Journal of Design Intelligence
https://www.ffspub.com/index.php/jdi
ISSN 3104-9001 (print)
E-mail: jdi.office@ffspub.com

Article

A User Preference Recommendation System for Industry 5.0 Based on DSD-Transformer

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Received: November 28, 2025 / Revised: January 5, 2026 / Accepted: January 14, 2026 / Published online: January 24, 2026

Abstract: Industry 5.0, characterized by the deep integration of the Internet of Things (IoT), artificial intelligence (AI), digital twins, and edge computing, represents a new paradigm for intelligent manufacturing and human–machine collaboration. By enabling real-time interaction between physical and cyber-physical systems, Industry 5.0 fosters personalized, adaptive, and sustainable production environments. However, the growing diversity of industrial products and user requirements presents challenges in effectively matching industrial users with suitable design solutions or manufacturing resources. Recommendation systems, particularly those based on Collaborative Filtering (CF), have emerged as powerful tools to address this issue by leveraging user preferences and behavioral data. Nevertheless, traditional CF algorithms often encounter efficiency bottlenecks when processing the high-dimensional, heterogeneous, and dynamic data typical of Industry 5.0 environments.To overcome these limitations, this paper proposes a clustering-based CF algorithm that improves recommendation efficiency by incorporating industrial user relationship modeling. Furthermore, a Density-Sensitive Distance Transformer (DSD-Transformer) framework is developed to enhance clustering precision and recommendation accuracy. Experimental evaluations conducted on real industrial datasets demonstrate that the proposed model significantly outperforms existing methods in both prediction accuracy and computational efficiency, making it well suited for Industry 5.0-oriented intelligent recommendation and decision-support applications.

Keywords: Industry 5.0; Internet of Things (IoT); Recommendation System; Collaborative Filtering; Transformer; Density-Sensitive Distance
https://doi.org/10.64509/jdi.11.53

1 Introduction

The advent of Industry 5.0 marks a new frontier for the development of the Internet of Things (IoT), representing a paradigm shift from purely automated manufacturing toward human–machine collaboration, cognitive intelligence, and sustainable, value-driven innovation [1]. By integrating IoT with advanced artificial intelligence (AI), digital-twin modeling, and edge computing technologies, Industry 5.0 enables seamless interaction between physical production systems and cyber intelligence [2]. This convergence empowers smart factories and intelligent services to dynamically adapt to user preferences, optimizing both operational efficiency and human-centered design [3].

In this evolving industrial ecosystem, IoT amplifies user interaction and situational awareness within intelligent manufacturing environments [4]. Freed from the rigid frameworks of Industry 4.0 automation, designers and engineers can now co-create with intelligent systems to achieve personalized, adaptive, and resilient production [5]. As industrial networks expand and smart terminals proliferate, massive volumes of heterogeneous user-product interaction data are generated, creating new challenges in effectively matching industrial users with appropriate design solutions and manufacturing resources [6].

To address this challenge, recommendation systems have emerged as vital decision-support tools in Industry 5.0. By

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[*]Academic Editor: Li Li

analyzing user preferences, operational behaviors, and contextual data, these systems assist decision-makers in identifying the most relevant products, components, or configurations for intelligent manufacturing [7]. Among existing methods, Collaborative Filtering (CF) has demonstrated strong capability in inferring user preferences through behavioral similarity. However, traditional CF algorithms encounter efficiency and scalability limitations when processing the large-scale, multidimensional, and dynamic data prevalent in Industry 5.0 environments [8].

To overcome these constraints, this study proposes a clustering-based collaborative filtering algorithm that leverages industrial user relationships to pre-classify users and thereby enhance recommendation efficiency. By integrating K-means clustering with industrial social-relation modeling, the algorithm reduces computational complexity and improves predictive accuracy. Furthermore, the use of Density-Sensitive Distance (DSD) metrics optimizes cluster initialization, ensuring more precise representation of user similarity in complex industrial datasets [9].

Beyond accuracy, secure data transmission and trusted identity authentication are essential foundations for reliable collaboration in Industry 5.0 networks [10]. Recent research in IoT security—such as zero-day attack detection in vehicular systems [11] and multi-device collaborative authentication [12]—provides the necessary infrastructure for trustworthy, privacy-preserving recommendation processes.

In Industry 5.0, collaborative relationships among human experts, intelligent agents, and connected machines profoundly influence industrial decision-making and personalized design. However, the openness and complexity of industrial data often introduce noise and redundancy, making it difficult to extract meaningful patterns. To address this issue, this paper employs the Transformer architecture [8], renowned for its self-attention mechanism, to effectively model correlations between user features, operational contexts, and behavioral signals [13]. Through Transformer-based learning, the system can filter and organize industrial relationship data more efficiently, thereby improving both the accuracy and interpretability of user preference classification [14].

The major contributions of this paper are summarized as follows:

1. We propose a collaborative filtering–based recommendation framework tailored to the needs of Industry 5.0, providing an effective mechanism for connecting industrial user requirements with intelligent product and service information.
2. To tackle the inefficiency of traditional CF in high-dimensional industrial data, we integrate Transformer-enhanced K-means clustering with density-sensitive distance (DSD) optimization, yielding a novel recommendation model termed DSD-Transformer.
3. Comprehensive experiments conducted on industrial user datasets validate the effectiveness of the proposed model, demonstrating superior recommendation accuracy, computational efficiency, and applicability in Industry 5.0 scenarios.

The remainder of this paper is organized as follows: Section 2 reviews background knowledge and related research on recommendation systems and Industry 5.0. Section 3 introduces the problem formulation and details the DSD-Transformer framework. Section 4 presents experimental evaluations, and Section 5 summarizes the main conclusions of this study.

2 Background and Related Work

2.1 Matching Industrial Users to Products in Industry 5.0

The emergence of Industry 5.0 represents a major evolution of industrial systems, emphasizing human–machine collaboration, cognitive intelligence, and personalized design within intelligent manufacturing environments [15]. Unlike traditional Industry 4.0, which focused primarily on automation and digital interconnectivity, Industry 5.0 integrates human creativity with advanced technologies such as artificial intelligence (AI), Internet of Things (IoT), digital twins, and edge computing, thereby enabling dynamic adaptation between users, products, and production systems [5]

As enterprises increasingly invest in intelligent infrastructures, smart factories are becoming more user-centric and adaptive. Governments and organizations around the world are developing Industry 5.0 initiatives that encourage sustainable and human-centered innovation [16]. At the same time, consumer and industrial behaviors are shifting toward data-driven customization, where design and production must align closely with individual user requirements. This shift generates a large and complex flow of interaction data between users and intelligent systems, introducing challenges in efficiently matching users with suitable industrial products or design solutions [15].

In traditional industrial contexts, manufacturers have relied on product-oriented strategies to satisfy general market demands. In contrast, Industry 5.0 promotes user-oriented and personalized production, supported by intelligent technologies capable of interpreting user needs, usage contexts, and design preferences [17]. This transformation relies on continuous feedback loops and data exchange between human operators and cyber-physical systems, allowing products and services to evolve with user expectations [18].

However, as industrial systems become more intelligent and interconnected, the volume and diversity of user–product data have increased dramatically [19]. The rapid generation of design information, coupled with heterogeneous industrial user groups, creates new barriers to accurate and efficient user–product matching.

Recommendation systems play a critical role in addressing this issue. They leverage explicit data directly provided by users (e.g., ratings, evaluations) as well as implicit behavioral data (e.g., clickstreams, access logs, sensor interactions) to identify products or configurations that best fit user preferences [20]. By predicting user needs and presenting relevant recommendations, these systems enhance decision-making efficiency and improve user satisfaction in intelligent manufacturing environments.

Recent research further demonstrates that incorporating social and collaborative information from industrial networks can significantly improve recommendation accuracy. In real-world manufacturing and service ecosystems, users often seek advice or validation from trusted peers before making a decision. This behavior aligns with the sociological principle of homophily, which suggests that individuals tend to associate with others who share similar preferences or behaviors [21].

By modeling collaborative relationships among industrial users—such as shared design objectives, co-creation activities, or similar purchasing histories—recommendation systems can identify deeper patterns of user similarity. These patterns enable more accurate user clustering and enhance the predictive power of preference models [22]. Consequently, recommendation systems informed by industrial social data can bridge the gap between human decision-making and intelligent automation, thereby accelerating personalized innovation in Industry 5.0.

2.2 Related Work

This section provides an overview of the current applications of recommendation systems in different industrial and intelligent scenarios, as well as the main algorithms commonly employed in existing recommendation frameworks.

2.2.1 Usage Scenarios for Recommendation Systems

Recommendation systems can be conceptualized as supervised learning models that analyze user interaction histories to predict items or services that users are likely to prefer. The data utilized in constructing these systems typically combines information about users, items, and user preferences. These preferences may appear as explicit data, such as numerical ratings or feedback, or as implicit behavioral data, such as browsing records, clickstreams, and review sentiments.

Recommendation systems have been applied across a variety of domains, including e-learning [23], e-commerce [24], and industrial management. Their growing popularity stems from the increasing need for personalized and context-aware decision support.

In the field of e-learning, recommendation systems help identify relevant educational resources tailored to learner profiles, improving both engagement and learning efficiency [25]. In e-commerce, recommendation systems have evolved from simple novelty features into core business intelligence tools, enabling personalized product discovery and dynamic marketing strategies. These systems analyze customer preferences and behavioral data to make timely and relevant product suggestions [26].

With the rise of Industry 5.0, recommendation systems are increasingly integrated into intelligent manufacturing and industrial service systems. In these environments, they support user-centric decision-making by connecting industrial users with suitable design configurations, production resources, or intelligent products [27]. By leveraging IoT-generated data, digital twin models, and edge computing infrastructures, recommendation systems play a key role in bridging human creativity and machine intelligence, enabling adaptive and personalized production in real time.

2.2.2 Different Recommendation Algorithms

Recommendation algorithms can be broadly categorized into content-based, collaborative filtering, and hybrid approaches.

Content-based recommendation systems [28] suggest items by evaluating their similarity to user preferences based on content attributes, such as product specifications or design features.

Collaborative filtering (CF) algorithms [29, 30] predict user preferences by identifying shared behavioral patterns among users or similar items

Hybrid recommendation systems integrate multiple models to combine the strengths of both content-based and collaborative filtering approaches.

Each type of algorithm presents specific advantages and limitations. Collaborative filtering performs effectively when sufficient user–item interaction data is available but may suffer from data sparsity and cold-start problems. Content-based systems rely heavily on the quality and availability of item feature data, requiring significant preprocessing and domain knowledge. Hybrid systems can overcome these issues but often introduce computational complexity and reduce interpretability.

Recent advances in deep learning and neural network architectures have significantly improved recommendation accuracy and scalability. Modeling users' dynamic preferences from sequential behavioral data remains a critical challenge for recommendation systems. For instance, Sun et al. [31] proposed BERT4Rec, a sequential recommendation model using deep bidirectional self-attention to capture temporal relationships in user behavior. Pei et al. [32] developed a personalized reordering model leveraging the Transformer architecture to model global item dependencies. Wu et al. [33] introduced the Stochastic Shared Embedding Personalized Transformer (SSE-PT), demonstrating that personalization through shared embedding regularization can improve ranking performance. Similarly, Zhang et al. [**?**] proposed an attention-based personalized graph neural network (A-PGNN) for session-aware recommendation, while Heidari et al. [34] used Transformer-based bidirectional encoders for sentiment classification in online review data.

Within Industry 5.0 environments, recommendation systems face distinct challenges due to the complexity and social interdependence of human–machine collaboration [35]. Industrial users often form collaborative networks through shared projects, design tasks, or manufacturing workflows, which naturally exhibit social group structures similar to those in online networks. Consequently, collaborative filtering methods are particularly well-suited for Industry 5.0 scenarios, as they can leverage user relationship data to enhance the accuracy of preference modeling [36].

To address the inherent limitations of conventional CF approaches in handling large-scale, multidimensional industrial data, this study integrates clustering techniques with a Transformer-based architecture, resulting in an improved algorithm—Density-Sensitive Distance Transformer (DSD-Transformer). This hybrid approach combines the contextual learning ability of Transformers with the structural efficiency of clustering, offering an effective and scalable framework for industrial user preference recommendation in Industry 5.0 [37].

2.3 Our Motivation

Regarded as an advanced phase in the evolution of digital transformation, Industry 5.0 represents a human-centered industrial paradigm that emphasizes collaboration between humans and intelligent systems, cognitive interaction, and personalized production. It transcends the limitations of traditional automation by establishing an interconnected ecosystem where humans, machines, and intelligent infrastructures jointly participate in decision-making and innovation. Through real-time data exchange enabled by IoT, edge computing, and digital twin technologies, Industry 5.0 allows geographically distributed participants to collaborate seamlessly within intelligent manufacturing networks, achieving shared goals in design, production, and optimization.

As industrial operations become increasingly intelligent and personalized, recommendation systems have emerged as essential tools to support decision-making in complex industrial environments. These systems can analyze user preferences, behavioral patterns, and production contexts to provide personalized recommendations for design configurations, production resources, or service options. Within Industry 5.0 ecosystems—where human engineers, AI agents, and machines continuously interact—recommendation systems play a key role in enhancing user experience, operational efficiency, and adaptive manufacturing performance.

However, compared with traditional IoT-based industrial systems, the openness, scale, and data complexity of Industry 5.0 environments introduce significant challenges. The vast amount of heterogeneous data generated from industrial users, sensors, and intelligent devices often leads to information redundancy and noise, making the accurate matching between users and products increasingly difficult.

To address these challenges and improve recommendation efficiency, this paper integrates K-means clustering into the classical collaborative filtering (CF) algorithm. By pre-classifying industrial users based on behavioral or relational similarity, the system reduces computational overhead and enhances recommendation accuracy. Clustering allows the system to identify latent structures within user groups—such as shared production preferences or design objectives—thereby improving the precision of the recommendation process.

Furthermore, to enhance the adaptability and intelligence of clustering, this study incorporates the Transformer architecture into the algorithm. The Transformer's self-attention mechanism can effectively model contextual dependencies among user features and capture deep correlations within industrial behavioral data. By integrating Transformer-based feature encoding with K-means clustering, the proposed framework can dynamically represent user intent and preferences in varying industrial contexts.

To address the randomness problem in selecting K-means cluster centers, a Density-Sensitive Distance (DSD) function is employed for cluster initialization. This optimization ensures that clusters are more representative of user distributions and improves the robustness of the recommendation process.

Taken together, to maximize the efficiency and accuracy of industrial user–product matching, this paper proposes a new recommendation algorithm, termed DSD-Transformer (Density-Sensitive Distance Transformer). The model combines the contextual learning capability of Transformer networks with the structural efficiency of clustering, providing a scalable and adaptive solution for intelligent recommendation within Industry 5.0 environments.

3 System Framework

3.1 Problem Formulation

In this section, we provide a brief explanation of the operation of collaborative filtering (CF) recommendation algorithms and demonstrate how classical CF methods can be employed to address the challenge of matching a large number of industrial products or design resources to users in an Industry 5.0 environment.

Recommendation systems have evolved from being auxiliary functions in early e-commerce platforms to becoming core intelligent decision-making tools in modern industrial systems [38]. By analyzing behavioral data collected from users, such as operational records, production feedback, and preference histories, a recommendation system can select industrial products, materials, or configurations that best meet individual requirements and production contexts.

In Industry 5.0, where IoT connectivity, edge intelligence, and digital twins enable seamless communication between physical and cyber-physical entities, recommendation systems play a vital role in realizing human–machine collaboration and personalized intelligent manufacturing. As illustrated in Figure 1, industrial users interact with connected devices and intelligent systems through wireless networks and edge computing infrastructures, receiving personalized recommendations for optimal products, materials, or operational strategies in real time.

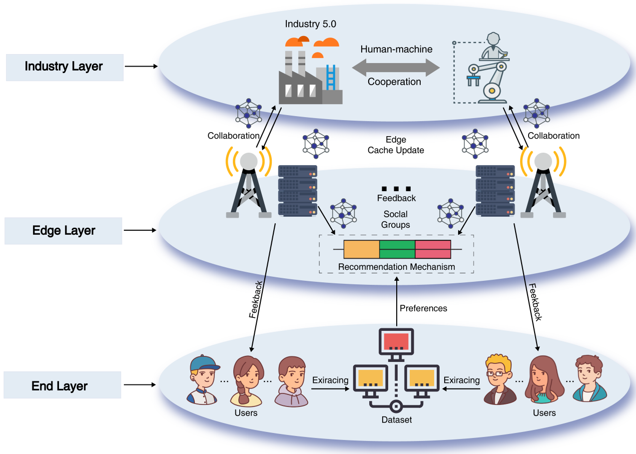

Figure 1: The relationship between users, wireless connectivity, edge computing technology, and Industry 5.0 intelligent manufacturing environments.

To identify related users or similar items, conventional collaborative filtering models typically employ user-based or item-based neighborhood algorithms. A user-based CF model generally involves three steps:

1. Determining the correlation among users.
2. Locating similar neighbors (users with comparable preferences or operational patterns.
3. Inferring a user's likely interest in an item based on the preferences of those similar neighbors.

To facilitate subsequent formulation, the key parameters and notations used in the CF model are summarized in Table 1.

Table 1: Meaning of the parameters

Notation	Description
u, v	Users
$\overline{s_u}$	user u's typical scores
$\overline{s_v}$	user v's typical scores
F_{ui}	for item i the user u's forecasted score
N_u	the neighbor set of user u

The core of the CF model lies in computing user similarity from historical evaluation or interaction data. The most common approach involves using Euclidean distance or related distance metrics. The similarity between users u and v can be expressed as:

$$sim\,(u,v) = distance = \sqrt{\sum_{i=1}^{n} \frac{(u_i - v_i)^2}{V\,[x_i]}}, \tag{1}$$

where u and V denote the feature vectors of two users, and $V\,[x_i]$ represents the variance corresponding to their feature attributes.

Once user similarity is determined, a subset of users most closely related to the target user is selected as the neighbor set, based on which the recommendation scores are estimated. The predicted preference value F_{ui} of user u for item i is calculated as:

$$F_{ui} = \overline{s_u} + \frac{\sum_{v \varepsilon N_u} sim\,(u,v)\,(s_{vi} - \overline{s_v})}{\sum_{v \varepsilon N_u} sim\,(u,v)}, \tag{2}$$

where $\overline{s_u}$ denotes the average score of user u, s_{vi} is the score given by neighbor v to item i, and N_u represents the set of users most similar to u. Finally, items with the highest predicted scores are selected and presented as the recommendation results.

Figure 2 presents the process of classical collaborative filtering in an Industry 5.0 context. For a new industrial user, the system first queries its relational data to determine the degree of association with other user groups. Then, by optimizing the dataset based on behavioral similarity and collaborative relationships, the system calculates user–group similarity. The most relevant user group is selected as the reference group, whose preference data are extracted for filtering and aggregation. Simultaneously, the historical operation logs and design decisions of the target user are retrieved to refine the recommendation space. After computing similarity-based ranking scores, the system generates a list of items with the highest recommendation values—representing optimal industrial products, configurations, or solutions for that user.

However, the classical collaborative filtering algorithm often fails to meet the real-time and large-scale recommendation demands of Industry 5.0. As the volume of industrial data continues to grow exponentially, traditional neighborhood-based methods suffer from low computational efficiency due to exhaustive similarity comparisons. Moreover, such methods tend to neglect synchronous evaluation behaviors among industrial users or machines, reducing recommendation accuracy when modeling complex, context-dependent user relationships.

3.2 System Optimisation

To enhance the effectiveness and efficiency of recommendation systems in Industry 5.0 environments, this study introduces the K-means clustering mechanism into the collaborative filtering framework. Although the K-means++ algorithm is well known for efficiently selecting initial cluster centers with reasonable separation, it assumes that the data distribution is approximately uniform and relies primarily on Euclidean distance. However, in the user embedding space generated by the proposed Cluster-former, industrial user preferences and collaborative relationships often exhibit high-density, irregular cluster structures, while other regions remain sparse or contain outliers. Under such conditions, K-means++ may initialize cluster centers in low-density regions, leading to unstable or suboptimal clustering outcomes.

To overcome this limitation, a Density-Sensitive Distance (DSD) approach is adopted. The DSD method integrates local density information with global shortest-path structures, enabling initial cluster centers to be distributed within more representative high-density areas. This allows the clustering to better capture the behavioral and relational patterns among industrial users. Although DSD incurs a higher computational cost, the cluster updates in this framework are performed infrequently (typically every few epochs), making the additional cost acceptable for Industry 5.0 recommendation scenarios where cluster stability and recommendation accuracy are prioritized.

Building on this, we propose a novel recommendation algorithm, termed DSD-Transformer (Density-Sensitive Distance Transformer), which combines the Transformer model with K-means clustering optimized using density-sensitive distance metrics. The algorithm introduces two key optimization components tailored to Industry 5.0 intelligent recommendation environments.

3.2.1 Cluster-former for Recommendation Efficiency

The Cluster-former module is designed as a customized adaptation of the standard Transformer architecture for industrial user behavior clustering. Unlike conventional Transformers that process entire sequences or sessions, the Cluster-former divides long user-interaction sequences into overlapping short segments using a sliding window mechanism with window size a and step size b. This enables the model to capture local behavioral patterns while preserving inter-segment continuity through overlapping attention.

Moreover, unlike sequence models such as BERT4Rec [31] or SSE-PT [33], which focus primarily on prediction or ranking, the Cluster-former explicitly generates latent user embeddings for clustering. These embeddings, aggregated

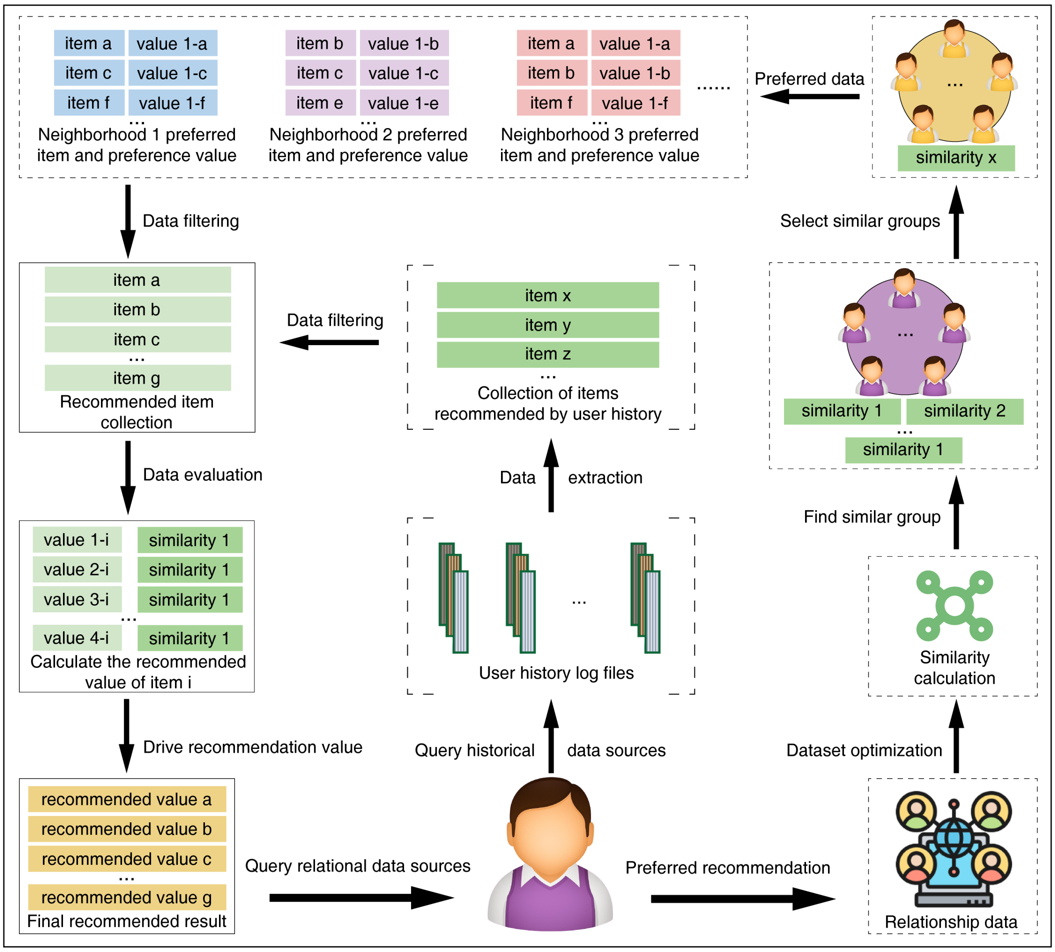

Figure 2: Flowchart of classic collaborative filtering.

across overlapping segments, are processed using a sparse self-attention mechanism applied within clusters. This approach preserves contextual coherence while significantly improving computational efficiency. To our knowledge, this structure has not been previously applied in collaborative filtering or Industry 5.0 recommendation research, representing a novel architecture integrating clustering and Transformer encoding.

The algorithmic procedure is as follows. The partitioning of a long user sequence group U into overlapping short user sequences with window size a and step b is formulated as:

$$H_k^0 = [Q; U[bk : (bk+a)]], \tag{3}$$

where $Q \in R^{q\times d}$ denotes the problem embedding for a given QA assignment and q represents the number of tokens in the problem description. $T \in R^{t\times d}$ gives the incorporation of all situations, the encoding sequence's identification is k, the sliding window's size is given by the variables a and b. $[id_{i1}]$ and $[id_{i2}]$ denotes the selection of rows between id_{i1} and id_{i2} denotes the selection of rows between id_{i1} and id_{i2} exponents of the matrix. $[\cdot;\cdot]$ indicates a sequence matrix in the rows. Since we want neighbouring user sequences to share useful information even when they are hidden, we allow overlap between user sequences by defining $b < a$. We attain as a result the mean of the Transformer concealed modes at the overlapping markers.

$$H_k^{n+1} = \text{Transformer}\left(H_k^n\right),$$

$$\begin{aligned}
H_k^{n+1}[q : q+a-b] += H_{k-1}^{n+1}[q+b : end],\\
H_k^{n+1}[q : q+a-b] /= 2,\\
H_k^{n+1}[q+b : end] += H_{k+1}^{n+1}[q : q+a+b],\\
H_k^{n+1}[q+b : end] /= 2.
\end{aligned} \tag{4}$$

The output of the K^{th} user sequence at the n^{th} level is $H_k^{n+1} \varepsilon R^{(t+1)\times d}$, combines the hidden states from user sequences with numbers $(k-1)$ and $(k+1)$.

Following that, the hidden state from the previous layer (the window layer that slides) is entered. The input to this layer is specified as after merging the overlap between the user sequence blocks as follows:

$$\overline{H}^n = [H_0^n[0 : t+b]; \ldots; H_K^n[0 : t+b]], \tag{5}$$

where $\overline{H}^n \in R^{\left(t\left[\frac{i}{b}\right]+i\right)\times d}$ is the hidden state to be clustered, and i is the number of tokens in the context.

Given that hidden states with higher cosine similarity tend to yield stronger attention weights, sparse self-attention is applied within each cluster rather than across the entire dataset, thus reducing computational overhead. The K-means algorithm is used for clustering, but to avoid instability from frequent centroid recalculations, the cluster centers are updated at a lower frequency (e.g., per epoch). Furthermore, to maintain consistency between iterations, the system records the nearest historical hidden states to prevent abrupt centroid shifts.

In this process, the resulting user embedding vectors encode not only behavioral similarity but also functional relationships and operational preferences within human–machine collaborative systems. Each user cluster can thus be interpreted as a "collaborative design group"—a set of engineers or operators exhibiting consistent preferences, production goals, or design strategies. This clustering significantly narrows the search space for CF-based recommendation while revealing the semantic and social structure underlying industrial interactions, thereby enhancing both interpretability and explainability of recommendations.

3.2.2 Clustering Center Optimization with K-means and Density-Sensitive Distance

The accuracy and stability of K-means clustering are highly dependent on initialization. Poorly chosen initial centroids can lead to local minima and unstable grouping results. To address this issue, we adopt an enhanced initialization strategy based on Density-Sensitive Distance (DSD), which adjusts cluster centers according to both spatial distance and local density information.

Inspired by related studies, this paper adopts the Density-Sensitive Distance (DSD) metric proposed by Tao et al. [39] to address the sensitivity of traditional clustering algorithms to noisy or unevenly distributed data. Building upon this, Erisoglu et al. [40] introduced an improved K-means initialization method that integrates density-sensitive distance to determine more representative initial cluster centers. In this approach, Euclidean distance is replaced with density-sensitive distance when constructing the similarity matrix, thereby enhancing clustering robustness and accuracy.In this study, an enhanced K-means algorithm incorporating density sensitivity is developed to further improve clustering performance and initialization stability.

The relevant definitions of the density-sensitive distance are as follows:

We define a graph $V = \{G, T\}$, where the sample points are represented as vertices G, and their connections as edges T. Let $p \in g_1$ denote a path between nodes p_1 and $p_{|p|}$, with a path length $l = |p-1|$. For each edge $(p_k, p_{k+1}) \in E, 1 \leq k \leq |p|$, the set of all possible paths connecting x_i and x_j, x_j, $x_i, x_j \in G$ is represented as p_{ij}. The density-sensitive distance between x_i and x_j is then defined as:

$$D_{ij} = \min_{p \in p_{ij}} \sum_{k=1}^{|p|} \left(e^{pd(p_k, p_{k+1})} - 1 \right), \tag{6}$$

$$D_p^{i,j} = \frac{1}{\eta^2} \ln \left(1 + D_{ij}\right)^2, \tag{7}$$

where $d(p_k, p_{k+1})$ represents the Euclidean distance between adjacent points p_k and p_{k+1}, and $\eta > 0$ is a scaling factor that adjusts the relative weighting between intra-cluster and inter-cluster distances. On the graph V, D_{ij} stands for the shortest path distance from node x_i to x_j, which is calculated as stated in Equation (6).

In the traditional K-means algorithm, initial cluster centers are selected randomly, which can significantly affect clustering accuracy and stability, leading to inconsistent results. To overcome this issue, we adopt the enhanced initialization strategy proposed by Erisoglu et al. [40], integrating density-sensitive distance into the centroid selection process. This approach is founded on two key principles: Cluster centroids should be located at positions with large mutual distances, and each centroid should lie within a region of relatively high data density.

The average density-sensitive distance is defined as:

$$D_{avg}^{\eta} = \frac{1}{C_n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} D_{ij}^{n}, \tag{8}$$

where C_n^2 gives the number of combinations of any two points picked randomly from all n sample points, and D_{ij}^{η} is the density-sensitive distance from x_i to x_j, the sample points. Identify the average number of samples point each sample point contains in the area around the point as P_{avg}. Point α is a dense point if the number of sample points included by D_{avg}^{η} in its vicinity is more than φP_{avg}, φ is the adjustment factor and is greater than 0. In our implementation, the adjustment factor φ is treated as a positive empirical constant that controls the strictness of dense-point selection. Unless otherwise stated, we set $\varphi = 1.0$, which corresponds to selecting sample points whose local neighborhood density is higher than the average density.

These are the initial phases in clustering centroid selection based on improvement in density sensitive distance:

Input: the original dataset, the quantity of clusters k.

Output: centers containing k clusters.

Step 1 Calculate the density sensitive distance $D_{j_1}^{\eta}$ according to Equation(6) and Equation(7).

Step 2 Calculate the average density-sensitive distance D_{avg}^{η} according to Equation (8).

Step 3 Determine how many sample points are contained in each sample point within the radius of D_{avg}^{η}, and find the set of all dense points contained therein with the number of sample points greater than φP_{avg}, denoted as P.

Step 4 The sample point in the sample set P with the maximum sample density is designated as the first initial clustering center, or c_1.

Step 5 Find the point c_2 that is the furthest away from point c_1 from P to serve as the second clustering center point.

Step 6 Solve for each point in turn until all centroids are selected.

The detailed algorithmic flow of the proposed DSD-Transformer is provided in Appendix A.

In summary, the proposed DSD-Transformer framework integrates the Density-Sensitive Distance (DSD) metric with the Cluster-former module through a synergistic clustering–attention mechanism tailored for Industry 5.0 recommendation environments. The Cluster-former encodes industrial user behavioral sequences via overlapping windows and multi-head self-attention to generate high-dimensional embeddings that capture cognitive and operational patterns. These embeddings are clustered using the K-means algorithm, whose initial centers are optimized with the DSD metric to ensure that centroids lie in high-density, representative regions of the embedding space. This optimization reduces clustering variance, enhances convergence, and improves interpretability. The resulting high-quality clusters partition the Transformer's attention space, enabling more efficient information encoding and personalized recommendations. Overall, this integration advances human-centered intelligence and data-driven decision-making, providing a scalable and interpretable solution for intelligent recommendation in Industry 5.0 systems.

3.3 Complexity analysis

To satisfy the real-time requirements of Industry 5.0 recommendation systems, we conduct a computational complexity analysis of the proposed DSD-Transformer framework. The framework comprises four major components:

Transformer sequence processing complexity: Long user sequences are segmented into overlapping windows of size a and stride b. Each window undergoes processing through N layers of Transformers. The single-layer, single-window complexity is $O\left(a^2 \cdot d\right)$, where d$d$ is the embedding dimension. The overall complexity is $O\left(N \cdot K \cdot a^2 \cdot d\right)$, where $K \approx T/b$ represents the number of windows.

K-means clustering complexity: Clustering T tokens with dimension d into hidden states. Single K-means iteration cost: $O(T \cdot k \cdot d)$ (k is the number of clusters). Cluster centers recalculated every E cycles (reduced frequency). Overall complexity: $O\left(E^{-1} \cdot T \cdot k \cdot d \cdot I\right)$ (I is the iteration count).

Density-Sensitive Distance (DSD) Optimization: Calculates pairwise distances among T samples, performs density-sensitive adjustments via graph-based shortest path traversal (Floyd-Warshall algorithm). Complexity: graph construction $O\left(T^3\right)$, center selection $O\left(T^2\right)$.

Collaborative Filtering (CF) Prediction: After clustering, calculates similarity only among U_c users within each cluster. Complexity: $O(U_c \cdot M)$ (M is item count).

Overall Complexity: The total runtime complexity of DSD-Transformer is $O\left(N \cdot K \cdot a^2 \cdot d + E^{-1} \cdot T \cdot k \cdot d \cdot I + T^3 + U_c \cdot M\right)$, where T denotes sequence length (number of tokens), Uc denotes the number of users per cluster after clustering ($U_c \ll U$), I denotes the number of iterations per K-means run, and a, b are sliding window parameters ($K \approx T/b$)

In practice, the cubic term from DSD optimization remains tractable due to moderate sequence lengths and low update frequency. For large-scale Industry 5.0 applications, approximate strategies—such as sparse graph construction or incremental clustering—can further reduce complexity to $O(T \log T)$ or $O\left(T^2\right)$, ensuring scalability and real-time responsiveness in intelligent, human–machine collaborative environments.

3.4 DSD-transformer based recommendations

Traditional recommender systems often struggle to efficiently process the large-scale, heterogeneous, and continuously expanding data generated in Industry 5.0 environments. To address this challenge, clustering-based collaborative filtering (CF) techniques are employed to reduce data complexity while maintaining high prediction accuracy. Clustering serves as a preprocessing step in CF, grouping users with similar behaviors or operational characteristics to enhance the precision and efficiency of subsequent recommendations.

In this study, a K-means-enhanced Transformer framework is developed, integrating traditional collaborative filtering with a clustering mechanism optimized for industrial user relationships. Unlike conventional CF methods that rely solely on user–item interactions, the proposed DSD-Transformer pre-classifies relational data based on users' social and collaborative relationships within industrial networks, improving the relevance between similar user groups and the target user. This design significantly enhances both the recommendation efficiency and the interpretability of system outcomes.

To mitigate the instability caused by random initialization in traditional K-means clustering—where selecting an outlier as an initial centroid can severely degrade results—this study employs Density-Sensitive Distance (DSD) to optimize the initialization process. DSD integrates both local density and global structural information to ensure that initial cluster centers are located in high-density, representative regions of the user embedding space. This yields a more stable and semantically meaningful clustering outcome, providing an improved foundation for CF-based inference. The overall workflow of the DSD-Transformer recommendation framework is illustrated in Figure 3.

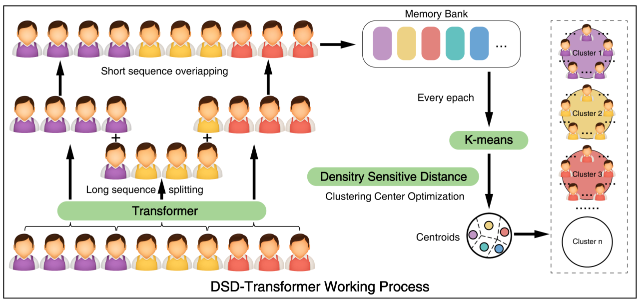

Figure 3: The proposed DSD-Transformer recommendation algorithm.

In practical Industry 5.0 scenarios, when a new user or operator enters the system, their relational and behavioral data are first queried from industrial databases and optimized for similarity computation. The system then calculates correlations with multiple collaborative user groups—based on shared production contexts, operational tasks, or decision patterns—to identify the most similar social–operational cluster. Preference data from this cluster are extracted to predict the new user's potential interests or task configurations.

Meanwhile, the system retrieves the target user's historical interaction logs from industrial IoT platforms to refine the recommendations. By excluding items or configurations already adopted by the user, the framework identifies a refined set of recommended industrial products, process parameters, or maintenance solutions. Finally, recommendation values for candidate items are calculated, and those with the highest relevance scores are presented to the user, achieving adaptive, human-centric, and context-aware recommendation outcomes suitable for intelligent decision support in Industry 5.0.

4 Trace-driven experiments

We created the following experimental verifications to confirm the efficacy and efficiency of our models.

4.1 Experimental Settings

To validate the DSD-Transformer model and evaluate the effectiveness of optimization strategies across different datasets, we collected two real-world datasets from an Industry 5.0 environment: the Industrial User Rating Database and the Industrial User Preference Database. We conducted algorithm performance validation tests on these datasets. The key configuration parameters for the experiments are as follows:

Dataset: validate the proposed approach, two proprietary datasets were constructed to represent industrial user–system interaction environments:

Industrial User Rating Database: This dataset includes approximately 5,000 users (operators, engineers, or decision-makers) and 10,000 industrial products, components, or service modules, with over 250,000 explicit user–item ratings on a 1–5 scale. The sparsity of approximately 0.5% reflects the practical characteristics of limited explicit evaluations in industrial systems. Ratings were collected from simulated IIoT platforms where users evaluate tools, parameters, or configurations based on performance and usability feedback.

Industrial User Preference Database: This dataset contains around 4,500 users and 8,000 industrial entities, recording implicit behavioral feedback such as selection frequency, interaction time, configuration adjustments, and preference signals. Approximately 300,000 interaction records are included, emphasizing behavioral and contextual engagement data rather than explicit ratings.

In both datasets, collaborative and social relationships are modeled through multiple channels, such as shared production lines, co-participation in maintenance tasks, or overlapping operational histories (e.g., users who configure or evaluate the same machines are considered behaviorally proximal). These connections are represented as undirected graphs, forming the structural basis for pre-clustering and social grouping. In these graphs, nodes represent industrial users, and edges indicate the existence of collaborative or social relationships between users derived from shared operational activities. Due to industrial confidentiality constraints, datasets are not publicly available but may be provided upon request under nondisclosure agreements.

Parameterization: The DSD-Transformer default parameters are configured as follows: the Cluster-former module uses a window size of $a = 10$ and a step size of $b = 4$, and the density-sensitive distance scaling factor is set to $\eta = 1.0$. The Transformer backbone network consists of $L = 3$ layers and $H = 6$ attention headers.The clustering factor is optimized to be $K = 4$ (based on the results in Figure 4,).The training The Adam optimizer was used in the training phase, with the learning rate set at and batch size of 128. Model performance was assessed by precision (P), recall (R), F-measure (F), mean absolute error (MAE) and mean average precision (MAP).

Baseline and variant models: To comprehensively evaluate the performance and robustness of the proposed DSD-Transformer framework, a comparative analysis was conducted against several established baseline models and ablation variants. The baseline models include Probabilistic Matrix Factorization (PMF) [41], Bayesian Probabilistic Matrix Factorization (BPMF) [42], SVD++ [43], and two Transformer-based recommendation models—BERT4Rec [31] and SSE-PT [33], which represent classical and modern paradigms in collaborative filtering and sequence-based recommendation. Beyond these, three ablation variants were designed to investigate the specific contributions of the proposed modules: Base-Transformer-CF (a base model that removes all clustering mechanisms), DSD-Transformer-NS (which replaces social clustering with stochas- tic clustering), and Full DSD-Transformer (which includes a social clustering module).

Implementing Rule: All experiments were performed on a server equipped with a dual 2.6 GHz Intel processor, 1 TB of RAM, and eight NVIDIA RTX 3060 GPUs; the software environment used the PyTorch implementation of the DSD-Transformer; the data was divided into an 80% training set and a 20% test set (randomly sampled); and the final results were reported as the average of 10 independent runs. The final results are reported as the average of 10 independent runs.

4.2 Experiment I: Algorithm Performance Validation

Evaluation Metrics: Using the precision (P), recall (R), F-measure (F), mean absolute error (MAE) and mean average precision (MAP) to examine the experimental results. They are calculated to be such:

$$R = \frac{|S(i) \cap Z(i)|}{|Z(i)|}, \tag{9}$$

$$P = \frac{|S(i) \cap Z(i)|}{|S(i)|}, \tag{10}$$

$$F-measure = \frac{2 * P * R}{P + R}, \tag{11}$$

where $S(i)$ denotes the total number of industrial resources or items recommended to user uu, and $Z(i)$ represents the set of items actually preferred or selected by that user.

A smaller MAE value indicates better recommendation accuracy and predictive reliability. Let the predicted preference set for user u be $\{d_1, d_2, \ldots, d_N\}$ and the corresponding ground truth scores be $\{t_1, t_2, \ldots, t_N\}$, then:

$$MAE = \frac{\sum_{i=1}^{N} |d_i - t_i|}{n}. \tag{12}$$

The MAP (Mean Average Precision) is calculated as:

$$MAP = \frac{1}{n} \sum_{i=1}^{n} precision_i, \tag{13}$$

Table 2: Performance comparison of PMF, BPMF, SVD++, BERT4Rec, SSE-PT and DSD-Transformer on two datasets

Dataset	Recommended method	R	P	F	MAE	MAP
Industrial User Rating Database	PMF	0.156	0.465	0.233	0.950	0.182
	BPMF	0.189	0.583	0.285	0.923	0.173
	SVD++	0.198	0.499	0.283	0.845	0.286
	BERT4Rec	0.237	0.671	0.350	0.865	0.301
	SSE-PT	0.236	0.647	0.347	0.768	0.421
	DSD-Transformer	0.293	0.743	0.418	0.755	0.463
Industrial User Preference Database	PMF	0.204	0.595	0.303	0.834	0.199
	BPMF	0.212	0.632	0.316	0.878	0.213
	SVD++	0.259	0.655	0.371	0.686	0.245
	BERT4Rec	0.278	0.693	0.396	0.647	0.202
	SSE-PT	0.303	0.657	0.415	0.632	0.378
	DSD-Transformer	0.329	0.754	0.458	0.598	0.531

where n represents the number of test cases or recommendation trials.

Comparison with Other Recommendation Models: To validate the proposed DSD-Transformer, we compared its performance against several state-of-the-art recommendation models widely used in intelligent decision-support and Industry 5.0 applications. These include Probabilistic Matrix Factorization (PMF) [41], Bayesian Probabilistic Matrix Factorization (BPMF) [42], SVD++ [43], and two Transformer-based recommendation models—BERT4Rec [31] and SSE-PT [33].

Table 2 summarizes the comparative results of all models. It can be observed that the proposed DSD-Transformer consistently achieves higher values of precision (P), recall (R), F-measure (F), mean absolute error (MAE) and mean average precision (MAP) compared to the baselines. This demonstrates its superior ability to capture complex user–resource interaction patterns and its effectiveness in processing large-scale industrial datasets characterized by high heterogeneity and social dependency.

Effect of Clustering Factor K: To further investigate the influence of the clustering parameter on model performance, experiments were conducted under different clustering factors K using two industrial datasets: the Industrial User Rating Database and the Industrial User Preference Database.As illustrated in Figure 4, the MAE of the DSD-Transformer decreases rapidly as the clustering coefficient increases at the beginning of the experiment. The optimal performance is achieved when $K = 4$, where the DSD-Transformer attains the lowest MAE and highest overall recommendation accuracy. In Figures 4(a) and 4(c), the MAE initially decreases and then increases with larger clustering factors, indicating that excessive cluster partitioning can reduce the representational accuracy of user neighborhoods. Meanwhile, Figures 4(b) and 4(d) show that the MAP of the DSD-Transformer consistently exceeds that of PMF, BPMF, SVD++, BERT4Rec, and SSE-PT across different settings. These results confirm that the DSD-Transformer achieves both superior clustering stability and higher-quality recommendations in Industry 5.0 human–machine collaborative environments.

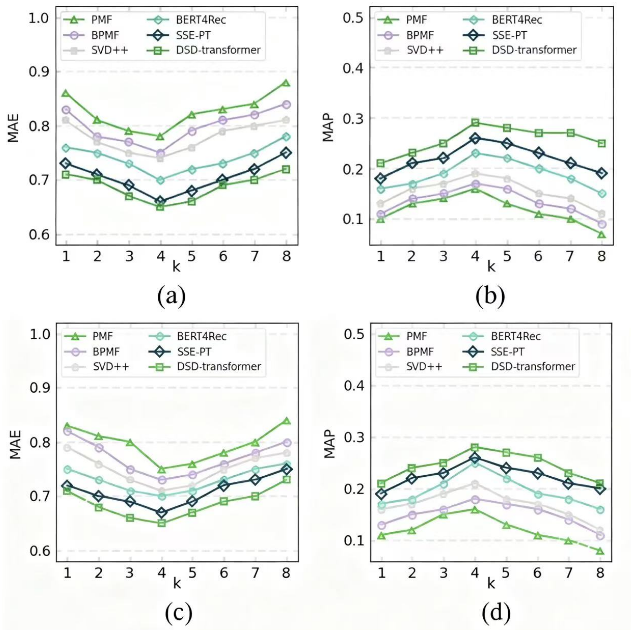

Figure 4: Performance on different K on Industrial User Rating Database and Industrial User Preference Database. (a) MAE vs. number of clusters (K) on the Industrial User Rating Database; (b) MAP vs. number of clusters (K) on the Industrial User Rating Database; (c) MAE vs. number of clusters (K) on the Industrial User Preference Database; (d) MAP vs. number of clusters (K) on the Industrial User Preference Database.

4.3 Experiment II: System Optimization Validation

Evaluation Metrics: In order to evaluate our proposed DSD-Transformer recommendation system and analyse its recommendation results, we introduced the following metrics: 1) the mean user satisfaction utility ($MUSU$) [44] achieved, and 2) the time complexity.

Evaluation Plan: To assess the optimization performance of the DSD-Transformer recommendation system, we implemented the model using PyTorch and conducted experiments on two real-world industrial interaction datasets. In Industry 5.0 scenarios, the recommendation system must operate efficiently under constrained computing resources and high interaction demands typical of human–cyber–physical systems. Therefore, the evaluation considered the maximum computational load of an industrial server environment.A total of 68 participants were invited to interact with the human–AI collaborative design platform, using the proposed DSD-Transformer system to receive personalized recommendations based on multi-relational user preference classification within the Industry 5.0 setting.

Implementation Rules: All algorithms were executed on a server equipped with dual 2.6 GHz Intel processors, 1 TB of RAM, and eight NVIDIA RTX 3060 GPUs. The social interaction datasets were randomly divided into an 80% training set and a 20% testing set, and the average results over 10 independent runs were reported.

Table 3 compares the proposed system's temporal complexity with that of other collaborative filtering methods. The average results of 100 independent tests are presented in Table 3. The experiments were conducted on a Dell Inspiron 173000 laptop equipped with a 10th generation Intel Core i7-1065G7 CPU (8 MB Cache, up to 3.9 GHz) and 16 GB RAM (2×8 GB DDR4, 2666 MHz), running the Ubuntu 19.04 operating system. As observed from Table III, the proposed system demonstrates the best runtime performance and computational efficiency among all compared methods.

Figure 5 illustrates that the Mean User Satisfaction Utility ($MUSU$) achieved by the DSD-Transformer significantly outperforms other recommendation systems. The DSD-Transformer exhibits particularly strong improvements on the Industrial User Rating Dataset, as it effectively models and predicts user preferences through multi-relational industrial social networks that capture human–machine collaboration and contextual dependencies in Industry 5.0 environments.

4.4 Experiment III: Ablation Analysis of Social Clustering Components

Evaluation Metrics: To quantify the contribution of social relationship modeling to recommendation performance, ablation experiments were conducted on three model variants: Base-Transformer-CF, DSD-Transformer-NS and Full DSD-Transformer.

Table 3: Time complexity comparison with other recommendation models

Dataset	System	Time complexity
Industrial User Rating Database	PMF	1.39
	BPMF	1.85
	SVD++	1.23
	BERT4Rec	1.17
	SSE-PT	2.32
	DSD-Transformer	1.12
Industrial User Preference Database	PMF	1.30
	BPMF	1.67
	SVD++	1.13
	BERT4Rec	1.09
	SSE-PT	2.09
	DSD-Transformer	1.04

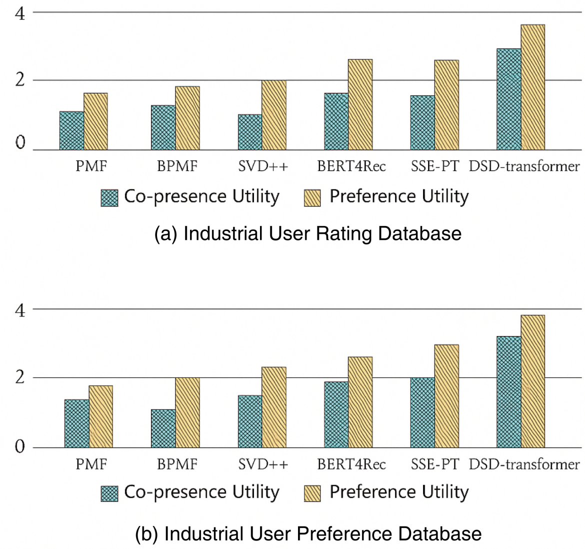

Figure 5: Average MUSU for each avatar in different datasets.

Performance was evaluated using Recall, Precision, F-measure, MAP, and MAE as defined in Equations (9–13).

As presented in Table 4, results on the Industrial User Rating and Industrial User Preference datasets show that the full DSD-Transformer significantly outperforms its variants in all metrics. Specifically, the F-measure improves by 20.5% (0.418→0.347) and 10.4% (0.458→0.415) over the DSD-Transformer-NS variant across the two datasets, while exceeding the Base-Transformer-CF model by up to 51.2%.The Base-Transformer-CF model, without clustering mechanisms, exhibits a sharp performance decline (e.g., a 40.5% drop in MAP), confirming the critical role of the social clustering component. In the Industrial User Preference dataset, the full DSD-Transformer attains a MAP of 0.531, outperforming the 0.378 achieved by the DSD-Transformer-NS variant, highlighting its capability in modeling implicit behavioral patterns.Overall, the social clustering mechanism significantly enhances cross-context recommendation accuracy, particularly in implicit preference mining, demonstrating its effectiveness in improving model generalization through structured semantic decoupling.

4.5 Experiment IV: Hyperparameter Sensitivity Analysis

Evaluation Metrics: To evaluate the robustness of the DSD-Transformer in Industry 5.0 recommendation environments, a hyperparameter sensitivity analysis was conducted using two datasets—Industrial User Rating and Industrial User Preference. The key hyperparameters analyzed include: window size a, step size b, density-sensitive scaling factor η, and Transformer architecture parameters (number of layers L and number of attention heads H). Evaluation metrics include MAE, MAP, and computational efficiency, defined in Equations (12) and (13).

Evaluation Scheme: A controlled variable methodology was adopted to evaluate the sensitivity of the proposed model to key hyperparameters, while maintaining the optimal clustering factor at $K = 4$ (as identified in Figure 4). In

Table 4: Comparison of the performance of Base-Transformer-CF, DSD-Transformer-NS, and full DSD-Transformer on the two datasets

Dataset	Model	R	P	F	MAE	MAP
Industrial User Rating Database	Base-Transformer-CF	0.198	0.499	0.283	0.845	0.286
	DSD-transformer-NS	0.236	0.647	0.347	0.768	0.421
	full DSD-Transformer	0.293	0.743	0.418	0.755	0.463
Industrial User Preference Database	Base-Transformer-CF	0.204	0.595	0.303	0.834	0.199
	DSD-transformer-NS	0.303	0.657	0.415	0.632	0.378
	Full DSD-Transformer	0.329	0.754	0.458	0.598	0.531

each experiment, only one parameter was varied at a time to isolate its individual effect on system performance. Specifically, the window size was set to $a \in \{6,8,10,12\}$, step size $b \in \{2,4,6\}$, the step size to $b \in \{2,4,6\}$ (ensuring $b < a$), the density-sensitive distance scaling factor to $\eta \in \{0.5,1,1.5,2\}$, and the Transformer architecture parameters were tested with the number of layers $L \in \{1,2,3,4\}$, and attention heads $H \in \{2,4,6,8\}$. The baseline configuration was defined as $a = 10, b = 4, \eta = 1, L = 2, H = 4$, representing the reference setup for comparative evaluation.

Implementation Rules: Implementation settings are identical to those in Experiment II.

As shown in Table 5, the model achieves optimal balance with $a = 10$, yielding the lowest MAE and highest MAP. A smaller window ($a = 6$) fails to capture sufficient local context, while a larger one ($a = 12$) increases computational cost. The optimal step size is $b = 4$, as a smaller step ($b = 2$) leads to redundant overlap and approximately 10% longer inference time.The best density-sensitive scaling factor is $\eta = 1$ ($MAE = 0.755/0.598, MAP = 0.463/0.531$). Extreme values ($\eta = 0.5$ or $2\eta = 2$) reduce effectiveness, suggesting that η is sensitive to data distribution but exhibits a clear optimal range.For the Transformer architecture, $L = 3$ layers provide a substantial MAP improvement (MAP up to 0.469/0.538), though deeper architectures ($L = 4$) yield diminishing returns with increased computation time. Similarly, $H = 6$ attention heads mark an inflection point ($MAP = 0.464/0.534$), beyond which accuracy saturates while cost increases.Overall, the model is moderately sensitive to a, b, and L, but relatively robust to η and H. The recommended configuration ($a = 10, b = 4, \eta = 1.0, L = 3, H = 6$) achieves the best trade-off between recommendation accuracy and computational efficiency, making it suitable for large-scale Industry 5.0 design intelligence applications.

Table 5: Effects of different a, b, η, L, H on Industrial User Rating Database and Industrial User Preference Database

Dataset	Parametric	Retrieve a value	MAE	MAP	Inference time
Industrial User Rating Database	a	6	0.789	0.421	1.12s
		8	0.768	0.446	1.18s
		10	0.755	0.463	1.20s
		12	0.762	0.452	1.36s
	b	2	0.761	0.447	1.31s
		4	0.755	0.463	1.20s
		6	0.767	0.439	1.14s
	η	0.5	0.773	0.444	1.19s
		1	0.755	0.463	1.20s
		1.5	0.759	0.456	1.20s
		2	0.766	0.439	1.20s
	L	1	0.771	0.440	1.06s
		2	0.755	0.463	1.20s
		3	0.748	0.469	1.37s
		4	0.746	0.470	1.61s
	H	2	0.760	0.457	1.16s
		4	0.755	0.463	1.20s
		6	0.752	0.464	1.25s
		8	0.751	0.465	1.31s
Industrial User Preference Database	a	6	0.622	0.488	1.15s
		8	0.609	0.513	1.20s
		10	0.598	0.531	1.22s
		12	0.604	0.519	1.39s
	b	2	0.606	0.516	1.34s
		4	0.598	0.531	1.22s
		6	0.610	0.509	1.17s
	η	0.5	0.614	0.506	1.21s
		1	0.598	0.531	1.22s
		1.5	0.601	0.525	1.22s
		2	0.608	0.510	1.23s
	L	1	0.611	0.507	1.08s
		2	0.598	0.531	1.22s
		3	0.590	0.538	1.40s
		4	0.588	0.539	1.65s
	H	2	0.604	0.525	1.19s
		4	0.598	0.531	1.22s
		6	0.594	0.534	1.28s
		8	0.593	0.535	1.34s

5 Conclusions

In this paper, we propose a collaborative filtering–based recommendation framework designed to address the challenge of efficiently matching industrial product and service information with user requirements in Industry 5.0 environments. Traditional collaborative filtering (CF) algorithms often exhibit inefficiency when processing large-scale, high-dimensional data generated within intelligent manufacturing and human–machine collaborative systems. To overcome these limitations, this study introduces an improved CF model that integrates a Transformer-based clustering mechanism with density-sensitive distance (DSD) optimization for enhanced initialization of cluster centers. This combination effectively balances global contextual modeling and local density representation, resulting in improved convergence stability and recommendation accuracy. Building upon these innovations, we develop a novel DSD-Transformer algorithm tailored to the needs of Industry 5.0, where data-driven decision-making and human-centered design intelligence are essential. The proposed algorithm not only enhances computational efficiency but also captures the social and collaborative dynamics intrinsic to human–machine–system interactions in industrial ecosystems. Experimental results based on real-world industrial datasets confirm that the DSD-Transformer achieves superior recommendation accuracy and faster computation compared to classical CF methods. These findings demonstrate the model's potential to serve as a robust and scalable recommendation foundation for intelligent design, production optimization, and adaptive decision-support applications within Industry 5.0-driven smart manufacturing and design intelligence systems. Despite the effectiveness of the proposed DSD-Transformer framework, the current model is trained in an offline manner with fixed clustering settings, which may limit its adaptability to highly dynamic industrial environments. Future work will explore online learning strategies and the integration of richer contextual information to further enhance scalability and real-time performance in Industry 5.0 applications.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

Conceptualization was carried out by Xiaoqun Dai and Ru Rao; methodology was developed by Ru Rao and Xinping Li; software implementation and system development were performed by Jie Zhang and Xiaoqun Dai; validation and testing of the proposed recommendation system were conducted by Xinping Li, and Jie Zhang; formal analysis and data interpretation were supported by Xiaoqun Dai ; investigation, including dataset collection and experiment design, was led by Ru Rao, Song Guo, and Xianyi Zeng; resources and infrastructure were provided by Xianyi Zeng; data curation and management were handled by Jie Zhang and Xiaoqun Dai; the original draft of the manuscript was written by Ru Rao and Jie Zhang; review and editing were performed by Xinping Li; visualization and figure preparation were completed by Song Guo and Xianyi Zeng; supervision and project administration were overseen by Xiaoqun Dai; funding acquisition was secured by Xiaoqun Dai. All authors have read and approved the final version of the manuscript.

Conflict of Interest

All the authors declare that they have no conflict of interest.

Data Available

The datasets generated or analyzed during the current study are available from the corresponding author upon reasonable request.

Ethical Approval

This study involved a system-level evaluation experiment in which 68 participants interacted with an industrial recommendation platform to assess system performance and user satisfaction. All participants were informed of the purpose of the study and participated voluntarily with informed consent. The experiment did not collect any personally identifiable information, sensitive personal data, or clinical information, and all interaction data were anonymized prior to analysis.

According to institutional and national guidelines, this study posed minimal risk to participants and therefore did not require formal ethical committee approval. The study was conducted in accordance with standard ethical principles for human-centered system evaluation.

Acknowledgements

The authors thank the colleagues and anonymous reviewers for their valuable comments and constructive suggestions.

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A Experiment Details

This appendix provides supplementary algorithmic details of the proposed DSD-Transformer framework to enhance reproducibility. These details are not included in the main text in order to maintain readability and focus on conceptual and experimental discussions.

Algorithm 1 presents the complete workflow of the DSD-Transformer based recommendation system designed for Industry 5.0 environments. The pseudocode explicitly describes the input preprocessing procedure, the Cluster-former embedding generation using overlapping sliding windows and Transformer encoding, the density-sensitive distance (DSD)–based initialization of K-means clustering centers, and the subsequent cluster-aware collaborative filtering process.

By providing a step-by-step algorithmic flow and clearly defining inputs and outputs, this appendix enables independent implementation of the proposed method without requiring access to proprietary source code or industrial datasets.

Algorithm 1 DSD-Transformer Based Industry 5.0 Recommendation

Require: User set U, Item set I, User–Item interaction matrix R, Industrial social/collaborative relationship graph G, Window size a, step size b, Number of clusters K
Ensure: Top-N recommended item list L_u for target user u
Input preprocessing
Extract user behavior sequences and collaborative relations from G
Construct initial user feature embeddings from R
Cluster-former embedding generation
for each user behavior sequence U **do**
    Partition U into overlapping windows with size a and step b
    for each window k **do**
        $H_k^{(0)} \leftarrow [Q; U[b \times k : (b \times k + a)]]$
        $H_k^{(n+1)} \leftarrow \text{Transformer}(H_k^{(n)})$
        Merge overlapping hidden states with adjacent windows
    end for
end for
Obtain unified user embedding matrix H
DSD-based clustering center initialization
Compute Density-Sensitive Distance (DSD) between user embeddings in H
Select k initial cluster centers from high-density regions using DSD
K-means clustering with DSD initialization
while cluster centers not converged **do**
    Assign each user embedding to the nearest cluster center
    Update cluster centers
end while
Cluster-aware collaborative filtering
Identify cluster C_u containing target user u
Compute user similarity only within C_u
for each item $i \in I$ **do**
    Predict rating F_{ui} using neighborhood-based CF
end for
Rank items by predicted scores F_{ui}
$L_u \leftarrow$ Top-N items
return L_u