Quantitative Modeling of Recommendation Systems Driven by Dynamic Preference Logic

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Abstract

With the wide application of recommendation systems in e-commerce and media scenarios, user preferences have shown obvious dynamics and contextual dependence. However, traditional collaborative filtering, matrix factorization and deep models mostly only fit static vectors and are difficult to explain the mechanisms behind the changes in preferences. To this end, this paper proposes a three-layer interpretable recommendation model DPDRS based on dynamic preference logic, achieving a transparent reasoning process from behavioral feedback to preference evolution and then to recommendation generation. The model constructs preference states that can be updated over time at the presentation layer based on long-term preferences, short-term preferences, and preference temperatures. Introduce the preference upgrade operator in the reasoning layer to strengthen or suppress the corresponding attributes through positive and negative feedback. In the generation layer, design a three-channel fusion structure of behavioral decision-making, attribute logic, and collaboration, and align behavioral semantics and attribute semantics with consistency loss. To adapt to different scenarios, in this paper, corresponding attribute matrices were constructed on datasets such as MovieLens-1M, and systematic comparisons were made with methods such as MAUT and CosRec. DPDRS achieved significant improvements in indicators such as Precision@10, Recall@10 and NDCG@10. In addition, diversity assessment, interpretability analysis, and multiple ablation experiments further verified the effectiveness of the preference escalation operator, attribute channel, consistency loss, and time decay mechanism. Overall, DPDRS has achieved interpretable dynamic recommendation based on logical reasoning, providing theoretical and practical support for the construction of a new generation of recommendation systems with the ability to model preference evolution.

Introduction

Recommendation systems, as an important technology for information filtering, are widely applied in e-commerce, social media and content platforms(Zhang et al. 2019). With the increase in the scale and complexity of interaction data, user behavior shows dynamics and strong context dependence(Quadrana, Cremonesi, and Jannach 2018). Although deep models and large language models have made progress in feature representation, their "black box" nature leads to a lack of explainable logical reasoning ability(Wu et al. 2024). In practical scenarios, user preferences continuously evolve over time and with changes in information. Therefore, how to formally model this dynamic preference logic and apply it to reliable and interpretable recommendations has become a key challenge in current research(Curmei et al. 2022).

The existing recommendation systems still have obvious deficiencies in preference modeling. Although traditional collaborative filtering and deep models can fit static preferences, their reasoning processes are not traceable and it is difficult to explain the reasons for recommendations. Although methods based on knowledge graphs or logical rules have certain interpretability, they rely on predefined static preference structures and are difficult to cope with the continuous evolution of user preferences(Guo et al. 2020). Since preference changes are often driven by internal logic, there is an urgent need for a theoretical framework that can formally describe the formation, update and reversal of preferences. Dynamic preference logic precisely provides such a foundation. Based on modal logic and possible world semantics, it regards preferences as relational structures that can change with cognitive events, and can strictly describe how information leads to preference updates, thereby introducing human-like logical reasoning capabilities to recommendation systems and achieving a paradigm shift from data-driven to logic-driven(Van Benthem and Liu 2007).

Building on the foregoing analysis, we propose a quantitative modelling approach for recommendation systems that is driven by dynamic preference logic. We first construct a formal model grounded in dynamic preference logic, treating a user's historical interactions as cognitive events and employing a preference-revision operator to adjust the preference structure on the fly, thereby capturing the evolution of user preferences(Liu 2011). We then introduce a hybrid framework that integrates logical inference with numerical estimation: at the logical level, priority sequences and revision operators deliver explainable reasoning; at the quantitative level, preference intensity, temporal weighting and feedback confidence are mapped into computable recommendation scores, balancing effectiveness with interpretability. This design enables the model to generate a transparent and traceable chain of reasons for every recommendation, ensuring a one-to-one correspondence between each recommendation result and the underlying preference rules together with their dynamic triggering conditions.

The main contributions of this paper are as follows:

- A recommendation system modeling framework based on dynamic preference logic was proposed.
- A hybrid scoring mechanism integrating logical reasoning and numerical estimation was constructed.
- Traceable and structured generation of recommendation explanations has been achieved.

Related Work

This research is based on the intersection of three fields: recommendation systems, preference logic, and artificial intelligence logic. This section will systematically review the current research status and progress in related fields, aiming to clarify the theoretical basis of the work in this paper and clearly position its contributions and innovations.

Current research status of recommendation systems: The development of recommendation systems reflects the evolution of technology from statistical association to semantic understanding and intent modeling. Early collaborative filtering and matrix factorization achieved matching by mining the latent vectors of users and items, but they heavily relied on co-occurrence data of ratings, which limited their performance in cold start and sparse scenarios, and lacked interpretability(Peake and Wang 2018). Content-based methods construct user profiles by analyzing the features of items, which are somewhat explanatory but tend to be limited to the existing range of interests(Deldjoo et al. 2020; Lops et al. 2019). The hybrid method attempts to integrate the two to enhance performance, but its essence still remains at the static pattern mining of historical behavior and is unable to depict the deep logical mechanism of the formation and change of user preferences.

In recent years, large language models (LLMs) have demonstrated great potential in recommendation systems(Li et al. 2024). With their powerful semantic understanding and generation capabilities, they can mine the semantics of items and generate natural and personalized recommendation reasons(Xu et al. 2024; Zhao et al. 2023). However, most existing methods use LLMS as feature extractors or generative recommenders. Their decision-making processes rely on the tacit knowledge within the model, and the reasoning paths are opaque and prone to "hallucinations"(Li et al. 2024; Van Benthem 2011). More importantly, LLMs do not inherently possess strict formal reasoning capabilities and thus find it difficult to handle problems that require logical constraints, such as dynamic changes in preferences.

To sum up, there are significant gaps in the current research on recommendation systems in terms of interpretability and dynamic logical reasoning. This paper aims to explore a new paradigm that introduces explicit logical reasoning mechanisms into recommendation systems to make up for the deficiencies of data-driven methods.

The theoretical foundation of preference logic: Preference logic provides an important tool for the formal description and reasoning of preference attitudes(Andersen and Rendsvig 2025). Dynamic preference logic, as the theoretical basis of this study, breaks through the static framework, regards preferences as the constantly evolving relationship due to cognitive events, and describes the update of information on the partial order structure through the preference upgrade operator. At the static level, preference logic mainly includes two types: modal preference logic based on the semantics of possible worlds, which describes the preference relationships between worlds from an overall perspective; And the first-order preference logic for attribute comparison, which characterizes the preference differences at the object level in a more refined way. The mechanism of preference upgrade and dynamic change constitutes the core of modeling user interest drift in this paper. Although existing research has systematically discussed the axiomatic forms of various upgrade operators, there is still a lack of exploration on how they can be combined with real user behavior data and serve large-scale recommendations(Van Benthem and Liu 2007). The work of this article is precisely an important attempt to promote the practical application of this logical theory on this basis.

Artificial intelligence logic methods: To build artificial intelligence systems with deep reasoning capabilities, logic provides a variety of formal tools, including default logic, non-monotonic reasoning and modal logic. Default logic achieves reasoning similar to common sense through retractable default rules, and its non-monotonicity is closely related to the contextualized changes in user preferences(Zhang et al. 2021). Modal logic and its extensions are used to model the knowledge, beliefs and other mental states of agents, which are precisely the internal driving forces for the evolution of preferences. Dynamic Epistemic Logic, especially Dynamic Epistemic Logic (DEL), further characterizes how information events update the cognitive structure of agents, providing a formal framework for analyzing "how recommendations or comments change users' cognition". This paper draws on DEL's perspective of information update and applies it to the dynamic modeling of preference relations, thereby constructing a user model that can continuously evolve along with the information flow.

Overall, although existing logical methods provide a solid foundation for explainable reasoning, there is still a gap compared with data-intensive applications(Xia et al. 2025). This paper aims to bridge this gap, taking dynamic preference logic as the core, and proposes a recommendation system framework that combines logical deduction ability with adaptability to real data.

Theoretical Basis

In intelligent information systems, user preferences are often simplified into static vectors. However, preferences in reality are highly dynamic, context-sensitive, and attribute-driven, constantly changing with time, tasks, and external information(Hwang and Lee 2025; Lin and Chen 2019). If the system fails to capture these evolutions, it will be difficult to generate recommendations that meet the current needs of users. Dynamic Preference Logic (DPL) provides a structured theoretical framework for this purpose, regarding preferences as logical states that can be updated with new information rather than a fixed distribution. This chapter will construct the structural model, proposition priority sequence, attribute preference representation and dynamic update mechanism of this paper based on DPL, and provide corresponding numerical explanations to lay a theoretical foundation for the subsequent model design.

Dynamic Preference Logic Framework

Dynamic preference logic aims to describe the preference relationships of users between different worlds through formal language and further depict how preferences change when receiving new information(Van Benthem and Liu 2007). Compared with traditional preference modeling, it has the following characteristics: Preference is not a simple vector, but a structural model composed of propositions, worlds, assignments and priority relationships. changes in preferences are triggered by logical operators, such as suggestion operators and cutting operators. New evidence will change the structure of preferences rather than just the scoring function. Based on this idea, we adopt the quadruple structure model to formally model preferences. In the possible world semantic framework, a preference model is typically represented as $M = \langle W, \preceq, V, P\rangle$.

Specifically:

1. W: the set of possible worlds (candidate objects).
   Any item, service, or content in the system can be regarded as a "world".
2. $\preceq$: the preference relation over worlds.
   If $w \preceq w'$, it means the user does not prefer w more than w'.
   In numerical models, this relation is usually induced by predicted scores or ranking functions.
3. V: the valuation function.
   $V(p) \subseteq W$ denotes the set of worlds that satisfy attribute proposition p.
   Attribute propositions may correspond to categories, styles, functions, or tags.
4. P: the priority sequence of propositions.
   This sequence reflects the user's importance ordering over attributes, such as "functionality $>$ appearance $>$ brand".

Based on this structure, when the system receives new user behaviors or feedback, the preference relation $\preceq$ and the priority sequence P may change, thereby leading to a dynamic adjustment of the recommendation results.

Numerical Interpretation of the Two-layer Semantic and Structural Model

The structural model contains two layers of semantics:

- Proposition layer (Attribute layer) : Describes the attribute propositions of the object and their priorities.
- World Layer (Object Layer) : Derive preferences for actual objects based on attribute preferences.

Traditional logical derivation starts from the propositional level preference and generates the world-level preference through Lifting rules(Van Benthem and Liu 2007). The numerical implementation in this paper modernizes this mechanism, enabling it to accept gradient optimization and be directly embedded in deep networks. The main contents include: The valuation function V is represented using a sparse attribute–world matrix; The priority sequence P is represented by learnable vectors W_{long} and W_{short}; Ordered Weighted Aggregation (OWA) is used in place of strict logical rules to provide a differentiable mechanism for lifting attribute priorities to world-level preferences; An attention-based reweighting mechanism is employed to ensure that the relative importance between different attributes can be dynamically adjusted; An augmented update operator is used to model the gradual upgrade of user preferences. This numeric formulation not only preserves the structural semantics of dynamic preference logic, but also enables seamless integration with deep learning techniques for end-to-end training and optimization.

Temporality and Incomplete Information

In real-world scenarios, user information is often incomplete and behavioral data exhibits clear temporal characteristics. Therefore, the preference logic introduces:

- Time decay function: Recent behaviors exert stronger influence on preferences, whereas distant behaviors have weaker impact.
- Confidence interval handling: Extreme behaviors trigger stronger attribute preference updates.
- Priority temperature: Used to adjust the "sharpness" of attribute ranking, determining how strongly the model focuses on central preference patterns.

This formulation makes preference not merely a structural variable, but a system state that evolves over time.Similarly, time-aware recommendation systems depict the attenuation and migration of user interests by explicitly modeling timestamps, time intervals, or continuous-time processes. Relevant studies have shown that reasonable modeling of time factors is a key factor in improving recommendation effectiveness and explanatory ability(Harshvardhan et al. 2022; Yeganegi, Haratizadeh, and Ebrahimi 2024).

This chapter, centering on the core idea of dynamic preference logic, systematically expounds the composition of preference structure, the expression of attribute propositions, the semantics of priority sequences, and the mechanism of preference evolution over time(Wei, Qin, and Ren 2022; Ding, Liu, and Hu 2022). Through formal description, we have clarified the framework in which preferences are jointly determined by "world - relationship - assignment - priority", and explained the derivation method of preferences between the proposition layer and the world layer. Meanwhile, the influence of factors such as time decay and incomplete information on preference updates was discussed, as well as how to transform logical rules into differentiable numerical expressions. The above theory provides a rigorous semantic foundation for the subsequent model construction.

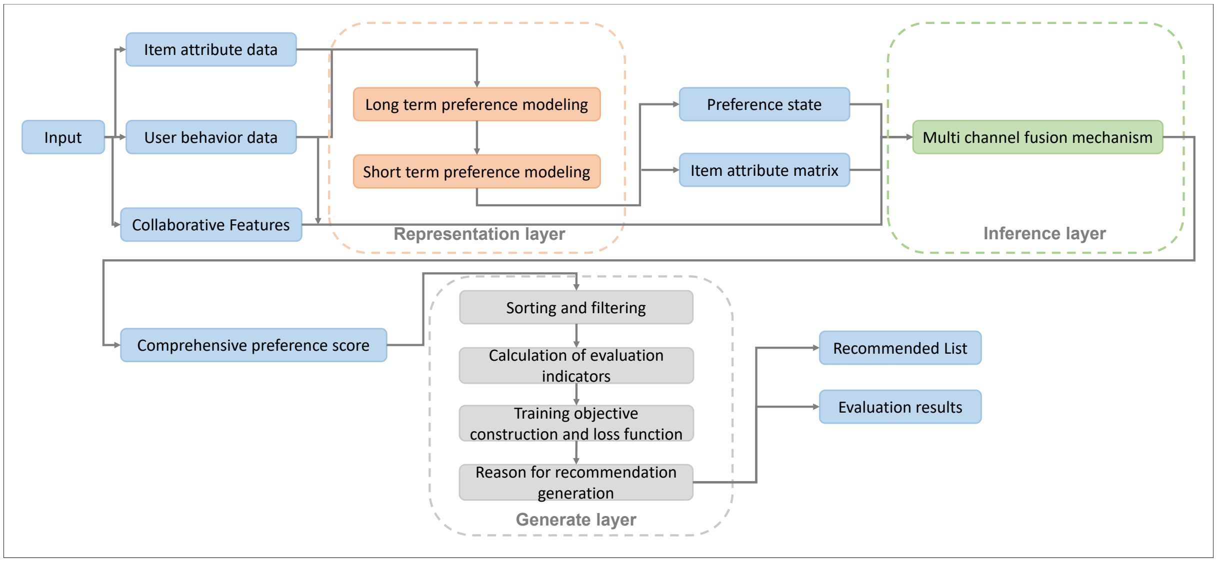

Figure 1: Overall architecture diagram of the DPDRS recommendation model

Dynamic Preference-driven Recommendation System Model

Based on the aforementioned theoretical framework, this chapter proposes the DPDRS model. This model transforms the structural semantics of preference logic into a deep representation, enabling it to achieve: explainability when dealing with dynamic, multi-attribute, and multi-feedback recommendation tasks; Evolvable; Fusible; Can be optimized.

Overall Structure of the Model

DPDRS integrates the structured semantics of dynamic preference logic into the deep learning framework, forming a unified model composed of three layers: "representation - reasoning - generation". The overall system not only retains the interpretability of preference logic but also possesses the capabilities of automatic learning and dynamic evolution. Its overall structure is shown in Figure 1.

The task of the presentation layer is to construct the basic state required for the system to operate. This layer provides an interpretable, learnable and time-varying preference basis for the subsequent reasoning process. The reasoning layer is responsible for simulating the process of deriving world preferences from propositional preferences in preference logic and is the core of the model. This layer generates the user's immediate preference score for a certain object, achieving the unification of logical semantics and depth representation. The reasoning layer, while aggregating behavioral evidence, takes into account the interaction between time decay and logical rules, which echoes the recent recommendation methods that combine time attention mechanisms with logical reasoning in terms of design concept(Luo et al. 2024). The generation layer ranks the global candidate objects based on the preference scores obtained from the reasoning layer, thereby obtaining the final recommended list. These three layers of structure together constitute the complete calculation process of DPDRS.

Presentation Layer

As the foundation of DPDRS, the core task of the presentation layer is to provide structured and learnable preference states and formalize the logical preference structure into differentiable expressions, laying the semantic foundation for subsequent reasoning and recommendation.

Proposition Assignment: To characterize the semantic features of each item, the system first defines a set of attribute propositions for each object. These propositions may correspond to category labels, style orientations, functional properties, quality levels, or various scenario-related attributes. Each item is represented by an attribute-proposition vector:

$$M_i = (m_{i1}, m_{i2}, \ldots, m_{ik}), \tag{1}$$

where $m_{ik} \in \{0, 1\}$ indicates whether item i satisfies the attribute proposition p_k. In the dynamic preference logic framework, the valuation function $V(p_k) \subseteq W$ is transformed into a numeric representation through this attribute matrix M, completing the mapping from logical semantics to numerical modeling. This matrix not only provides interpretable semantic support for the reasoning process but also enables attribute-level preferences to be directly optimized through learning.

Proposition Priority Sequence: To characterize a user's preference structure at the attribute level, the system assigns each user a time-varying preference state. This state consists of three components:

- long-term preference vector W_u^{long}
  Used to describe the user's stable attribute tendencies that remain consistent over long time spans.
- short-term preference vector W_u^{short}
  Used to capture the user's immediate interests reflected in recent behaviors, thereby modeling short-term fluctuations in preference.

- preference temperature τ_u
  Used to control the "smoothness" of the distribution, regulating how sharp or diffuse the attribute preferences appear.

Considering temporal effects, the system applies a decay function to adjust the influence of short-term behaviors according to the elapsed time Δt:

$$g(\Delta t) = e^{-\lambda_t \Delta t}, \tag{2}$$

where λ_t is the time decay coefficient. The decay function allows the system to naturally distinguish the contributions of recent behaviors from distant ones. Based on this formulation, the user's attribute preference distribution at time t is given by:

$$W_u(t) = \mathrm{softmax}\big(W_u^{\text{long}} + g(\Delta t) \cdot W_u^{\text{short}}\big). \tag{3}$$

This distribution provides a clear semantic interpretation: it reflects the user's relative attention to different attribute propositions at the current moment, serving as a key intermediate variable in the DPDRS reasoning process.

Reasoning Layer

The inference layer is the core computing module of DPDRS. Its function is to make immediate preference inferences for candidate objects based on the dynamic preference states provided by the presentation layer. This layer generates the user's comprehensive preference score at the current moment through a multi-channel fusion mechanism. The inference layer contains three complementary preference channels and upgrade operators, as shown in Figure 2.

Behavioral Preference Channel The behavioral preference channel is used to capture the user's behavioral habits and implicit tendencies. By learning user and item behavioral embeddings, the system can model the latent behavioral patterns expressed through long-term interactions.

$$D_{ui} = \langle \theta_u, \psi_i \rangle, \tag{4}$$

where θ_u and ψ_i denote the behavioral feature vectors of the user and the item, respectively. This channel reflects "what the user has historically liked", providing a direct representation of the user's behavioral patterns.

Attribute Logical Channel The logical preference channel represents the core theoretical innovation of DPDRS. It models the dynamic "lifting" process in preference logic, which maps attribute-level preferences to object-level evaluations. Specifically, based on the user's attribute preference distribution $W_u(t)$, the system reorders and reweights the attribute-proposition vector of each item, and computes the logic-driven preference score using a differentiable aggregation function:

$$P_{ui} = \mathrm{OWA}\big(W_u(t), M_i, \tau_u\big). \tag{5}$$

This process effectively realizes the semantic transition from attribute priorities to object-level ranking results, enabling the recommendation outcome to retain clear logical interpretability.

Collaborative Preference Channel The collaborative preference channel supplements the information beyond the user's behavioral preference and attribute-based preference. This channel captures the latent structural similarity between users and items through collaborative embeddings:

$$CF_{ui} = \langle c_u, c_i \rangle. \tag{6}$$

This component enhances the model's ability to handle sparse or weak-feature items, making the reasoning layer more robust.

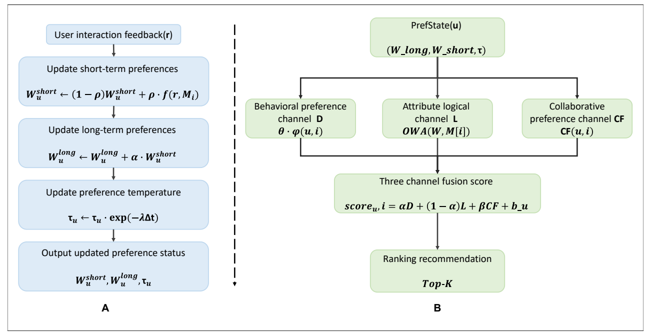

Figure 2: A is the preference update operator module, and B is the three-channel fusion inference module.

Comprehensive Preference Score The outputs of the three channels are further integrated to obtain the instantaneous preference score of user u for item i:

$$\mathrm{score}_{ui} = \alpha D_{ui} + (1-\alpha) P_{ui} + \beta CF_{ui} + b_u + b_i + b_0, \tag{7}$$

where α controls the influence proportion between the behavioral channel and the logical channel, and β adjusts the weight of the collaborative channel. This score serves as the final ranking signal, determining the recommendation results produced by the system at the current state.

Preference Upgrade Operator The reasoning layer not only needs to generate the preference score at the current moment, but also continuously update the preference status based on user feedback. To this end, DPDRS introduces a preference upgrade operator in it, converting explicit ratings or implicit feedback into incremental updates of attribute preferences(Van Benthem and Liu 2007), and by locally adjusting the proposition priority sequence, the system gradually corrects and strengthens user preferences after each interaction(Liu 2011).

Feedback Quantization and Confidence Interval Partitioning: Let the feedback of user u to item i be normalized to the interval $[0, 1]$, denoted as y_u. Based on the strength of the feedback, the system divides it into three cases:

- High-confidence positive feedback: $y \geq conf_{\text{pos}}$
  The user is considered to clearly "like" the item, and the corresponding attribute preferences should be strengthened.
- High-confidence negative feedback: $y \leq conf_{\text{neg}}$
  The user is considered to clearly "dislike" the item, and the corresponding attribute preferences should be suppressed.

- Medium-confidence feedback: $conf_{\mathrm{neg}} < y < conf_{\mathrm{pos}}$ This feedback is not sufficiently informative and is therefore ignored to avoid noisy updates of the preference state.

Here, $conf_{\mathrm{pos}}$ and $conf_{\mathrm{neg}}$ are hyperparameters used to determine the activation thresholds for updating user preferences.

Preference Update Mechanism: When the preference update operator acts on the user's long-term preference vector W_u^{long} and short-term preference vector W_u^{short}, the attribute vector of item i is denoted as

$$E_i = M_i \in \{0,1\}^K. \tag{8}$$

The update rules for the preference state are given as follows.

Positive feedback (reinforcement), when $y \geq conf_{\mathrm{pos}}$:

$$W_u^{\mathrm{short}} \leftarrow (1-\rho)\, W_u^{\mathrm{short}} + \rho \cdot sE_i, \tag{9}$$

$$W_u^{\mathrm{long}} \leftarrow W_u^{\mathrm{long}} + \alpha_{\mathrm{upd}} \cdot sE_i. \tag{10}$$

Negative feedback (suppression), when $y \leq conf_{\mathrm{neg}}$:

$$W_u^{\mathrm{short}} \leftarrow (1-\rho)\, W_u^{\mathrm{short}} - \rho \cdot sE_i, \tag{11}$$

$$W_u^{\mathrm{long}} \leftarrow W_u^{\mathrm{long}} - \alpha_{\mathrm{upd}} \cdot sE_i. \tag{12}$$

Here, $\rho \in (0,1)$ is the EMA coefficient used to update the short-term preference, controlling how strongly new evidence influences the short-term state. The parameter $\alpha_{\mathrm{upd}} > 0$ denotes the step size for updating the long-term preference, ensuring that a small amount of high-confidence feedback can leave a lasting effect on the long-term structure. Finally, s is a scaling factor that determines the magnitude of preference change induced by a single sample. It can be seen that the short-term preference follows an exponential moving average, which reflects the cumulative effect of recent behaviors, whereas the long-term preference is updated with a smaller step size, modeling the gradual formation or correction of stable interests.

Coupling with Time Decay and the Representation Layer: In DPDRS, the attribute preference distribution of users at time t in the representation layer is shown in Formula (3). where $g(\Delta t) = e^{-\lambda_t \Delta t}$ is the time decay function. The preference update operator only modifies the internal states W_u^{long} and W_u^{short}, while the actual distribution $W_u(t)$ is recomputed at each interaction according to the current time gap Δt.

This design yields two main advantages. First, it naturally models memory decay: even if the short-term preference is strongly updated at a certain moment, its influence on $W_u(t)$ will gradually diminish when no further related behaviors occur, owing to the effect of $g(\Delta t)$. Second, it avoids state explosion, since temporal information is encoded directly within the preference state rather than stored as additional parameters for each interaction, ensuring that the model size does not grow with the length of the interaction history.

Design of the Generation Layer

The generation layer is located at the very top of DPDRS. This layer enables the system to complete the crucial transformation from "preference inference" to "decision output".

Recommendation List Generation The aggregated preference score score_{ui} produced by the reasoning layer represents the instantaneous preference degree of user u for item i at time t. Based on this score, the system first ranks all candidate items:

$$\pi_u = \mathrm{argsort}_{i \in W}\big(-\mathrm{score}_{ui}\big), \tag{13}$$

where π_u denotes the ranking sequence for user u. The final top-K recommendation list is then obtained by taking the first K elements of this sequence:

$$\mathrm{Rec}_u = \pi_u[1:K]. \tag{14}$$

This procedure implements the notion of "world preference" in preference logic: the priority relation over worlds is realized through numerical ranking and is directly reflected in the final recommendation results. To avoid repeatedly recommending items that the user has already consumed, items that have appeared in the user's interaction history can be filtered from the front part of the ranking list, ensuring that the recommendation results remain informative.

Construction of Training Objectives To make the recommendation results more in line with users' true preferences, a ranking-driven loss function is introduced in the training part of the generation layer(Tang et al. 2023). DPDRS employs objective functions suitable for implicit feedback and sorting optimization, including:

Bayesian Personalized Ranking (BPR) Loss Based on Ranking: For each positive feedback sample i of user u, the system selects one or more negative samples j to construct pairwise comparisons. The BPR loss is defined as

$$\mathcal{L}_{\mathrm{BPR}} = -\log \sigma\big(\mathrm{score}_{ui} - \mathrm{score}_{uj}\big). \tag{15}$$

This loss encourages the model to satisfy $\mathrm{score}_{ui} > \mathrm{score}_{uj}$, thereby improving the accuracy of the ranking. To further enhance training stability, DPDRS introduces a multi-negative sampling mechanism, enabling the model to process multiple negative samples within a single training step, which strengthens its discrimination ability.

Consistency Loss: Since the reasoning layer combines three channels—behavioral preference, logical preference, and collaborative preference—the recommendation layer introduces a structural consistency constraint during training. The consistency loss is defined as

$$\mathcal{L}_{\mathrm{cons}} = \|D_{ui} - P_{ui}\|^2, \tag{16}$$

which encourages the different preference channels to remain internally aligned, thereby enhancing both interpretability and robustness of the dynamic preference state. This idea is in spirit consistent with the practice of aligning representations from different perspectives through consistency constraints in multi-view representation learning(Chen et al. 2022; Zhou et al. 2023).

Overall Training Objective: The final loss function is composed of the above components:

$$\mathcal{L} = \mathcal{L}_{\mathrm{BPR}} + \gamma\, \mathcal{L}_{\mathrm{cons}}, \tag{17}$$

where γ is a weighting coefficient that controls the balance between ranking accuracy and consistency across preference channels. During the training stage, the recommendation layer backpropagates this loss, allowing the preference

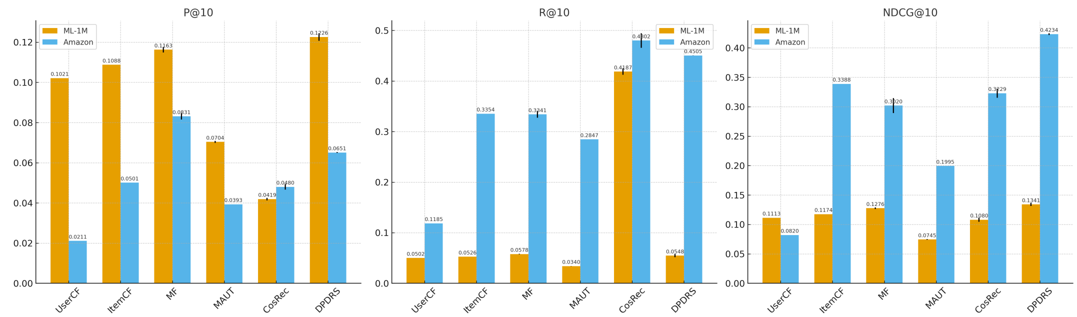

Figure 3: Results of different methods on ML-1M and Amazon datasets (P@10, R@10 and NDCG@10).

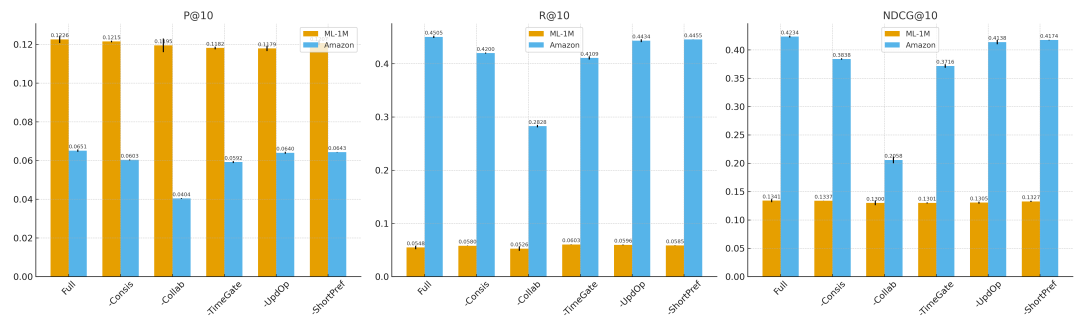

Figure 4: Ablation study of DPDRS on ML-1M and Amazon datasets.

vectors, logical weights, time decay factor, and collaborative representations to be jointly optimized. This enables the entire DPDRS framework to form a unified, learnable, and interpretable dynamic preference modeling paradigm.

Experimental Design and Result Analysis

Experimental Design

To comprehensively verify the effectiveness of the DPDRS model proposed in this paper, this section conducts a systematic discussion from aspects such as the experimental environment, dataset processing, and attribute matrix construction.

All experiments in this study were conducted under a unified software and hardware environment. The server is equipped with an Intel Xeon w5-3425 processor and 128 GB of memory, and the experimental platform is based on Python 3.12 and PyTorch.

To evaluate the generalization ability of DPDRS across different recommendation scenarios, we adopt two representative datasets: MovieLens-1M and Amazon Fine Food Reviews, and consider all non-interacted items as the ranking space. For MovieLens-1M, the data are first grouped by user ID and then strictly ordered by timestamp to reconstruct the true interaction sequences. A temporal split is applied to construct the training, validation, and test sets, ensuring that no future information is used during prediction. The rating values in the interval $[1, 5]$ are linearly normalized to $[0, 1]$ to improve numerical stability during training, using the following transformation:

$$y = \frac{r - 1}{4}. \tag{18}$$

For the Amazon Fine Food Reviews dataset, the *Summary* and *Text* fields are cleaned and merged, and user interaction sequences are reconstructed in chronological order using the same temporal split strategy as in MovieLens. Unlike MovieLens, the Amazon dataset contains rich textual reviews that can be used to construct semantic attributes. Previous studies have shown that jointly modeling textual and temporal information can significantly improve recommendation performance in scenarios with abundant review content and clear temporal patterns(Rabiu et al. 2022; Ding, Liu, and Hu 2022) Therefore, this dataset provides a more rigorous test of DPDRS's capability in logical preference updating and attribute-level reasoning.

The attribute matrix M is a core input to the logical reasoning channel, transforming each item from a single vector into a set of interpretable attributes. Different attribute representations are constructed for the two datasets, enabling DPDRS to perform preference reasoning in an abstract attribute space. For MovieLens-1M, M is derived from structured metadata such as genres, decades, rating buckets, and popularity buckets, all of which have clear semantic boundaries. For the Amazon Fine Food Reviews dataset, M is built from aspects and sentiments extracted from natural language reviews. For a given aspect a, its positive sentiment ratio is defined as:

$$p_a^+ = \frac{c_a^+}{c_a^+ + c_a^-}. \tag{19}$$

Dataset	UserCF	ItemCF	MF	MAUT	CosRec	DPDRS	Full	-Consis	-Collab	-TimeGate	-UpdOp	-ShortPref
	Baselines						DPDRS and its ablations					
ML-1M												
Precision@10	.1021	.1088	.1163	.0704	.0419	.1226	.1226	.1215	.1195	.1182	.1179	.1207
Recall@10	.0502	.0526	.0578	.0340	.4187	.0548	.0548	.0580	.0526	.0603	.0596	.0585
NDCG@10	.1113	.1174	.1276	.0745	.1080	.1341	.1341	.1337	.1300	.1301	.1305	.1327
Amazon												
Precision@10	.0211	.0501	.0831	.0393	.0480	.0660	.0660	.0603	.0404	.0592	.0564	.0644
Recall@10	.1185	.3354	.3341	.2847	.4802	.4500	.4500	.4200	.2828	.4109	.3474	.4452
NDCG@10	.0820	.3388	.3020	.1995	.3229	.4400	.4400	.3838	.2058	.3716	.3263	.4178

Table 1: Overall performance (P@10, R@10, NDCG@10) of baselines and ablation variants of DPDRS on ML-1M and Amazon.

Here, c^+ and c^- denote the numbers of positive and negative sentences related to aspect a, respectively. To enhance the interpretability of logical reasoning, the sentiment strength is discretized into three levels (low, medium, high), and all categorical textual attributes are encoded using independent one-hot vectors. The resulting Amazon attribute matrix contains nearly fifty dimensions, representing an innovative practice of constructing logic-ready attribute vectors from natural language. Existing studies have also shown that aspect–sentiment features can improve prediction accuracy while providing finer-grained explanatory support(Liu, Zhang, and Gulla 2021; Gajula 2025).

A multi-seed strategy is employed for training and evaluation across all models, and the final results are reported in terms of the mean and standard deviation (Ovaisi et al. 2022; Bauer, Said, and Zangerle 2024).

Comparative Experiment and Ablation Experiment

To comprehensively validate the effectiveness of DPDRS, we conduct both comparative experiments and ablation studies on these two datasets. For the comparative experiments, representative baseline methods including UserCF, ItemCF, MF, CosRec, and MAUT(Aljunid et al. 2025; Koren, Bell, and Volinsky 2009; Akpan and Morimoto 2022; Yan et al. 2019) are selected, covering major paradigms such as collaborative filtering, matrix factorization, sequential modeling, and multi-attribute recommendation. The corresponding results are shown in Fig. 3. Meanwhile, systematic ablation studies are further carried out to examine the impact of each component of DPDRS from the perspectives of behavioral modeling, attribute-level logical reasoning, temporal dynamics, and preference evolution, with the results presented in Fig. 4. Table 1 shows the specific results of the comparison and ablation experiments.

Comprehensive experiments show that DPDRS consistently ranks at the top in ranking accuracy, recall capacity and overall utility. Its edge comes from unifying behavioral evidence, attribute rules and collaborative signals within a dynamic-preference-logic framework. Compared with UserCF/ItemCF, it replaces static co-occurrence matrices with a time-aware upgrade operator, largely alleviating interest drift. Against latent-factor models it decomposes each user–item interaction into an interpretable sequence of propositions, worlds and priority orders, cutting random errors inherent in latent dimensions and yielding smaller variance and higher stability. Relative to MAUT it continuously revises the preference structure through differentiable upgrades, preventing multi-attribute utilities from falling into logical conflicts under sparse feedback. In contrast to CosRec it explicitly injects attribute semantics into sequential inference, equipping short-term signals with traceable explanatory chains. Ablation studies further reveal that removing the consistency constraint, collaborative channel or temporal gate causes the steepest drops, confirming that behavior-attribute alignment, group-signal supplementation and time-decay modeling are the main pillars of performance. The preference-upgrade operator and short-term buffer, though less dramatic, still supply indispensable corrections in sparse scenarios. Overall, the modules complement and couple with one another; the full architecture maintains high interpretability while jointly capturing long-term preference evolution and short-term contextual feedback, validating the integrated advantages of a modular design grounded in dynamic preference logic in terms of accuracy, robustness and explainability.

Conclusion

In summary, the DPDRS proposed in this paper achieves structured expression, logical reasoning and interpretable generation of user preferences by organically integrating dynamic preference logic with a deep learning framework. The experimental results show that this model demonstrates stable and superior performance in different datasets and multiple recommendation paradigms, verifying the key roles of preference upgrade operators, attribute logic channels, and temporal dynamic modeling in characterizing users' true intentions. Further ablation studies also show that the modules form a complementary and collaborative overall structure. The absence of any part will weaken the model's reasoning ability and recommendation quality. Overall, DPDRS not only outperforms existing methods in terms of accuracy, but also offers new solutions in terms of interpretability, adaptability and logical consistency, laying a theoretical foundation and practical value for the construction of a new generation of recommendation systems with logical reasoning capabilities.

References

Akpan, U.; and Morimoto, R. 2022. An application of Multi-Attribute Utility Theory (MAUT) to the prioritization of rural roads to improve rural accessibility in Nigeria. *Socio-Economic Planning Sciences*, 82: 101256.

Aljunid, M. F.; Manjaiah, D.; Hooshmand, M. K.; Ali, W. A.; Shetty, A. M.; and Alzoubah, S. Q. 2025. A collaborative filtering recommender systems: Survey. *Neurocomputing*, 617: 128718.

Andersen, F. J.; and Rendsvig, R. K. 2025. Believing in default rules: inclusive default reasoning. *Synthese*, 205(6): 225.

Bauer, C.; Said, A.; and Zangerle, E. 2024. Evaluation Perspectives of Recommender Systems: Driving Research and Education (Dagstuhl Seminar 24211). *Dagstuhl Reports*, 14(5): 58–172.

Chen, M.-S.; Lin, J.-Q.; Li, X.-L.; Liu, B.-Y.; Wang, C.-D.; Huang, D.; and Lai, J.-H. 2022. Representation learning in multi-view clustering: A literature review. *Data Science and Engineering*, 7(3): 225–241.

Curmei, M.; Haupt, A. A.; Recht, B.; and Hadfield-Menell, D. 2022. Towards psychologically-grounded dynamic preference models. In *Proceedings of the 16th ACM Conference on Recommender Systems*, 35–48.

Deldjoo, Y.; Schedl, M.; Cremonesi, P.; and Pasi, G. 2020. Recommender systems leveraging multimedia content. *ACM Computing Surveys (CSUR)*, 53(5): 1–38.

Ding, H.; Liu, Q.; and Hu, G. 2022. TDTMF: A recommendation model based on user temporal interest drift and latent review topic evolution with regularization factor. *Information Processing & Management*, 59(5): 103037.

Gajula, Y. 2025. Sentiment-Aware Recommendation Systems in E-Commerce: A Review from a Natural Language Processing Perspective. *arXiv preprint arXiv:2505.03828*.

Guo, Q.; Zhuang, F.; Qin, C.; Zhu, H.; Xie, X.; Xiong, H.; and He, Q. 2020. A survey on knowledge graph-based recommender systems. *IEEE Transactions on Knowledge and Data Engineering*, 34(8): 3549–3568.

Harshvardhan, G.; Gourisaria, M. K.; Rautaray, S. S.; and Pandey, M. 2022. UBMTR: Unsupervised Boltzmann machine-based time-aware recommendation system. *Journal of King Saud University-Computer and Information Sciences*, 34(8): 6400–6413.

Hwang, J.; and Lee, H. 2025. From knowledge tracing to preference tracing: Capturing dynamic user preferences for personalized recommendation. *Electronic Commerce Research and Applications*, 101527.

Koren, Y.; Bell, R.; and Volinsky, C. 2009. Matrix factorization techniques for recommender systems. *Computer*, 42(8): 30–37.

Li, L.; Zhang, Y.; Liu, D.; and Chen, L. 2024. Large language models for generative recommendation: A survey and visionary discussions. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, 10146–10159.

Lin, Z.; and Chen, H. 2019. Recommendation over time: a probabilistic model of time-aware recommender systems. *Science China Information Sciences*, 62(11): 212105.

Liu, F. 2011. *Reasoning about preference dynamics*, volume 354. Springer Science & Business Media.

Liu, P.; Zhang, L.; and Gulla, J. A. 2021. Multilingual review-aware deep recommender system via aspect-based sentiment analysis. *ACM Transactions on Information Systems (TOIS)*, 39(2): 1–33.

Lops, P.; Jannach, D.; Musto, C.; Bogers, T.; and Koolen, M. 2019. Trends in content-based recommendation: Preface to the special issue on Recommender systems based on rich item descriptions. *User Modeling and User-Adapted Interaction*, 29(2): 239–249.

Luo, Z.; Huang, Z.; Tang, J.; Hou, Y.; and Gao, Y. 2024. Time-aware self-attention meets logic reasoning in recommender systems. In *2024 International Joint Conference on Neural Networks (IJCNN)*, 1–8. IEEE.

Ovaisi, Z.; Heinecke, S.; Li, J.; Zhang, Y.; Zheleva, E.; and Xiong, C. 2022. Rgrecsys: A toolkit for robustness evaluation of recommender systems. In *Proceedings of the fifteenth ACM international conference on web search and data mining*, 1597–1600.

Peake, G.; and Wang, J. 2018. Explanation mining: Post hoc interpretability of latent factor models for recommendation systems. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*, 2060–2069.

Quadrana, M.; Cremonesi, P.; and Jannach, D. 2018. Sequence-aware recommender systems. *ACM computing surveys (CSUR)*, 51(4): 1–36.

Rabiu, I.; Salim, N.; Da'u, A.; and Nasser, M. 2022. Modeling sentimental bias and temporal dynamics for adaptive deep recommendation system. *Expert Systems with Applications*, 191: 116262.

Tang, H.; Zhao, G.; He, Y.; Wu, Y.; and Qian, X. 2023. Ranking-based contrastive loss for recommendation systems. *Knowledge-Based Systems*, 261: 110180.

Van Benthem, J. 2011. *Logical dynamics of information and interaction*. Cambridge University Press.

Van Benthem, J.; and Liu, F. 2007. Dynamic logic of preference upgrade. *Journal of Applied Non-Classical Logics*, 17(2): 157–182.

Wei, C.; Qin, J.; and Ren, Q. 2022. A ranking recommendation algorithm based on dynamic user preference. *Sensors*, 22(22): 8683.

Wu, L.; Zheng, Z.; Qiu, Z.; Wang, H.; Gu, H.; Shen, T.; Qin, C.; Zhu, C.; Zhu, H.; Liu, Q.; et al. 2024. A survey on large language models for recommendation. *World Wide Web*, 27(5): 60.

Xia, J.; Li, D.; Gu, H.; Lu, T.; Zhang, P.; Shang, L.; and Gu, N. 2025. Oracle-guided Dynamic User Preference Modeling for Sequential Recommendation. In *Proceedings of the Eighteenth ACM International Conference on Web Search and Data Mining*, 363–372.

Xu, L.; Zhang, J.; Li, B.; Wang, J.; Cai, M.; Zhao, W. X.; and Wen, J.-R. 2024. Prompting large language models for recommender systems: A comprehensive framework and empirical analysis. *arXiv preprint arXiv:2401.04997*.

Yan, A.; Cheng, S.; Kang, W.-C.; Wan, M.; and McAuley, J. 2019. CosRec: 2D convolutional neural networks for sequential recommendation. In *Proceedings of the 28th ACM international conference on information and knowledge management*, 2173–2176.

Yeganegi, R.; Haratizadeh, S.; and Ebrahimi, M. 2024. Star: A session-based time-aware recommender system. *Neurocomputing*, 573: 127104.

Zhang, J.; Chen, B.; Zhang, L.; Ke, X.; and Ding, H. 2021. Neural, symbolic and neural-symbolic reasoning on knowledge graphs. *AI Open*, 2: 14–35.

Zhang, S.; Yao, L.; Sun, A.; and Tay, Y. 2019. Deep learning based recommender system: A survey and new perspectives. *ACM computing surveys (CSUR)*, 52(1): 1–38.

Zhao, W. X.; Zhou, K.; Li, J.; Tang, T.; Wang, X.; Hou, Y.; Min, Y.; Zhang, B.; Zhang, J.; Dong, Z.; et al. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 1(2).

Zhou, Y.; Zheng, Q.; Bai, S.; and Zhu, J. 2023. Semantically consistent multi-view representation learning. *Knowledge-Based Systems*, 278: 110899.