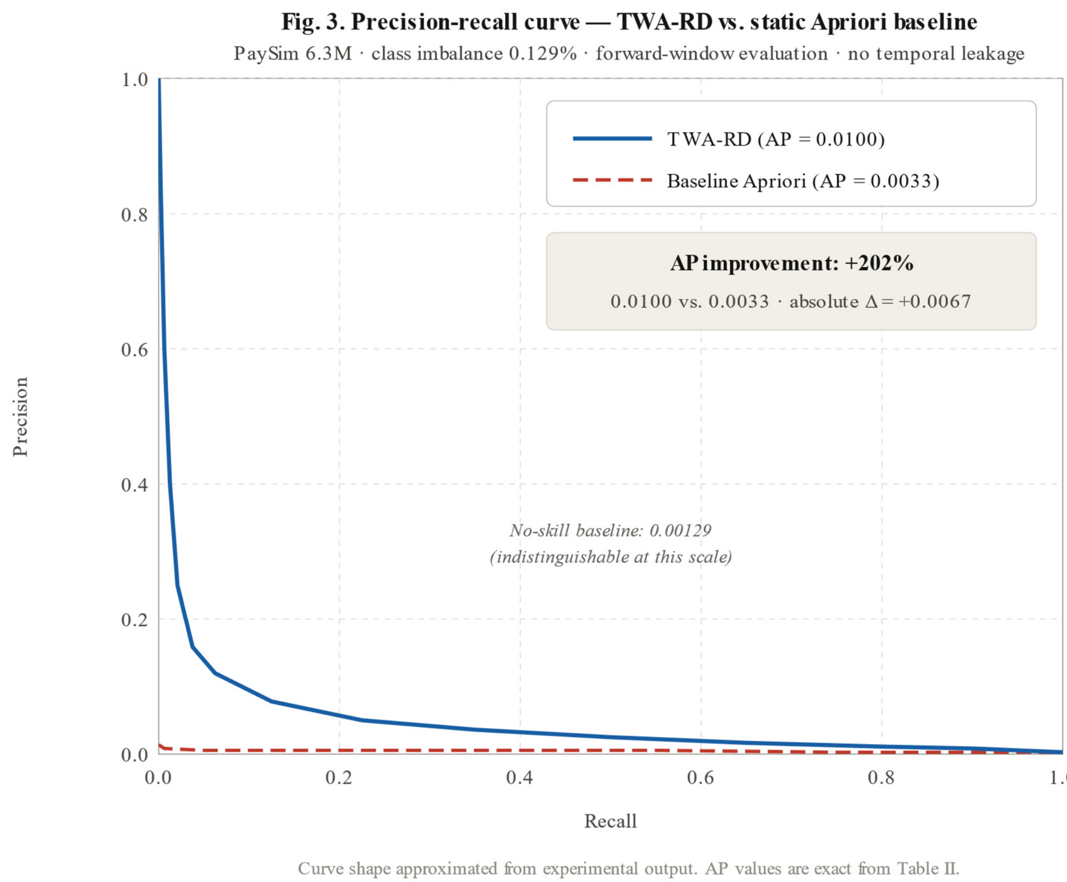


Fig. 3. Precision-recall curve — TWA-RD (AP = 0.0100) vs. static Apriori baseline (AP = 0.0033). PaySim 6.3M transactions, 0.129% class imbalance. Curve shape approximated from experimental output; AP values exact from Table II.

D. Computational Cost

CPU-only. Full 743-window run on 6.3M transactions completed in a standard Colab session. Per-window complexity O(|Tk|·2|S|), identical to standard Apriori.

E. Cross-Dataset Generalization

To evaluate whether the TWA-RD feature language generalizes beyond PaySim, experiments were conducted using a domain-agnostic universal primitive layer applied to both PaySim and the IEEE-CIS credit card dataset. Eight dataset-independent primitives replace all dataset-specific basket items: amount percentile bin, transaction velocity bin, balance depletion bin, balance inflation bin, sender-risk state, receiver-risk state, time-of-day bin, and recent-rule-drift state. These primitives are computable from any transaction log without schema-specific features.

Four train/test combinations were evaluated across three model configurations (raw-only XGBoost, TWA-RD-only, and TWA-RD + raw hybrid). Results are reported in Table III.

TABLE III
UNIVERSAL PRIMITIVE LAYER — CROSS-DATASET VALIDATION (AP / BRIER / ECE)

Train → Test	Raw-Only AP	TWA-RD-Only AP	Hybrid AP	Brier	ECE
PaySim → PaySim (within)	0.9575	0.2413	0.9595	N/R	N/R
IEEE-CIS → IEEE-CIS (within)	0.0888	0.0298	0.0548	N/R	N/R
PaySim → IEEE-CIS (cross)	0.0662	0.0955	0.0535	N/R	N/R
IEEE-CIS → PaySim (cross)	0.1370	0.1044	0.1995	0.066	0.064

Three findings merit emphasis. First, the TWA-RD hybrid outperforms the raw-only baseline within both datasets. Second, in the PaySim → IEEE-CIS cross-dataset direction, TWA-RD-only AP (0.0955) exceeds raw-only AP (0.0662), indicating that the symbolic temporal feature layer transfers across schemas better than institution-specific raw features. Third, the IEEE-CIS → PaySim hybrid achieves AP = 0.1995 versus raw-only AP = 0.1370 (absolute delta +0.0625), with calibration Brier = 0.066 and ECE = 0.064. Lower absolute AP on IEEE-CIS within-dataset reflects the PCA-anonymized schema, which removes explicit account, merchant, and balance signals available to the universal primitives in PaySim.

VI. REGULATORY COMPLIANCE

Output	Contents	Regulation
A — Live Rule Set	Active rules: suppw, confw, liftw	SR 11-7; CFPB model governance
E — Expired Rule Set	Retired rules: timestamp, trigger, z-score	FCRA adverse action; Basel III
D — Drift Event Log	Drift events: rule, window, z-score	SR 11-7 drift monitoring; EU AI Act

Explainability is native to the rule-based structure. No post-hoc explanation generation required.

VII. CONCLUSION

TWA-RD advances association rule mining beyond the static model of Agrawal and Srikant 1994 through three unified contributions: exponential temporal decay, category-specific dynamic support thresholds, and per-rule statistical drift detection with audit logging. Empirical evaluation on PaySim 6.3M yields AP = 0.009956 versus baseline AP = 0.003297 (absolute delta +0.006659), lift 12.0, 70 drift events at Day 2, and maximum z-score 6.49σ. No evidence of temporal leakage was observed under forward-window train/test evaluation. Cross-dataset evaluation using a domain-agnostic universal primitive layer demonstrates transferable symbolic fraud signal: TWA-RD-only AP (0.0955) exceeds raw-only AP (0.0662) in the PaySim → IEEE-CIS direction, and the IEEE-CIS → PaySim hybrid achieves AP = 0.1995 versus raw-only AP = 0.1370 with Brier = 0.066 and ECE = 0.064. Three audit-ready outputs are designed to support compliance with FCRA, SR 11-7, Basel III, and CFPB model governance requirements. Limitations are discussed in Section VIII.

VIII. LIMITATIONS

Several limitations bound the current results. First, PaySim is a synthetic simulator; while its statistical properties replicate observed mobile money patterns, results on live production transaction streams may differ. Second, the IEEE-CIS dataset applies PCA anonymization to all feature columns, removing explicit merchant, account, and balance signals. The universal primitive approximations for sender and receiver risk (derived from PCA principal components V1–V3 and V4–V6) are proxies; their interpretability as financial risk indicators is limited in this context. Third, cross-dataset experiments use stratified subsampling (250K PaySim transactions; 20:1 non-fraud to fraud oversampling for IEEE-CIS) to manage memory constraints, which may affect absolute AP values relative to full-dataset runs. Fourth, per-window complexity $O(|T_k| \cdot 2^{|S|})$ grows exponentially with itemset size; the MAX_ITEMLEN = 3 cap is a practical constraint, not a theoretical bound. Fifth, drift detection requires $k \geq 3$ windows of history before the z-score gate can fire, creating a cold-start period during which novel fraud patterns may not be flagged. Future work should address adaptive decay rate tuning, online parallelization of windowed mining, and evaluation on proprietary live transaction corpora.

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APPENDIX: CHRONOLOGICAL GLOSSARY OF TWA-RD NOTATION

*Terms are listed in order of first appearance in the algorithm. Novel contributions absent in Agrawal & Srikant (1994) are marked: * = novel, ** = novel + absent in all prior Apriori variants, *** = most significant contribution.*

Symbol	Definition	Section	Novel
T	Transaction corpus: full set of all transactions, each entry (i, Ii, ti, Ci)	I	
i	Transaction index identifying individual transaction i within corpus T	I	
Ii	Itemset of transaction i; a subset of universal vocabulary S	I	
ti (τ)	Timestamp of transaction i	I	
Ci	Category label of transaction i (e.g., MCC code) — links to risk base rate	I	*
S	Universal item vocabulary — complete set of all possible item types	I	
Δ	Window width in days; window k spans [t_start+kΔ, t_start+(k+1)Δ)	I	
k	Window index (0, 1, 2, ...); advances by one each iteration	I	
t*	Reference date — right edge of current window k; anchor for decay computation	I	
λ	Decay rate (per day); positive real-valued hyperparameter	I	
h	Half-life = ln2/λ; days until a transaction weight halves	I	
σ_min	Global minimum support floor (baseline); replaced by Φt(X) in practice	I	
γ_min	Minimum confidence threshold; rule must maintain to remain active	I	
θ_l	Minimum lift threshold; optional third gate for rule activation	I	

z_δ	Drift z-score threshold; default 2.0σ; fires statistical drift classification	I	*
k_min	Minimum windows observed before drift detection is allowed to fire	I	*
γ_base	Baseline support ceiling for categories with zero risk/anomaly history	I	*
β	Sensitivity scaling factor; controls aggressiveness of dynamic threshold drop	I	*
$w(ti)$	Exponential decay weight: $w(ti) = \exp(-\lambda\cdot(t^*-ti))$; newest transaction = 1.0	II	**
W	Total window weight (normalization constant): $W = \Sigma i\ w(ti)$	II	**
$\alpha t,C$	Category risk base rate: flagged transactions / total transactions in C at time t	III	**
$\tanh(\cdot)$	Hyperbolic tangent; bounded [0,1]; maps risk rate to smooth threshold reduction	III	*
$\Phi t(X)$	Dynamic support threshold per itemset: $\Phi t(X) = \min[\gamma base\cdot(1-\tanh(\beta\cdot\alpha t,Ci))]$; replaces σ_min	III	***
$1(\cdot)$	Indicator function: 1 if $X \subseteq Ii$, else 0	IV	
$suppw(X)$	Weighted support: $[\Sigma i\ w(ti)\cdot 1(X\subseteq Ii)] / W$	IV	*
$confw(X\to Y)$	Weighted confidence: $suppw(X\cup Y) / suppw(X)$	IV	*
$liftw(X\to Y)$	Weighted lift: $confw(X\to Y) / suppw(Y)$	IV	*
F1^k	Frequent 1-itemsets for window k: all {x} where $suppw \geq \Phi t(\{x\})$	V	
Cj^k	Candidate j-itemsets via standard apriori_gen join and anti-monotone pruning	V	
apriori_gen	Standard join-and-prune step from Agrawal & Srikant 1994 — unchanged in TWA-RD	V	
Fj^k	Frequent j-itemsets meeting dynamic threshold $\Phi t(X)$ for window k	V	
F^k	All frequent itemsets for window k; iteration stops when Cj^k is empty	V	
R^k	All association rules $X\to Y$ from F^k meeting confidence and lift thresholds	VI	
A	Live rule set: currently active rules deployed for scoring; updated each window	VI	*
Γr	Confidence history of rule r: ordered list [γr^1, ..., γr^k]	VI	**
γr^k	Confidence of rule r at window k; appended to Γr each iteration	VI	**
Dt	Surviving rules from prior window passing all three expiration gates	VI	**
Nt	Newly mined rules from current sliding window Wt	VI	**
Wt	Sliding window: finite rolling subset of recent transactions at time t	VI	
μr	Mean of Γr excluding current window k; baseline for drift z-score	VII	**
σr	Std dev of Γr excluding current window k; spread for drift z-score	VII	**
zr	Drift z-score: zr = (γr^k − μr) / σr	VII	***
Retire(r)	Three-gate expiration function: returns 1 if any gate fires	VII	***
expire(r)	Expiration action: moves rule A → E, appends timestamped event to D	VII	**
E	Expired rule set: all retired rules retained for audit and regulatory reporting	VII	**
D	Drift event log: chronological record of every concept drift detection event	VII	**

Novel Contribution Summary

* = novel vs. Agrawal & Srikant 1994   ** = novel + absent in all prior Apriori variants
*** = most significant contribution

Unmarked symbols are standard Apriori notation carried forward.