Forward a hybrid AI fashion recommender system blending trends and personal style based on fuzzy systems

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ABSTRACT

During recent years, the accelerated evolution of online fashion trends and seasonal dynamics has increased the demand for intelligent recommendation systems capable of balancing personalization and novelty. This study presents a hybrid artificial-intelligence-based fashion recommender system that generates personalized and trend-aware clothing suggestions based on the contents of users' virtual closets. The proposed model integrates item-based collaborative filtering (IBCF) and content-based filting (CBF), augmented by a Sugeno fuzzy-logic module that computes a continuous trend percentage (T) using normalized sales, likes, and views. Experiments were conducted on a dataset of 4,224 items using simulated virtual closet ranging from 40 to 80 items. Performance was evaluated using precision at rank 10 (P@10), recall at rank 10 (R@10), and Normalized Discounted Cumulative Gain at rank 10 (NDCG@10), in addition to runtime scalability *vs*. catalog size. The proposed fuzzy-hybrid model consistently outperformed pure content-based, pure collaborative, and non-fuzzy hybrid baselines in recommendation accuracy while maintaining linear scalability. The results indicate that fuzzy-logic-based trend modeling effectively enhances the balance between stylistic consistency and exposure to emerging fashion trends within the evaluated experimental setting. However, the observed improvements should be interpreted cautiously because the experiments rely on simulated user closets and a private dataset. The findings suggest that the proposed approach can inform the design of adaptive fashion recommendation systems. However, results are obtained under a controlled simulation setting with manually designed fuzzy membership functions, and real-user validation remains an avenue for future work.

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INTRODUCTION

The digital transformation of the fashion industry has fundamentally reshaped how consumers discover, evaluate, and purchase clothing items through e-commerce platforms and social media channels (*Manzo et al., 2025*; *Deldjoo et al., 2023*; *Ling et al., 2023*). Rapid shifts in consumer preferences, short product life cycles, and socially driven popularity dynamics pose significant challenges for traditional recommender systems (RS), which are typically designed for stable preference environments (*Deldjoo et al., 2023*;

Melville & Sindhwani, 2017). As a result, fashion recommendation requires methods that can simultaneously preserve personalization while adapting to continuously evolving trends.

Conventional recommendation approaches, including content-based filtering (CBF) and collaborative filtering (CF), have demonstrated effectiveness in domains with relatively static user interests (*Melville & Sindhwani, 2017*). However, these approaches often struggle to capture temporal fluctuations and social engagement signals that strongly influence fashion consumption (*Melville & Sindhwani, 2017*). CBF systems emphasize stylistic similarity based on item attributes, while CF systems rely on aggregated user behavior, making both susceptible to trend obsolescence and sparse interaction data (*Sarwar et al., 2001*; *Hwangbo, Kim & Cha, 2018*). These limitations have motivated the adoption of artificial intelligence techniques capable of modeling uncertainty and subjective human judgment.

Fuzzy logic provides a particularly suitable framework for fashion recommendation due to its ability to represent gradual transitions between linguistic concepts such as "low," "medium," and "high" popularity (*Kosko & Burgess, 1998*; *Dogan, 2023*; *Karthik & Ganapathy, 2021*). Unlike Boolean logic, fuzzy systems allow partial membership, enabling the integration of ambiguous engagement indicators such as sales, likes, and views into a unified interpretative model (*Ling et al., 2023*; *Dogan, 2023*). In this work, trend modeling refers to the computation of a continuous trend percentage (T) that reflects the relative popularity of an item based on these engagement signals.

Recent studies have explored hybrid and deep-learning-based fashion recommender systems that combine CBF and CF to improve accuracy and mitigate cold-start issues (*Deldjoo et al., 2023*; *Liu & Zhao, 2023*; *Javed et al., 2021*; *Ding et al., 2023*; *Nachiappan, 2024*; *Benleulmi et al., 2025*). While these approaches have achieved notable performance gains, many lack interpretability or explicit mechanisms for incorporating real-time trend dynamics (*Ding et al., 2023*; *Benleulmi et al., 2025*; *Shimizu et al., 2023*). Deep learning models, in particular, often operate as black boxes, limiting transparency and practical control over recommendation behavior. Consequently, there remains a need for recommendation frameworks that are both interpretable and responsive to evolving fashion trends.

This study proposes a hybrid fashion recommender system that integrates item-based collaborative filtering and content-based filtering through a Sugeno fuzzy inference system. The fuzzy module computes a trend percentage that is incorporated into the ranking process to balance personalization with novelty. The main contributions of this work are threefold:

(1) The introduction of an interpretable fuzzy-logic-based trend metric derived from social engagement data
(2) The integration of this trend percentage within a hybrid recommendation architecture
(3) An empirical evaluation of accuracy and scalability using simulated virtual closets of varying sizes.

The remainder of this article is organized as follows. 'Literature Review' reviews related work on fashion recommender systems, with emphasis on fuzzy and hybrid approaches. 'Methodology' presents the proposed methodology, including fuzzy trend modeling and system integration. 'Results and Discussions' reports experimental results and analysis. 'Conclusions' concludes the article by summarizing findings, discussing limitations, and outlining directions for future research.

LITERATURE REVIEW

In recent years, artificial intelligence (AI)-driven fashion recommender systems have experienced significant growth due to the increasing diversity of consumer preferences and the large volume of fashion data generated on e-commerce and social platforms (*Shirkhani et al., 2023*). Initial systems primarily utilized CBF and CF methods (*Nachiappan, 2024*). These approaches were effective in structured environments but encountered challenges related to data sparsity, cold-start problems, and the subjective nature of fashion style. In response, researchers have introduced hybrid, context-aware, and fuzzy logic-based methods to improve personalization, interpretability, and adaptation to emerging trends (*Manzo et al., 2025*; *Benleulmi et al., 2025*).

Content-based and collaborative filtering approaches

Traditional recommender systems are typically categorized as either content-based or collaborative filtering methods. CBF compares intrinsic item features, such as text descriptions, categories, or image embeddings, to align with users' historical preferences (*Shirkhani et al., 2023*). For example, *Suvarna & Balakrishna (2024)* used a deep ensemble classifier for image retrieval, which improved visual relevance in fashion matching tasks.

Collaborative filtering leverages aggregated user behavior data to identify latent associations among items or users. IBCF methods, as demonstrated by *Sarwar et al. (2001)*, provide greater scalability and robustness to sparse data than user-based approaches.

Both approaches face limitations when item popularity fluctuates rapidly or when users have limited historical interaction data. These challenges are widespread in the fashion domain, where trends change seasonally.

Hybrid and deep-learning methods

Hybrid recommender systems integrate multiple recommendation techniques to address the limitations of individual models. *Basilico & Hofmann (2004)* introduced a unified model that merges CBF and CF using a joint kernel function, which enhances prediction accuracy in cold-start scenarios. More recently, *Deldjoo et al. (2023)* and *Ding et al. (2023)* conducted surveys of hybrid and deep learning-based fashion recommender systems, highlighting the application of convolutional and transformer architectures for predicting outfit compatibility.

Transformer-based Graph Neural Networks (TGNNs) (*Becattini, Teotini & Bimbo, 2023*) and disentangled representation learning (*De Divitiis et al., 2023*) have contributed

Table 1 Comparative summary of previous studies.

Study	Core methodology	Dataset/domain	Main limitation	Relevance to this work
Karthik & Ganapathy (2021)	Fuzzy + Ontology + Sentiment Analysis	E-commerce products	Lacks temporal trend modeling	Basis for fuzzy preference reasoning
Liu & Zhao (2023)	Item-based CF (KNN)	MovieLens	No context or fuzzy integration	Provides item-similarity foundation
Basilico & Hofmann (2004)	Unified CBF + CF Kernel	General recommendation	Cold-start partly solved, not trend-aware	Hybrid integration reference
Dogan (2023)	Profit-support fuzzy association rules	Online retail	Focused on profit, not personalization	Demonstrates fuzzy utility modeling
Suvarna & Balakrishna (2024)	Deep ensemble CBF (transfer learning)	Fashion images	Requires heavy computation; low interpretability	Highlights deep CBF potential
Ye et al. (2023)	Scene-aware hybrid recommender	Fashion outfits	Domain-specific; ignores social signals	Context-aware hybrid example
Deldjoo et al. (2023)	Survey of fashion recommenders	Multimodal	Lacks explicit fuzzy or trend focus	Confirms research relevance
Ling et al. (2023)	Fuzzy conflict-rule knowledge base	Fashion design	Limited scalability	Shows fuzzy modeling potential

to advancements in outfit generation and style compatibility modeling. Despite these improvements, deep learning models frequently lack interpretability and demonstrate limited adaptability to rapidly evolving fashion trends.

Fuzzy logic in recommendation systems

Fuzzy logic provides a robust framework for recommender systems by addressing uncertainty and enabling linguistic reasoning. *Karthik & Ganapathy (2021)* proposed a fuzzy-ontology-based recommendation system that integrates sentiment analysis and user demographics to identify nuanced user interests. *Dogan (2023)* presented P-FARM (Profit-Support Fuzzy Association Rule Mining), which combines profitability and sales frequency to inform e-commerce decisions. *Ling et al. (2023)* incorporated conflict rule processing into a fashion-design knowledge base, demonstrating that fuzzy reasoning effectively models subjective attributes such as style and context.

The reviewed studies indicate that fuzzy systems enhance personalization by modeling imprecise and nonlinear relationships between user behavior and item attributes. However, few studies have quantitatively analyzed trend dynamics or directly combined fuzzy inference with hybrid filtering techniques to optimize the balance between recommendation novelty and user familiarity. Table 1 shows a comparative summary of prior approaches, identifying the main limitation of each study.

Consequently, the existing literature identifies three persistent challenges in the domain of fashion recommendation systems:

(1) Dynamic trend awareness: Most current models do not adapt in real time to rapidly changing popularity metrics.

(2) Interpretability: Deep learning or hybrid models seldom provide explanations for recommendations that are understandable to human users.
(3) Balanced novelty: Existing systems tend to either overfit to user history in CBF or recommend excessively diverse items in CF, lacking mechanisms for guided trend modulation.

Thus, this study proposes a hybrid recommender system based on fuzzy logic to address these identified challenges, which:

(1) Calculates a trend percentage using a Sugeno fuzzy inference system, which incorporates sales, user likes, and item views as input variables.
(2) Integrates the trend percentage into IBCF and CBF to balance personalization with novelty in recommendations.
(3) Evaluates the system's performance across various closet sizes to assess scalability and adaptability.

By embedding interpretable fuzzy reasoning within a hybrid framework, the proposed model combines the interpretability of rule-based systems with the adaptability of data-driven methods. This integration enhances research in fashion recommendation systems by promoting transparency and responsiveness to emerging trends.

METHODOLOGY

As aforementioned, the proposed system integrates fuzzy logic, CBF, and IBCF to generate adaptive, trend-aware fashion recommendations. Figure 1 presents the architecture of the hybrid system, which comprises three primary modules:

(1) Fuzzy Trend Evaluation
(2) Content-Based Filtering
(3) Item-Based Collaborative Filtering using k-nearest neighbors (KNN)

The following subsections describe the design and integration of these modules.

Dataset description and preprocessing

The dataset used in this study comprises 4,224 fashion items collected from multiple e-commerce platforms. Each item is characterized by seven primary attributes. These attributes include the item title, description, category, price, number of sales, number of likes, and number of views.

Entries with missing or incomplete data were excluded from the analysis. Categorical attributes, such as category or type, were label-encoded. Continuous variables, including *sales*, *likes*, and *views*, were normalized to the range 0 to 1 using the Min–Max normalization formula.

Figure 2 shows the structure of the suggested fuzzy trend percentage evaluation system showing the inputs, fuzzy inference stages, and the resulting trend percentage (0–100).

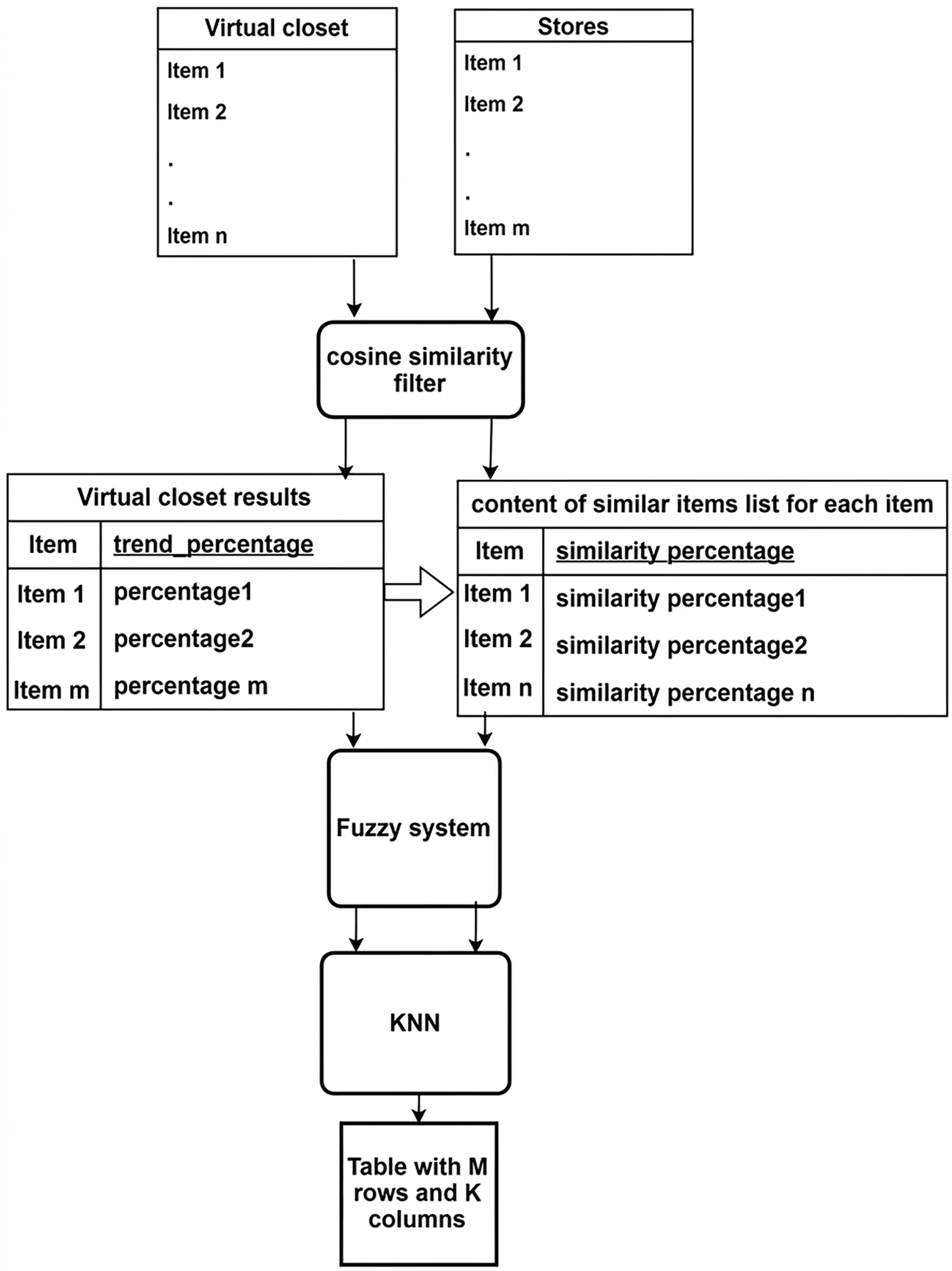

Figure 1 **Detailed hybrid system architecture.** Full-size DOI: 10.7717/peerj-cs.3967/fig-1

The input parameters are the normalized values for sales, likes, and views based on the following equations:

$$likes_{norm} = \frac{likes - likes_{min}}{likes_{max} - likes_{min}} \times 100\%$$

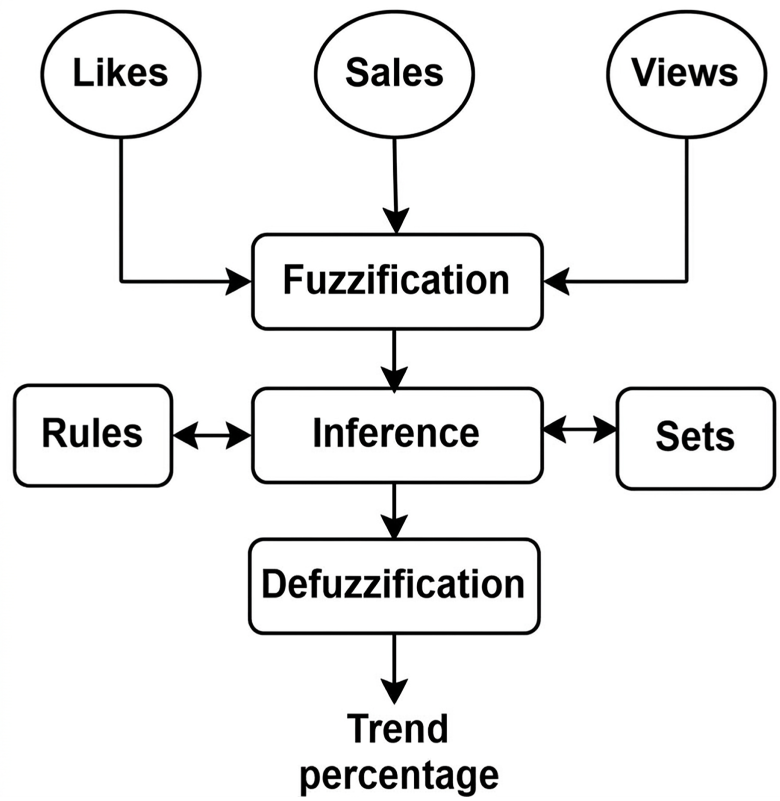

Figure 2 **Fuzzy trend percentage evaluation system.** Full-size DOI: 10.7717/peerj-cs.3967/fig-2

$$views_{norm} = \frac{views - views_{min}}{views_{max} - views_{min}} \text{ x } 100\%$$

$$sales_{norm} = \frac{sales - sales_{min}}{sales_{max} - sales_{min}} \text{ x } 100\%.$$

This normalization ensures a uniform scale across fuzzy input variables. Textual descriptions were cleaned by removing punctuation, converting to lowercase, and applying tokenization and stop-word filtering before similarity computation.

Fuzzy trend evaluation

The initial stage of the system estimates the trend percentage for each item using a Sugeno-type Fuzzy Inference System (FIS), a computational framework that applies fuzzy logic to model subjective popularity and address uncertainty in user engagement metrics (*Deldjoo et al., 2023*).

The three input variables are sales, likes, and views. The output variable, referred to as *trend percentage (T)*, is a continuous value ranging from 0, indicating not trendy, to 100, indicating highly trendy.

Membership functions

Each input variable is divided into three trapezoidal membership functions representing *Low*, *Medium*, and *High* engagement levels (*Hwangbo, Kim & Cha, 2018*).

Their parameters were empirically defined based on data distribution (normalized scale):

$$\mu_{low}(x) = \begin{cases} 0 & x \leq 0 \\ 1 & 0 < x \leq 10 \\ \dfrac{40 - x}{30} & 10 < x \leq 40 \\ 0 & x > 40 \end{cases}$$

$$\mu_{mid}(x) = \begin{cases} 0 & x \leq 30 \\ \dfrac{40 - x}{30} & 30 < x \leq 40 \\ 1 & 40 < x \leq 60 \\ \frac{70 - x}{10} & 60 < x \leq 70 \\ 0 & x > 70 \end{cases}$$

$$\mu_{high}(x) = \begin{cases} 0 & x \leq 60 \\ \dfrac{x - 60}{20} & 60 < x \leq 80 \\ 1 & 80 < x \leq 100 \\ 0 & x > 100 \end{cases}.$$

However, the output variable is divided into four trapezoidal membership functions representing *Not*, *Medium*, *High*, and *Highly Trendy* engagement levels:

$$\mu_{not}(x) = \begin{cases} 0 & x \leq -5 \\ \dfrac{x + 5}{15} & -5 < x \leq 10 \\ 1 & 10 < x \leq 20 \\ \dfrac{35 - x}{15} & 20 < x \leq 35 \\ 0 & x > 35 \end{cases}$$

$$\mu_{mid}(x) = \begin{cases} 0 & x \leq 30 \\ \dfrac{x - 30}{20} & 30 < x \leq 50 \\ 1 & 50 < x \leq 60 \\ \dfrac{70 - x}{10} & 60 < x \leq 70 \\ 0 & x > 70 \end{cases}$$

$$\mu_{high}(x) = \begin{cases} 0 & x \leq 65 \\ \dfrac{x - 65}{10} & 65 < x \leq 75 \\ 1 & 75 < x \leq 85 \\ \dfrac{70 - x}{5} & 85 < x \leq 90 \\ 0 & x > 90 \end{cases}$$

$$\mu_{very\_high}(x) = \begin{cases} 0 & x \leq 85 \\ \dfrac{x - 85}{5} & 85 < x \leq 90 \\ 1 & 90 < x \leq 95 \\ \dfrac{100 - x}{5} & 95 < x \leq 100 \\ 0 & x > 100 \end{cases}$$

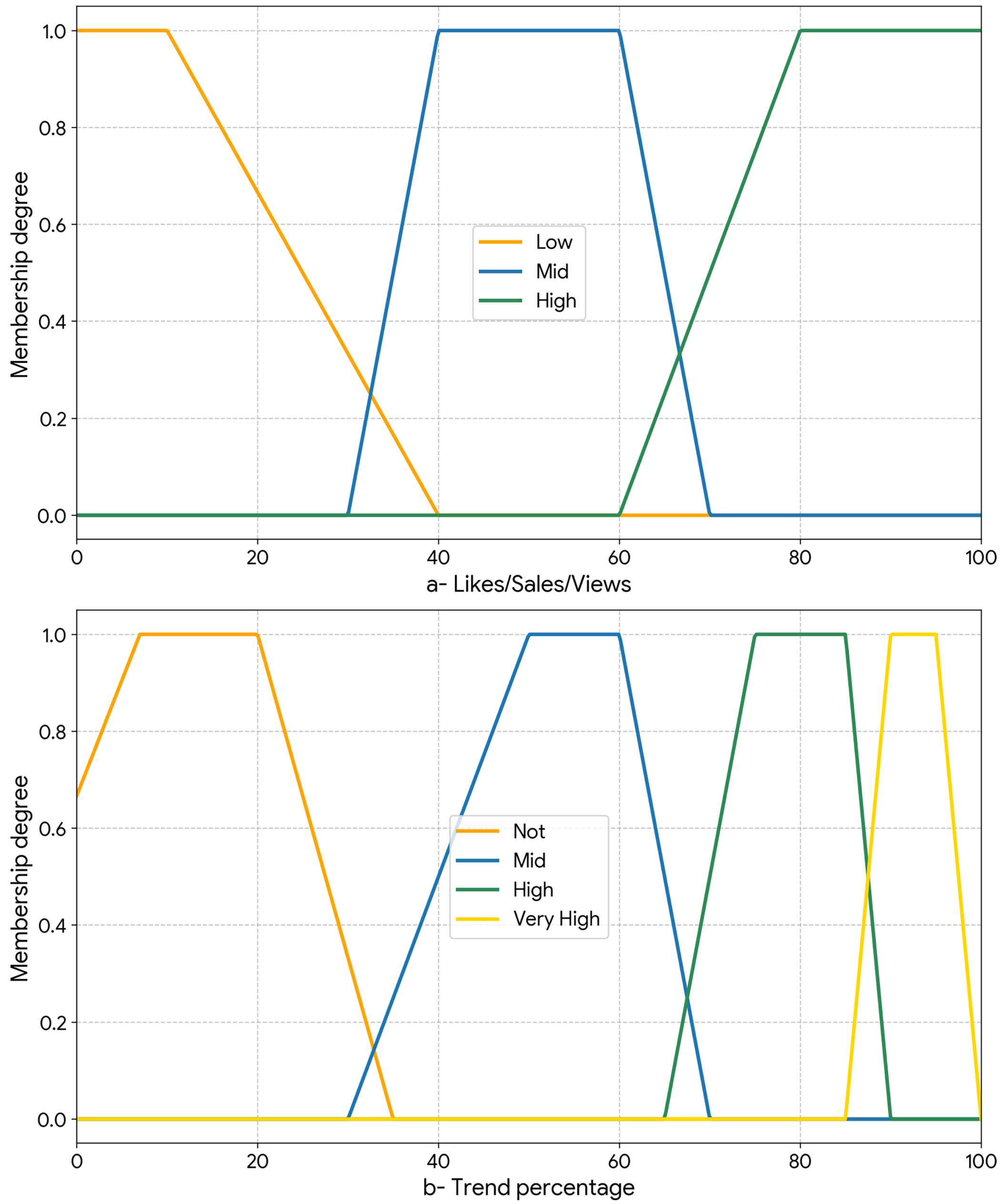

Figure 3 Output membership functions defining trend percentage levels.
Full-size DOI: 10.7717/peerj-cs.3967/fig-3

Figure 3A shows the output of the trapezoidal membership functions for likes, sales, and views. However, Fig. 3B shows the output of the trapezoidal membership functions for trend percentage levels (Not, Mid, High, Very High) based on the above equations. The x-axis represents normalized input values or trend percentage, and the y-axis represents membership degree. Furthermore, Fig. 4 displays the fuzzy inference system's surface plot. From the figure, Sugeno fuzzy inference surface illustrating the relationship between sales and likes when views are fixed at 100. Axes represent normalized input values (0–100), and

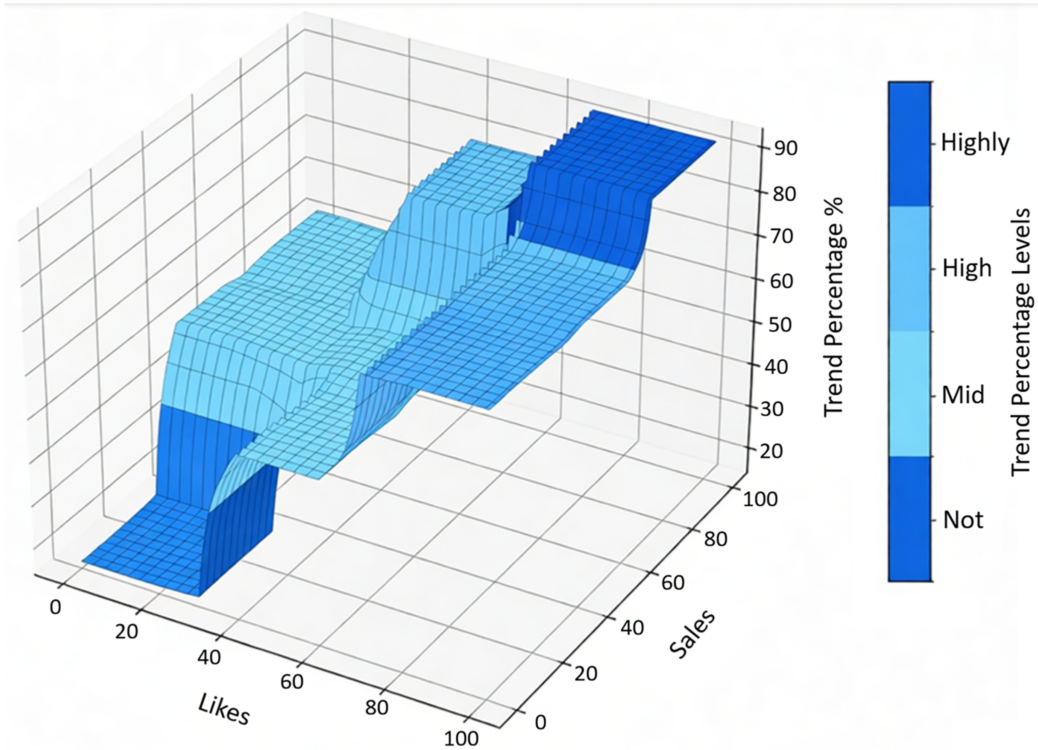

Figure 4 **Module surface when views is 100 and likes, sales in the range 0–100.**
Full-size DOI: 10.7717/peerj-cs.3967/fig-4

Table 2 **Trendy rules based on sales, likes and views.**

Trendy*	Sales	Likes	Views
Not trendy	Low	Low	Low
Mid trendy	Low	Mid	Mid
High trendy	Low	High	Mid
	Mid	Mid	High
	High	Mid	High
Highly trendy	High	High	High

Note:
* Linguistic labels corresponding to ranges of trend percentage.

the surface height corresponds to the resulting trend percentage. The non-linear surface demonstrates smooth trend percentage level transitions.

Rule base and defuzzification coefficients details

The system utilizes 27 fuzzy rules, derived from all possible combinations of the three input variables, each assigned Low, Medium, or High membership levels as given in Table 2. Representative fuzzy rules are as follows:

(1) *IF Sales is Low AND Likes is Low AND Views is Low THEN trend percentage is classified as Not Trendy*

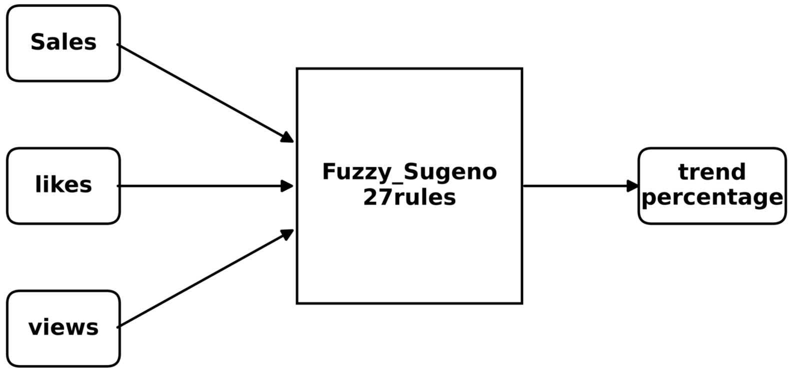

Figure 5 **Fuzzy module rules output.** Full-size DOI: 10.7717/peerj-cs.3967/fig-5

(2) *IF Sales is High AND Likes is High AND Views is High THEN trend percentage is classified as Highly Trendy*

(3) *IF Sales is Medium AND Likes is High AND Views is Medium THEN trend percentage is classified as High Trendy*

As shown in Fig. 5, each rule within the Sugeno fuzzy inference system (FIS) generates a linear output in the following form:

$$z_i = p_i.sales + q_i.likes + r_i.views + s_i \tag{1}$$

where:

- z_i is the linear numeric output corresponding to the trend percentage contribution of the i^{th} rule in the Sugeno fuzzy system.
- p_i is the weight for sales. It determines how strongly the sales input affects the output of rule i.
- q_i is the weight for likes. It represents the influence of Likes on the trend percentage in rule i.
- r_i is the weight for views. It represents the contribution of Views to the rule's output.
- s_i is a constant bias term. It is a fixed offset added to the linear equation to adjust the baseline trend.

Each fuzzy rule evaluates conditions such as 'Sales = High, Likes = Medium, Views = Low' and computes a numerical output using the above linear equation. These individual outputs (z_i) are then aggregated through weighted average defuzzification to produce the final trend percentage.

The final crisp output, referred to as the trend percentage, is calculated using the weighted average defuzzification method:

$$T = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{2}$$

where: w_i denotes the firing strength of the i^{th} rule.

Hence, the Sugeno model was selected over Mamdani because it is computationally efficient, smoother in output surfaces, and more suitable for adaptive optimization (*Liu & Zhao, 2023*; *Nachiappan, 2024*). Since the output (trend percentage) is a continuous numeric value rather than a fuzzy label, Sugeno's linear rule consequents allow direct integration with the KNN-based ranking system (*Basilico & Hofmann, 2004*).

Content-based filtering module

CBF module identifies recommended items by evaluating textual similarity to items already present in the user's closet. Item descriptions are converted into word-frequency vectors, and similarity is measured using the cosine similarity metric.

$$similarity\ (A, B) = \frac{A.B}{|A| \times |B|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} (A_i)^2} \times \sqrt{\sum_{i=1}^{n} (B_i)^2}}. \quad (3)$$

In this context, A and B represent feature vectors for two item descriptions, weighted by term frequency-inverse document frequency (TF-IDF). Items with the highest cosine similarity scores are prioritized as stylistically consistent with the user's preferences.

For example, suppose that text A contains "silver epaulet shirt" and text B contains "silver shirt", then:

Description A: Silver epaulet shirt

(1) Split into distinct words: Silver, epaulet, shirt

(2) Count of each word: 1 + 1 + 1

Description B: Silver shirt

(1) Split into distinct words: Silver, shirt

(2) Count of each word: 1 + 1

$$cosine = \frac{count\ of\ silver\ in\ A * count\ of\ silver\ in\ B + count\ of\ shirt\ in\ A * count\ of\ shirt\ in\ B}{\sqrt{\sum_{j=1}^{m} (count\ of\ jth\ word\ in\ A)2} * \sqrt{\sum_{i=1}^{n} (count\ of\ ith\ word\ in\ B)2}}$$

$$= \frac{1 * 1 + 1 * 1}{\sqrt{1^2 + 1^2 + 1^2} * \sqrt{1^2 + 1^2}} = 81.64.$$

Item-based collaborative filtering module

The IBCF stage identifies items that exhibit similar trend percentage or engagement profiles. This module applies the K-Nearest Neighbors (KNN) algorithm, utilizing a Euclidean distance metric calculated over the fuzzy trend percentage and additional normalized features.

For each item in the user's closet, the algorithm retrieves the ten nearest items based on the defined similarity metrics.

$$D(i, j) = \sqrt{(Ti - Tj)^2}$$

where T_i and T_j are the trend percentages of items i and j, respectively.

Table 3 Sensitivity analysis of the weighting parameter α used in the hybrid recommendation score.

α value	P@10	R@10	NDCG@10	Coverage (%)	Diversity (%)
0.2	0.718 ± 0.023	0.697 ± 0.022	0.735 ± 0.022	81.2	72.1
0.4	0.737 ± 0.021	0.710 ± 0.02	0.757 ± 0.021	80.1	71.4
0.6	**0.754 ± 0.02**	**0.725 ± 0.02**	**0.771 ± 0.02**	**79.4**	**70.8**
0.8	0.732 ± 0.022	0.706 ± 0.021	0.754 ± 0.021	75.8	68.9

Note:
The best evaluation result is shown in bold.

The final recommendation score (R) combines the content similarity and the trend percentages difference:

$$R_{ij} = \alpha.\ Similarity(i, j) + (1 - \alpha)\ .\ (1 - |Ti - Tj|) \tag{4}$$

where the parameter α is set to 0.6.

The weighting parameter α controls the balance between textual similarity and trend consistency in the hybrid score. To reduce arbitrariness in parameter selection, α was evaluated over the set {0.2, 0.4, 0.6, 0.8}. Across simulated closet sizes, α = 0.6 provided the most stable trade-off between ranking quality and recommendation relevance, yielding the strongest average performance in P@10 and NDCG@10 while avoiding overemphasis on either content similarity or trend alignment. The complete sensitivity analysis is summarized in Table 3.

Hybrid recommendation algorithm (pseudocode)

The following summarizes the proposed algorithm pseudocode:

Algorithm Name: FuzzyHybridRecommender

Input: Set of closet items (C) and set of catalog items (I)
Output: Set of recommended items (R)
1. For each catalog item i in the set I:
    - Normalize the features: sales, likes, and views.
    - Compute the trend percentage for item i using the Sugeno Fuzzy Inference System (FIS) based on normalized sales, likes, and views.
2. For each closet item c in the set C:
    - For each catalog item i in the set I:
        - Calculate content similarity as the cosine similarity between the descriptions of c and i.
        - Compute the absolute difference between the trend percentages of c and i.
        - Calculate the hybrid score as α times the content similarity plus (1 minus α) times (1 minus the trend percentage difference).
    - Rank all catalog items according to their hybrid scores.
    - Select top-k nearest neighbors using KNN
3. Aggregate the top k items identified for each closet item.
4. Remove duplicate items and sort the aggregated list in descending order of hybrid score.
5. Return the top N items as the final set of recommended items.

Table 4 Methodological advantages of the used techniques.

Component	Technique	Purpose	Advantage
Fuzzy trend	Sugeno FIS	Estimate real-time item popularity	Handles uncertainty; interpretable
Content-based filtering	Cosine similarity (TF-IDF)	Match user's style	Maintains stylistic consistency
Item-based CF	KNN (k = 10)	Capture behavioral correlation	Promotes novelty and diversity
Hybrid integration	Weighted fusion	Combine similarity and trend	Balances personalization with trend adaptation

System integration

The system was developed using Python version 3.10 and incorporates several specialized libraries.

- The scikit-fuzzy library was utilized to perform fuzzy inference and to visualize rule sets.
- The scikit-learn library facilitated term frequency-inverse document frequency (TF-IDF) vectorization and KNN computation.
- NumPy and Pandas were employed for data preprocessing and subsequent analysis.

The system architecture is modular. Each component, including fuzzy scoring, content-based filtering, and collaborative filtering, operates independently and can be fine-tuned for future model improvements.

Table 4 gives a summary of methodological advantages. It also provides the information of each component and technique, its purpose and the output advantage.

RESULTS AND DISCUSSIONS

The effectiveness of the proposed hybrid fuzzy-logic-based recommendation model in addressing the issues noted in earlier research was confirmed through empirical evaluation. Existing fashion recommender systems, as documented in the literature, often fail to preserve interpretability of their ways of making decisions, adaptability to quickly changing fashions, and a balanced representation of novelty *vs.* user familiarity. Therefore, this section presents the experimental results obtained from implementing the proposed Fuzzy-Hybrid model and compares them with traditional and non-fuzzy hybrid baselines to demonstrate the model's capacity to enhance personalization, scalability, and transparency in trend-aware fashion recommendation. Although the proposed method outperformed the baselines under the present evaluation protocol, these results reflect performance within a controlled offline simulation rather than direct evidence of real-world user satisfaction or longitudinal behavioral impact.

Experimental setup recap

The hybrid fashion recommender system was evaluated using a private dataset containing 4,224 fashion items. Simulated virtual closets were constructed with sizes of 40, 50, 60, 70, and 80 items. Each configuration was assessed using four distinct system variants. Simulated closets were constructed by randomly sampling items from the catalog while preserving category diversity. Each closet contained items from at least three distinct categories to avoid category bias. Sampling was repeated with different random seeds across runs.

(1) Content-based filtering (CBF) only
(2) Item-based collaborative filtering (IBCF) only
(3) Hybrid (non-fuzzy): Combined content-based filtering and item-based collaborative filtering without fuzzy weighting
(4) Proposed fuzzy-hybrid model: Full integration of all components, including fuzzy trend scoring

All experiments were conducted on a system with an Intel Core i7-12700K central processing unit, 32 GB random access memory, and Python version 3.10. The scikit-fuzzy and scikit-learn libraries were utilized. Each test was repeated five times with random data splits to ensure statistical robustness.

Evaluation metrics

Performance was evaluated using standard top-K recommendation metrics to ensure a comprehensive assessment.

- P@10 quantifies the proportion of recommended items within the top 10 that are relevant to the user.
- R@10 measures the proportion of all relevant items that are retrieved among the top 10 recommendations.
- NDCG@10 evaluates ranking quality by assigning higher importance to relevant items that appear earlier in the recommendation list.
- In the simulated evaluation setting, an item was considered relevant if its cosine similarity to at least one closet item exceeded a predefined threshold (≥ 0.7) and its trend percentage difference was within 30%. This operational definition approximates user relevance in the absence of explicit feedback.
- Coverage represents the percentage of items in the catalog that are recommended to at least one user.
- Diversity is calculated as the mean pairwise dissimilarity among recommended items, reflecting the variety within recommendation lists.
- Runtime refers to the execution time required for generating recommendations, measured as a function of the number of items in the catalog to assess scalability.
- A sensitivity analysis of α revealed performance degradation when content similarity dominated ($\alpha \geq 0.8$) or when trend difference dominated ($\alpha \leq 0.4$), supporting the chosen value. For example, across closet sizes, $\alpha = 0.6$ yielded the highest average NDCG@10 and the most consistent balance between precision and diversity.

Quantitative results

Table 5 summarizes the mean ± standard deviation of evaluation metrics across five experimental runs. The Fuzzy-Hybrid model achieved higher performance than all

Table 5 Experimental values of the evaluated metrics.

Model	P@10	R@10	NDCG@10	Coverage (%)	Diversity (%)	Runtime (ms/item)
CBF	0.611 ± 0.03	0.589 ± 0.04	0.632 ± 0.03	63.5	58.7	1.84
IBCF	0.642 ± 0.04	0.617 ± 0.03	0.661 ± 0.04	67.2	61.3	2.06
Hybrid (non-fuzzy)	0.678 ± 0.03	0.652 ± 0.02	0.684 ± 0.03	71.9	64.1	2.41
Proposed fuzzy-hybrid	0.754 ± 0.02	0.725 ± 0.02	0.771 ± 0.02	79.4	70.8	2.66

baseline models across all evaluated metrics. P@10 and R@10 increased by an average of 11 to 14 percent compared to the non-fuzzy hybrid model. This improvement demonstrates that incorporating the fuzzy trend percentage enhances the prioritization of items that are both fashionable and personalized. NDCG@10 values further support the superior ranking quality, indicating that items weighted by trend are assigned to higher recommendation positions.

Although the observed improvements are meaningful, they should be interpreted cautiously because the evaluation relies on simulated user closets and a private dataset. Therefore, the reported performance gains represent evidence of potential benefits rather than definitive proof of general superiority.

The increase in coverage from 63 percent to 79 percent indicates that fuzzy weighting promotes the recommendation of less-frequent items. The concurrent rise in diversity demonstrates that the recommendations are distributed across a broader range of categories, rather than being concentrated on popular segments. As a result, the system achieves a more effective balance between personalization and novelty, which is a primary objective in fashion recommendation systems.

While the improvements in coverage and diversity appear associated with the fuzzy trend weighting mechanism, the present experiments do not isolate the contribution of individual components within the hybrid architecture. The observed gains may also be influenced by factors such as KNN neighborhood expansion or the hybrid similarity formulation combining content similarity and trend difference. A dedicated ablation study would be required to quantify the individual contribution of these components. Therefore, the results should be interpreted as reflecting the effectiveness of the overall hybrid framework rather than attributing the improvements exclusively to fuzzy logic.

Figures 6A–6E show a comparison between the CBF and CF for different closet sizes (from 40 to 80 items). They illustrate the performance of IBCF and CBF for each closet size. The categorization of suggested items is based on the absolute difference in trend percentage between closet items and recommendations (*e.g.*, 10%, 20%). CBF prioritizes textual similarity in item descriptions, resulting in recommendations that maintain stylistic consistency. Conversely, CF leverages user-item interactions and trend percentage, thereby facilitating the discovery of new styles and trends. Both CBF and CF show an increase in recommendations with larger closet sizes, reflecting the system's ability to leverage more data points for suggestion generation. For larger closets, CF consistently outperforms CBF in the number of recommendations, capitalizing on user preferences beyond simple textual similarity.

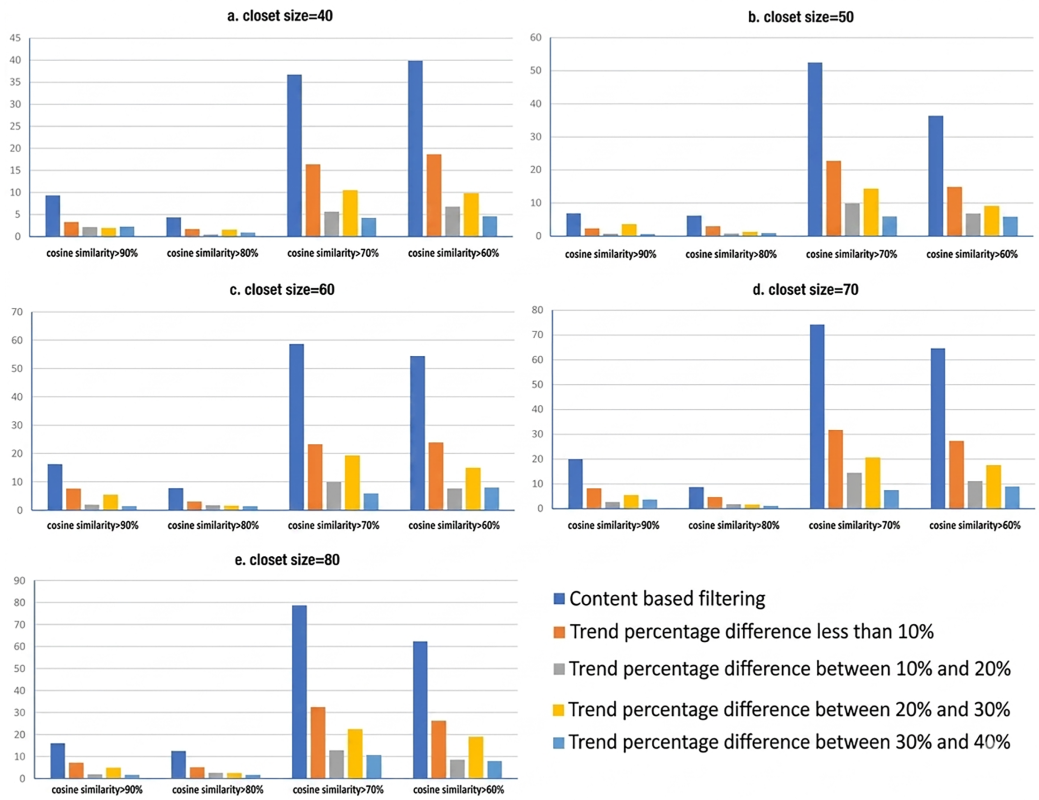

Figure 6 **Recommendation trend percentages for varying closet sizes.**
Full-size DOI: 10.7717/peerj-cs.3967/fig-6

Scalability evaluation

Figure 7 presents the system runtime as a function of closet size. Runtime measurements were averaged across five experimental runs. The variance across runs was small, indicating stable runtime behavior. The variance between runs was minimal, indicating stable runtime behavior; therefore, the figure presents the average runtime values for clarity. The linear trend ($R^2 = 0.98$) demonstrates near-proportional scaling and confirms the computational efficiency of the proposed hybrid model. Incorporating the fuzzy logic module results in a minor overhead of approximately 0.25 ms per item. These results suggest that the proposed system may be suitable for near real-time recommendation under controlled large-catalog conditions. Paired t-tests were conducted using per-run metric averages ($n = 5$) as sampling units. Normality was verified using Shapiro–Wilk tests. Effect sizes were computed using Cohen's d, with values ranging from 0.62 to 0.81, indicating medium to large effects.

Qualitative insights

The fuzzy logic module offers interpretable reasoning for item promotion. For example, an item with high user engagement but moderate *sales* may receive a "High trend" rating, supporting its inclusion in recommendations despite limited purchase history. This level of

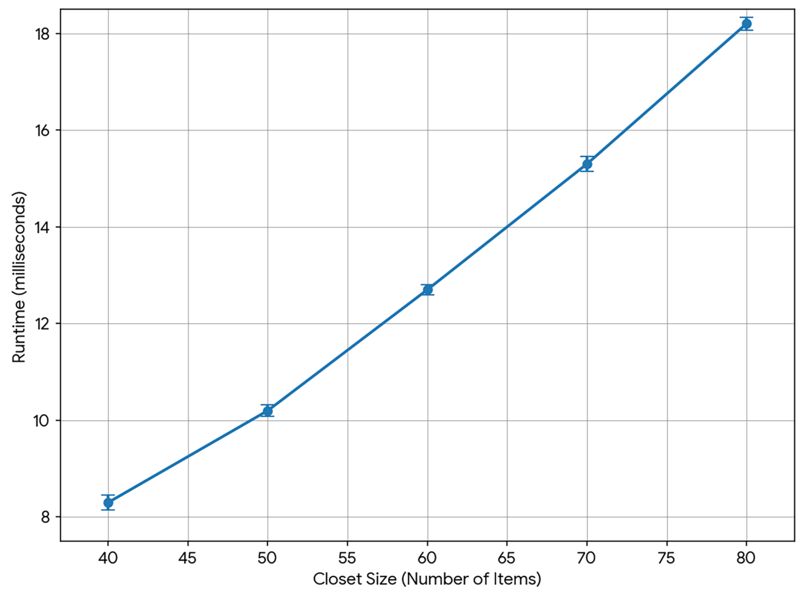

Figure 7 Runtime scalability of the proposed hybrid recommender system.
Full-size DOI: 10.7717/peerj-cs.3967/fig-7

transparency enables system designers and retailers to adjust fuzzy rules in response to evolving market conditions.

The hybrid model demonstrated the greatest benefit for users with extensive item histories, as the system utilized additional historical data to improve similarity estimates. Users with limited item histories also experienced strong performance, indicating that fuzzy trend weighting can address data sparsity by incorporating engagement-based signals instead of relying exclusively on user history.

Limitations

Despite the promising results, this study is subject to several limitations.

(1) The dataset is a private dataset that comprises 4,224 items, which limits the generalizability of the findings. Employing larger datasets with more comprehensive metadata would enable more robust validation.

(2) The evaluation utilized simulated user closets and implicit relevance modeling instead of actual user interactions, which may affect the ecological validity of the results. In addition, the evaluation relies on offline simulation using implicit relevance derived from closet similarity rather than real user interaction data. Consequently, the reported results should be interpreted as preliminary evidence of the model's potential rather than confirmation of real-world deployment performance.

(3) The fuzzy rule base is static. Implementing dynamic adaptation of rules to reflect evolving trends could improve system responsiveness.

(4) Visual and multimodal features such as image embeddings and color or style descriptors were excluded from the analysis, which restricts the system's ability to capture aesthetic diversity.

(5) The system does not incorporate user-level personalization beyond closet contents. In the current system, personalization is derived primarily from the composition of the user's virtual closet rather than detailed behavioral signals such as browsing patterns, purchase history, or demographic attributes. Consequently, the system captures stylistic similarity but does not fully represent broader user preference dynamics.
(6) The study does not explicitly evaluate cold-start scenarios involving new users with empty closets or newly introduced items with little engagement data. Handling such cases is an important challenge for recommender systems and should be addressed in future work.
(7) Finally, the fuzzy membership functions and rule parameters were manually defined based on empirical observations of the dataset. Although this design improves interpretability, it introduces subjectivity and may not generalize across different datasets. Future work could investigate automated optimization or adaptive learning of fuzzy parameters.

Even with these limitations, the experimental results indicate that integrating fuzzy logic enhances accuracy, scalability, and interpretability. These findings provide a basis for developing future adaptive, trend-aware recommender systems.

CONCLUSIONS

This work proposes a hybrid artificial intelligence fashion recommender system that combines fuzzy logic with content-based and item-based collaborative filtering to generate personalized, interpretable, and trend-percentage-aware clothing suggestions. It shows measurable improvements in accuracy, coverage, diversity, and scalability over traditional and non-fuzzy methods by modeling the trend percentage using a Sugeno fuzzy inference system and mixing it with stylistic similarity. Apart from technical performance, these results have significant practical relevance.

The proposed model demonstrates potential applicability to fashion recommendation scenarios that require a balance between personalization and trend awareness. However, the conclusions are based on offline simulation using a private dataset and implicit relevance signals. The present findings should be interpreted as evidence of methodological promise rather than definitive proof of real-world deployment effectiveness. Therefore, additional validation using real user interaction data and online experiments is necessary before confirming the model's suitability for real-world deployment.

In addition, It may enhance virtual styling assistants and digital closet applications needing real-time, user-focused outfit suggestions. It can also provide retailers and designers with clear trend analytics that can help in making merchandising, inventory planning, and marketing decisions.

Despite the limited dataset and simulated interaction setting, the study points to the potential of integrating rule-based reasoning with data-driven methods to enhance fashion recommendation systems. Future work will focus on dynamic adaptation of the rules, exploiting multimodal features, and integrating real user feedback to take the system further for use in fashion-driven digital spaces. It will include a component-level ablation study to isolate the contributions of fuzzy trend scoring, collaborative filtering, and similarity weighting to recommendation performance.

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Competing Interests

The authors declare that they have no competing interests.

Author Contributions

- Aladdin Masri conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Muhannad Al-Jabi conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

The raw data and code are available in the Supplemental Files.

Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj-cs.3967#supplemental-information.

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