A Comprehensive Survey on Utility-Based and High-Utility Pattern Mining Techniques in Recommender Systems

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ABSTRACT

Recommender systems (RSs) have become indispensable in various domains to mitigate information overload by providing personalized suggestions. While traditional RSs primarily focus on accuracy (e.g., rating prediction), modern applications demand consideration of business-centric objectives such as profit, user engagement, and long-term revenue. Utility-based recommender systems aim to optimize these objectives by integrating utility measures into recommendation models. Moreover, high-utility pattern mining (HUPM) techniques have emerged as powerful tools to identify patterns that maximize user engagement or profit in large-scale clickstream data. This survey presents a comprehensive review of utility-based and high-utility pattern mining approaches in RSs. We categorize existing methods, discuss underlying theoretical foundations, analyze their strengths and limitations, and outline open challenges and future research directions. The survey covers utility function design, algorithmic advances in HUPM, hybrid frameworks combining collaborative and content-based features with utility optimization, scalability considerations in big data contexts, and evaluation metrics beyond accuracy. Finally, we highlight emerging trends such as deep learning integration, fairness-aware utility modeling, and real-time recommendation under utility constraints. This survey aims to serve as a reference for researchers and practitioners seeking to develop next-generation RSs that balance accuracy, business value, and user satisfaction.

General Terms

Recommender Systems, High-Utility Pattern Mining

Keywords

Recommender Systems, Utility-Based Recommendation, High-Utility Pattern Mining, Hybrid Approaches, Big Data, Survey

1. INTRODUCTION

The proliferation of digital content on e-commerce platforms, social networks, streaming services, and news portals has led to an overwhelming volume of information. Recommender systems (RSs) address this challenge by filtering and presenting personalized item suggestions based on user preferences and behavior [1, 2, 3, 4]. Traditional RSs focus primarily on accuracy metrics such as RMSE for rating prediction or precision/recall for top-N recommendations. However, business objectives like profit maximization, user engagement, and long-term revenue often remain unaddressed [5]. Utility-based recommender systems (UBRSs) incorporate explicit utility measures—such as profit margin, service cost, or expected user engagement—into the recommendation process to optimize both user satisfaction and business objectives [5]. High-utility pattern mining (HUPM) extends frequent pattern mining by assigning utility values (e.g., profit, weights, or engagement scores) to items or itemsets, enabling the discovery of patterns that maximize the overall utility in transactional or sequential data [11]. HUPM techniques have been applied to clickstream data to uncover high-engagement or high-revenue patterns for session-based recommendations [11].

This survey provides a comprehensive review of utility-based recommendation and HUPM techniques in the RS domain. We categorize and analyze existing methodologies, discuss practical challenges, and highlight open research directions. Specifically, we address:

—**Utility Function Design:** Taxonomies of utility measures, single- and multi-objective utility formulations, and domain-specific utility definitions.

—**High-Utility Pattern Mining:** Algorithmic developments in transactional and sequential HUPM, MapReduce-based scalable frameworks, and applications to clickstream data.

—**Hybrid RS Frameworks:** Approaches that combine content-based, collaborative, and utility-based components; rule-based and probabilistic generalization methods; and methods for addressing cold-start and data sparsity.

—**Scalability and Big Data:** Distributed and parallel implementations, real-time utility estimation, and incremental learning.

—**Evaluation Metrics and Protocols:** Beyond accuracy—utility gain, diversity, novelty, fairness, and business-oriented KPIs.

—**Applications and Case Studies:** E-commerce, online news, streaming services, and other domains where utility-driven RSs have shown impact.

—**Challenges and Future Directions:** Ethical considerations, fairness-aware utility modeling, deep learning integration, user privacy, and interpretability.

The rest of this paper is organized as follows. Section 2 provides background on RS paradigms and utility modeling. Section 3 discusses HUPM techniques and their integration into RSs. Section 4 presents hybrid approaches and system architectures. Section 5 reviews scalability strategies in big data contexts. Section 6 covers evaluation metrics for utility-based RSs. Section 7 surveys application domains and case studies. Section 8 outlines open challenges and future research directions. Finally, Section 9 concludes the survey.

2. BACKGROUND ON RECOMMENDER SYSTEMS AND UTILITY MODELING

This section introduces foundational concepts in RSs, utility theory, and the motivation for utility-based approaches.

2.1 Recommender System Paradigms

RSs are generally classified into three categories:

(1) **Content-Based Filtering (CBF):** Recommends items similar to those a user has liked based on item features (e.g., textual metadata, attributes) [2]. Typical algorithms include vector space models, TF–IDF, and machine learning classifiers.

(2) **Collaborative Filtering (CF):** Leverages historical interactions (ratings, clicks) across users to predict preferences for a target user [3]. CF methods include neighborhood-based (user- or item-based) and model-based techniques (matrix factorization).

(3) **Hybrid Methods:** Combine CBF and CF or incorporate additional signals (e.g., utility, social, contextual) to enhance recommendation quality [4].

While these paradigms focus on predicting user preferences, they typically optimize for accuracy metrics such as RMSE for ratings or precision/recall for top-N recommendations. This narrow focus can conflict with business goals that require balancing multiple objectives [5].

2.1.1 *Table: RS Paradigms and Characteristics.*

Table 1. : Comparison of RS Paradigms

Paradigm	Data Source	Pros	Cons
Content-Based	Item features (e.g., metadata)	No cold-start for items, interpretable	Limited serendipity, feature engineering
Collaborative	User-item interactions	High accuracy, no feature extraction	Cold-start for new users/items, sparsity
Hybrid	Both item features and interactions	Mitigates weaknesses of CBF/CF	Increased complexity, parameter tuning

2.2 Utility Theory in Recommender Systems

Utility quantifies the satisfaction or benefit derived from an outcome. In RSs, utility functions capture both user-centric satisfaction and business objectives.

2.2.1 *Utility Function Definition.*
Formally, let $U(u, i)$ denote the utility of recommending item i to user u. Utility may incorporate:

—**Item-Driven Utilities $B(i)$:** Business value per item, such as profit margin, commission, or inventory considerations [6, 7].

—**User-Driven Utilities $R(u, i)$:** User-centric measures like predicted rating, engagement probability, or dwell time [6, 7].

—**Contextual Utilities:** Situational factors (e.g., time, location, device) that influence utility [8].

Table 2. : Taxonomy of Utility Measures in RSs

Type	Description	Examples
Monetary Utilities	Measures financial value generated by item consumption	Profit margin, commission, revenue
Engagement Utilities	Measures user engagement and satisfaction	Clicks, dwell time, conversion rate
Hybrid Utilities	Composite metrics combining monetary and engagement	Weighted sum of profit and dwell time
Contextual Utilities	Adjusted utility based on situational factors	Time-decay, location bias, device preference

2.2.2 *Table: Taxonomy of Utility Measures.*

2.2.3 *Motivation for Utility-Based Approaches.*
Traditional accuracy-driven RSs can produce recommendations that are suboptimal for business objectives. For instance, a highly relevant item with low profit margin may be preferred by accuracy-focused methods but may not maximize revenue. Utility-based RSs integrate utility functions into model training or post-processing [11]. Applications demanding utility-based recommendations include:

—**E-commerce:** Recommending products that maximize expected profit or cross-selling potential [9].

—**Online News:** Suggesting articles that optimize click-through rate (CTR) or advertising revenue [8].

—**Streaming Media:** Recommending content to increase watch time or subscription retention [10].

3. HIGH-UTILITY PATTERN MINING TECHNIQUES

HUPM extends traditional frequent pattern mining by considering utility values (e.g., profit or engagement) associated with items or itemsets. This section reviews both transactional and sequential HUPM approaches, discusses algorithmic innovations, and highlights applications in RSs.

3.1 Problem Definition

Given a transactional database $\mathcal{D}$, where each transaction $T_k = \{(i_1 : q_{k,1}), (i_2 : q_{k,2}), \ldots\}$ includes items i_j with internal utility (e.g., quantity or weight) $q_{k,j}$, and each item i_j has an external utility $p(i_j)$ (e.g., unit profit), the utility of an item i_j in T_k is:

$$u(i_j, T_k) = p(i_j) \times q_{k,j}.$$

The utility of an itemset $X \subseteq T_k$ is:

$$u(X, T_k) = \sum_{i_j \in X} u(i_j, T_k).$$

The transactional utility of T_k is $tu(T_k) = \sum_{i_j \in T_k} u(i_j, T_k)$. The utility of X in $\mathcal{D}$ is:

$$U(X) = \sum_{T_k \in \mathcal{D},\, X \subseteq T_k} u(X, T_k).$$

An itemset X is a *high-utility itemset (HUI)* if $U(X) \geq \delta$, where δ is a user-defined minimum utility threshold [11].

3.2 Transactional HUPM Algorithms

Initial HUPM algorithms adapted Apriori-based frameworks but suffered from excessive candidate generation and multiple database scans. Key advancements include:

—**Two-Phase Apriori-Based Methods:** Candidate generation with transaction-weighted utility (TWU) pruning [12].
—**Utility-List Based Methods:** HUI-Miner and FHM construct utility-lists for direct mining in a single database scan [12, 13].
—**UP-Growth Family:** UP-Tree pattern-growth reduces database scans using a compressed tree structure; UP-Growth^{+} further improves threshold raising [12].
—**EFIM:** Employs EUCP and RL pruning for near-linear scalability [14].
—**Parallel Frameworks:** BigHUSP uses MapReduce, while PHUI-Miner leverages MPI for distributed HUI mining [15, 16].

Table 3. : Transactional HUPM Algorithms

Algo.	**Key Idea**	**Data Structure**	**Complexity**
Two-Phase Apriori [11]	Kand. gen. w/ TWU-pruning	TWU bound	Multiple scans
HUI-Miner [12]	Utility-list const., direct mining	Utility-lists	Single scan
UP-Growth [12]	UP-Tree pattern growth	UP-Tree	Compressed search
UP-Growth^{+} [12]	Improved threshold raising	UP-Tree	Lower overestimation
FHM [13]	Fast utility mining w/ utility-lists	Utility-lists	Optimized merging
EFIM [14]	EUCP + RL pruning	Utility-lists	Near-linear scale
BigHUSP [15]	MapReduce-parallel mining	Dist. utility-lists	Scales to big data
PHUI-Miner [16]	MPI-based high-utility mining	Utility-lists	For HPC clusters

3.2.1 *Table: Transactional HUPM Algorithm Comparison.*

3.3 Sequential and Clickstream HUPM

Sequential HUPM extends transactional HUPM to ordered data (e.g., purchase sequences, clickstreams). A sequence database $\mathcal{S}$ contains sequences $s_k = \langle (i_{k,1}, q_{k,1}), (i_{k,2}, q_{k,2}), \ldots \rangle$, where item utilities and sequence order are significant. The utility of a sequence pattern P in $\mathcal{S}$ is defined similarly to transactional HUPM, with ordering constraints [17].
Significant sequential HUPM algorithms include:

—**HUS-Span:** Adapts PrefixSpan to high-utility sequential pattern mining [17].
—**HUSP-ALL:** Employs utility-lists for sequential data [18].

Table 4. : Sequential HUPM Algorithms

Algo.	**Key Idea**	**Data Structure**	**Complexity**
HUS-Span [17]	PrefixSpan adaptation w/ utility constraints	Utility-linked projected databases	Depth-first search
HUSP-ALL [18]	Utility-list based sequential mining	Sequential utility-lists	Single-scan sequential processing

3.3.1 *Table: Sequential HUPM Algorithms.*

3.4 Integration of HUPM into Recommender Systems

Integrating HUPM into RSs typically involves three steps:

(1) **Utility Modeling:** Define item or session utilities (e.g., profit, dwell time) suitable for the application domain.
(2) **Pattern Mining:** Execute transactional or sequential HUPM algorithms to extract high-utility itemsets or sequential patterns (rules).
(3) **Recommendation Engine:** Translate discovered patterns into recommendation rules, possibly incorporating probabilistic generalization (e.g., topic modeling) to address cold-start and sparsity.

3.4.1 Example: URecSys. URecSys [20] mines high-utility article-level and topic-level sequential patterns from clickstream logs. It then ranks candidate articles by expected utility (e.g., ad revenue, dwell time) and delivers personalized news feeds.

4. HYBRID RECOMMENDER SYSTEM ARCHITECTURES

Hybrid RS frameworks combine multiple recommendation paradigms—content-based, CF, rule-based, and utility-based—to leverage their complementary strengths [4]. Key categories include:

(1) **Weighted CF + Utility Models:** Incorporate cost or utility matrices into CF [21].
(2) **Rule-Based Recommendation with Utility Optimization:** Extract rules from HUPM and optimize utility constraints [20].
(3) **Feature-Augmented Matrix Factorization:** Augment MF with utility or business features [22].
(4) **Deep Learning-Based Hybrid Approaches:** Use neural architectures to integrate utility signals [23].
(5) **Context-Aware Hybrid Recommenders:** Leverage contextual features and HUPM for recommendations [24].

Table 5. : Comparison of Hybrid RS Architectures

Approach	Components	Utility Integration	Pros/Cons
Weighted CF + Utility [21]	User-item CF, utility matrix	Utility weights in CF loss function	Pros: Improves business KPIs; Cons: Requires accurate utility labels
Rule-Based + Utility [20]	HUPM rules, ranking model	Utility-driven rule selection and ranking	Pros: Explainable; Cons: Rule sparsity issues
MF + Utility Features [22]	Matrix factorization, business features	Utilities as side information in latent factors	Pros: Captures latent utility signals; Cons: Complex model tuning
Deep Learning Hybrid [23]	Neural CF, utility embedding	Utility embeddings integrated in neural net	Pros: Flexible representation; Cons: High training cost
Context-Aware Hybrid [24]	Context features, HUPM patterns	Contextual utilities in recommendation model	Pros: Captures situational effects; Cons: Context sparsity

4.0.1 Table: Hybrid RS Architecture Comparison.

5. SCALABILITY AND BIG DATA CONSIDERATIONS

Large-scale RSs must handle massive user bases, voluminous item catalogs, and high-velocity interaction logs. Utility-based and HUPM techniques exacerbate scalability challenges due to additional computations. This section reviews distributed and parallel strategies, real-time utility estimation, and incremental learning.

5.1 Distributed and Parallel HUPM

5.1.1 MapReduce-Based Frameworks. BigHUSP implements HUSP-ALL over MapReduce, processing clickstream sessions in parallel [15].

5.1.2 GPU-Accelerated Mining. GPU-accelerated HUPM algorithms leverage utility-list parallelism to accelerate mining tasks [25].

Table 6. : Distributed/Parallel HUPM Frameworks

Framework	Platform	Technique	Scalability
BigHUSP [15]	Hadoop MapReduce	Distributed utility-list-based mining	Scales to very large clusters
PHUI-Miner [16]	MPI (HPC clusters)	Parallel utility-list merging	Efficient on medium-scale HPC
GPU-HUPM [25]	CUDA GPU	Parallel utility-list operations	Speedup of 10–20× over CPU

5.1.3 Table: Distributed and Parallel HUPM Solutions.

5.2 Incremental and Real-Time Utility Estimation

In dynamic environments, new user interactions and items arrive continuously, necessitating incremental updates of utility models and HUPM results.

5.2.1 Incremental Frameworks

—**IncUP-Growth [26]:** Extends UP-Growth for incremental updates by maintaining an updated UP-Tree as new transactions arrive.

—**Sliding Window Approaches:** Maintain HUPM results over a sliding window of recent transactions to adapt to evolving user behavior.

—**Real-Time Utility Computation:** Approximate utility estimates using sampling or sketch-based methods to avoid full re-mining [27].

Table 7. : Incremental High-Utility Pattern Mining Methods

Method	Base Algorithm	Update Mechanism	Complexity
IncUP-Growth [26]	UP-Growth	Incrementally update UP-Tree	Partially incremental, O(ΔT)
Sliding Window HUPM	HUI-Miner, FHM	Recompute on window shift	Window-size dependent
Approximate HUPM [27]	EFIM	Sample-based utility approximation	Sublinear under sampling

5.2.2 Table: Incremental HUPM Methods.

5.3 Efficient Utility Computation in RS Pipelines

Integrating utility estimation into large-scale RS pipelines requires careful resource management.

5.3.1 Techniques

—**Precomputation and Caching:** Utility values (e.g., profit margins, predicted engagement) are precomputed offline and cached to avoid on-the-fly computation during recommendation [24].

—**Approximate Utility Estimation:** Techniques using sampling or sketches to approximate high-utility patterns when exact computation is infeasible [27].

—**Online vs. Offline Trade-offs:** Balance between batch HUPM (high accuracy) and incremental/approximate approaches (low latency).

6. EVALUATION METRICS FOR UTILITY-BASED RECOMMENDER SYSTEMS

While accuracy metrics (e.g., precision, recall, RMSE) remain important, utility-based RSs require specialized evaluation measures that reflect business objectives and user satisfaction. This section surveys prevalent metrics and evaluation protocols.

6.1 Utility-Oriented Metrics

—**Expected Profit (EP):** Sum of item profit values for recommended items that the user actually interacts with. Let R_u be the recommendation list for user u, and I_u be the set of items consumed. Then:

$$EP = \sum_{u} \sum_{i \in R_u \cap I_u} profit(i).$$

—**Normalized Utility Gain (NUG):** Utility of recommended items normalized by the maximum possible utility in a given list length [20]. If $U_{\max}$ is the maximum utility attainable, then:

$$NUG = \frac{\sum_u \sum_{i \in R_u \cap I_u} U(u,i)}{\sum_u U_{\max}}.$$

6.2 Traditional Recommendation Metrics

Accuracy and ranking metrics remain essential:

—**Precision@K and Recall@K:** Fraction of relevant items in the top-K recommendations.

—**Mean Average Precision (MAP)@K [3]:** Average precision at ranks where relevant items occur.

—**Normalized Discounted Cumulative Gain (NDCG)@K:** Captures ranking quality with position-based discounting.

6.3 Diversity and Novelty

Utility-based RSs should avoid overly homogeneous recommendations that may increase profit but degrade user satisfaction. Metrics include:

—**Intra-List Diversity (ILD) [3]:** One minus the average pairwise similarity between items in a recommendation list.

—**Novelty:** Measures how unexpected the recommendations are, often computed as the inverse popularity of recommended items.

6.4 Fairness and Ethical Metrics

In utility-driven RSs, optimizing for profit can introduce biases or unfairness. Metrics for fairness include:

—**Exposure Bias [35]:** Measures distributional equity of item exposure among suppliers or categories.

—**Aggregate Diversity:** The proportion of unique items recommended across the entire user base.

—**Provider Fairness:** Ensures that smaller or less popular providers receive a fair share of exposure [34].

6.4.1 *Table: Evaluation Metric Comparison.*

Table 8. : Evaluation Metrics for Utility-Based RSs

Metric	Description	Formula / Note
Expected Profit	Sum of profits from user interactions	$EP = \sum_u \sum_{i \in R_u \cap I_u} profit(i)$
Normalized Utility Gain	Utility relative to optimal	$NUG = \frac{\sum_u \sum_{i \in R_u \cap I_u} U(u,i)}{\sum_u U_{\max}}$
Precision@K	Fraction of relevant items in top-K	$\frac{\lvert\{i \in R_u : i \in I_u\}\rvert}{K}$
Recall@K	Fraction of relevant items retrieved	$\frac{\lvert\{i \in R_u : i \in I_u\}\rvert}{\lvert I_u \rvert}$
NDCG@K	Discounted gain of ranking positions	$DCG = \sum_{i=1}^{K} \frac{2^{rel(i)}-1}{\log_2(i+1)}$
ILD	Intra-list diversity across all pairs	$1 - \frac{1}{K(K-1)} \sum_{i \neq j} sim(i,j)$
Exposure Bias	Equity of item exposures	Variance or Gini-based measurement over exposures

7. APPLICATIONS AND CASE STUDIES

Utility-based and HUPM-driven RSs have been applied across various domains. We present representative case studies illustrating their effectiveness.

7.1 E-commerce Product Recommendation

7.1.1 *Profit-Aware Recommendation.*
Tang et al. propose a two-stage CF model where the first stage generates candidate items based on user preferences, and the second stage re-ranks candidates to maximize expected profit [9]. Their approach improves overall revenue by 15% compared to accuracy-only methods.

7.1.2 *Cross-Selling via High-Utility Itemsets.*
Liu et al. employ sequential HUPM on transactional purchase logs to discover high-utility itemsets for cross-selling strategies [19]. By recommending items that frequently co-occur with high profit margins, click-through rates increased by 12%.

Table 9. : E-commerce Case Studies

Study Outcome	Method	Dataset
Tang et al. [9] +15% revenue gain	Two-stage CF + Profit re-ranking	Retail transactions (1M records)
Liu et al. [19] +12% CTR for cross-sell	Sequential HUPM for cross-selling	Online retail logs (500K sessions)
Pham et al. [18] +10% profit uplift	Contextual HUPM with time window	E-commerce browsing logs (2M events)

7.1.3 *Table: E-commerce Case Study Summary.*

7.2 Online News Recommendation

7.2.1 *URecSys: Rule-Based Utility-Driven News RS.*
Kumar and Thakur present URecSys, which extracts high-utility sequential patterns from clickstream data to recommend news articles that maximize engagement and ad revenue [20]. In a real-world deployment on a major news portal, URecSys improved CTR by 9% and overall ad revenue by 7%.

7.2.2 *Engagement-Optimized News Feed.*
Yi et al. integrate dwell time into a CF framework, weighting user–item interactions by predicted engagement to optimize personalization [10]. This method increased average session length by 12%.

7.2.3 *Table: Online News Case Studies.*

7.3 Streaming Media Recommendation

7.3.1 *Deep Reinforcement Utility Optimization.*
Zhang et al. develop a deep reinforcement learning (DRL) framework that learns

Table 10. : Online News Case Studies

Study	Method	Dataset	Outcome
Kumar & Thakur [20]	URecSys (HUPM + Rule-based)	News click-streams (1.2M sessions)	+9% CTR, +7% ad revenue
Yi et al. [10]	Dwell time-weighted CF	News logs (800K reads)	+12% session length
Liang et al. [24]	Contextual HUPM news RS	Multi-source news logs (2.5M events)	+8% engagement utility

policies to recommend content by maximizing long-term watch time and ad revenue [23]. Their method outperformed baseline CF by 14% in watch time and 10% in ad revenue on a real streaming platform dataset.

7.3.2 Sequential HUPM for Watch Sequence Mining. Liu et al. apply HUS-Span to 10 million watch sessions to mine high-utility watch sequences for content recommendation [**?**]. They improved overall watch time by 11% and subscription retention by 5%.

Table 11. : Streaming Media Case Studies

Study	Method	Dataset	Outcome
Zhang et al. [23]	DRL for utility optimization	Streaming logs (5M sessions)	+14% watch time, +10% ad revenue
Liu et al. [**?**]	HUS-Span on watch sessions	Video platform (10M sessions)	+11% watch time, +5% retention
Pham et al. [18]	Time-aware HUPM for recommendation	Streaming service logs (3.5M events)	+9% engagement utility

7.3.3 Table: Streaming Media Case Studies.

7.4 Location-Based and Context-Aware Recommendation

7.4.1 Restaurant Recommendations with Utility Constraints. Xu et al. propose a context-aware RS for restaurant recommendation, incorporating user preferences, profit margins, and seasonal trends [37]. They achieved a 13% increase in reservation conversions.

7.4.2 Travel Package Recommendation. Wang et al. integrate user preferences, profit margins, and seasonal constraints to recommend travel packages that maximize platform revenue and user satisfaction [33]. The system improved booking rates by 12%.

Table 12. : Contextual and Location-Based Case Studies

Study	Method	Dataset	Outcome
Xu et al. [37]	Contextual HUPM for restaurants	Dining logs (400K visits)	+13% reservation conversion
Wang et al. [33]	Hybrid utility-driven travel RS	Travel bookings (250K)	+12% booking rate
Pham et al. [18]	Contextual multi-utility HUPM	Mixed domain logs (800K events)	+10% combined utility uplift

7.4.3 Table: Location-Based/Contextual Case Studies.

8. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite extensive progress, utility-based and HUPM-driven RSs face several open challenges. We highlight key areas for future exploration.

8.1 Fairness, Accountability, and Transparency

Optimizing utility (e.g., profit) can exacerbate biases, disadvantaging niche content or less popular suppliers. Future work should:

—**Develop Fairness-Aware Utility Models:** Incorporate fairness constraints to balance utility and equitable exposure [34, 36].
—**Accountability Mechanisms:** Ensure transparent decision-making paths for stakeholders, including explainable utility influences.
—**Bias Detection and Mitigation:** Develop metrics and methods to identify and correct systematic biases introduced by utility optimization.

8.2 Privacy-Preserving Utility Modeling

Utility-based RSs often require sensitive business data (e.g., profit margins) and user engagement logs, raising privacy concerns. Research directions include:

—**Federated Utility Learning:** Learn utility models in a decentralized manner without sharing raw data [29].
—**Differentially Private HUPM:** Apply DP mechanisms to HUPM algorithms to preserve privacy [30].
—**Secure Multi-Party Computation (SMPC):** Enable collaborative utility computation across stakeholders without data leakage [28].

8.3 Dynamic and Contextual Utility Adaptation

User preferences and business objectives evolve over time. Research opportunities:

—**Temporal Utility Modeling:** Develop time-aware utility functions that adapt to seasonality, trends, and user lifecycle changes [27].
—**Contextual Multi-Objective Optimization:** Integrate multiple utility objectives (e.g., short-term profit vs. long-term engagement) in dynamic contexts [27].

8.4 Deep Learning Integration

Deep neural networks offer expressive power for modeling complex utility functions and user–item interactions. Promising directions include:

—**Neural Utility Modeling:** Use deep architectures (e.g., attention-based, graph neural networks) to learn latent utility representations jointly with preference embeddings [38].
—**End-to-End Utility-Optimized Architectures:** Develop unified frameworks that directly optimize for utility objectives during training [33].

8.5 Explainability and Interpretability

Users and stakeholders require understanding of why certain items are recommended, particularly when business incentives influence suggestions:

—**Rule-Based Explanations:** Leverage high-utility rules from HUPM to generate human-interpretable explanations (e.g., "Users who read articles A and B often engage with high-revenue article C") [38].

—**Post-Hoc Interpretation Methods:** Apply model-agnostic explainers (e.g., SHAP, LIME) to utility-based models to highlight key factors [39].

8.6 Multi-Stakeholder Recommendation

Traditional RSs focus on user–item utility, but modern scenarios involve multiple stakeholders (e.g., vendors, advertisers, platform owners). Future research should:

—**Develop Multi-Stakeholder Utility Models:** Balance utilities of different parties (e.g., user satisfaction, vendor profit, platform engagement) [34, 36].

—**Game-Theoretic Approaches:** Model interactions among stakeholders as strategic games to achieve equilibrium solutions [36].

8.7 Cross-Domain and Transfer Learning

Utility-based patterns in one domain (e.g., e-commerce) may inform recommendations in related domains (e.g., social commerce). Research directions:

—**Cross-Domain HUPM:** Extend HUPM to mine high-utility patterns across multiple related datasets (e.g., user purchase and browsing logs) [31].

—**Transfer Learning of Utility Functions:** Adapt utility models learned in one domain to another using heterogeneous relations [32].

9. CONCLUSION

This survey presented a comprehensive overview of utility-based recommender systems and high-utility pattern mining techniques. We began by discussing foundational RS paradigms and utility theory, highlighting the need to balance user satisfaction and business objectives. We reviewed transactional and sequential HUPM algorithms, emphasizing their application in clickstream analysis and rule-based recommendation. Hybrid RS architectures that integrate content-based, collaborative, and utility-driven components were categorized and analyzed. Scalability considerations, including distributed HUPM, GPU acceleration, and incremental learning, were surveyed. We then examined evaluation metrics tailored to utility-based RSs, including profit gain, diversity, and fairness metrics. Representative applications in e-commerce, online news, streaming media, and context-aware recommendation illustrated the practical impact of utility-driven approaches. Finally, we outlined open challenges and future research directions, including fairness-aware utility modeling, privacy preservation, dynamic utility adaptation, deep learning integration, explainability, multi-stakeholder optimization, and cross-domain transfer.

As the volume and variety of digital content continue to grow, developing next-generation RSs that optimize for multiple objectives—accuracy, profit, engagement, fairness—remains a critical research frontier. Utility-based and high-utility pattern mining techniques offer compelling tools to meet this challenge. We hope this survey serves as a foundational reference and inspires further advances in building RSs that deliver value to users and businesses alike.

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