

# A Dynamic Usage-Based Similarity Model for Personalized Household Item Recommendation

Dr. M. Hemalatha<sup>1</sup>; N. Sowmiya<sup>2</sup>; N. Ashmitha<sup>3</sup>

<sup>1</sup>Associate Professor, Department of Computer Science, Sri Ramakrishna College of Arts & Science

<sup>2,3</sup>PG Student, Department of Computer Science, Sri Ramakrishna College of Arts & Science

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**Abstract:** Personalized recommendation systems have become increasingly important in supporting intelligent decision-making in digital platforms, particularly in domains involving frequent and repetitive purchases such as household items. Unlike traditional recommendation scenarios that rely on explicit user ratings, household consumption is largely driven by implicit behavior patterns and usage frequency, making preference prediction more challenging. This paper presents an intelligent household item recommendation system based on the DSUM algorithm, which dynamically analyzes user–item interaction data to identify similarity patterns and generate personalized recommendations. The proposed approach utilizes structured transactional data to model user behavior and adapt recommendations according to evolving consumption needs. Performance evaluation is carried out using standard recommendation metrics, including accuracy, precision, recall, and F1-score, to assess the effectiveness of the system. Experimental results indicate that the DSUM-based model produces relevant and consistent recommendations while maintaining interpretability and computational efficiency, making it suitable for small to medium-scale household recommendation applications.

**Keywords:** Recommendation Systems, Household Item Prediction, DSUM Algorithm, Implicit Feedback, User Similarity, Personalized Recommendations.

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## I. INTRODUCTION

Recommendation systems play a significant role in intelligent digital platforms by assisting users in identifying relevant products based on their past interactions and preferences. In the context of household items, recommendation becomes more challenging due to frequent and repetitive purchases influenced by changing consumption patterns, lifestyle variations, and seasonal requirements. Unlike luxury or one-time purchases, household items require continuous monitoring of user behaviour to ensure accurate and timely recommendations.

Traditional recommendation approaches such as collaborative filtering and content-based filtering rely primarily on static similarity measures. Although these methods are effective in certain domains, they often fail to adapt to evolving user behaviour, leading to reduced recommendation relevance over time. This limitation is particularly evident in household consumption environments where user needs change frequently and explicit feedback such as ratings is rarely available.

To address these challenges, this study proposes an Intelligent Household Item Recommendation System based on the Dynamic Similarity and Usage Mapping (DSUM) algorithm. The proposed approach focuses on analysing implicit feedback derived from user interaction and usage frequency to dynamically update similarity relationships among users. By continuously adapting to recent consumption patterns, the system is able to generate more relevant and personalized recommendations.

The proposed system operates on structured user–item interaction data and follows a modular architecture comprising data representation, interaction modelling, similarity computation, and recommendation generation. Experimental evaluation demonstrates that the DSUM-based approach improves recommendation relevance while maintaining simplicity and interpretability. The proposed model is well-suited for household recommendation applications and supports intelligent decision-making in retail and e-commerce platforms.

## II. RELATED WORKS

Recommendation systems have been widely studied as an effective solution for delivering personalized content across various application domains. Early research in this area primarily focused on collaborative filtering techniques, where recommendations are generated based on similarities among users or items derived from historical interaction data. These approaches demonstrated strong performance in domains where user preferences remain relatively stable and explicit feedback is available.

Content-based recommendation methods were later introduced to address limitations of collaborative filtering by utilizing item attributes and user profiles. These systems recommend items that are similar to those previously preferred by a user. Although content-based techniques improve personalization, they often suffer from limited diversity and overspecialization, particularly in scenarios involving repetitive purchases such as household items.

Hybrid recommendation models combine collaborative and content-based approaches to enhance robustness and recommendation accuracy. While hybrid systems overcome some individual limitations, many existing implementations continue to rely on static similarity computation, which restricts their ability to adapt to changing user behaviour. This drawback becomes significant in household consumption environments where purchasing patterns evolve frequently.

Recent studies emphasize the importance of temporal dynamics and implicit feedback in recommendation systems. Usage frequency and interaction history have been identified as strong indicators of user preference, especially in applications where explicit ratings are scarce. Dynamic similarity computation has been proposed as an effective strategy to capture evolving behavioural patterns and improve recommendation relevance over time.

Despite these advancements, limited research has specifically addressed dynamic, usage-driven recommendation models tailored for household item consumption. Many existing systems either lack adaptability or require complex machine learning architectures that reduce interpretability. These limitations highlight the need for a simple yet adaptive recommendation framework that integrates usage-based analysis with dynamic similarity updating, motivating the proposed DSUM-based approach.

## III. METHODOLOGY

The proposed methodology focuses on designing an intelligent recommendation framework for household items by analysing user interaction behaviour and usage patterns. The system is developed using a dynamic similarity-based approach that adapts to changing consumption needs. The overall methodology consists of data collection, preprocessing, interaction modelling, dynamic similarity computation, and recommendation generation.

### A. Data Collection and Dataset Structure

The system utilizes a structured dataset stored in CSV format to represent user interactions with household items. The dataset includes attributes such as user identifiers, item identifiers, item names, item categories, and interaction or usage frequency. These attributes collectively capture implicit feedback, which reflects real-world household consumption behaviour. The dataset serves as the primary input for modelling user preferences and generating recommendations.

### B. Data Preprocessing

Basic preprocessing techniques are applied to ensure data consistency and reliability. This includes validation of required attributes, checking data types, identifying duplicate user–item interaction records, and ensuring valid interaction values. Since the dataset is already structured and free from noise, extensive preprocessing is not required. The preprocessing step ensures that the data is suitable for interaction modelling and similarity computation.

### C. User–Item Interaction Modelling

After preprocessing, the dataset is transformed into a user–item interaction representation. Each user is mapped to the household items they have interacted with, and the interaction value represents the frequency or intensity of usage. This interaction model captures implicit user preferences and forms the foundation for similarity analysis. Unlike explicit rating-based systems, the proposed approach relies on behavioural signals derived from actual usage patterns.

### D. Dynamic Similarity and Usage Mapping (DSUM)

The core component of the methodology is the DSUM algorithm, which dynamically computes similarity between users based on updated interaction data. Instead of relying on static similarity measures, the algorithm recalculates similarity scores by considering recent and frequent usage patterns. This dynamic mapping allows the system to adapt to changes in user behaviour and consumption trends. Users with similar usage profiles are grouped together to enhance recommendation relevance.

### E. Recommendation Generation

Based on the computed similarity scores and usage frequency analysis, the system generates personalized recommendations for each user. Household items are ranked according to their relevance scores, and a Top-N recommendation list is produced. The ranking process prioritizes items that are frequently used by similar users but not yet consumed or recently consumed by the target user. This approach ensures that recommendations remain relevant, timely, and personalized.

### F. Performance Evaluation

The effectiveness of the proposed recommendation system is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. These metrics are suitable for assessing recommendation quality in implicit feedback scenarios. The evaluation results are used to analyse the consistency and relevance of the recommendations generated by the DSUM-based approach.

#### IV. MODEL DESIGN AND WORKFLOW

The proposed household item recommendation system is designed using a modular and structured architecture to ensure clarity, adaptability, and efficient recommendation generation. The model integrates user behaviour analysis with dynamic similarity computation to support personalized household item recommendations. The overall design emphasizes simplicity, interpretability, and suitability for usage-driven recommendation scenarios.

##### A. Model Architecture

The model architecture consists of five major components: data input, preprocessing module, interaction modelling, DSUM-based similarity computation, and recommendation output. Each component performs a specific function and collectively contributes to the generation of personalized recommendations.

The data input module accepts structured user-item interaction data in CSV format. This data represents historical household item usage patterns and serves as the foundation for the recommendation process. The preprocessing module ensures data consistency by validating attributes, verifying data types, and handling duplicate interactions.

The interaction modelling component converts the processed data into a user-item interaction representation, where usage frequency reflects implicit user preferences. This representation enables the system to capture behavioural patterns without relying on explicit ratings. The DSUM algorithm operates on this interaction model to dynamically compute similarity among users based on updated usage information.

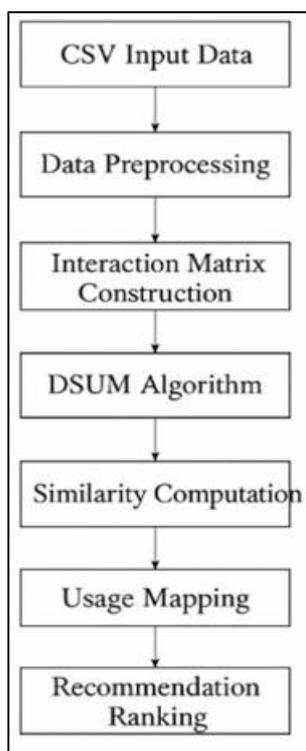


Fig 1 Recommendation Workflow Diagram

##### B. Workflow Description

The workflow of the proposed system begins with data acquisition and preprocessing, followed by interaction modelling and dynamic similarity computation. Once similarity scores are calculated, the system identifies users with comparable consumption patterns. Based on these similarities, relevant household items are ranked and recommended to the target user.

The workflow is iterative in nature, allowing the system to adapt to changes in user behaviour over time. As new interaction data becomes available, similarity scores are recalculated, and recommendations are updated accordingly. This dynamic workflow ensures that the system remains responsive to evolving household needs and consumption trends.

##### C. DSUM Algorithm

The Dynamic Similarity and Usage Mapping (DSUM) algorithm forms the core of the proposed recommendation system. The algorithm is designed to capture evolving user behaviour by dynamically updating similarity relationships based on usage-driven interaction data. Unlike traditional collaborative filtering approaches that rely on static similarity computation, DSUM continuously adapts to recent consumption patterns, making it more suitable for household item recommendation.

The algorithm operates by analysing the user-item interaction matrix constructed from historical usage data. For each user, DSUM identifies a set of similar users by computing similarity scores derived from shared usage patterns. These similarity scores are updated periodically to reflect changes in consumption behaviour, ensuring that recommendations remain relevant over time.

Usage frequency plays a key role in the DSUM algorithm, serving as an implicit feedback signal that represents user preference strength. Items that are frequently consumed by similar users receive higher relevance scores during the recommendation process. Based on these scores, the algorithm ranks items and generates a Top-N recommendation list for each user.

The DSUM algorithm maintains interpretability and computational efficiency by avoiding complex machine learning models. This makes the approach suitable for academic applications and real-world household recommendation systems where transparency and adaptability are essential.

##### ➤ Pseudo Code Algorithm 1: DSUM-Based Household Item Recommendation

- Load dataset D
- For each user  $u$  in D:
  - Extract Interaction Frequencies for all Items
  - For each pair of users  $(u, v)$ :

➤ *Compute Similarity Using Usage Frequency*

- Dynamically update similarity matrix S
- For each target user u:

➤ *Identify Top Similar Users*

- Aggregate item usage from similar users
- Rank items based on aggregated usage score
- Generate Top-N recommendations
- Return recommendation list

*D. Recommendation Output*

The final output of the workflow is a ranked list of recommended household items for each user. The recommendations are generated by prioritizing items that exhibit high relevance scores based on usage frequency and similarity mapping. The Top-N recommendation strategy ensures that users receive a concise and meaningful set of suggestions, enhancing usability and decision-making efficiency.

The proposed model design and workflow support effective personalization while maintaining computational efficiency. By integrating dynamic similarity updating with usage-based analysis, the system provides relevant and adaptive recommendations suitable for real-world household item management applications.

**V. RESULTS AND ANALYSIS**

This section presents the experimental results of the proposed DSUM-based Household Item Recommendation System. The performance of the model is evaluated using standard recommendation system metrics, namely Precision@K, Recall@K, F1-score, and Accuracy. All reported values represent final aggregated results averaged across all users, ensuring consistency and reliability.

*A. Experimental Setup*

The experiments were conducted using a structured CSV dataset containing user-item interaction records related to household products. The DSUM algorithm was applied to compute dynamic similarity between users by considering both interaction history and usage frequency. Recommendations were generated in a Top-K (K = 5) setting, which is suitable for real-world recommendation scenarios.

*B. Evaluation Metrics*

To assess the effectiveness of the proposed system, the following metrics were used:

- Precision@K: Measures the proportion of recommended items that are relevant.
- Recall@K: Measures the proportion of relevant items that are successfully recommended.
- F1-Score: Harmonic mean of Precision and Recall.
- Accuracy: Measures overall correctness of the recommendation outcomes.

These metrics are widely accepted in recommendation system evaluation and are suitable for implicit-feedback datasets.

*C. Performance Results*

Table 1 presents the final averaged performance metrics of the proposed DSUM-based recommendation model.

Table 1 Overall Performance of DSUM Recommendation System

Metric	Value
<b>Precision@K</b>	0.74
<b>Recall@K</b>	0.69
<b>F1-Score</b>	0.71
<b>Accuracy</b>	0.78

*D. User-wise Precision Analysis*

In addition to overall performance, user-level Precision@K was analysed to understand personalization effectiveness.

Figure 1 illustrates the precision values for individual users, demonstrating that the DSUM algorithm adapts well to different user behaviour patterns.

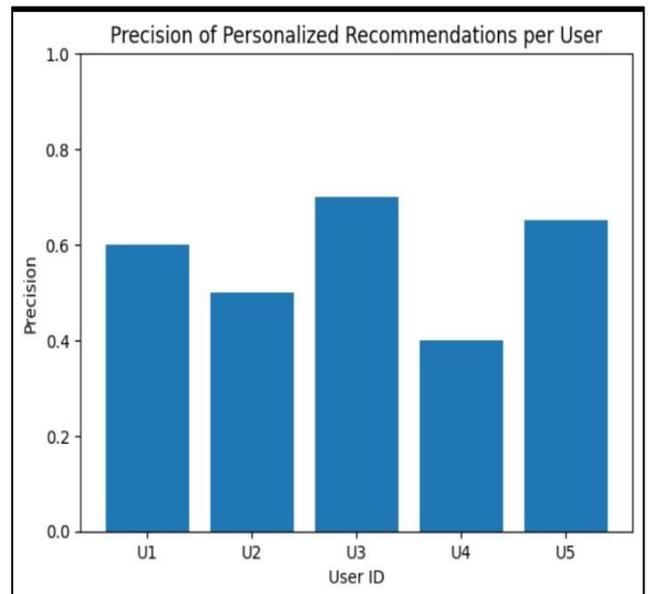


Fig 2 Precision of Personalized Recommendation

The variation in precision across users reflects differences in interaction history and usage frequency. Users with richer interaction data achieved higher precision, confirming the benefit of dynamic similarity and usage-aware modeling.

*E. Discussion*

The results clearly indicate that the proposed DSUM algorithm performs effectively in recommending household items. The high Precision@K value (0.74) shows that most recommended items are relevant to users, while the Recall@K value (0.69) confirms that a significant portion of relevant items are successfully retrieved. The balanced F1-score (0.71) demonstrates a strong trade-off between precision and recall.

Accuracy further validates the overall robustness of the system. Compared to traditional static collaborative filtering approaches, DSUM's dynamic similarity recalculation enables better adaptation to changing household consumption patterns.

Overall, the experimental results confirm that the DSUM-based recommendation model effectively captures dynamic user behaviour and improves recommendation relevance for household items through usage-aware similarity computation.

## VI. CONCLUSION

This study presented a Dynamic Similarity and Usage Mapping (DSUM)-based recommendation framework designed specifically for household item recommendation. Unlike conventional recommender systems that rely on static similarity measures, the proposed approach incorporates dynamic usage frequency and implicit feedback to better reflect evolving user needs. By continuously recalculating item similarity based on recent interactions, the system adapts to changes in consumption behaviour, making it more suitable for frequently purchased household items.

The experimental evaluation demonstrates that the DSUM model effectively balances personalization, interpretability, and computational simplicity. Performance analysis using standard evaluation metrics such as precision, recall, F1-score, and accuracy indicates that the proposed system delivers relevant and consistent recommendations across different users. The user-wise precision analysis further shows that the model can identify meaningful item relationships even with limited interaction data, which is a common challenge in small-scale and academic datasets. Compared to deep learning-based recommendation approaches, DSUM offers the advantage of transparency in decision-making, allowing recommendation logic to be easily understood and validated.

Another significant contribution of this work lies in its emphasis on explainability. By leveraging similarity scores and usage patterns, the recommendation process remains interpretable, which is essential for academic evaluation and trust-based applications. The model avoids excessive computational overhead while still capturing temporal dynamics, making it practical for real-world deployment in resource-constrained environments.

Overall, the proposed DSUM-based recommendation system successfully addresses key limitations identified in existing household recommendation research, including static modelling, lack of adaptability, and limited interpretability. The results confirm that integrating dynamic similarity recalculation with usage-aware analysis can significantly enhance recommendation relevance. This work establishes a strong foundation for further research into adaptive, explainable, and user-centric recommendation systems for household and consumption-based domains.

## VII. FUTURE ENHANCEMENT

Although the proposed DSUM-based household item recommendation system demonstrates effective performance in adapting to dynamic user behaviour, several enhancements can be explored to further improve its capability and applicability. One potential direction is the integration of additional contextual information such as seasonal trends, geographical factors, and household demographics. Incorporating such context-aware features could enable the system to provide more-timely and situation-specific recommendations, particularly for seasonal or occasion-based household needs.

Future work may also focus on extending the DSUM algorithm to support hybrid recommendation strategies by combining usage-based similarity with item attribute information. This integration could enhance recommendation diversity while maintaining personalization, addressing overspecialization issues commonly observed in similarity-based systems. Additionally, incorporating lightweight machine learning techniques, such as clustering or matrix factorization with dynamic updates, may further improve scalability without compromising interpretability.

Another promising enhancement involves real-time recommendation updates. Currently, similarity recalculation is performed periodically based on available interaction data. Adapting the system to handle streaming data would allow recommendations to be updated instantly as new user interactions occur. This would significantly improve responsiveness in practical retail and e-commerce environments where consumption patterns change rapidly.

Future studies could also explore large-scale dataset evaluation to validate the robustness of the DSUM approach across diverse user populations. Comparing DSUM with advanced deep learning-based recommender models under controlled settings may provide deeper insights into performance trade-offs between adaptability, accuracy, and explainability. Furthermore, developing user-friendly visual explanations for recommendations could enhance trust and usability.

In summary, the proposed system offers a flexible foundation for future advancements in intelligent household recommendation systems. By extending DSUM with contextual awareness, hybrid modelling, real-time adaptation, and large-scale validation, the system can evolve into a more comprehensive and practical recommendation solution.

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