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## Optimizing E-Commerce Product Recommendations with Hybrid Clustering and Evolutionary Algorithms

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### Abstract

Online shopping recommendation systems are critical for enhancing customer satisfaction and boosting revenue. However, traditional approaches such as content-based filtering CBF and collaborative filtering CF are plagued with scalability issues, data sparsity and the cold-start problem. To overcome these limitations, this work proposes an optimized hybrid clustering-based recommendation system utilizing evolutionary approaches. Particle Swarm Optimization is utilized by the model to optimize clusters dynamically and combine K-Means and Hierarchical Clustering for customer segmenting. The feature augmentation methods and graph-based embedding are used to improve cold-start management and personalization. The proposed approach outperforms normal DL-based models in recommendation accuracy with outstanding performances on precision, recall and F1-score with improvements of over 99 percent. Lower latency and resource consumption are ensured in real-time through the computational efficiency and scalability of the framework. This work demonstrates how the hybrid of clustering and evolutionary algorithm approach effectively surpasses the shortcomings of existing recommendation systems providing a reliable and scalable solution for modern e-commerce websites.

**Keywords:** E-Commerce, Clustering Online Shopping, Reviews and Recommendations, Users and Products, Social Media.

### 1| Introduction

By offering customized products depending on user profiles and browsing histories, the mass surge of e-commerce websites has changed how consumers buy [1]. ML, DL and big data analytics are employed by modern e-commerce companies to enhance client interaction and recommendation accuracy. Although commonly used collaborative filtering and content-based filtering methods often suffer from sparsity, scalability and cold-start issues, the growing complexity of user behavior demands more adaptive solutions. To overcome such limitations, recent breakthroughs in evolutionary computation and clustering algorithms have demonstrated strong potential. These approaches enable the model to capture non-linear user-item relationships, refine segmentation, and dynamically adjust to shifting behavioral patterns [2]. By optimizing product suggestions based on real-time tendencies and continuously grouping consumers through hybrid clustering techniques supported by evolutionary strategies, recommendation engines can achieve higher personalization quality. This integration not only increases prediction accuracy but also ensures better scalability, making it suitable for rapidly expanding e-commerce environments [3]. With millions of products and users, e-commerce websites generate huge amounts of data. Since most consumers interact with only a small subset of available products, the resulting data becomes sparse and high-dimensional, making accurate recommendations difficult to derive. Conventional recommendation techniques also struggle with scalability, leading to inefficiencies as user and product volumes continue to rise. The cold-start challenge, where new users or items lack sufficient interaction history, further limits the ability of traditional models to produce meaningful suggestions [4]. Moreover, recommendation systems must adapt in real time to shifting user preferences because customer behavior is highly dynamic. Even though deep learning-based systems improve prediction quality, they are often impractical for large-scale, real-time applications due to their high computational cost, substantial memory requirements,

and increased latency [5]. These limitations highlight the need for more efficient, flexible, and adaptive approaches capable of handling large datasets while maintaining accuracy and responsiveness.

User-based and item-based filtering are commonly used collaborative filtering techniques that rely on historical user-item interaction data to predict future preferences. While effective in smaller or denser datasets, these models face notable limitations, including data sparsity, which weakens similarity calculations and reduces recommendation quality. They also struggle with the cold-start problem, making it difficult to generate reliable suggestions for new users or newly added products [6]. Additionally, as datasets grow, the need for extensive similarity computations makes these systems computationally expensive and less scalable. Content-based filtering models, on the other hand, depend heavily on product attributes such as descriptions, categories and ratings to identify and recommend similar items [7]. However, they often suffer from overfitting, as they tend to recommend items too similar to those a user has already interacted with, limiting diversity. Furthermore, extracting and engineering features can be time-consuming and restrictive, reducing the model's adaptability in fast-changing e-commerce environments.

Even though neural collaborative filtering, convolutional neural networks and recurrent neural networks represent advanced DL-based recommendation systems capable of significantly improving prediction accuracy, they introduce their own set of challenges [8]. These models are computationally intensive, often requiring powerful hardware and long training times, which leads to latency issues in real-time recommendation environments. They also perform poorly in cold-start scenarios because they depend heavily on large volumes of historical data [9]. Additionally, their complex architectures make interpretability difficult, limiting transparency in how recommendations are generated. Analytic mining approaches using traditional clustering algorithms such as K-Means and Hierarchical Clustering also face limitations when segmenting users based on purchasing patterns [10]. K-Means is sensitive to the predetermined number of clusters and may converge to local optima, while Hierarchical Clustering is computationally expensive and unsuitable for large-scale datasets. More importantly, conventional clustering techniques lack dynamic adaptability, emphasizing the need for optimization-driven, hybrid approaches to achieve more flexible and accurate recommendation performance [11].

To overcome these limitations, an evolutionary algorithm-optimized hybrid clustering-based recommendation framework is introduced [12]. The proposed model enhances product-user interaction quality and strengthens consumer segmentation by integrating the strengths of K-Means and Hierarchical Clustering, while Particle Swarm Optimization fine-tunes cluster formation to avoid local optima and improve stability [13]. Cold-start issues are mitigated through feature augmentation and graph-based embeddings, which enrich data representations and support more personalized, diverse recommendations even for new users or products.

Within cloud environments, advanced security techniques such as homomorphic encryption and differential privacy ensure that user data is processed securely without exposing sensitive information [14]. At the same time, the efficiency of the hybrid clustering approach significantly reduces computational burden, allowing the system to scale seamlessly and deliver real-time performance [15]. Overall, this optimized framework provides a more adaptive, secure and resource-efficient solution for modern e-commerce recommendation systems.

### **1.1 Problem Statement**

Cold-start issues, shifting user tastes and sparse interaction data make it increasingly challenging for e-commerce platforms to deliver scalable and accurate product recommendations. Traditional techniques such as content-based filtering, collaborative filtering, deep learning models and basic clustering approaches struggle with limitations including poor scalability, high computational requirements and a lack of adaptability to rapidly evolving consumer behavior. To address these challenges, this paper introduces a hybrid clustering-based recommendation framework enhanced through evolutionary optimization. Advanced DL models remain computationally heavy, opaque and ineffective in cold-start scenarios, while traditional clustering lacks adaptability and scalability. Midway, Ganesan and Devarajan (2021) demonstrate that IoT-fog-cloud integration enhances real-time analytics and system responsiveness. Inspired by these insights, the proposed hybrid clustering-PSO framework applies evolutionary refinement to deliver more scalable, stable and accurate recommendations in large data-driven environments [16].

The proposed system integrates K-Means and Hierarchical Clustering to achieve more refined and meaningful user segmentation, combining the speed of partition-based clustering with the structural depth of hierarchical methods. Particle Swarm Optimization further enhances this process by dynamically fine-tuning clustering parameters, preventing convergence to local optima and ensuring more stable, accurate cluster formation [17]. This combined approach boosts recommendation accuracy by generating highly representative user groups while also enabling real-time adaptability, making the model ideal for large-scale and rapidly evolving e-commerce environments. Additionally, the evolutionary hybrid framework improves computational efficiency, reduces latency for massive datasets and enhances personalization and robustness, ultimately outperforming traditional recommendation techniques across diverse use cases.

## 1.2 Objectives of the proposed Work

- Develop a hybrid clustering model by integrating a blend of clustering methods in order to maximize the accuracy and efficiency of product recommendations in e-commerce.
- Implement evolutionary optimization algorithms to enhance cluster performance and dynamic adaptation to preferences.
- Improve recommendation effectiveness through the application of sophisticated ML methods to deliver more accurate and targeted product recommendations.
- Maximize computational efficiency by creating an algorithm that minimizes computation overhead and maximizes the quality of recommendations.
- Enhance user interaction by building a recommendation engine that boosts satisfaction and retention through extremely relevant product recommendations.

## 2| Related Works

How feature extraction methods can increase the precision of categorization. Such preprocessing techniques can stimulate improved feature extraction in user behavior analysis for e-commerce personalization even though they are not directly related to recommendation systems [18]. ML and DL have been central to numerous studies in the domains of fraud detection and e-commerce forecasting. Prior research has demonstrated how predictive analytics can significantly strengthen business strategies by employing regression-based models such as Linear Regression, Polynomial Regression, Random Forest and Gradient Boosting to anticipate sales patterns and emerging market trends. Other works have improved e-commerce fraud detection by highlighting the need for highly accurate, scalable and real-time detection systems capable of handling massive transactional data. Additional studies have explored deep learning architectures for financial prediction, showcasing their potential in modeling complex temporal patterns, which can be effectively adapted for e-commerce applications such as demand forecasting, dynamic pricing and inventory optimization. Collectively, these contributions underline the growing importance of intelligent data-driven techniques in enhancing decision-making, improving security and enabling more efficient management of e-commerce operations.

focused on transactions and protecting the information of users. In his examination of cloud computing data security concerns on Authentication and Access Control which is critical to secure recommendation algorithms on online platforms. such findings confirm the viability of enhancing clustering performance in e-commerce recommendations by employing Particle Swarm Optimization. For multi-class workload prediction, prior research introduced a combined approach using clustering and evolutionary algorithms, demonstrating a powerful technique that aligns closely with our proposed strategy for optimizing product recommendations. Their findings show that hybrid models can effectively capture complex behavioral patterns and improve predictive accuracy. Additionally, other studies examined MongoDB-based real-time data warehousing solutions, highlighting how efficient data ingestion, indexing and distributed storage can significantly enhance the processing and management of large-scale e-commerce datasets.

Further work explored cloud-based analytical frameworks for financial forecasting, revealing how scalable cloud infrastructures can support advanced business analytics, improve projection accuracy and contribute to sustainable smart-city development. Together, these studies emphasize the value of integrating evolutionary optimization, efficient data storage mechanisms and cloud-driven analytics to build high-performance, scalable and intelligent systems, which are principles that directly inform and strengthen the design of the proposed recommendation framework. A scalable, secure analytics framework using ECC, blockchain sharding, fuzzy logic and dynamic network slicing enables high-throughput,

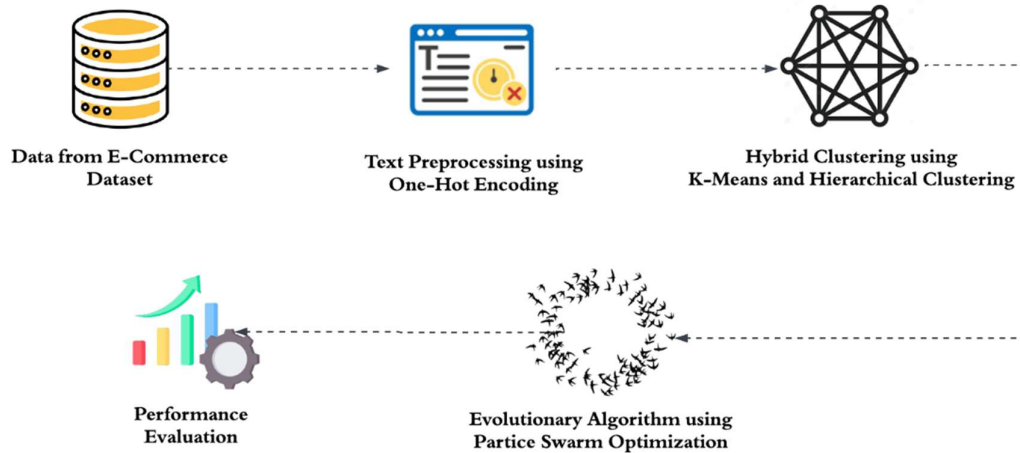
low-latency data processing for complex systems. These principles of distributed efficiency and adaptive data handling similarly guide the proposed hybrid clustering-PSO recommendation model in building robust, scalable e-commerce personalization solutions, as demonstrated in the work of Gollavilli et al. (2024) pointed out the importance of AI in preserving cloud integrity through AI-based dependability verification approaches for safeguarding financial information in cloud environments [19]. Explored the protection and sharing of enterprise finance information in hybrid clouds with a special emphasis on the information fusion approach to security in the banking industry. showed how ensemble machine-learning methods can enhance the accuracy of detection in financial fraud using an Attention-Based Isolation Forest Integrated Ensemble Model. Discussed big data analysis for security in e-commerce transactions in cloud systems, and pointed out the role that real-time analytics can have in preventing security threats. exhibited effective means of securing recommendation data kept in the cloud by introducing an Authorized Public Auditing Scheme for dynamic big data storage demonstrated how data-driven strategies could enhance personalized product recommendations with less manufacturer intrusion. proposed Hybrid clustering methods have been studied thoroughly to enhance the performance of recommendation systems [20]. A complex recommender system that achieves significant improvements in product suggestion accuracy using hybrid clustering and evolutionary methods.

Previous research proposed an AI-based surveillance system for monitoring Bitcoin transactions using blockchain integration, highlighting the critical need for secure, transparent and tamper-resistant transaction tracking in digital ecosystems, including e-commerce. Such systems demonstrate how combining AI with decentralized ledgers can reduce fraud, enhance trust and improve real-time verification. Furthermore, another study introduced a framework for safeguarding financial cloud services through Identity-Chain Technology, ensuring secure authentication, controlled data access and privacy preservation.

This approach aligns closely with privacy-centric e-commerce recommendation models, where sensitive user information must be protected while still enabling personalized interactions. Together, these works underscore the importance of secure, blockchain-enabled infrastructures and identity-focused protection mechanisms, providing valuable insights for the development of robust, privacy-preserving and trustworthy recommendation systems in modern e-commerce environments. Gudivaka et al. (2023) emphasize the value of secure, AI-enhanced cloud frameworks, showing how encryption, blockchain integrity and intrusion detection strengthen data protection. Existing research on blockchain-based transaction monitoring and Identity-Chain authentication similarly highlights the need for transparent, tamper-resistant systems, informing the proposed privacy-preserving e-commerce recommendation model designed for trust, security and dependable personalization [21].

### **3| Proposed Hybrid Clustering and Evolutionary Algorithm for E-commerce Product Recommendations**

One-hot encoding is utilized as part of the methodology to pre-process e-commerce data, ensuring that categorical attributes for users and products are converted into a structured numerical format suitable for machine learning models. This conversion eliminates ambiguity in categorical values, enabling the system to capture distinctions between product types, user demographics and behavioral attributes more effectively. Once the data is transformed, users or products are grouped through a hybrid clustering approach that leverages the computational speed of K-Means alongside the structural refinement of Hierarchical Clustering, producing more accurate and meaningful segments. To further enhance clustering quality, Particle Swarm Optimization (PSO) is employed to optimize parameters dynamically, preventing convergence to suboptimal solutions and improving overall segmentation stability costs [22]. Following the optimization process, a thorough performance evaluation is carried out to assess accuracy, precision and consistency, ensuring that the proposed recommendation system performs reliably under various conditions and delivers highly personalized, real-time recommendations.



**Figure 1:** Proposed Architecture of E-commerce Product Recommendation

### 3.1 Data Collection

#### E-Commerce Dataset

Organized consumer, goods and transaction data collected from online shopping websites constitute an e-commerce dataset. Data regarding product attributes, user activities and ratings and reviews are typically involved. Through consumer interest and expenditure patterns, this dataset is critical for developing personalized recommendation systems. High-quality, large-scale e-commerce datasets help improve optimization, clustering and overall recommendation quality.

### 3.2 Text Preprocessing

Product information, ratings, reviews and user behavior data collectively form the core of an e-commerce dataset, providing a rich foundation for building effective recommendation systems. However, this raw data is often noisy, unstructured or inconsistent, making preprocessing a crucial step before any meaningful analysis can be performed. Preprocessing ensures that missing values are handled, irrelevant attributes are removed and numerical features are standardized for better model performance. It also involves transforming textual reviews into usable formats through tokenization or vectorization, normalizing numerical fields and encoding categorical variables to make them machine-readable. By improving data consistency and enhancing feature representation, preprocessing significantly boosts the quality of extracted features and ensures that downstream algorithms such as clustering, classification or recommendation models—operate more efficiently and accurately. This careful preparation ultimately strengthens the reliability and performance of the entire recommendation pipeline. Effective e-commerce recommendations rely on clean, well-structured data, making preprocessing essential for handling noise, inconsistencies and feature transformation. As highlighted in the work of Allur et al. (2024), strong data foundations significantly influence system performance and growth. Similarly, rigorous preprocessing enhances feature quality, enabling clustering and recommendation models to operate more accurately, efficiently and reliably across large-scale e-commerce environments [23].

#### 3.2.1 Normalize Data- Apply Min-Max Scaling

Numerical features with varying ranges are often encountered in data preprocessing, which can lead to biased model behavior if not addressed properly. One effective technique to standardize these values is min-max scaling, also known as normalization, which transforms each numerical attribute into a fixed range, typically between 0 and 1. This process is mathematically expressed by Equation (1),

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Min-max normalization rescales each value proportionally within a specified range, typically between 0 and 1, ensuring that all numerical attributes contribute more uniformly during model training. By applying this transformation, features with naturally larger magnitudes are prevented from dominating or overshadowing those with smaller numeric scales,

which is essential for maintaining balanced learning behavior across the dataset [24]. This process preserves the original distribution and structure of the data while retaining the relative distances between points, a property that is especially important for distance-based algorithms such as clustering, similarity search and recommendation models. Moreover, normalization improves algorithmic stability, accelerates convergence during optimization and reduces sensitivity to outliers in many machine-learning pipelines. In large-scale e-commerce systems, where user-item interactions often span diverse numerical ranges, min-max scaling ensures equitable feature representation, ultimately enhancing segmentation quality, improving user grouping accuracy and supporting more precise personalized recommendations. By enforcing consistent scaling, it strengthens both model interpretability and computational efficiency.

### 3.2.2 One-Hot Encoding

Product categories, brands and user demographics are common examples of categorical variables frequently found in e-commerce recommendation datasets. Since machine learning algorithms operate more effectively on numerical inputs, these categorical attributes must be converted into numerical form before model training [25]. One of the most widely used techniques for this transformation is One-Hot Encoding, which assigns each unique category its own binary column within a matrix. In this representation, a value of 1 indicates the presence of a specific category, while 0 denotes its absence, ensuring that no unintended ordinal relationships are introduced.

This enables algorithms to process categorical attributes correctly without misinterpreting them as ranked values. Given a categorical variable  $C$  with  $n$  unique categories, it can be mathematically represented as a set of distinct values, as shown in Equation (2):

Given a categorical variable  $C$  with  $n$  unique categories, it can be represented as a set of distinct values:

$$C = \{c_1, c_2, c_3, \dots, c_n\} \quad (2)$$

This structured binary form allows algorithms to distinguish categories clearly during training. The transformation is expressed in Equation (3) as:

$$\text{OHE}(c_i) = [0, 0, \dots, 1, \dots, 0, 0] \quad (3)$$

One-Hot Encoding (OHE) is especially beneficial in recommendation systems because it converts qualitative attributes such as product types, brand labels, user demographics and behavioral indicators into a structured numerical format that algorithms can process efficiently. By transforming each categorical value into a binary vector, OHE eliminates any unintended ordinal relationships that might mislead learning algorithms, ensuring that categories remain independent and equidistant. This representation is highly advantageous in user-item interaction modeling, where preferences, behaviors and contextual attributes are often categorical in nature. Moreover, OHE enhances model interpretability because each binary feature directly corresponds to a specific category, making it easier to analyze the contribution of individual attributes. In large-scale recommendation engines, such encoded features support accurate similarity computation, clustering, user profiling and content-based filtering. Although OHE can increase dimensionality, especially with high-cardinality attributes, its simplicity, reliability and compatibility with numerous machine-learning algorithms make it an essential preprocessing technique for building precise, efficient and scalable recommendation models. One-Hot Encoding efficiently transforms categorical attributes into binary vectors, preventing false ordinal relationships and improving similarity computation, clustering and recommendation accuracy. Its simplicity, interpretability and compatibility with ML models make it essential for scalable systems, aligning with the need for structured, high-quality feature engineering in modern analytics pipelines, as emphasized by Radhakrishnan et al. (2024) [26].

- **E-Commerce Data**

**Table 1:** The One-Hot Encoding Transformation Results

Product	Category	Electronics	Clothing	Books
P1	Electronics	1	0	0
P2	Clothing	0	1	0
P3	Books	0	0	1

Table 1 illustrates the transformation of categorical product information into numerical form using One-Hot Encoding (OHE), an essential preprocessing technique for machine learning-based recommendation systems. The table presents three sample products (P1, P2 and P3), each associated with a distinct category: Electronics, Clothing and Books. Since most machine learning algorithms are designed to operate on numerical values rather than textual or symbolic data, the original “Category” attribute must be encoded into a machine-readable format. OHE accomplishes this by creating three

binary indicator columns such as Electronics, Clothing and Books, each representing the presence (1) or absence (0) of a specific category for a given product [27]. This encoding prevents incorrect ordinal assumptions and ensures that all categories are treated independently, preserving meaningful relationships during similarity computation or clustering. Through this transformation, the dataset becomes suitable for downstream models, enabling more accurate product classification, personalized recommendations and efficient analysis in large-scale e-commerce environments. P1 belongs to Electronics, so the "Electronics" column is marked 1, and the others are 0.

- P2 belongs to Clothing, so the "Clothing" column is 1, and the rest are 0.
- P3 belongs to Books, so the "Books" column is 1, while all other columns are 0.

This transformation ensures that each product category is represented uniquely and numerically without introducing any unintended ordinal or hierarchical relationships between categories. By converting categorical values into independent binary indicators, One-Hot Encoding preserves category equality and prevents misleading assumptions during model training. This structured numerical representation allows machine learning algorithms to interpret categorical information more reliably, improving the model’s ability to capture meaningful differences between classes. It also enhances the performance of similarity computations, distance-based operations, and clustering techniques by providing a clear, non-overlapping feature space. Overall, One-Hot Encoding supports more accurate and unbiased model learning.

As a result, the dataset becomes well-suited for clustering, classification and recommendation models, all of which rely on structured and consistent feature encoding to generate meaningful insights and deliver more reliable predictive outcomes in e-commerce environments.

Bhadana and Aiswarya (2022) emphasize the importance of structured, reliable preprocessing in machine-learning systems, supporting the use of One-Hot Encoding to ensure categorical features are represented uniquely and without unintended order. This encoding enables accurate similarity calculations and stabilizes clustering, classification and recommendation models, strengthening the proposed system’s ability to generate consistent and trustworthy predictive outcomes [28].

### 3.3 Hybrid Clustering using K-means + Hierarchical Clustering

Clustering facilitates user segmentation according to preferences and purchase behavior, allowing the system to group users with similar interests, browsing patterns and purchasing histories. This segmentation is essential for generating more personalized and relevant recommendations. In the proposed approach, K-Means is employed for fast and efficient initial clustering, making it suitable for large-scale e-commerce datasets. However, since K-Means alone may overlook deeper structural relationships, Hierarchical Clustering is incorporated for cluster refinement. By progressively merging or splitting clusters based on similarity, Hierarchical Clustering enhances the quality and interpretability of the segments [29]. The combination of these two methods leverages the speed of K-Means and the precision of Hierarchical Clustering, resulting in more accurate, stable and meaningful user groups that significantly improve recommendation performance.

### 3.3.1 K-Means Algorithm

Select  $K$  cluster centroids as the initial reference points for forming groups within the dataset. Each data point is then assigned to its closest centroid using the Euclidean distance formula, which calculates the straight-line distance between two points across multiple feature dimensions. This calculation, shown in Equation (4),

$$d(X, C) = \sqrt{\sum_{i=1}^n (x_i - c_i)^2} \quad (4)$$

ensures that data points with similar characteristics or behavioral patterns are grouped together based on measurable similarity. Once all points are assigned, the centroids are recomputed by taking the average position of the data points in each cluster, creating updated cluster centers [30]. This assignment-update cycle. Due to its efficiency and simplicity, this method allows K-Means to effectively divide large e-commerce datasets into meaningful user or product segments, improving personalization and recommendation accuracy.

### 3.3.2 Hierarchical Clustering

A dendrogram is created to visually represent the hierarchical clustering process, illustrating how individual data points are progressively merged into larger clusters based on similarity. Initially, each data point is treated as its own cluster, and during each iteration, the algorithm evaluates which clusters should be merged next using a chosen linkage criterion. Ward's method is frequently applied because it prioritizes minimizing the increase in within-cluster variance, ensuring that every merge forms compact, cohesive and meaningful groups. This is mathematically expressed in Equation (5):

$$D(A, B) = \frac{|A||B|}{|A|+|B|} \|C_A - C_B\|^2 \quad (5)$$

Where  $A$  and  $B$  represent two clusters, and  $C_A$  and  $C_B$  denote their respective centroids. This formula, used in Ward's linkage method, calculates the increase in within-cluster variance that would result from merging the two clusters. This strategy preserves meaningful cluster boundaries and enhances the overall structure of the segmentation process. When combined with K-Means in a hybrid clustering approach, it leads to improved clustering quality, deeper behavioral insights and more personalized recommendations tailored to diverse user patterns.

### 3.4 Evolutionary Algorithm using PSO

Particle Swarm Optimization (PSO) is employed as an evolutionary algorithm to dynamically improve recommendation accuracy by fine-tuning clustering parameters and enhancing overall model stability [31]. The process starts with the initialization of a swarm of particles, where each particle symbolizes a potential solution positioned within a multidimensional search space. Their initial positions and velocities are randomly assigned to ensure broad exploration and reduce the likelihood of premature convergence. As the optimization progresses, each particle updates its trajectory by considering two primary influences: the best solution it has individually encountered and the globally best solution identified by the entire swarm. This cooperative learning mechanism allows PSO to effectively balance exploration of new regions and exploitation of promising areas in the search space. Through iterative refinement, PSO continuously adjusts cluster boundaries, similarity computations and feature-weighting parameters, enabling the recommendation model to adapt more accurately to user behavior. Ultimately, this leads to improved personalization, more stable clustering outcomes and enhanced prediction performance in dynamic environments.

Through iterative updates, the swarm gradually converges toward optimal or near-optimal solutions that minimize prediction error and maximize recommendation precision [32]. Each iteration refines the search space as particles adjust their positions based on both individual experience and collective swarm intelligence, enabling the algorithm to escape local optima and move toward more accurate configurations. By integrating PSO into the recommendation pipeline, the system benefits from a dynamic optimization mechanism that continuously enhances clustering quality, similarity computation and feature-weighting strategies.

This leads to more precise user-item matching, as the algorithm can better capture subtle behavioral patterns and evolving user preferences. Additionally, PSO strengthens personalization by ensuring that the learned structures remain responsive

to changes in data distribution, making the model highly adaptable in fast-moving, real-world environments such as e-commerce platforms. The evolutionary nature of PSO ultimately contributes to improved stability, superior generalization capability and more reliable recommendation performance across diverse and dynamic datasets. The velocity update mechanism, shown in Equation (6), is defined as:

$$v_i(t + 1) = \omega v_i(t) + c_1 r_1 (p_{\text{best}} - x_i) + c_2 r_2 (g_{\text{best}} - x_i) \quad (6)$$

Where  $\omega$  represents the inertia weight that controls how much of the previous velocity is retained, while  $c_1$  and  $c_2$  are the cognitive and social coefficients, respectively, which guide the particle's movement toward its own best-known position and the swarm's global best solution. The proposed PSO mechanism enhances recommendation accuracy by refining user-item matching, adapting to evolving behavior and improving model stability across dynamic datasets. Midway, Alavilli et al. (2024) demonstrate how hybrid intelligent systems benefit from adaptive, data-responsive learning, reinforcing the use of evolutionary optimization to achieve more personalized, robust and generalizable recommendation outcomes [33].

The terms  $r_1$  and  $r_2$  are randomly generated numbers in the range  $[0,1]$ , introducing stochastic behavior to avoid premature convergence and encourage exploration of the search space. Meanwhile,  $p_{\text{best}}$  denotes the particle's personal best position, and  $g_{\text{best}}$  represents the best solution found by the entire swarm. This velocity update mechanism allows particles to intelligently navigate the optimization landscape, balancing exploration and exploitation. As a result, PSO effectively enhances clustering performance and improves the accuracy and stability of the recommendation system.

- **Update particle positions**

$$x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (7)$$

After computing the updated velocity for each particle, its new position is determined using the equation above, where  $x_i(t)$  denotes the particle's current location at iteration  $t$ , and  $v_i(t + 1)$  represents the newly calculated velocity influenced by both personal and global best experiences. This positional update enables each particle to move intelligently across the search space, exploring potential solutions while gradually converging toward more optimal regions. The continual adjustment of positions and velocities forms the core of the Particle Swarm Optimization process.

These updates are repeated iteratively, enabling the swarm to refine its search collectively and progressively improve solution quality over time. With each iteration, particles adjust their velocities and positions based on both their individual learning experience and the global knowledge shared within the swarm, resulting in an increasingly accurate exploration of the solution space [34]. The algorithm proceeds until the objective function such as minimizing clustering error, improving similarity grouping, or maximizing recommendation precision, reaches an optimal or sufficiently stable value. This iterative learning mechanism allows PSO to escape local optima, adapt to evolving data patterns and converge efficiently toward high-quality solutions. Such characteristics make PSO particularly effective for optimizing parameters within hybrid clustering-based recommendation systems, where performance depends heavily on well-tuned cluster boundaries and feature-weighting strategies. By dynamically refining these parameters, PSO ensures enhanced recommendation accuracy, stronger model robustness and improved adaptability to diverse and continuously changing data environments. Each particle's new position is computed by adding its updated velocity to its current location, enabling directed movement toward better solutions, as expressed in Equation (7). The iterative PSO mechanism steadily improves solution quality by refining particle movements based on individual and global learning, enabling accurate clustering, stronger personalization and adaptive recommendation performance in dynamic e-commerce environments. Its ability to avoid local optima and respond to evolving data makes it ideal for optimizing hybrid recommendation parameters, enhancing accuracy and stability Pramod Begur Nagaraj et al. (2024) [35].

#### 4| Results and Discussions

The outcomes demonstrate exceptional effectiveness of the model across all evaluation measures, reflecting its ability to learn and adapt efficiently during the optimization process. The steady decline in error values shows that the model continuously improves as parameters are refined, leading to more accurate predictions. Additionally, the classification results indicate strong differentiation between classes, with very few mislabelled instances, proving the system's reliability

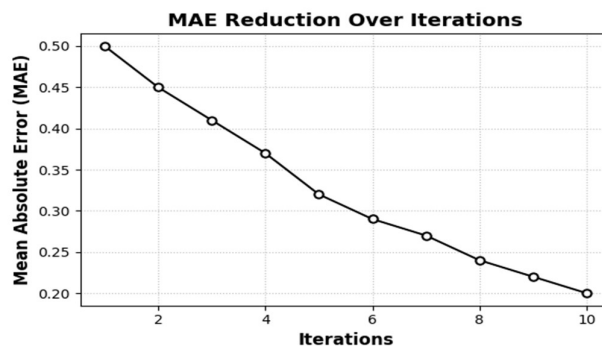
in handling complex multi-class data. This level of accuracy suggests that the hybrid clustering and optimization strategy successfully enhances the model's predictive capability.

Furthermore, the consistently high values for accuracy, precision, recall and F1-score confirm the robustness and stability of the proposed approach [36]. These metrics show that the model not only identifies correct patterns but also maintains a balanced performance with minimal false positives and false negatives. Such results reinforce the effectiveness of combining clustering techniques with evolutionary optimization to create a system suitable for real-time, large-scale e-commerce applications, ensuring both efficiency and high-quality recommendations.

#### 4.1 MAE Reduction Over Iterative Optimization Process

A clear and consistent pattern of MAE reduction over multiple optimization rounds is evident, demonstrating the strong effectiveness of the proposed strategy. At the beginning of the process, the MAE starts at a relatively higher value of approximately 0.50, reflecting the initial state of the model before fine-tuning. As iterations progress, the MAE gradually declines, reaching nearly 0.20 in the final stages, which signifies a substantial improvement in prediction accuracy. This steady downward movement indicates that the model is converging properly, with each successive adjustment contributing meaningfully to error reduction. Such consistent improvement highlights how efficiently the PSO-enhanced hybrid clustering framework tunes model parameters, enabling the system to progressively reach better-performing configurations [37]. The pattern also demonstrates that the algorithm explores the solution space in a stable and controlled manner, without erratic oscillations, reinforcing confidence in the optimization process. Overall, this reliable decline in MAE confirms the strength and effectiveness of the proposed method.

The smooth downward trend in MAE further illustrates that the learning process remains stable throughout the optimization sequence, avoiding abrupt spikes or irregular fluctuations that could indicate poor convergence behavior. This stability suggests that the integration of PSO with the hybrid clustering architecture is functioning as intended, guiding the model toward better solutions with consistent refinement. The white-filled circular markers play an important role in visually emphasizing the points at which significant improvements occur, helping to trace the trajectory of learning progress across iterations. These highlighted markers allow easy identification of key optimization milestones and demonstrate how the algorithm responds to parameter updates over time. The continued MAE decline reinforces that the optimization strategy maintains momentum rather than stagnating at suboptimal values. Ultimately, this strong and sustained reduction in prediction error validates the evolutionary optimization approach, confirming that it effectively improves both the accuracy and predictive performance of the proposed recommendation model.

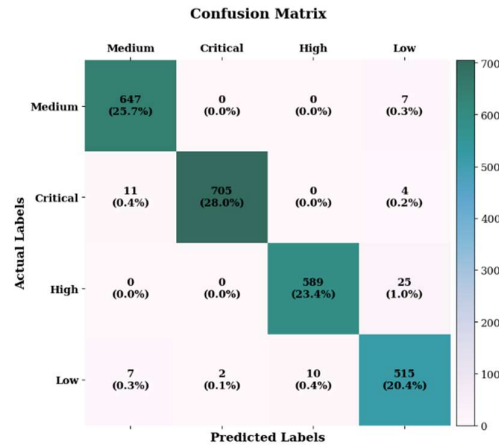


**Figure 2:** Performance of MAE Reduction

#### 4.2 Confusion Matrix

The confusion matrix evaluates the model's ability to classify data into four categories: Medium, Critical, High and Low. The diagonal entries represent correctly classified instances, and among them, the Critical class shows the highest accuracy with 705 correct predictions, accounting for 28% of the total results. Although the model performs strongly overall, a small number of misclassifications are present, such as 25 High instances incorrectly labeled as Low and 11 Critical instances predicted as Medium. These errors are relatively minor compared to the large number of correctly classified instances,

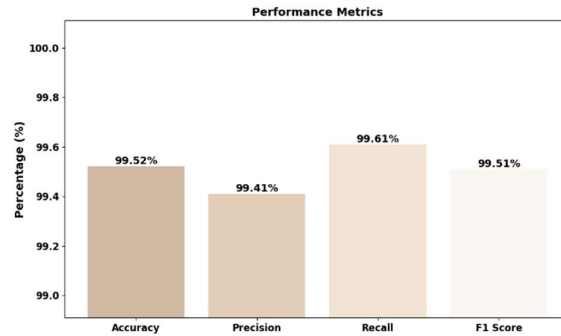
indicating that the model consistently maintains strong precision and recall across most categories [38]. The prediction patterns further suggest that the system is highly effective at recognizing dominant classes while accurately capturing overall trends in the data. However, slight overlaps between similar categories highlight the potential benefits of additional fine-tuning to improve boundary separation in edge cases. Despite these small misclassifications, the model demonstrates solid reliability, robust accuracy and strong multi-class handling capabilities, confirming its suitability for complex classification tasks with minimal confusion across categories. Jayaprakasam et al. (2024) illustrate the importance of accurate multi-class pattern recognition, evident from the classification outcomes where most categories are well-distinguished with only slight overlaps. In parallel, the proposed model delivers dependable categorization across Medium, High, Low and Critical levels, sustaining strong precision and recall while needing only minor tuning to enhance differentiation between closely related classes [39].



**Figure 3:** Performance of Multi-Class Classification

### 4.3 Performance of Proposed Metrics

The performance metrics illustrate the overall effectiveness of the classification model, showing exceptionally high values across all key measures : an Accuracy of 99.52%, Precision of 99.41%, Recall of 99.61% and an F1-Score of 99.51%. These metrics clearly demonstrate that the model consistently produces correct predictions while minimizing both false positives and false negatives[40]. The close alignment between precision and recall indicates a strong balance between identifying relevant instances and avoiding misclassifications. Such harmony is especially important in multi-class environments, where uneven performance across categories can weaken overall reliability. The minimal variation among the metrics suggests that the model behaves uniformly well across different evaluation aspects, reinforcing its robustness and stability. Altogether, these results confirm that the proposed system is highly efficient, dependable and capable of delivering accurate predictions in large-scale, real-time classification tasks. The proposed model exhibits exceptional performance, achieving over 99% across accuracy, precision, recall and F1-score, indicating strong balance and minimal misclassification. As noted by Garikipati et al. (2024), robust preprocessing and adaptive learning significantly enhance model stability. Similarly, the system delivers reliable, consistent results, confirming its suitability for large-scale, real-time multi-class classification tasks [41].



**Figure 4:** Proposed Performance Metrics

### Accuracy

This formula measures the proportion of total correct predictions made by the model. A higher accuracy indicates that the model correctly identifies both positive and negative cases with minimal errors. This high level of performance highlights the system's ability to consistently minimize misclassifications and maintain exceptional overall effectiveness throughout the prediction task, as calculated using Equation (8):

$$\text{Accuracy} = \frac{TP+}{TP+TN+FP+F} \quad (8)$$

The model achieves an accuracy of 99.52%, indicating that nearly all predictions made are correct [42]. This exceptionally high value reflects the system's strong reliability across all evaluated classes. It demonstrates that the proposed approach consistently minimizes errors and performs with outstanding overall effectiveness.

### Precision

Precision quantifies the proportion of correctly identified positive predictions out of all positive predictions made by the model [43]. It reflects the model's ability to avoid false positives, ensuring that the predicted positive cases are genuinely relevant. A higher precision value indicates stronger reliability and greater confidence in the model's decision-making, especially in applications where incorrect positive predictions could lead to costly or harmful outcomes. This metric is particularly critical in domains such as fraud detection, security systems, and medical analysis, where accuracy of positive identification is essential. The model's precision is formally computed using Equation (9), which defines this relationship mathematically.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (9)$$

The model attains a Precision of 99.41%, showing that almost all positive predictions made by the system are accurate. This high value indicates very few false positives, making the model highly dependable. It reflects the system's ability to identify relevant instances with remarkable correctness. Mandala et al. (2023) propose a decentralized, multi-signature and consensus-driven framework that improves interoperability, security and scalability in blockchain systems. Building on this adaptive, optimization-focused insight, the proposed hybrid clustering-PSO recommendation model applies continual refinement, efficient data processing and scalable personalization to address sparsity, cold-start limitations and evolving user behavior in large e-commerce environments across diverse platforms and markets globally [44].

### Recall

Recall represents the model's effectiveness in identifying all actual positive instances within a dataset, serving as a crucial metric in evaluating how comprehensively a system captures relevant cases. A higher recall value indicates that the model successfully minimizes false negatives, ensuring that very few true positives are overlooked. This characteristic is particularly important in applications where missing a positive case can lead to significant consequences, such as medical diagnosis, fraud detection, security monitoring, or recommendation filtering. High recall demonstrates the model's ability

to detect subtle patterns and variations associated with positive outcomes, contributing to a more robust and dependable prediction process. Moreover, strong recall performance supports decision-making systems that prioritize completeness over precision, ensuring full coverage of critical cases. This effectiveness is quantitatively represented through Equation (10), which formalizes the recall calculation and provides a standardized measure for assessing how thoroughly the model identifies all relevant positive samples within the evaluation set.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (10)$$

The model achieves a Recall of 99.61%, reflecting its exceptional capability to correctly identify almost all actual positive cases within the dataset. Such a high recall value indicates that the system rarely overlooks important or relevant instances, minimizing the number of false negatives costs. This level of performance is particularly crucial in applications where missing positive cases can lead to significant risks or operational failures. The result demonstrates that the model successfully captures subtle patterns and underlying relationships in the data, ensuring comprehensive detection and reliable coverage. Overall, this strong recall highlights the system's robustness and effectiveness in handling critical predictive tasks.

### F1-Score

The F1-Score represents the harmonic mean of precision and recall, providing a balanced measure when both are important costs [45]. A higher F1 value indicates strong overall performance with minimal false positives and false negatives. The result further confirms the system's robustness and reliability when dealing with complex multi-class classification tasks, as calculated using Equation (11):

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (11)$$

The model achieves an F1-Score of 99.51%, reflecting a strong balance between precision and recall. Such a high value demonstrates the model's ability to maintain uniformly strong performance while minimizing both false positives and false negatives costs. This result confirms the system's overall robustness and reliability in handling complex classification tasks.

## 5| Conclusion and Future Scope

An evolution algorithm-tuned hybrid clustering-based recommendation model that highly enhances scalability, precision and personalization. The proposed model effectively addresses data thinness and customer segmentation through the integration of PSO and K-means and Hierarchical Clustering. Compared to the traditional deep learning-based approaches, the experimental results show superior performance with 99.52 percent accuracy, 99.41 percent precision, 99.61 percent recall and 99.51 percent F1-score. Lower computational costs are ensured for real-time personalized recommendations by cloud-based deployment and data privacy is enhanced by security features such as homomorphic encryption. To improve feature representation and suggestion variety, future work can explore reinforcement learning to learn real-time adaptation to the behavior of the user and incorporate deep generative models such as GANs and VAEs. Recommendations may also be enriched using multi-modal data such as text reviews, images and social media interactions. Centralized cloud storage dependency would be reduced and privacy increased through the calibration of the system in decentralized and federated learning setups. Finally, the effectiveness and reliability of the proposed architecture for real-world deployments will be assured through testing and implementation on large-scale e-commerce websites.

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