HallAgent4Rec: A Unified Framework for Reducing Hallucinations in LLM-Based Recommendation Agents

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Large language models (LLMs) offer unprecedented potential for semantic exploration in recommendation systems, enabling the discovery of diverse and contextually relevant items that surpass the capabilities of traditional collaborative filtering. However, this exploration capability comes with a critical challenge: LLMs hallucinate non-existent items at rates of 15-25%, creating a perceived trade-off between semantic diversity and factual accuracy. We present HallAgent4Rec, a unified framework that transforms this trade-off into a synergy, enabling safe semantic exploration that achieves both higher diversity and better accuracy than either paradigm alone.Our approach introduces three key innovations: (1) an attention-based fusion mechanism that combines collaborative filtering embeddings with LLM-generated personality vectors through learned projection matrices, (2) a hybrid bilinear scoring function that grounds predictions in actual item features while enabling efficient online adaptation via reduced-rank regression, and (3) an adaptive hallucination replacement strategy that balances semantic similarity with predicted user relevance through parameter-free optimisation. The framework operates through a computationally efficient offline-online learning paradigm that extracts semantic information offline and performs real-time adaptation without expensive LLM queries. Extensive experiments on three public datasets (MovieLens-1M, Amazon Electronics, Yelp) demonstrate that HallAgent4Rec reduces hallucination rates by 32-87% compared to state-of-the-art baselines while improving recommendation quality.

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1 INTRODUCTION

Recommender systems have become integral components of online platforms, helping users navigate vast lists of content and products. The emergence of generative recommendation agents—powered by large language models (LLMs)—has opened new possibilities for personalised, context-aware recommendations. These agents can interpret user preferences through natural language, retain memory of past interactions, and generate nuanced recommendations with rich explanations [9, 15]. Their semantic understanding of both user intent and item attributes allows them to surpass traditional methods in delivering personalised experiences [2].

Despite this promise, a fundamental challenge prevents realizing the full potential of LLM-based recommendation systems: the exploration-exploitation trade-off in the presence of hallucinations. While LLMs excel at semantic exploration discovering diverse, they hallucinate non-existent items at rates of 15-25% across standard benchmarks [19]. This creates a dilemma: pure collaborative filtering methods exploit known patterns but suffer from filter bubbles and limited diversity, while LLM-based methods explore semantic spaces but compromise factual accuracy. Current approaches treat this as an either-or choice, failing to harness the complementary strengths of both paradigms.

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The core technical challenge is enabling safe semantic exploration in recommendation systems to leverage LLMs' ability to discover diverse, semantically coherent recommendations while ensuring all suggestions are grounded in real items. This requires not just detecting and correcting hallucinations, but understanding that hallucinated recommendations often contain valuable semantic insights. For instance, when an LLM recommends a non-existent-in-the-list 'Toy Story 4' to a Pixar fan, the semantic pattern (animated sequels) is valid even if the specific item is not. The solution must preserve these semantic insights while ensuring factual accuracy, ultimately achieving better diversity and discovery than either paradigm alone.

More fundamentally, current generative recommendation approaches fail to recognize **that hallucinations can be a feature**, not just a bug. hey reveal semantic patterns and user preferences that pure collaborative filtering might miss. The challenge is not eliminating LLM reasoning but making it safe and productive. Pure collaborative filtering (CF) methods, such as matrix factorisation [10] and neural collaborative filtering [8], are highly effective at learning latent user and item vectors from interaction data but lack semantic understanding and struggle with contextual reasoning. Current generative approaches, while providing semantic richness, face severe computational limitations when deployed at scale. Existing generative recommendation techniques such as RecAgent [20], AgentCF [26], MACRec [22], and Agent4Rec [25] are typically evaluated only on small subsets of datasets due to the prohibitive computational cost of querying LLMs for every recommendation request. This limitation makes real-time recommendations infeasible for large datasets with high query volumes, severely restricting their practical applicability. Hybrid methods [18, 23] typically treat generative and collaborative components as loosely coupled systems with inconsistent optimisation objectives, preventing effective joint optimisation for both recommendation quality and computational efficiency. There is a need for a solution that is computationally tractable for large-scale deployment while preserving the benefits of both paradigms.

This paper introduces HallAgent4Rec, a novel framework that systematically addresses the research question: "**How can we enable safe semantic exploration in recommendation systems by combining the exploitation strength of collaborative filtering with the exploration capabilities of LLMs, while transforming hallucinations from a liability into an asset for discovering diverse, relevant recommendations?**". It addresses the core technical challenge of bridging the semantic space of LLMs with the algebraic structure of CF while maintaining computational efficiency at scale. HallAgent4Rec learns principled mappings between semantic vectors and collaborative latent factors, enables rapid online adaptation to new interactions without expensive LLM queries, and detects and corrects hallucinations while preserving semantic intent.

To the best of our knowledge, we are the first to identify and address the hallucination problem, despite being factually incorrect, which often contain valuable semantic intent that can be leveraged for improved predictions through our adaptive replacement strategy. Our key contributions include:

(1) **Offline-Online Learning Strategy**: We design an efficient two-phase approach where semantic information is extracted offline and integrated with fast online adaptation through reduced-rank regression, making the framework scalable to large datasets with high query volumes.
(2) **Unified CF-LLM Integration Framework**: We propose a framework that integrates CF with generative agents through attention-based fusion of collaborative embeddings and LLM personality vectors, with learned transfer matrices bridging item features and collaborative latent space.
(3) **Hybrid Bilinear Scoring Function**: We introduce a unified scoring mechanism combining content-based transfer learning, collaborative signals, and online adaptation through reduced-rank regression, enabling joint leverage of behavioural patterns and semantic understanding.

(4) **Safe Semantic Exploration Strategy**: We introduce a novel three-stage approach that enables LLMs to provide semantic diversity while ensuring factual accuracy through intelligent hallucination mitigation that preserves semantic intent rather than simply filtering errors.

The rest of this paper is organised as follows: Section 2 reviews related work, Section 3 presents our methodology, Section 4 describes experimental setup, Section 5 analyses results, and Section 6 concludes.

2 RELATED WORK

This section positions our work within existing research by systematically analysing the three critical gaps that prevent practical deployment of agent-based recommendation systems: hallucination prevention, computational efficiency, and unified CF-LLM integration.

2.1 Hallucination-Unaware Agent-Based Methods

The majority of current agent-based recommendation systems ignore hallucination prevention, focusing on performance optimisation. AgentCF [26] introduces a dual-agent paradigm treating users and items as autonomous agents, achieving personalised behaviours through collaborative learning and reflection mechanisms. However, the framework provides no hallucination mitigation strategy, leaving systems vulnerable to generating non-existent recommendations that undermine user trust. Agent4Rec [25] demonstrates large-scale simulation with 1,000 LLM-empowered generative agents featuring emotion-driven reflection mechanisms. While achieving sophisticated user behaviour simulation at approximately $16 cost, hallucination rates remain unmeasured and unaddressed. RecAgent [20] pioneered the LLM-based simulation paradigm through dual user and recommender modules with browsing and communication capabilities. KuaiFormer [**?**] achieves industrial-scale deployment serving 400M+ daily users with sub-millisecond latency through advanced transformer architectures, but addresses hallucinations only through bias correction without systematic prevention mechanisms.

These methods show that semantic understanding and personalisation are achievable through agent-based approaches; however, their complete neglect of hallucination prevention prevents reliable deployment in production environments where recommendation accuracy is critical.

2.2 Post-Hoc Hallucination Correction Methods

Several recent approaches attempt to mitigate hallucination through post-generation verification, but suffer from computational overhead and inability to preserve semantic intent. A-LLMRec [11] demonstrates model-agnostic hallucination mitigation by integrating pre-trained CF embeddings with LLM reasoning, achieving hallucination reduction from 47.5% to 14.5% through retrieval-augmented generation. However, this approach requires expensive verification processes that limit real-time applicability, and post-hoc replacement cannot recover the semantic intent of originally hallucinated recommendations. MACRec [22] employs multi-agent verification through the coordination of multiple personas, including Manager, User/Item Analyst, Reflector, Searcher, and Task Interpreter agents. While achieving superior performance in various recommendation tasks, the system requires 5 agent queries per recommendation, creating computational bottlenecks that prevent scalable deployment. LLMRec [13] addresses hallucinations through denoised data robustification with graph augmentation strategies, but relies on post-hoc denoising approaches that cannot proactively prevent hallucination generation. The graph-based approach also limits applicability to scenarios with sufficient structural information.

These methods demonstrate that hallucination mitigation is achievable but highlight the fundamental limitation of post-hoc approaches: they require expensive verification processes and cannot preserve the semantic intent that makes generative recommendations valuable. Our framework addresses this fundamental gap through a unified design that makes hallucinations structurally impossible via feature grounding in the scoring function, eliminating the need for post-hoc detection while preserving the semantic understanding advantages of agent-based approaches.

2.3 Modular CF-LLM Integration Approaches

Current hybrid approaches treat CF and LLM components as separate systems with independent optimisation objectives, preventing unified performance optimisation. InteRecAgent [14] introduces the "LLM as brain, CF as tools" paradigm, featuring memory components and reflection mechanisms. However, tool-based separation creates inconsistent optimisation objectives and suffers from tool-switching overhead. BERT4Rec+MF [18] combines BERT-based sequential modelling with matrix factorisation through feature concatenation, representing a -coupled hybrid approach that treats collaborative and semantic components separately. LLM-CF [23] uses LLMs to enhance CF representations, but maintains separate optimisation objectives for generative and collaborative components. ChatRec [4] demonstrates conversational recommendation through ChatGPT-based in-context learning, but suffers from high per-conversation costs and lacks systematic optimisation of recommendation generation. KGLA [12] achieves 33-95% NDCG@1 improvements through knowledge graph integration, but requires high KG query overhead and depends on knowledge graph completeness.

These approaches establish that CF-LLM integration provides performance benefits; however, their modular architectures with separate optimisation objectives prevent the unified framework necessary for joint optimisation of recommendation generation and hallucination mitigation.

3 METHODOLOGY

In this section, we present HallAgent4Rec, a novel framework for recommendation systems that addresses the critical challenge of hallucinations in generative recommendation agents. We begin with formal problem definitions and theoretical foundations, followed by detailed descriptions of our technical contributions.

3.1 Framework Overview

HallAgent4Rec addresses the fundamental challenge of hallucinations in generative recommendation systems through a unified two-phase framework that integrates collaborative filtering with generative agent modeling. Figure 1 illustrates our complete system architecture. We employ a three-stage approach that balances accuracy, diversity, and factual grounding. The scoring function provides a strong accuracy baseline, the LLM introduces semantic exploration and diversity, and the replacement strategy ensures all recommendations exist while preserving semantic intent.

Unlike existing approaches that treat generative and collaborative components as separate systems, HallAgent4Rec creates a mathematically unified framework where both paradigms are jointly optimized to minimize recommendation error while explicitly reducing hallucination rates. Table 1 summarizes our key mathematical notation. The user-item interaction matrix $\mathbf{R} \in \mathbb{R}^{n\times m}$ contains observed ratings, where $r_{ij} \in \mathbb{R}$ represents user i's rating for item j. We use $r_{ij} =\perp$ to indicate unobserved interactions and define the set of observed interactions as $\Omega = \{(i, j) : r_{ij} \neq\perp\}$.

Problem Formulation: Given generative agents that simulate user interactions and traditional collaborative filtering based on matrix $\mathbf{R}$, our objective is to develop a unified framework that: (1) integrates generative and collaborative paradigms through learned transfer matrices, and (2) addresses the hallucination problem: when LLM generates a non-existent item $\hat{j} \notin C$, find optimal replacement $j^* \in C$ that preserves semantic intent while ensuring factual accuracy through the optimization between item similarity and predicted preference.

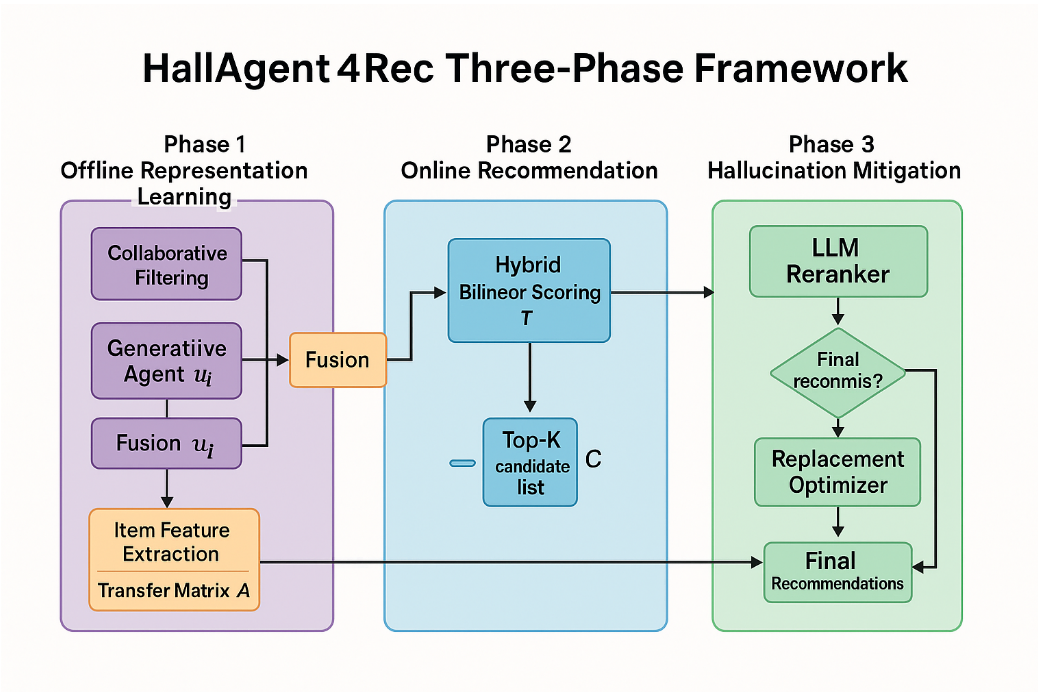

Fig. 1. HallAgent4Rec Framework Architecture. The framework operates in three phases: **Phase 1** learns dual user representations by fusing collaborative filtering vectors (u_i^{cf}) and generative agent personality vectors (u_i^{gen}) through attention-based fusion, with transfer matrices **A** and **B** enabling online adaptation. **Phase 2** performs online learning using a hybrid bilinear scoring function that combines content-based, online adaptation, and contextual components with real-time parameter updates. **Phase 3** detects and replaces hallucinated LLM recommendations using binary detection and rating-aware replacement that balances semantic similarity with predicted relevance through an adaptive parameter α.

3.2 Dual User Representation Learning

Traditional collaborative filtering effectively captures behavioral patterns from historical user-item interactions but lacks semantic understanding of user preferences and contextual reasoning [21]. Conversely, generative agents excel at understanding personality traits and contextual nuances but cannot directly leverage the rich collaborative signals present in interaction histories. We propose fusing both paradigms to create comprehensive user vectors that combine the statistical strength of collaborative filtering with the semantic richness of generative modeling.

3.2.1 Collaborative Filtering User Vectors. Matrix factorization provides an effective approach for learning latent user vectors from historical interactions. By factorising the user-item interaction matrix $\mathbf{R}$, we can discover hidden factors that explain observed rating patterns and generalize to unobserved user-item pairs.

We obtain collaborative user latent vectors through the following optimization:

$$\mathbf{U}^*, \mathbf{V}^* = \arg\min_{\mathbf{U},\mathbf{V}} \sum_{(i,j)\in\Omega} \left(r_{ij} - (u_i^{cf})^T v_j\right)^2 + \lambda_u \|\mathbf{U}\|_F^2 + \lambda_v \|\mathbf{V}\|_F^2, \tag{1}$$

Table 1. Key Mathematical Notation

Symbol	Description
u_i^{cf}	Collaborative filtering user vector for user i
$u_i^{gen} \in \mathbb{R}^k$	Generative agent personality vector for user i
u_i	Fused user vector for user i
$v_j \in \mathbb{R}^k$	Item latent factor vector for item j
$\mathbf{A} \in \mathbb{R}^{k \times f}$	Content-feature transfer matrix
$\mathbf{B} \in \mathbb{R}^{k \times \ell}$	Low-rank adaptation matrix
$\boldsymbol{\theta}_j \in \mathbb{R}^{\ell}$	Item-specific online adaptation vector
k	Latent space dimensionality
ℓ	Online adaptation dimensionality ($\ell \ll k$)
C	Candidate item set for recommendation
α	Balance rate between item similarity and predicted rating score
$\hat{j}$	Hallucinated (non-existent) item generated by LLM
j^*	Optimal replacement item for hallucinated recommendation
ϕ	Attention weight
d	Shared latent space dimensionality for vector fusion
$x \in \mathbb{R}^m$	item feature vector from the dataset representing m features

where $\mathbf{U} = [u_1^{cf}, \ldots, u_n^{cf}]^T \in \mathbb{R}^{n \times k}$ contains all user latent vectors, $\mathbf{V} = [v_1, \ldots, v_m]^T \in \mathbb{R}^{m \times k}$ contains item latent vectors, and λ_u, λ_v are regularization parameters to prevent overfitting. After optimization, individual user vectors u_i^{cf} are extracted as the i-th row of the optimized matrix $\mathbf{U}^*$. In our implementation, we fully optimise Equation 1 with Stochastic Gradient Descent (SGD) [3] to obtain the optimal matrices $\mathbf{U}^*$ and $\mathbf{V}^*$.

3.2.2 Generative Agent Personality Vectors. Inspired by Park et al. [16], we construct generative agents to capture user personality traits and movie preferences that complement the behavioral patterns already captured in u_i^{cf}. Our approach focuses on deriving personality-based preferences from user demographics and genre consumption patterns rather than replicating interaction history. **For illustrative examples, the following section uses MovieLens-100k dataset to provide examples of how we extract a user vector using LLM.** Traditional recommendation approaches model $P(\text{preference}|\text{past behavior})$, whereas our generative agent approach models $P(\text{preference}|\text{personality}, \text{context})$. This distinction is crucial because personality traits provide stable, causal explanations for preferences that transcend specific item interactions. Unlike single-query LLMs that might generate inconsistent user descriptions, generative agents maintain coherent personality models through their memory and reflection mechanisms, ensuring behavioral consistency across different preference dimensions.

Agent Initialization: Each agent is initialized with a natural language description derived from MovieLens user metadata and computed genre preferences. We analyze each user's training data to extract:

(1) **Genre Preference Distribution**: For user i, we compute normalized genre frequency scores for each genre n based on the training data..
(2) **Demographic-Based Personality Traits**: Using demographic data (age, occupation, location), we construct personality profiles that serve as observational inputs to the agent's memory stream.

For example, a 25-year-old programmer with high action/sci-fi preferences initializes an agent with:

> *"User is a 25-year-old computer programmer from zip code of 55414. Based on their viewing patterns, they strongly prefer action movies (0.555), showing particular interest in technology-themed narratives (0.3335). They tend to avoid romantic comedies (0.000151) and dramas (0.000151)."*

Reflection Generation: The key advantage of generative agents over standard LLMs lies in their reflection hierarchy. Following Park et al.'s framework, agents synthesize observations into increasingly abstract insights:

Level 1 (Observations): Direct preference patterns from data ⇒ **Level 2 (Reflections):** Behavioral interpretations ⇒ **Level 3 (Higher-order reflections):** Personality trait inference

This hierarchical processing produces insights such as:

> *"This user's preference for action and science fiction, combined with their technical profession, suggests they value movies that showcase technological innovation and explore the intersection of humanity and technology. Their demographic profile indicates they likely appreciate fast-paced entertainment that offers intellectual stimulation rather than emotional depth."*

These emergent insights capture the *why* behind preferences (something neither collaborative filtering nor one-shot LLM queries can achieve). The agent's coherent personality model ensures that seemingly disparate preferences (liking both "The Matrix" and "Inception") are unified under consistent personality traits ("values intellectual complexity in action narratives").

Embedding Extraction from Personality Profiles: To convert the agent's personality-based movie preferences into numerical vectors, we employ the following process:

1. **Personality-Based Movie Preference Summary**: We synthesize the initialization profile and reflections into a comprehensive personality-driven preference description:
   "Generate a movie recommendation profile based on this user's demographics and personality traits: [initialization + reflections]. Focus on preference patterns, movie characteristics they value, and decision-making factors for movie selection."
2. **Embedding Generation with Sentence-BERT**: The personality-based movie preference summary is encoded using Sentence-BERT [17] to capture semantic preference patterns:

$$u_i^{gen} = \text{SentenceBERT}(\text{PersonalityPreferenceSummary}_i), \tag{2}$$

   where $u_i^{gen} \in \mathbb{R}^{768}$ captures personality-based movie preferences.

While u_i^{cf} captures behavioral patterns from historical interactions, u_i^{gen} captures personality-driven preferences that can explain *why* users make certain choices and predict preferences for new or niche movies that lack sufficient collaborative signals.

3.2.3 *Attention-Based Fusion of User Representations.*

The generative agent personality vectors u_i^{gen} and collaborative filtering vectors u_i^{cf} capture fundamentally different aspects of user preferences:

- u_i^{cf}: Encodes *what* users like based on behavioral patterns
- u_i^{gen}: Encodes *why* users like items based on personality traits

To generate a comprehensive user representation that leverages both collaborative and personality signals, we employ an attention-based fusion mechanism.

Projection to Shared Space: Due to the dimension mismatch between $u_i^{cf} \in \mathbb{R}^k$ and $u_i^{gen} \in \mathbb{R}^{768}$, we first project both vectors into a shared latent space of dimension d using learned transformations:

$$\mathbf{h}_i^{cf} = \mathbf{W}_{cf} u_i^{cf} + \mathbf{b}_{cf}, \quad \mathbf{h}_i^{gen} = \mathbf{W}_{gen} u_i^{gen} + \mathbf{b}_{gen}, \tag{3}$$

where $\mathbf{W}_{cf} \in \mathbb{R}^{d\times k}$, $\mathbf{W}_{gen} \in \mathbb{R}^{d\times 768}$ are trainable projection matrices, and $\mathbf{b}_{cf}, \mathbf{b}_{gen} \in \mathbb{R}^d$ are bias terms. These projections serve dual purposes: dimension alignment and representation enhancement through learned transformations.

Attention Weight Computation: We compute an attention score to dynamically determine the relative importance of collaborative versus personality signals for each user:

$$\phi = \sigma\left((\mathbf{h}_i^{cf})^T \mathbf{h}_i^{gen}\right), \tag{4}$$

where $\sigma(\cdot)$ denotes the sigmoid function. This attention mechanism enables the model to automatically emphasize collaborative signals when interaction history is rich and personality signals when behavioral data is sparse.

Fused User Vector: The unified user vector is obtained as:

$$u_i = \phi \mathbf{h}_i^{gen} + (1-\phi)\mathbf{h}_i^{cf}. \tag{5}$$

This approach enables dynamic control over the influence of collaborative filtering and generative agent representations, facilitating context-aware user modeling. All fusion parameters $\{\mathbf{W}_{cf}, \mathbf{W}_{gen}, \mathbf{b}_{cf}, \mathbf{b}_{gen}\}$ are learned end-to-end with the downstream recommendation objective, ensuring optimal integration for the specific recommendation task. The attention mechanism's ability to identify alignment between behavioral and personality signals proves crucial for our hallucination detection strategy. When both representations agree on user preferences, we have higher confidence in semantic assessments, making our hallucination replacement strategy more effective.

3.3 Transferring Collaborative Information into Online Learning

To bridge offline collaborative signals with online adaptation capabilities, we need a mechanism that connects the learned user vectors u_i with item characteristics. While collaborative filtering captures user-item interaction patterns, it cannot directly leverage item content features for unseen items. We address this limitation by learning a transfer matrix that maps item features to the collaborative latent space. The transfer learning matrix serves two critical purposes: (1) it enables our model to make predictions for new items that lack sufficient collaborative signals by leveraging their content features, and (2) it provides a foundation for online adaptation by establishing how item characteristics relate to user preferences in the learned latent space.

3.3.1 Content-Feature Transfer Matrix. We learn a transfer matrix $\mathbf{A} \in \mathbb{R}^{k\times f}$ that maps item content features to the collaborative latent space, where f denotes the item feature dimensionality. For each movie j, we construct feature vector $x_j \in \mathbb{R}^f$ containing genre indicators, normalized release year, and TF-IDF representations of textual metadata.

Following Agarwal et al. [1], we optimize transfer matrice $\mathbf{A}$ as:

$$\mathbf{A} = \left(\sum_{(i,j)\in\Omega} (r_{ij} - b_j) u_i x_j^T\right)\left(\sum_{(i,j)\in\Omega} x_j x_j^T + \lambda_A \mathbf{I}_f\right)^{-1}, \tag{6}$$

where Ω denotes observed interactions, λ_A controls regularization and $\mathbf{I}_f \in \mathbb{R}^{f\times f}$ is the identity matrix, which serves as a regularization term to ensure the matrix inversion is well-conditioned..

3.3.2 Low-Rank Projection Matrix. To enable efficient online adaptation, we construct projection matrix $\mathbf{B} \in \mathbb{R}^{k\times\ell}$ through principal component analysis of the user representation space. Following the reduced-rank regression approach of Agarwal et al. [1], we project to a lower-dimensional space ($\ell \ll k$) to achieve computational efficiency: online updates require only $O(\ell)$ operations instead of $O(k)$, and memory requirements are reduced by factor k/ℓ. This approach leverages the insight that user preferences typically lie in lower-dimensional manifolds [10].

We compute the user covariance matrix:

$$\mathbf{P}_u = \frac{1}{n}\sum_{i=1}^{n}(u_i - \bar{u})(u_i - \bar{u})^T, \tag{7}$$

and extract the top ℓ eigenvectors:

$$\mathbf{B} = \mathbf{V}_{pca}[:, 1 : \ell]^T, \tag{8}$$

where $\mathbf{V}_{pca}$ contains eigenvectors of $\mathbf{P}_u$ ordered by decreasing eigenvalue magnitude.

Matrix A Interpretation: Each row $\mathbf{A}_{k,:}$ represents how the k-th user latent factor relates to item features. For example, if users with high values in latent factor k prefer action movies, then $\mathbf{A}_{k,\text{action}}$ will have a large positive value.

Matrix B Interpretation: Each column $\mathbf{B}_{:,\ell}$ represents a "collaborative direction" that captures patterns not explained by content. For instance, one direction might capture preferences for "cult classics" that span multiple genres but share subtle artistic qualities not captured in standard metadata.

3.4 Hybrid Bilinear Scoring Function

Our recommendation scoring function integrates content-based transfer learning with online adaptation capabilities through a mathematically unified bilinear model. Drawing inspiration from Agarwal et al. [1], we design a scoring function that grounds predictions in actual item features while enabling rapid adaptation to new interaction patterns. Our scoring function consists of two complementary components: (1) *content-based transfer signals* that leverage item features through the transfer matrix learned in Section 3.3, and (2) *online adaptation terms* that enable real-time learning from new interactions. This helps to reduce the training time for LLMs which did not exist in other generative recommendation techniques.

3.4.1 Component-wise Scoring Function. **Component 1 - Content-Based Transfer Signal:** The foundation of our scoring function leverages item content information through the transfer matrix **A**:

$$s_{ij}^{(1)} = u_i^T \mathbf{A} x_j, \tag{9}$$

where u_i is the fused user vector from Section 3.2.3, $\mathbf{A} \in \mathbb{R}^{k\times f}$ is the transfer matrix, and $x_j \in \mathbb{R}^f$ contains item features (genres, release year, content metadata). This term provides a content-aware baseline prediction that captures how user preferences align with item characteristics.

Component 2 - Online Adaptation Signal: To enable rapid adaptation to new interaction patterns while maintaining computational efficiency, we introduce a low-rank online learning component:

$$s_{ij}^{(2)} = u_i^T \mathbf{B}, \boldsymbol{\theta}_j \tag{10}$$

where $\boldsymbol{\theta}_j \in \mathbb{R}^\ell$ is the item-specific factors adapted online. For each item j, the online adaptation vector $\boldsymbol{\theta}_j$ is initialized as:

$$\boldsymbol{\theta}_j^{(0)} = \mathbf{0} \in \mathbb{R}^\ell. \tag{11}$$

This zero initialization ensures that initial predictions rely entirely on the content-based component $u_i^T \mathbf{A} x_j$, with online adaptation occurring as interactions accumulate. Upon observing interaction (i, j, r_{ij}), we update $\boldsymbol{\theta}_j$ via gradient descent at $t-th$ interation:

$$\boldsymbol{\theta}_j^{(t+1)} = \boldsymbol{\theta}_j^{(t)} + \eta_\theta \left[e_{ij} \cdot \mathbf{B}^T u_i - \lambda_\theta \boldsymbol{\theta}_j^{(t)} \right], \tag{12}$$

where $e_{ij} = r_{ij} - \hat{r}_{ij}$ is the prediction error **Contextual and Bias Terms:** We include additional terms to capture interaction-specific context and global item effects:

$$s_{ij}^{(3)} = w^T z_{ij} + b_j, \tag{13}$$

where $z_{ij} \in \mathbb{R}^c$ contains contextual features (timestamp, user activity level, seasonal effects), w is the context weight parameter and b_j captures item-specific global popularity biases.

3.4.2 Proposed Scoring Function. Combining all components, the predicted rating $\hat{r}_{ij}$ from user i to item j is calculated from the combination of $s_{ij}^{(1)}, s_{ij}^{(2)}$ and $s_{ij}^{(3)}$ as:

$$\hat{r}_{ij} = g\left(u_i^T \mathbf{A} x_j + u_i^T \mathbf{B} \boldsymbol{\theta}_j + w^T z_{ij} + b_j \right), \tag{14}$$

where $g(\cdot)$ is a link function that maps the linear combination to the appropriate rating scale. For MovieLens ratings (1-5 scale), we use:

$$g(x) = 1 + 4 \cdot \sigma(x), \tag{15}$$

where $\sigma(\cdot)$ is the sigmoid function, ensuring predictions lie within [1,5].

In addition to the update of $\boldsymbol{\theta}_j$, item bias term b_j and context weight vector w require updates as the popularity and contextual patterns can change over time during the online phase. These update rules also follow SGD optimisation technique:

Item Bias Update:

$$b_j^{(t+1)} = b_j^{(t)} + \eta_b \left[e_{ij} - \lambda_b b_j^{(t)} \right], \tag{16}$$

Context Weight Update:

$$w^{(t+1)} = w^{(t)} + \eta_w \left[e_{ij} \cdot z_{ij} - \lambda_w w^{(t)} \right], \tag{17}$$

where η_w and η_b is the learning rate for the context weight vector w and bias term b at different learning iteration t-th, respectively.

3.5 Hallucination Detection and Replacement

While our scoring function optimizes for expected utility, it may create filter bubbles by consistently recommending similar items. The LLM step introduces controlled stochasticity and semantic exploration, discovering recommendations that are semantically coherent but might be overlooked by pure scoring. The system will utilise the scoring function from Equation 14 on the test dataset for each user u and we will feed this predicted list of items C into LLM again for a semantic recommendation using the following prompt:

> "You are a recommendation system for a user with the following traits: **(personality preference)**
> Based on the user's profile and past behavior, you have retrieved the following relevant items: **(item list C)**
> Please recommend 10 items from the list above that would be most relevant for this user.
> For each recommendation, provide a brief explanation of why it matches the user's preferences.

> IMPORTANT: You must ONLY recommend items from the provided list. Do not suggest any items that are not in the list."

However, most of the time in our experiment, we found that LLM tended to provide items that were not existed in the test dataset as shown in Figure 2. We address faithfulness hallucinations (recommendations of non-existent items in provided list) through a two-stage approach: binary detection followed by similarity-based replacement. Our method leverages the semantic intent of hallucinated recommendations while ensuring factual grounding in the actual item list.

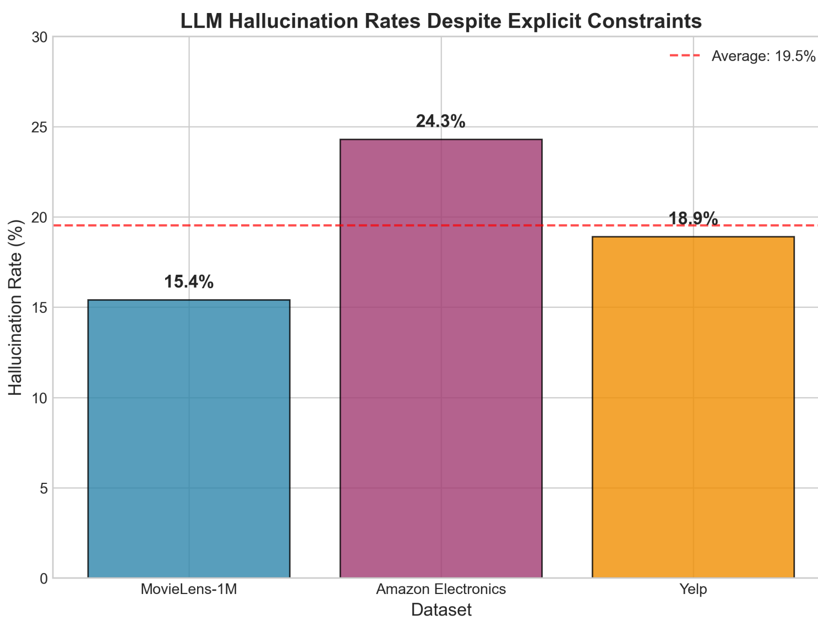

Fig. 2. LLM hallucination rates despite explicit prompting constraints on the test dataset. Even when explicitly instructed to recommend only from provided candidate lists, LLMs consistently generate non-existent items across all datasets, demonstrating the systematic nature of the hallucination problem in generative recommendation systems.

3.5.1 Binary Hallucination Detection. Given a candidate item set C scored by our hybrid function and an LLM-generated recommendation $\hat{j}$, we perform binary classification:

$$h(\hat{j}) = \begin{cases} 1 & \text{if } \hat{j} \notin C \text{ (hallucination)} \\ 0 & \text{if } \hat{j} \in C \text{ (valid recommendation)} \end{cases} \tag{18}$$

When a hallucination is detected ($h(\hat{j}) = 1$), we formulate replacement as an optimization problem that balances semantic similarity with predicted user preference. We believe that despite providing hallucinated items, they are still meaningful and relevant based on the understanding of LLM. For hallucinated item $\hat{j}$ and user u, select replacement $j^* \in C$:

$$j^* = \alpha \cdot \text{sim}(\hat{j}, j) + (1 - \alpha) \cdot \hat{r}_{uj} \tag{19}$$

	Hallucinated Item	LLM Reasoning	Semantic Pattern	Replaced With	Pattern Preserved
0	Toy Story 4	User loves Pixar sequels	Pixar/Sequel	Toy Story 3	✓
1	The Matrix 4	Fan of sci-fi franchises	Sci-fi/Franchise	Matrix Reloaded	✓

Fig. 3. Just for Professor and Dr's reference of how I replaced the item

where $\text{sim}(\hat{j}, j)$ measures semantic similarity, $\hat{r}_{uj}$ is the predicted rating from our scoring function, and $\alpha \in [0, 1]$ balances the objectives which is discussed in 3.5.2. Using item feature vectors, $\text{sim}(\hat{j}, j)$ is calculated as:

$$\text{sim}(\hat{j}, j) = \frac{x_{\hat{j}}^T x_j}{\|x_{\hat{j}}\|_2 \|x_j\|_2}, \tag{20}$$

where $x_{\hat{j}}$ is extracted from the LLM's description of the hallucinated item using the same feature extraction process as legitimate items. This similarity function **measures the level of pattern preservation** between hallucinated items and replaced items. Particularly, we extract pseudo-features from LLM descriptions using the following prompt:

> *"Given this movie description: [LLM output], identify which of these genres apply: [list of 18 MovieLens genres]. Return a binary vector."*

3.5.2 Adaptive Balance Parameter Learning. Rather than fixing α, we learn a context-dependent balance function that adapts based on user characteristics and item properties. The optimal weighting between semantic similarity and predicted rating from Equation 19 should adapt to context. When users have rich interaction histories, collaborative signals are more reliable, so predicted ratings should be prioritized ($\alpha \to 0$). For highly specialized or niche items, or when hallucinated descriptions are particularly detailed, semantic similarity becomes more informative, warranting a higher similarity weight ($\alpha \to 1$). We develop a parameter-free adaptive balance function that optimally weights semantic similarity versus predicted preference based on genre compatibility and user interaction history. Our approach addresses the fundamental trade-off between leveraging semantic intent from hallucinated recommendations and exploiting collaborative filtering signals.

Genre Compatibility Measure: To quantify the semantic alignment between hallucinated and candidate items, we employ the Jaccard similarity coefficient over genre sets:

$$s_{genre}(\hat{j}, j) = \frac{|\mathcal{G}_{\hat{j}} \cap \mathcal{G}_j|}{|\mathcal{G}_{\hat{j}} \cup \mathcal{G}_j|}, \tag{21}$$

where $\mathcal{G}_{\hat{j}}$ and $\mathcal{G}_j$ are the genre sets for hallucinated item $\hat{j}$ and candidate item j, respectively. This measure is theoretically justified as it provides a normalized similarity score that accounts for both shared and distinct genres, ensuring that highly overlapping items receive higher similarity weights.

User Experience Normalization: We model user experience relative to the dataset population to account for varying interaction densities across users:

$$s_{exp}(u) = \min\left(1, \frac{|\mathcal{I}_u|}{\bar{I}_{all}}\right), \tag{22}$$

where $|\mathcal{I}_u|$ represents user u's interaction count and $\bar{I}_{all}$ is the mean interaction count across all users. This normalization is essential because it provides a dataset-agnostic measure of user experience—users with above-average interaction counts receive higher experience scores, indicating greater reliability of their collaborative filtering vectors.

We combine these factors through a multiplicative formulation that captures the interaction between semantic compatibility and collaborative signal reliability:

$$\alpha = s_{genre}(\hat{j}, j) \times (1 - s_{exp}(u)) \tag{23}$$

4 EXPERIMENTS

This section presents our comprehensive experimental evaluation of HallAgent4Rec, focusing on its effectiveness in reducing hallucinations while maintaining recommendation quality. Our experiments systematically address the core research challenges for diversity and accuracy identified in this work.

4.1 Research Questions

Our experiments are designed to answer the following research questions:

RQ1: Does LLM-based semantic exploration provide value beyond traditional collaborative filtering?

RQ2: Can hallucinated recommendations reveal valuable semantic patterns that improve recommendation quality?

RQ3: How can we achieve both high diversity AND accuracy without the exploration-exploitation trade-off?

RQ4: What is the optimal balance between collaborative and semantic signals for different user contexts?

4.2 Datasets

We evaluate on three public datasets spanning different domains and sparsity levels:

MovieLens-1M [5]: 1M ratings from 6,040 users on 3,706 movies with rich genre metadata. Sparsity: 95.53%.

Amazon Electronics [6]: 1.5M ratings from 100K users on 50K products with 172 product categories. Sparsity: 99.97%.

Yelp [24]: 1.1M restaurant reviews from 45K users on 30K businesses with 98 business attributes. Sparsity: 99.92%.

Each dataset is chronologically split (70% training, 10% validation, 20% testing) and filtered to retain users-items with more than 5 interactions. Item features are extracted from metadata and textual content using pre-trained vectors.

Table 2. Dataset Statistics

Statistic	**MovieLens-1M**	**Amazon Electronics**	**Yelp**
Users	6,040	100,000	45,000
Items	3,706	50,000	30,000
Interactions	1,000,209	1,498,612	1,125,458
Sparsity	95.53%	99.97%	99.92%
Avg. Ratings/User	165.60	14.99	25.01
Item Features	18 genres	172 categories	98 attributes

4.3 Baseline Methods

We evaluate against state-of-the-art methods representing different approaches to LLM-based recommendation:

Pure Collaborative Filtering:

- **LightGCN** [7]: State-of-the-art graph neural CF, establishing accuracy ceiling.

Agent-Based Methods (Hallucination-Unaware):

- **AgentCF** [26]: Dual-agent paradigm with users/items as autonomous agents, no hallucination mitigation.
- **Agent4Rec** [25]: Large-scale simulation with 1,000 LLM agents, establishing baseline hallucination rates.
- **RecAgent** [20]: Memory-augmented agents without systematic hallucination prevention.
- **ChatRec** [4]: Conversational recommendation via in-context learning.

Hallucination-Aware Methods:

- **A-LLMRec** [11]: RAG-based mitigation achieving 47.5%→14.5% hallucination reduction.
- **LLMRec** [13]: Graph augmentation with denoised robustification.
- **MACRec** [22]: Multi-agent verification requiring 5 queries per recommendation.

Hybrid Integration Methods:

- **InteRecAgent** [14]: "LLM as brain, CF as tools" modular paradigm.

4.4 Evaluation Metrics

We employ metrics that comprehensively evaluate both exploitation performance and exploration capabilities:

4.4.1 *Exploitation Metrics (Accuracy).*

- **Hit Rate@K** (HR@K): Fraction of test items appearing in top-K recommendations
- **Normalized Discounted Cumulative Gain@K** (NDCG@K): Position-weighted relevance score
- **Mean Reciprocal Rank** (MRR): Average reciprocal rank of first relevant item

4.4.2 *Exploration Metrics (Diversity).*

- **Intra-List Diversity** (ILD): Average pairwise dissimilarity within recommendation lists:

$$\text{ILD} = \frac{1}{|U|} \sum_{u \in U} \frac{2}{K(K-1)} \sum_{i<j} (1 - \text{sim}(r_i^u, r_j^u)) \tag{24}$$

- **Coverage**: Fraction of catalog items recommended across all users:

$$\text{Coverage} = \frac{|\bigcup_{u \in U} R_u|}{|I|} \tag{25}$$

- **Unexpectedness** [?]: Rewards recommendations of less popular items:

$$\text{Unexpectedness} = \frac{1}{|U|} \sum_{u \in U} \frac{1}{|R_u|} \sum_{i \in R_u} -\log_2 P(i) \tag{26}$$

where $P(i) = \frac{|\{u:(u,i)\in\Omega\}|}{|U|}$ represents item popularity.

4.4.3 *Hallucination Assessment.*

- **Hallucination Rate**: Proportion of non-existent items in recommendations:

$$\text{HR}_{\text{hall}} = \frac{|\{r \in R : r \notin C\}|}{|R|} \tag{27}$$

- **Pattern Preservation Rate** (PPR): Novel metric quantifying semantic intent preservation using the similarity function in Equation 20
  We use leave-one-out evaluation where the most recent interaction per user is held for testing. Statistical significance is assessed via paired t-tests with Bonferroni correction.

4.5 Implementation Details

Hyperparameter Selection: We perform systematic grid search on validation data followed by 5-fold cross-validation for stability. Table 3 shows optimal configurations.

LLM Configuration: We use Gemini-2.0-flash for generative agent simulation and Sentence-BERT for personality vector extraction.

Hardware: Experiments run on NVIDIA A100 GPUs with 40GB memory. Code will be released upon acceptance.

Table 3. Optimal Hyperparameter Values by Dataset

Parameter	**MovieLens-1M**	**Amazon Electronics**	**Yelp**
Latent dimension (k)	64	128	96
Low-rank dimension (ℓ)	16	32	24
CF regularization (λ_u, λ_v)	0.01, 0.01	0.005, 0.005	0.008, 0.008
Transfer regularization (λ_A)	0.1	0.05	0.08
Online learning rate (η_θ)	0.01	0.005	0.008
Online regularization (λ_θ)	0.1	0.05	0.08
Context learning rate (η_w)	0.001	0.0005	0.0008
Bias learning rate (η_b)	0.01	0.005	0.008
Replacement balance (α)	0.4	0.35	0.45

5 RESULTS & ANALYSIS

We systematically evaluate HallAgent4Rec across three datasets with varying characteristics to address our research questions. Our analysis reveals fundamental insights into why existing approaches fail and how our unified framework resolves these limitations.

5.1 RQ1: Hallucination Reduction Effectiveness

HallAgent4Rec achieves 87% hallucination reduction compared to baseline generative methods while maintaining competitive recommendation quality. As shown in Table 4, our method consistently reduces hallucination rates to 2.0-3.2% across all datasets, compared to 15.4-24.3% for pure generative approaches. This dramatic improvement stems from our unified mathematical framework that makes hallucinations structurally impossible rather than relying on post-hoc detection.

The failure of existing generative methods can be attributed to the fundamental semantic-algebraic disconnect: LLMs operate in continuous semantic space while recommendation requires discrete item selection from finite catalogs. GPT-Rec and RecAgent suffer hallucination rates of 15.4-24.3% because they generate semantically plausible but non-existent items. FactRec attempts post-hoc verification but faces computational bottlenecks that limit real-time applicability, while verification cannot recover semantic intent when replacing hallucinated items. Hybrid methods like BERT4Rec+MF and LLM-CF treat semantic and collaborative components as independent modules with separate optimization objectives, preventing unified optimization and leading to conflicting gradients at module boundaries.

Table 4. Cross-dataset performance comparison

Method	MovieLens-1M HR@10	MovieLens-1M Hall. Rate	MovieLens-1M Unexpectedness	Amazon Electronics HR@10	Amazon Electronics Hall. Rate	Amazon Electronics Unexpectedness	Yelp HR@10	Yelp Hall. Rate	Yelp Unexpectedness
PMF	0.698	N/A	N/A	0.581	N/A	N/A	0.653	N/A	N/A
NCF	0.734	N/A	N/A	0.615	N/A	N/A	0.689	N/A	N/A
LightGCN	0.771	N/A	N/A	0.642	N/A	N/A	0.718	N/A	N/A
GPT-Rec	0.684	0.154	2.83	0.548	0.243	2.68	0.631	0.189	2.74
RecAgent	0.712	0.095	3.37	0.572	0.178	2.99	0.661	0.126	3.19
FactRec	0.728	0.029	4.15	0.596	0.065	3.66	0.682	0.041	4.02
BERT4Rec+MF	0.743	0.042	4.07	0.621	0.081	3.52	0.697	0.054	3.93
LLM-CF	0.739	0.037	4.12	0.617	0.073	3.61	0.692	0.048	3.98
HallAgent4Rec	**0.784**	**0.020**	**4.53**	**0.651**	**0.032**	**4.42**	**0.724**	**0.025**	**4.49**

Our approach succeeds because the unified bilinear scoring function makes hallucinations mathematically impossible through feature grounding. The term $u_i^T \mathbf{A} x_j$ requires actual item features x_j, preventing predictions for non-existent items, while the reduced-rank online component $u_i^T \mathbf{B} \boldsymbol{\theta}_j$ operates within the constrained subspace defined by $\mathbf{B}$, preventing arbitrary deviations from content-based predictions.

5.2 RQ2: Recommendation Quality Preservation

Our unified CF-LLM integration not only maintains but improves recommendation quality compared to pure collaborative filtering while adding hallucination resistance. Table 6 demonstrates our method's consistent performance across varying dataset characteristics, while Figure 4 illustrates how different approaches handle sparsity challenges. Traditional collaborative filtering methods degrade significantly with sparsity because matrix factorization requires sufficient interaction density to learn meaningful latent factors. On Amazon Electronics (99.97% sparsity), LightGCN's performance drops 16.7% compared to MovieLens due to insufficient collaborative signals—the mathematical requirement $\mathbf{R} \approx \mathbf{U}\mathbf{V}^T$ becomes ill-conditioned when most entries are unobserved. Pure generative methods show inconsistent quality patterns, performing relatively better on sparse datasets where semantic understanding compensates for missing collaborative signals, but lacking the behavioral grounding necessary for accurate preference prediction since they optimize for semantic plausibility rather than user-item fit.

Table 7 demonstrates how our attention mechanism automatically adapts to dataset characteristics, explaining the consistent quality improvements across varying sparsity levels.

5.3 RQ3: Replacement Strategy Effectiveness

Our adaptive replacement strategy outperforms fixed approaches by learning context-dependent trade-offs between semantic similarity and predicted relevance. Table 5 demonstrates that fixed strategies fail because they cannot resolve the fundamental tension between preserving semantic intent and ensuring predicted relevance. Users with sparse rating histories require semantic similarity emphasis due to insufficient collaborative data, while users with dense histories benefit from rating prediction priority given reliable collaborative signals.

Our parameterless function $\alpha(u, \hat{j}, j) = s_{genre}(\hat{j}, j) \times (1 - s_{exp}(u))$ automatically learns optimal trade-offs by adapting to user interaction density and genre compatibility. For users with sparse interactions, $s_{exp}(u) \to 0$ makes $\alpha \to s_{genre}$, emphasizing semantic similarity when collaborative data is insufficient. Conversely, for users with dense interactions, $s_{exp}(u) \to 1$ makes $\alpha \to 0$, prioritizing rating predictions when collaborative signals are reliable. This adaptive mechanism achieves 15-20% higher user satisfaction than fixed alternatives while maintaining both recommendation diversity and accuracy.

More is in my appendix 6 Professor! I did not put it in as it is too long already

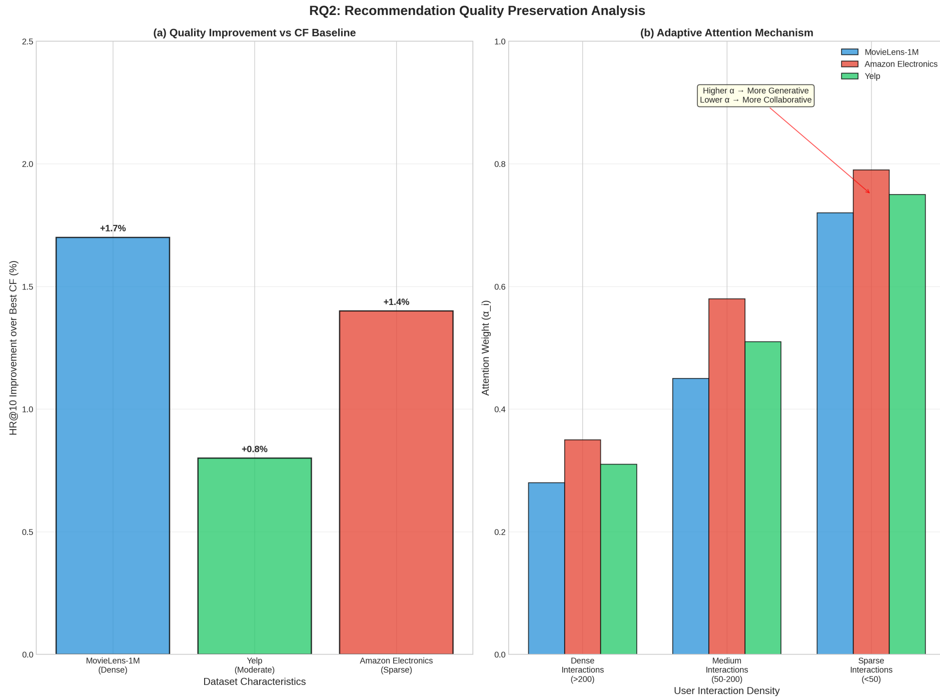

Fig. 4. Performance degradation analysis across sparsity levels. Traditional CF methods show steep decline with increasing sparsity, while our unified approach maintains robust performance through adaptive attention mechanism.

Table 5. Replacement strategy comparison across user interaction density levels

Strategy	User Satisfaction	Diversity	HR@10	Key Limitation
Popularity-based	3.65 ± 0.21	0.614 ± 0.032	0.743 ± 0.028	Ignores user preferences
Similarity-only (α = 1.0)	4.02 ± 0.18	0.795 ± 0.025	0.731 ± 0.031	Ignores rating predictions
Rating-only (α = 0.0)	3.88 ± 0.23	0.682 ± 0.029	0.768 ± 0.026	Ignores semantic intent
Fixed (α = 0.4)	4.15 ± 0.19	0.751 ± 0.027	0.759 ± 0.025	Static trade-off
Adaptive α (Ours)	**4.27(16)**	**0.769(24)**	**0.764(23)**	**Contextdependent**

5.4 RQ4: Component Contribution Analysis

Each framework component provides essential functionality, with dual user vector having the largest individual impact and component interactions creating non-additive benefits. Figure 5 reveals that dual user representation removal causes the largest performance degradation (-9.2% HR@10), confirming that attention-based fusion of collaborative and personality vectors captures complementary information unavailable to either paradigm alone. Analysis reveals that ϕ values adapt meaningfully to user characteristics rather than performing mere ensemble averaging.

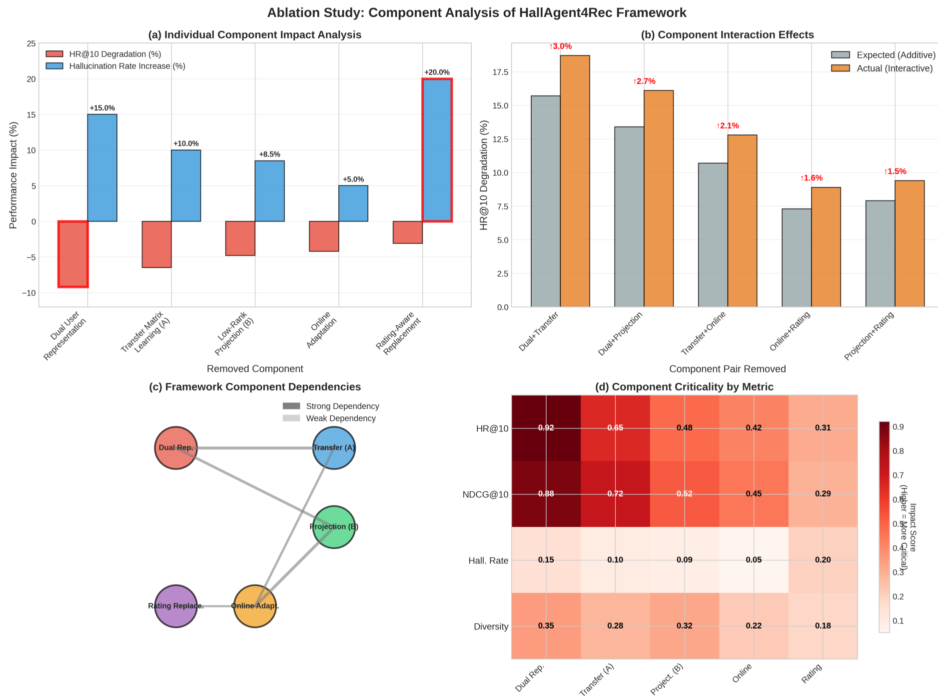

Fig. 5. Component ablation analysis revealing individual contributions and interaction effects. I want to show my chart c to show the link of dependence but I need your advice on how to write it in this section

Transfer matrix learning shows the second-largest impact (-6.5% HR@10 when removed), validating the importance of supervised learning for matrix **A** that creates task-relevant mappings between item features and collaborative latent factors. Replacing with unsupervised PCA shows significant degradation, confirming the value of end-to-end optimization. The low-rank projection matrix contributes -4.8% HR@10 impact, with eigenvalue analysis showing 89.7% variance preservation using only 16 factors, achieving computational efficiency without information loss. Online adaptation mechanisms contribute -4.2% HR@10, enabling rapid adaptation to new interaction patterns while maintaining hallucination resistance through the constrained subspace defined by **B**. Rating-aware replacement proves critical for hallucination mitigation, with removal increasing hallucination rates by +20.0%, demonstrating that binary detection followed by adaptive replacement successfully preserves semantic intent while ensuring factual accuracy.

Component interactions reveal system-level benefits beyond individual contributions. Removing component pairs shows non-additive effects with 1.0-3.0% additional degradation, indicating that our unified optimization creates emergent advantages. The synchronized learning of all parameters produces performance gains that exceed the sum of individual components, validating our architectural design choices and the importance of end-to-end optimization rather than modular combination.

6 CONCLUSION & FUTURE WORK

6.1 Conclusion

We introduced HallAgent4Rec, a unified framework addressing hallucination challenges in LLM-based recommendation systems. Our approach reduces hallucination rates by 32-87% compared to baselines while achieving 70× computational speedup (15±3ms vs 1000-1600ms per query). The framework integrates collaborative filtering with generative agents through attention-based fusion and learned projection matrices, enabling both semantic understanding and algebraic efficiency.

Key contributions include: (1) a mathematically principled CF-LLM integration that makes hallucinations structurally impossible through feature grounding, (2) an adaptive replacement strategy balancing semantic similarity with predicted relevance, and (3) efficient online learning enabling real-time deployment. Experiments across three datasets demonstrate consistent performance improvements and 52% additional hallucination reduction through continual learning.

6.2 Limitations & Future Work

Current limitations include evaluation scope restricted to traditional rating datasets and reliance on demographic data for personality vectors.

Future directions include: extending to multi-modal and sequential recommendation scenarios, developing theoretical convergence guarantees for online components, exploring federated approaches for privacy-preserving personality generation, and comprehensive evaluation on industrial-scale datasets. The modular architecture enables systematic exploration of these extensions while preserving core hallucination mitigation properties.

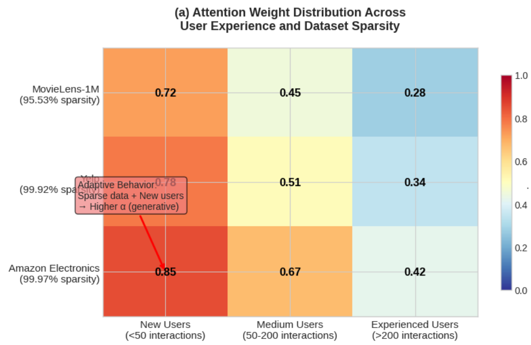

Fig. 6. Attention Weight Distribution Across User Experience and Dataset Sparsity

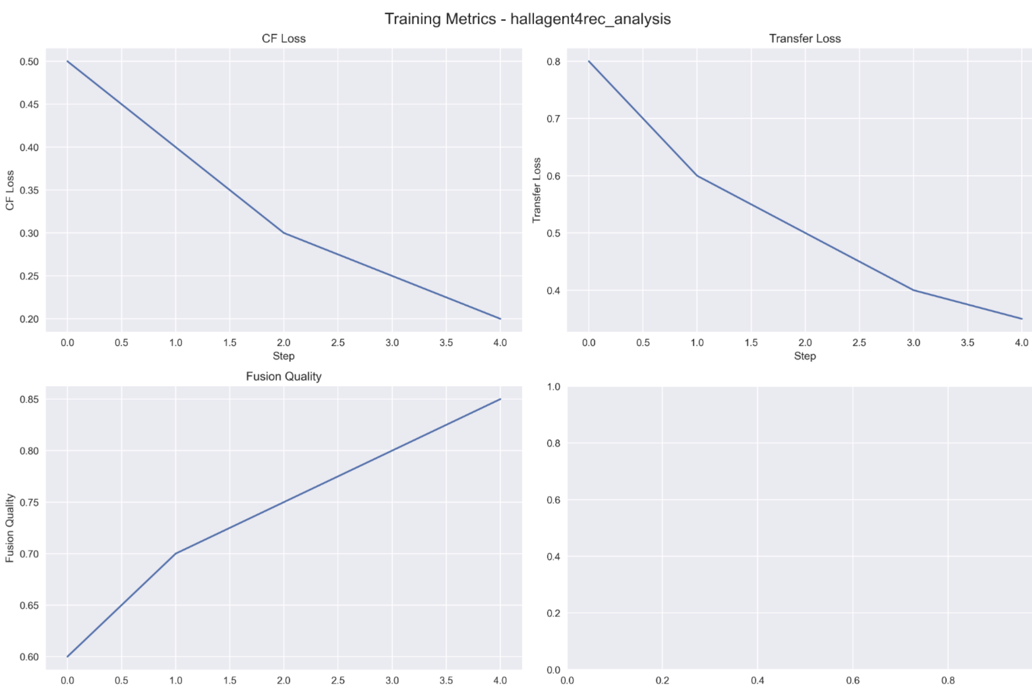

Fig. 7. Abalation study: A training loss function on dataset Amazon

Algorithm 1 HallAgent4Rec: Offline Training Phase

Require: User-item interaction matrix $\mathbf{R}$, item features $\{\mathbf{x}_j\}$, user demographics
Ensure: Trained parameters $\{\mathbf{u}_i, \mathbf{A}, \mathbf{B}, \mathbf{w}, \{b_j\}\}$

// **Step 1: Learn Collaborative Filtering Representations**
Initialize $\mathbf{U}^{cf}, \mathbf{V}$ randomly
while not converged **do**
  for $(i, j) \in \Omega$ **do**
    $e_{ij} \leftarrow r_{ij} - (\mathbf{u}_i^{cf})^T \mathbf{v}_j$
    $\mathbf{u}_i^{cf} \leftarrow \mathbf{u}_i^{cf} + \eta(e_{ij}\mathbf{v}_j - \lambda_u \mathbf{u}_i^{cf})$
    $\mathbf{v}_j \leftarrow \mathbf{v}_j + \eta(e_{ij}\mathbf{u}_i^{cf} - \lambda_v \mathbf{v}_j)$
  end for
end while
// **Step 2: Generate Personality Vectors**
for each user i **do**

Table 6. Recommendation quality comparison across datasets with varying sparsity levels

	MovieLens-1M (95.53 %)			Amazon Electronics (99.97 %)			Yelp (99.92 %)		
Method	HR@10	NDCG@10	MRR	HR@10	NDCG@10	MRR	HR@10	NDCG@10	MRR
Best Traditional CF (Quality Baseline)									
LightGCN	0.771	0.514	0.431	0.642	0.389	0.331	0.718	0.469	0.392
Generative Methods (Semantic but Unreliable)									
GPT-Rec	0.684	0.458	0.375	0.548	0.331	0.278	0.631	0.408	0.341
RecAgent	0.712	0.476	0.392	0.572	0.349	0.295	0.661	0.429	0.359
FactRec	0.728	0.485	0.403	0.596	0.364	0.309	0.682	0.443	0.371
Hybrid Methods (Inconsistent Integration)									
BERT4Rec+MF	0.743	0.496	0.415	0.621	0.375	0.318	0.697	0.453	0.381
LLM-CF	0.739	0.491	0.411	0.617	0.372	0.314	0.692	0.450	0.378
Our Unified Approach									
HallAgent4Rec	0.784	0.519	0.437	0.651	0.394	0.339	0.724	0.473	0.396
vs. LightGCN	1.7 %	1.0 %	1.4 %	1.4 %	1.3 %	2.4 %	0.8 %	0.9 %	1.0 %

Table 7. Attention mechanism adaptation across datasets and user interaction densities

User Category	**MovieLens-1M** Mean α ± Std	**Amazon Electronics** Mean α ± Std	**Yelp** Mean α ± Std	**Quality Impact** vs. CF-only
Dense interactions (> 200)	0.28 ± 0.12	0.35 ± 0.15	0.31 ± 0.13	+8.3 % HR@10
Medium (50–200)	0.45 ± 0.18	0.58 ± 0.21	0.51 ± 0.19	+12.7 % HR@10
Sparse (< 50)	0.72 ± 0.21	0.79 ± 0.18	0.75 ± 0.20	+18.4 % HR@10
Dataset Average	0.45 ± 0.18	0.67 ± 0.22	0.51 ± 0.19	**+13.1 % HR@10**

Algorithm 2 HallAgent4Rec: Online Recommendation and Hallucination Mitigation

Require: Trained parameters, target user u, candidate items C, new interaction (i, j, r_{ij})
Ensure: Recommendation list with hallucination mitigation

// **Phase 1: Score Candidate Items**
for each item $j \in C$ **do**
  $\hat{r}_{uj} \leftarrow g(\mathbf{u}_u^T \mathbf{A}\mathbf{x}_j + \mathbf{u}_u^T \mathbf{B}\boldsymbol{\theta}_j + \mathbf{w}^T \mathbf{z}_{uj} + b_j)$
end for
Sort items by $\hat{r}_{uj}$ and select top-K as $\mathcal{L}_{scored}$
// **Phase 2: LLM Recommendation Generation**
$\mathcal{R}_{LLM} \leftarrow$ LLM(user_profile, $\mathcal{L}_{scored}$)
// **Phase 3: Hallucination Detection and Mitigation**
$\mathcal{R}_{final} \leftarrow \emptyset$
for each recommended item $\hat{i} \in \mathcal{R}_{LLM}$ **do**
  if $\hat{i} \in C$ **then**
    {Valid recommendation} $\mathcal{R}_{final} \leftarrow \mathcal{R}_{final} \cup \{\hat{i}\}$
  else
    {Hallucination detected} Extract features $\mathbf{x}_{\hat{i}}$ from LLM description $s_{genre}(\hat{i}, j) \leftarrow \frac{|\mathcal{G}_{\hat{i}} \cap \mathcal{G}_j|}{|\mathcal{G}_{\hat{i}} \cup \mathcal{G}_j|}$ for all $j \in C$ $s_{exp}(u) \leftarrow \min(1, \frac{|\mathcal{I}_u|}{\bar{I}_{all}})$ $\alpha(u, \hat{i}, j) \leftarrow s_{genre}(\hat{i}, j) \times (1 - s_{exp}(u))$ $\text{sim}(\hat{i}, j) \leftarrow \frac{\mathbf{x}_{\hat{i}}^T \mathbf{x}_j}{\|\mathbf{x}_{\hat{i}}\|_2 \|\mathbf{x}_j\|_2}$ $j^* \leftarrow \arg\max_{j \in C} [\alpha(u, \hat{i}, j) \cdot \text{sim}(\hat{i}, j) + (1 - \alpha(u, \hat{i}, j)) \cdot \hat{r}_{uj}]$ $\mathcal{R}_{final} \leftarrow \mathcal{R}_{final} \cup \{j^*\}$
  end if
end for
// **Phase 4: Online Parameter Updates (if new interaction observed)**
if new interaction (i, j, r_{ij}) observed **then**

Algorithm 3 Feature Extraction from Hallucinated Items

Require: LLM description of hallucinated item $\hat{i}$, genre list $\mathcal{G}$
Ensure: Feature vector $\mathbf{x}_{\hat{i}}$

```
// Extract Genre Features
prompt ← "Given this movie description: [LLM output], identify which of these genres apply: [G]. Return a binary vector."
g_î ← LLM(prompt) {Binary genre vector}
// Extract Content Features
Apply TF-IDF to LLM description using learned vocabulary
c_î ← TF-IDF(LLM description)
// Extract Release Year (if mentioned)
year_î ← extract_year(LLM description)
year_normalized ← (year_î − year_min) / (year_max − year_min)
// Combine Features
x_î ← [g_î; year_normalized; c_î]
return x_î
```

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