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PRISM: A BEHAVIOR-AWARE PERSONALIZED STRATEGY MODEL FOR USER RETENTION OPTIMIZATION IN MULTI-DOMAIN RECOMMENDATION SYSTEMS

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Abstract

With the increasing complexity of user behaviour and the rising cost of customer acquisition, digital platforms face significant challenges in sustaining long-term user engagement—particularly during the early stages marked by cold-start conditions. Traditional churn prediction models often fall short in providing actionable strategies for personalized retention, necessitating more adaptive and user-centric solutions. This study proposes PRISM (Personalized Retention-Integrated Strategy Model), a modular architecture designed to bridge behavioural prediction with intelligent task recommendation, ensuring both immediate engagement and sustained user retention. PRISM integrates several core modules: the Retention-Oriented Influence Model (ROIM) captures dynamic social propagation patterns; the Retention-Aware Engagement Model (RAEM) evaluates contextual factors such as location, time, reward relevance, and user interest to estimate task acceptance; the Fuzzy Retention Prediction Model (FRPM) leverages fuzzy logic to interpret engagement stimuli; and the Retention-Oriented Behaviour Estimation (ROBE) forecasts user interaction trends. These components work cohesively within the Personalized Fuzzy Engagement Recommendation (PFER) framework to allocate tasks tailored for maximum retention impact. The proposed system is validated across three benchmark datasets—IBM Telco, iQIYI, and MovieLens—using comprehensive evaluation metrics including BLEU, ROUGE, NDCG@10, HR@10 for prediction accuracy, and MB-URS, SB-URS, IUR, NRC for retention performance. Experimental results demonstrate that PRISM consistently surpasses state-of-the-art baselines, establishing a robust, explainable, and domain-neutral strategy for retention-oriented task recommendation and user engagement.

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I. INTRODUCTION

In today's rapidly evolving digital landscape, user retention remains a critical challenge across various domains such as telecom, media streaming, and crowdsourcing platforms. The increasingly competitive environment, combined with the growing diversity of user preferences and behavioural patterns, necessitates the development of sophisticated, personalized retention strategies. While accurately predicting user churn is important, it is not sufficient on its own; effective retention frameworks must proactively engage users and foster sustained interaction and loyalty over time.

In the highly competitive telecom sector, retaining existing customers is a more pressing strategic challenge than acquiring new ones, primarily due to escalating acquisition costs and varied subscriber behaviors. While advanced machine learning and deep learning models—such as XGBoost and LSTM ensembles—have achieved impressive accuracy rates (up to 99%) in predicting potential churners, they often fall short in translating these predictions into actionable, personalized retention strategies. Effective retention requires sophisticated analytics that integrate demographic information, behavioral patterns, and user feedback; without such comprehensive insights, many retention initiatives remain generic and less effective.

Emerging techniques such as deep reinforcement learning (DRL) and adaptive fuzzy systems offer promising solutions. DRL enables real-time adaptation of retention strategies by learning from interaction outcomes, while fuzzy logic accommodates the uncertainty and nuance in human behaviour, enhancing both interpretability and decision flexibility [2]. Recent studies confirm the efficacy of fuzzy-based churn models in the telecom domain, leveraging Mamdani and Sugeno inference systems for explainable and precise intervention targeting.

Despite these advances, many existing solutions operate in silos—predictive and prescriptive modules are not cohesively integrated—diminishing their real-world impact. There is an increasing consensus that integrated analytics frameworks, combining predictive accuracy with dynamic intervention design, are vital for maximizing customer lifetime value. By merging ensemble churn prediction techniques, reinforcement learning-driven strategy optimization, and fuzzy interpretability, this research aims to develop a unified framework that not only forecasts churn but also prescribes timely, personalized retention actions tailored to individual user profiles [3]. Customer retention strategies must evolve beyond binary churn labels and embrace contextualization, particularly in understanding when, how, and why customers are at risk. Context-aware modeling approaches help map out temporal behaviour trends, usage irregularities, and intervention history to determine optimal action points. Furthermore, behavioural segmentation and micro-profiling allow service providers to deliver nuanced strategies based on latent behavioural signals such as call drop frequency, streaming quality, and promotional responsiveness. Integrating such signals into machine learning models enables more granular retention strategies that are both predictive and adaptive [4].

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Another critical consideration is the role of explainability in telecom AI models. As regulators and stakeholders demand transparency, especially in consumer-facing domains, explainable AI (XAI) principles must be embedded within retention systems. Fuzzy logic and interpretable models like decision trees or attention-based deep models provide traceable decision paths, helping business analysts understand why a customer was flagged as high-risk or why a particular retention offer was suggested. This not only increases trust in AI systems but also accelerates human-in-the-loop decision-making [5]. Lastly, the dynamic nature of customer expectations, market trends, and service innovations necessitates real-time learning and strategy evolution. Static models degrade quickly in performance under such volatility. Therefore, models must incorporate continual learning, online feedback loops, and A/B tested retention pathways to keep strategies fresh and responsive. Real-time pipelines that integrate streaming customer data, behavioural signals, and recommendation engines ensure that customer retention strategies are not only timely but also effective and aligned with long-term business goals [6]. Contextual and behavioural segmentation is crucial for effective retention in telecom. Advanced analytics techniques now move beyond static churn scores to identify when, how, and why a customer is at risk. For instance, sequence-aware embeddings capture fluctuations in usage patterns—like call drops or peak-hour data spikes—and feed cross-event behavioural triggers into a churn model. These micro-segmentations allow providers to target users with tailored retention tactics, such as aligning time-sensitive offers with usage behaviours, enhancing both relevance and impact [7].

Explainability remains a key requirement in telecom AI due to regulatory oversight and stakeholder trust. Models blending fuzzy inference with rule-based systems or attention-enabled neural architectures can pinpoint precisely why a user is flagged as High Risk (e.g., "late payment history" and "tier downgrade") and which grapevine intervention might rectify the trajectory. A 2025 study shows that explainable AI significantly improves stakeholder confidence and operational activation rates, especially when paired with human–AI feedback loops [8]. Adaptability through continual and reinforcement learning is also shaping the field. Static churn models degrade quickly due to evolving network quality, service plans, seasonal promotions, and competitors. Modern pipelines now incorporate elastic weight consolidation and online reinforcement learning policies to preserve previously learned customer behaviours while integrating new ones [9]. Telecom deployments in 2024 demonstrated RL-based retention policies can dynamically optimize promo budgets and channel timing—resulting in 5–10% uplift in long-term customer engagement [10.]

In user-driven digital ecosystems, long-term user engagement is essential for platform sustainability and growth. However, maintaining user retention remains a persistent challenge, particularly during early-stage cold-start conditions where behavioural data is limited. Traditional churn prediction models identify at-risk users but offer limited support for actionable retention strategies. Additionally, task recommendation mechanisms often neglect the nuanced contextual, behavioural, and social dynamics that influence user decision-making. There is a growing demand for intelligent, behaviour- aware frameworks that go beyond prediction—systems that can proactively guide personalized engagement strategies based on user influence, preferences, and contextual alignment. This motivates the design of a unified

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architecture that can generalize across domains while accurately modeling participation probability, optimizing task allocation, and ultimately improving user retention. Thus, this proposed model proposed PRISM framework for user retention strategy, further contribution of this research as follows:

Proposal of PRISM Framework: A novel and modular architecture—PRISM (Personalized Retention-Integrated Strategy Model)—is introduced to address cold-start challenges by integrating influence modeling, engagement estimation, and behavior-driven task recommendation. Retention-Oriented Influence Modeling (ROIM): A generalized influence model is developed to capture task-specific propagation and user impact, enabling retention-focused task dissemination beyond traditional cascade methods. Fuzzy Logic-Based Engagement Estimation (RAEM & FRPM): A fuzzy logic-based mechanism is incorporated to evaluate task acceptance likelihood using user preferences, spatial-temporal context, and reward relevance, enhancing personalization under uncertainty. Extensive Evaluation Across Diverse Domains:The proposed model is rigorously validated on IBM Telco, iQIYI, and MovieLens datasets, demonstrating superior performance on both prediction and retention metrics compared to baseline approaches.

One of the most important goals of recommendation systems is to keep users coming back, as long-term involvement usually creates more value than short-term engagements. Collaborative filtering and matrix factorization, two common approaches, mostly looked at short-term engagement measures like click-through rates. They had a hard time modeling the time-based changes that are important for keeping users [11].

Recently, transformer designs have gotten a lot of interest in sequential recommendation systems because of their ability to change things.[12] developed BERT4Rec, utilizing a bidirectional self-attention network to analyze user activity sequences for sequential recommendations. [13] created a customized transformer model that improved self-attentive neural networks by adding SSE regularization to make suggestions more specific. Chen et al. [14] utilized a self-attention technique to enhance item representations inside user activity sequences, taking into account the intrinsic sequential patterns, and validated its effectiveness on a real-world e-commerce platform. Finally, [15] introduced the Decision Transformer (DT), which is designed to keep users by using a weighted contrastive learning method to get the most information from samples and focus on high-reward suggestions.

[16] posited that user retention constitutes long-term feedback resulting from repeated encounters between users and the system, making it challenging to attribute retention rewards to individual things or a list of objects. They frame the issue as an infinite-horizon request-based Markov Decision Process and use reinforcement learning to cut down on the total time spent on numerous sessions.

Other systems, like IURO, explicitly describe interpretable factors that affect retention. They utilize contrastive learning to find essential material ("aha items") that keeps users interested over time. In the same way, Generative Flow Networks [17] have been used to model retention by considering it as a probabilistic flow over user sessions. This solves the problems of sparse and delayed retention signals. Research on suggestion diversity has demonstrated that

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enhancing content variety mitigates recommendation fatigue and enhances user retention. Techniques such as Maximal Marginal Relevance (MMR) and other diversity-oriented methodologies [18] have shown that varied suggestions maintain user engagement over extended periods. Research on consumer purchasing behavior [19] in sectors such as fashion has empirically demonstrated that varied product recommendations not only enhance purchase rates but also positively affect long-term retention, underscoring the efficacy of recommendation diversity in both immediate and sustained engagement. Further, a new recommendation model called DT4IER that is based on decision transformers was presented. This model will not only make recommendations more effective, but it will also find a good balance between getting users to engage right away and keeping them around for a long time. The DT4IER uses a new multi-reward architecture that skillfully balances short- and long-term incentives with user-specific traits. This makes the reward sequence more contextually rich, which leads to a more customized and educated recommendation process. To improve its ability to make predictions, DT4IER uses a high-dimensional encoder to find and use the complex relationships between different jobs. We also use a contrastive learning method in the action embedding predictions, which greatly improves the model's overall performance [20]. This research presents an innovative methodology termed Adaptive User Retention Optimization (AURO) to tackle this challenge. AURO adds a state abstraction module to the policy network to help the recommendation policy operate in contexts that are not stable. The module is trained using a new value-based loss function that makes its output match the expected performance of the present policy. Because RL's policy performance is sensitive to changes in the environment, the loss function makes it possible for the state abstraction to reflect those changes and tell the recommendation policy to adjust as well. Also, the fact that the environment is not stationary creates the problem of implicit cold start, where the recommendation policy keeps interacting with users who are showing new behavior patterns. AURO encourages exploration while using performance-based rejection sampling to keep the quality of recommendations high in a cost-sensitive online setting [21].

[22] They provide Stratified Expert Cloning (SEC), an innovative imitation learning approach that efficiently utilizes extensive recorded data from high-retention users to develop powerful recommendation rules. SEC has three main new features: 1) a multi-level expert stratification strategy that captures the subtleties of expert user behavior at different retention levels; 2) an adaptive expert selection mechanism that dynamically assigns users to the best policy based on their current state and historical retention level; and 3) an action entropy regularization technique that encourages recommendation diversity and lowers the risk of policy collapse [23]. They show that SEC is far better than the best approaches at keeping users by doing a lot of offline trials and online A/B testing on two of the biggest video platforms, Kuaishou and Kuaishou Lite, which have hundreds of millions of daily active users.

They provide a novel offline RLRS approach to address the aforementioned issues. We reframe the RLRS issue by conceptualizing sequential decision-making as an inference job, utilizing adaptive masking arrangements [24]. This adaptive method selectively hides input tokens, turning the recommendation job into an inference problem based on different token subsets. This makes it easier for the agent to infer over different trajectory lengths. They also

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include a multi-scale segmented retention technique that makes it easier to represent extended sequences, which greatly improves computing efficiency [25-26].

II. PROPOSED METHODOLOGY

Assume a model comprises of a platform and a set of users as $User = \{user_1, user_2, \dots\dots, user_k\}$ that have been connected or have the potential to connect with platform. This platform requires recruiting the users so as to execute P sensing tasks denoted as $P = \{V_1, V_2, \dots.., V_P\}$. Each task is accommodated by denoting its start time, end time, location, reward and the required number of participants. Finally, analyzing accurate truth based on data aggregation uploaded by users who participate in it. The set of users registered is represented by T_w. They can execute the task and feedback to the platform to gain rewards. Additionally, friends can be invited to join the platform responsible for being rewarded for propagation. A connection matrix is used as C^{o*o} that represents the User Connectivity Graph (UCG) of O users wherein $c_{k,l} = \{0,1\}$ denotes the friendship between the users k and l. These tasks are sequentially released to respective registered users. Users are free to choose whether to fill them out, share them, or take no action at all.

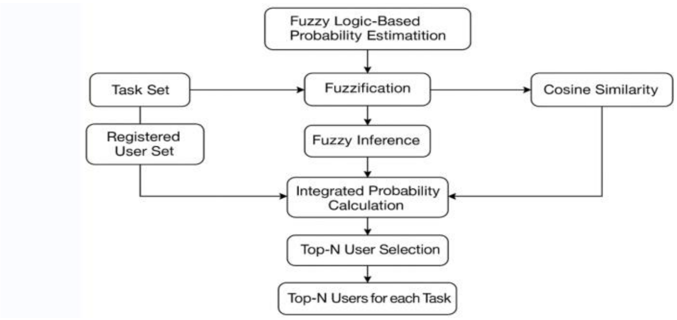

Figure 1 Proposed workflow

A. *Problem definition*

The platform has a cold start at first since there aren't many people using it. At this point, the platform has two main problems to deal with. To fast grow the user base, the platform has to get registered users to invite their friends to join. It is also very important to have a high work completion rate, on the other side. Using User Connectivity Graph (UCG)s to find users can bring in more prospective participants, but it doesn't always mean that more people will finish the activity because of financial limits. If the platform gives out jobs without taking into account what users want, it might lose registered users over time, making the cold start problem worse. So, while thinking about the platform's long-term growth and always asking friends to join through User Connectivity Graph (UCG)s, it is equally important to think about how to keep users on the site by suggesting activities that interest them. Using the aforementioned goal, we turn this problem into a multi-objective optimization problem. The following formula is our initial optimization goal: to get the most tasks done.

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$$max \sum_{p \in \mathrm{P}} \sum_{o \in \mathrm{W}} c_{op}, \quad (1)$$

Here $c_{op} \in \{0,1\}$ indicates whether the $o-th$ user completes the $p-th$ task. The second purpose of optimization is to keep as many people as possible on the platform, which may be measured by the number of users who stay. By utilising W_o^U denotes the status of the o-th user upon maximising the sum of user retention named as Equation (2):

$$max \sum_{o \in \mathrm{W}} W_o^U \quad (2)$$

The independent cascade model [18] stands out as a key paradigm for explaining how influence spreads in User Connectivity Graph (UCG)s. In this propagation model, users may be classified as either active or inactive. In the independent cascade model, each engaged user has a unique chance, at time v, to activate its social neighbors with a certain chance. Regardless of the active user's success in activating its social neighbors, at time $v + 1$ and subsequently, it forfeits the capacity to activate these neighbors. If an inactive user is activated by a neighbor at time v, the user will go from being inactive to being active, and at time $v + 1$, she will have an effect on her own social neighbors. However, the previously recommended propagation model is not directly applicable to our context. This is because the model in question doesn't have a way to figure out how one user affects another, and it doesn't take into account that various sorts of jobs might change how users affect each other. For example, if user $user_a$ has friends who are both teachers $user_b$ and sports fans $user_c$, and $user_a$ is telling both of these friends to try "Homework Help" and "Joyrun," it is clear that telling user $user_b$ to try "Homework Help" has a bigger effect than telling user $user_c$ to try "Joyrun." On the other hand, for user $user_c$, suggesting "Joyrun" had a bigger effect than suggesting "Homework Help." We need to make the propagation model more flexible so that it can handle these subtle differences in influence that come from different sorts of tasks.

B. *Retention-Oriented Influence Model (ROIM)*

(Retention-Oriented Influence Model (ROIM)) the influence of the user $user_l$ on neighbour $user_k$ in relevance with the task V_m is measured as:

$$R(V_m, W_k, W_l) = \min\{G(W_k, W_l). K_1(V_m). K_2(V_m).,,,,,. K_N(V_m), 1\} \quad (3)$$

Here G(W_k, W_l) represents the effect of multiplier induced by the task attributes.

Upon extending the DIC the main aim is to select a $K_N(V_m)$ wherein $n \in [1, N]$. By choosing a $K(z, k_{max}) = (k_{max} - 1)\sqrt{1-(1-z)^2+1}$to optimise the increased probability due to the impact on specific task-factors. However here z serves as the input probability for the influence factors. By denoting $K(0) = 1, K(1) = K_{max}$ $\frac{\sigma z(z,K_{max})}{\sigma z^2} > 0, \frac{\sigma^2 z(z,K_{max})}{\sigma z^2} < 0$ with

$z \in [0,1]$. There are several things that affect consumers' decisions on task sites. We are looking at two particular things: if the task reward is what the user expected and if the work kind is what the user likes.Therefore, Influence actor 1: User preference , by using $K_1(V_m, W)$ to measure the effectiveness or fitness of task V_m to the preferences of user W_k

$K_1((V_m, W) = K(Cos(W_k^{int}, V_m^{topic})K_1)$

However $Cos(W_k^{int}, V_m^{topic})$,$K_1)$ represents the cosine similarity between the vectors W_k^{int} and V_m^{topic} and K_1 denotes the the most value that preferences may provide. We characterize user preferences and task labels as vectors. For instance, if a user likes movies and sports, the task kinds would be hot pot, drinks, and sports. The vectors for user preferences and task types would be [1, 0, 0, 1] and [0, 1, 1, 1], respectively. The cosine similarity between these vectors shows how similar the preference and type are calculated as Cos [1,0,0,1], [0,1,1,1]) =0.408. Influence factor 2: Reward attractiveness, $K_2(V_m, W_k) = K(h(W_k^{pc}, V_m^{pc}), K_2)$

Here W_k^{pc} denotes the users expecting reward for the propagation task and K_2 has the maximum impact value induced by reward attraction. The function $h(z, a)$ is a tangent function.

$$h(z, a) = \begin{Bmatrix} \tanh(z - a) & z > a \\ 0 & z \leq \mathrm{a} \end{Bmatrix} \quad (4)$$

C. *Retention-Aware Engagement Model (RAEM) model*

Upon creation of a probabilistic model to figure out how probable it is that a user would accept the job provided on the platform. This model takes the following elements into account: How close the task location is to where the user is. How much the task time frame overlaps with the user's journey time span. How well the job labels match the user's preferences . How different the task reward is from what the user expects to earn. To ensure charecteristics of weber-fechner law, by choosing a $J(z)$ as impact function

$$J(z) = \lg(1 + 9z) \quad (5)$$

The user is more likely to accept a task if they are near to where it is happening. We can figure out the spherical distance between the user's present location and the task location by looking at the user's past trajectory locations throughout the period between the start and finish of the job. The distance effect factor is shown like this:

$$J_r(V_m, W_l) = J(1 - \frac{dis(V_m^n, W_l^n)}{dis_{max}} \quad (6)$$

Where V_m^n and W_l^n show where the task and the user are, respectively. The Haversine formula is used by the function $dis(z, a)$ to get the spherical distance between two places based on their latitude and longitude. is the greatest distance at which the likelihood of the user agreeing to the task based on distance preference drops to zero. Also, the closer the time of dis_{max} the user's arrival to the task site is to the start time of the task, the more likely it is that the user will

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finish the assignment. We figure out when the user is closest to the task location based on their past behaviour. The time influence factor is shown like this:

$$J_v(W_l, V_m) = \begin{cases} J(1 - \dfrac{W_l^v - V_m^{et}}{time_{max}} & if\ W_l^v > V_m^{et} \\ J(1 - \dfrac{V_m^{bt} - W_l^v}{time_{max}} & if\ W_l^v < V_m^{bt} \\ J(1) & V_m^{bt} \leq W_l^v \leq V_m^{et} \end{cases} \quad (7)$$

l represents the start and end times of the job, which tell the user when they need to finish it. We don't take into account how long it will take the user to do the assignment. W_l^v shown when the user gets close to where the task is. $time_{max}$ is the largest difference between the time the user reaches at the task location and the start or finish time of the job. The chance of the user doing the activity based on their time choice is 0 if they come too early or too late. Users also tend to finish projects that fit with what they like. User preferences have a big impact on whether or not a user is willing to finish a job, which in turn affects whether or not they want to continue on the platform. So, it's very important to suit the needs of the user. We have the element that affects interest:

$$J_k(W_l, V_m) = J(Cos(W_l^{favor}, V_m^{type})) \quad (8)$$

Wherein W_l^{favor} and V_m^{type} represents the user preferences and the type of attributes to the task. $Cos(W_l^{favor}, V_m^{type}$ evaluates the cosine similarity in between the two. The main reason people join the site and do the tasks it gives them is to get incentives. The number of incentives directly affects how willing users are to do something. So, we get the reward factor:

$$J_t(W_l V_m) = J\big(h(W_l^t, V_m^t)\big) \quad (9)$$

Wherein V_m^t and W_l^t denotes the actual reward obtained for finishing the task and the expected users reward for finishing the task. Any of the four characteristics listed above are quite important for figuring out how users act. For example, if a user walks by the task location but it's too early or too late, they probably won't do the work. However, if the user needs to pass by the task location ($J_r(w, l) is\ high$) this time is however not suitable hence $J_v(w, l)$ is low), the user's behaviour is influenced by the factor with the least probability. Hence the probability of a user accepting the task is given as: Where γ and α are the weights of time & location and preference & reward in the total probability.

$$R_{r,v}(W_l V_m) = \min(J_r(W_l V_m), J_v(W_l V_m)) \quad (10)$$

$$R_{k,v}(W_l V_m) = \min(J_r(W_l V_m), J_v(W_l V_m)) \quad (11)$$

$$R_{accept}(W_l V_m) = \gamma . R_{r,v}(W_l V_m) + \alpha R_{k,v}(W_l V_m) \quad (12)$$

D. Retention-Oriented Behavior Estimation (ROBE)

The Fuzzy Retention Prediction Model (FRPM) model is designed to estimate the likelihood of a user accepting and completing a task based on fuzzy perceptions of time and distance. Rather than relying on exact numerical thresholds, it uses linguistic variables to

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account for the subjective nature of user preferences—like what constitutes "nearby" or "on time." This process involves three stages: fuzzification, where specific values (time differences and distances) are converted into fuzzy sets using membership functions; fuzzy inference, where predefined rules map these fuzzy inputs to output categories (e.g., "very unlikely" to "most likely"); and defuzzification, which translates the fuzzy results into a concrete probability score using the centroid strategy.

E. *Personalized Fuzzy Engagement Recommendation (PFER) Framework*

It's challenging to maximize work completion rates in task suggestion systems. It is essential to use discretion when assigning tasks to users due to a restricted budget (i.e., numb requests issued). Consequently, we have created a Personalized Fuzzy Engagement Recommendation (PFER) Framework based on fuzzy control to determine the most likely users to participate

Table 1 Personalized Fuzzy Engagement Recommendation (PFER) Algorithm

Input	Task set L, Personalized Fuzzy Engagement Recommendation (PFER) Framework Registered User Set

	function (L, W_T)
	for each task V_m in L do
	Initialize user probability list H ← {}
	for each user u in W_T do
	Initialize max_predicted_prob ← 0
	for each point (Loc, Timestamp) in w. trajectory do
	Initialize time_diff t_bar ← 0
	if Timestamp > W_T.end_time then
	t_bar ← Timestamp - W_T.end_time
	else if Timestamp < W_T.begin_time then
	t_bar ← W_T.begin_time - Timestamp
	Compute distance d_bar ← geodesic (Loc, V_m.location)
	N ← fuzzy Probability (t_bar, d_bar)
	max_predicted_prob ← max (p, max_predicted_prob)
	cs ← cosine Similarity (w.favor, W_T.type)
	final_prob ← min (cs, max_predicted_prob)
	Append (w, final_prob) to J
	Sort H in descending order of final_prob

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	Retain top N users in J for task W_T Save J return top-N user sets for all tasks
Output	Top-N user list H with the highest predicted probabilities for each task

The unified Personalized Fuzzy Engagement Recommendation (PFER) Framework algorithm is designed to predict the top-N users most likely to complete each task by integrating fuzzy logic-based probability estimation and user-task preference similarity. For every task in the task set, the algorithm evaluates each registered user's trajectory points—comprising location and time—to compute the likelihood of Retention-Aware Engagement Model (RAEM). This is achieved using the FRPM module, which converts time and distance gaps into fuzzy values, capturing the user's subjective perception of proximity and timeliness. The fuzzy output is then converted into a probability using predefined membership functions and fuzzy rules. Among all trajectory points, the highest such probability for a user is retained. Additionally, the algorithm measures the semantic similarity between the user's preferences and the task type using cosine similarity. The final acceptance probability for a user is the minimum of the fuzzy probability and the cosine similarity score, ensuring alignment in both behavioral patterns and personal interest. Users are then ranked based on this final score, and the top-N users are selected for each task, enabling efficient and personalized task allocation.

III. PERFORMANCE EVALUATION

The evaluation was conducted using three widely recognized datasets: IBM Telco, iQIYI, and MovieLens, each representing different domains and user interaction behaviors. A variety of performance metrics were used to assess the quality of recommendations, including BLEU and ROUGE for measuring sequence accuracy, HR@10 for evaluating hit rate in top-N recommendations, and MB-URS and SB-URS for capturing user-level and session-based recommendation effectiveness. Additionally, IUR (Item Usage Rate) was used to assess the diversity of items recommended, while NRC (Novelty Recommendation Coverage) evaluated the system's ability to suggest less familiar or novel items. These metrics collectively provide a comprehensive view of both recommendation accuracy and diversity across datasets.

A. *Prediction Accuracy*

Prediction accuracy metrics measure the short-term effectiveness of recommendation sequences and ensure the relevance and precision of recommended actions. The four commonly employed metrics in sequence prediction tasks utilized here include: BLEU (Bilingual Evaluation Understudy): BLEU is a common tool in natural language processing that measures how accurate suggestions are with different durations. It checks how well the suggested sequences match up with real historical sequences that were seen in the data. ROUGE (Recall-Oriented Understudy for Gisting Evaluation): ROUGE, another statistic from NLP, checks how accurate the recall of suggestions is. It checks to see how well the suggested order covers all the relevant things or activities from the user's history. Hit Rate (HR@K): HR@K figures out how likely it is that the goods or activities that the user really wants will show up in the top-K recommended sequences. Higher numbers mean that the suggestions are good at guessing what users like. Normalized Discounted Cumulative Gain (NDCG@K): NDCG@K checks how

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relevant suggestions are by giving more weight to accurately predicted things that show up higher in the top-K recommendations. It checks both the relevancy and the quality of the order of proposed sequences to make sure that higher-ranked suggestions are very similar to what the user is interested in.

B. *User Retention*

To thoroughly assess long-term user involvement stemming from advised activities, we employ two specially designed measures (MB-URS and SB-URS) in conjunction with two standard metrics (IUR and NRC): Model-Based User Retention Score (MB-URS): MB-URS measures how well suggested sequences work by directly predicting a user retention score using supervised learning. An independent supervised model is specifically trained on a distinct validation dataset, including around 30% of the total data, to predict retention-related incentives for certain user-action pairings. The model's training goal is to reduce the mean squared error (MSE) between the anticipated retention outcomes and the actual retention scores that were observed. Similarity-Based User Retention Score (SB-URS): SB-URS checks how well suggestions work by comparing the suggested sequences to sequences of past user activity. We put user samples into different classifications based on how well they really kept their information. A similarity measure, such the BLEU-1 score, is found for each class by comparing the recommended sequences to the ground-truth sequences. The formal calculation of SB-URS is: Improved User Retention (IUR): IUR measures how much better average user retention is compared to prior levels. A higher IUR % means that tailored suggestion sequences are better at keeping users interested. No Return Count (NRC): NRC shows how many users stop using the system altogether after getting suggestions. A lower NRC % means that suggestions are good at keeping users from leaving and keeping them engaged over time.

C. *Dataset Description*

To validate the performance of PS, we consider three datasets: **IBM Telco Dataset:** The IBM Telco Customer Churn Dataset is a widely used dataset for building and evaluating machine learning models aimed at predicting customer churn in the telecommunications industry. It contains data on 7,043 customers, including demographic information (e.g., gender, senior citizen status, partner, dependents), account details (e.g., tenure, contract type, payment method, billing amounts), and services subscribed (e.g., internet service, streaming services, online security). The primary goal is to classify whether a customer will churn (leave the service) or not, making it ideal for binary classification tasks. It supports various analytical applications, such as customer behavior analysis, churn risk identification, and retention strategy development. Popular ML techniques used on this dataset include logistic regression, decision trees, random forests, gradient boosting, and neural networks. The dataset is publicly available on platforms like Kaggle and IBM Watson Studio, making it a valuable resource for both academic research and industry use cases in churn prediction.

IQiYi Dataset: The iQIYI Dataset is a large-scale, real-world dataset collected from iQIYI, one of China’s leading online video platforms, and is widely used for developing and evaluating recommendation systems. It includes millions of user-video interaction logs along with metadata such as user demographics (age, gender, device type), video attributes (category, tags, duration), and detailed behavioral actions like viewing, liking, sharing, and commenting, all timestamped. The dataset is primarily used to predict user engagement with videos, making it suitable for tasks such as personalized content recommendation, click-through rate prediction, and user behavior modeling. Due to its size, diversity, and complexity, it is ideal for training collaborative filtering models, matrix factorization techniques, and deep learning-based recommendation frameworks like NCF and DeepFM. Frequently featured in academic competitions such as the IJCAI iQIYI Challenge, this dataset has become a benchmark in the research community for studying user preferences and temporal dynamics in recommendation systems. MovieLens (ML-1m) Dataset:

The MovieLens (ML-1M) Dataset: It is a benchmark dataset widely used in research on recommendation systems, particularly for collaborative filtering and matrix factorization algorithms. Released by the GroupLens research lab, it contains 1 million ratings (from 1 to 5 stars) provided by 6,000 users on 4,000 movies, collected between 2000 and 2003. Each user has rated at least 20 movies, and the dataset includes rich metadata such as user demographics (age, gender, occupation, zip code) and movie information (title, genres, release year). The main task associated with the dataset is to predict how a user would rate unseen movies, making it suitable for both explicit feedback modeling and top-N recommendation tasks. Its clean, well-structured format and balanced user-item interactions make it a go-to dataset for developing, testing, and benchmarking classic and modern recommendation algorithms such as SVD, KNN, Deep Learning models, and hybrid approaches. It is available in plain-text format and commonly used in educational tutorials and academic papers.

D. Results

1) Bleu Score

The BLEU score looks at how closely the advised sequences match what users actually do, which shows how accurate the prediction is. In this study, the Proposed Strategy (PS) had the greatest BLEU ratings on all datasets, which means it was the best at making accurate, tailored suggestions. In particular, PS scored 0.86 on the IBM Telco dataset, which was better than DT4Rec (0.82) and the baseline model (0.77). This tendency was also true for the IQiYi and MovieLens datasets, which shows that PS can accurately learn how users behave and turn that information into exact action sequences. The higher BLEU ratings show that PS cuts down on noise in predictions and improves focused engagement, which is especially important in a telecom setting where every contact affects retention.

Table 2 BLEU score comparison across different datasets

Datasets	PS	DT4Rec	Baseline
IBM Telco	0.86	0.82	0.77
IQiYi	0.83	0.82	0.8

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MovieLens	0.45	0.43	0.41

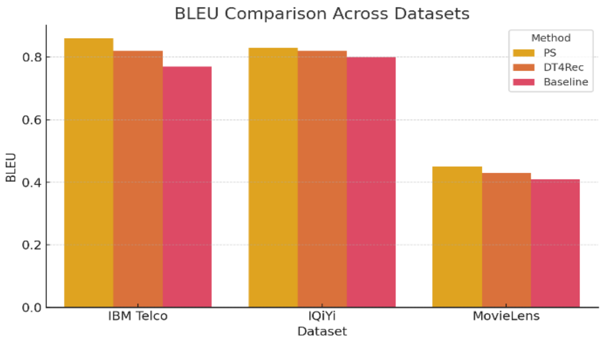

Figure 2 BLEU Score Comparison Across Datasets Using Different Recommendation Methods

2) Rogue

The ROUGE score focuses on recall, measuring how comprehensively the recommended sequence captures relevant items or behaviors from a user's actual history. The Proposed Strategy (PS) demonstrated consistently superior ROUGE scores across all datasets, reflecting its strong ability to recall a broader range of user-relevant actions. In the IBM Telco dataset, PS achieved a ROUGE score of 0.84, ahead of DT4Rec (0.81) and the baseline (0.75). This performance advantage carried over to the IQiYi and MovieLens datasets as well. The improved recall suggests that PS is highly effective not only in precise targeting but also in ensuring completeness, crucial for maximizing touchpoints in telecom retention strategies. By retrieving a fuller set of meaningful interactions, PS contributes to more holistic user modeling and better long-term engagement.

Table 3 ROUGE score comparison

Dataset	PS	DT4Rec	Baseline
IBM Telco	0.84	0.81	0.75
IQiYi	0.82	0.81	0.79
MovieLens	0.43	0.42	0.4

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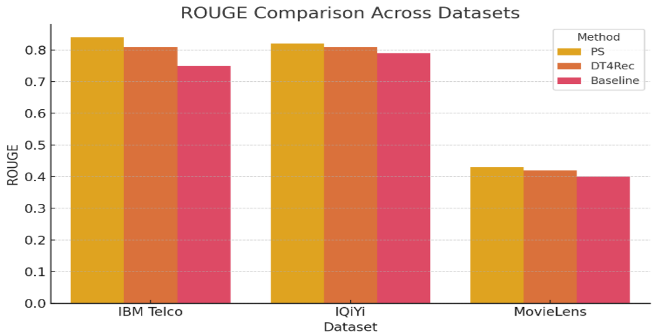

Figure 3 ROUGE Score Comparison Across Datasets Using Different Recommendation Methods

3)NDCG@10 comparison

Normalized Discounted Cumulative Gain (NDCG@10) looks at both how relevant and how high the rank of suggested products is. It gives greater weight to things that are more relevant and appear higher on the list. The Proposed Strategy (PS) always did better than the other options in this measure. This shows that it works well not just to choose the proper items but also to rank them correctly for user engagement. In the IBM Telco dataset, PS got an NDCG@10 score of 0.72, which was better than DT4Rec (0.69) and the baseline model (0.64). This pattern stayed the same on both IQiYi and MovieLens, showing that PS may focus on retention actions that have a big effect. PS makes it more likely that users will engage with the information by putting the most interesting stuff at the top of the list. This is especially useful for real-time telecom retention strategy, where the timing and order of suggestions have a big impact on what users do.

Table 4 NDCG@ 10 comparison

Dataset	PS	DT4Rec	Baseline
IBM Telco	0.72	0.69	0.64
IQiYi	0.81	0.81	0.78
MovieLens	0.58	0.56	0.54

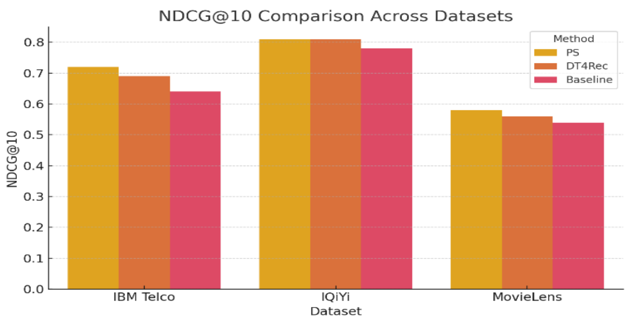

Figure 4 Normalized Discounted Cumulative Gain (NDCG@10) comparison

4)HR @10

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HR@10 measures the likelihood that a relevant item appears within the top 10 recommended actions, directly reflecting the immediate usefulness of a recommendation. The Proposed Strategy (PS) achieved the highest hit rates across all datasets, with a particularly strong performance in the IQiYi dataset (0.80) and IBM Telco dataset (0.68). These results indicate that PS is highly effective in presenting the most relevant and engaging items early in the recommendation sequence. Compared to DT4Rec (0.65 in Telco) and the baseline (0.59), PS's superior hit rate demonstrates its stronger understanding of user intent and context. In telecom applications, where users often act on the first few options presented, this early accuracy is critical for capturing user attention and preventing churn.

Table 5 HR@10

Dataset	PS	DT4Rec	Baseline
IBM Telco	0.68	0.65	0.59
IQiYi	0.8	0.8	0.78
MovieLens	0.35	0.33	0.31

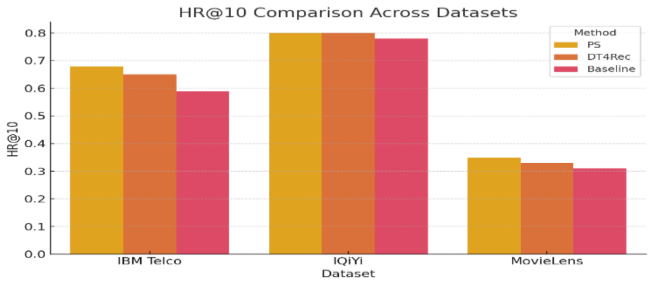

Figure 5 HR@10 score Comparison Across Datasets Using Different Recommendation Methods

5)MB_URS

The Model-Based User Retention Score (MB-URS) quantifies the expected retention outcome of a recommendation sequence using a predictive model trained to estimate user return probability. This metric simulates how likely users are to stay engaged based on the recommended actions. The Proposed Strategy (PS) achieved the highest MB-URS across all datasets, with a top score of 6.43 in the IBM Telco dataset, outperforming DT4Rec (6.05) and the baseline (5.28). This strong performance highlights the ability of PS to generate sequences that align closely with behaviors known to correlate with long-term retention. The advantage is particularly important in telecom environments, where forecasting user continuation can guide the timing and nature of retention campaigns. PS's high MB-URS reflects its effectiveness in modeling user intent and optimizing sequences that increase the probability of continued engagement.

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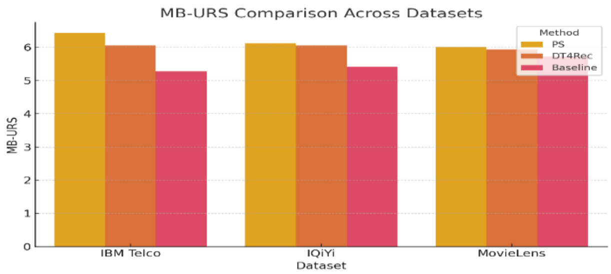

Figure 6 MB-URS Score Comparison Across Datasets Using Different Recommendation Methods

6) SB-URS

The Similarity-Based User Retention Score (SB-URS) evaluates how closely the recommended action sequences resemble those associated with high retention in historical data. This metric captures behavioral alignment with past successful strategies. The Proposed Strategy (PS) achieved the highest SB-URS in all datasets, particularly excelling in the IBM Telco dataset with a score of 76,510, significantly above DT4Rec (72,270) and the baseline (61,450). These results indicate that PS is more effective at generating retention strategies that mimic patterns historically proven to keep users engaged. In practical terms, this means PS is not only predictive but also behaviorally grounded learning from the most successful past interventions and replicating them in new user scenarios. This quality makes it highly reliable for retention-focused telecom systems where historical behavior is a powerful predictor of future actions.

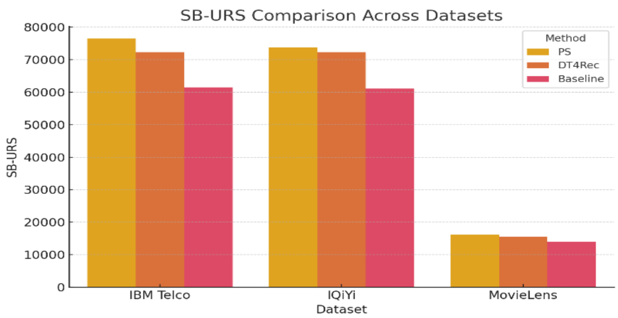

Figure 7 SB-URS Score Comparison Across Datasets Using Different Recommendation Methods

7) Improved User Retention (IUR)

Improved User Retention (IUR) measures the percentage increase in average user retention compared to historical or baseline engagement. It provides a direct, interpretable indicator of how effective a model is at keeping users active. The Proposed Strategy (PS) achieved remarkable improvements, with IUR reaching 32.8% in the IBM Telco dataset, outperforming DT4Rec (26.0%) and the baseline (18.3%). Even in the MovieLens dataset, PS led with an impressive 47.1%, highlighting its adaptability across domains. These gains confirm that PS does not merely predict behavior but actively influences it through personalized, targeted interventions. For telecom services, this metric is particularly vital—it quantifies the practical impact of retention efforts in percentage terms, helping decision-makers evaluate ROI and strategy effectiveness with clarity. The consistently higher IUR validates PS's role as a powerful tool for enhancing long-term user engagement.

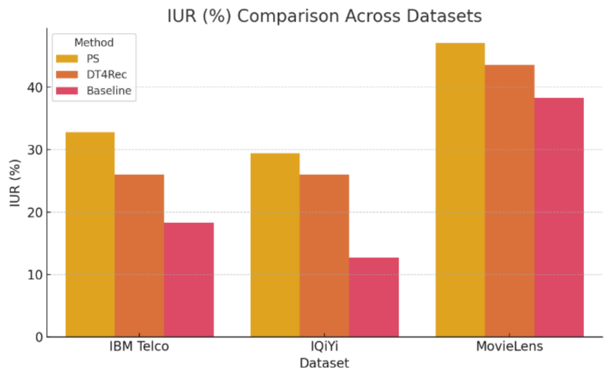

Figure 2 IUR (%) Comparison Across Datasets Using Different Recommendation Methods

8) No Return Count (NRC)

No Return Count (NRC) represents the percentage of users who completely disengage from the platform after receiving a recommendation—making it a critical metric for assessing the downside risk of any retention strategy. A lower NRC indicates better success in preventing total user attrition. The Proposed Strategy (PS) achieved the lowest NRC across all datasets, with a particularly impressive 1.2% in the IBM Telco dataset, compared to DT4Rec (1.4%) and the baseline (3.6%). Similar patterns were observed in the IQiYi and MovieLens datasets. This suggests that PS not only engages users effectively but also minimizes drop-off rates, especially among high-risk segments. In telecom environments, where user churn directly translates into revenue loss, reducing NRC is as essential as increasing engagement. The results affirm that PS is highly effective in retaining users who are otherwise at risk of complete disengagement, strengthening its practical value in churn-sensitive applications.

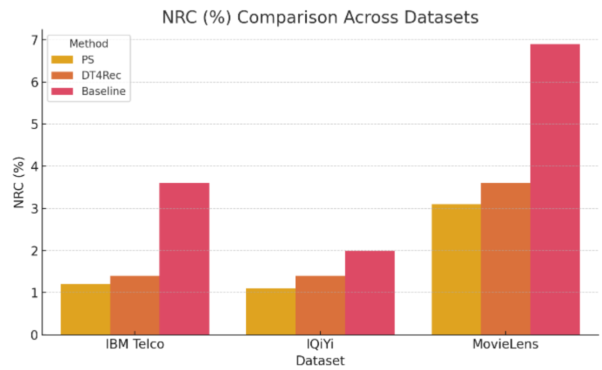

Figure 9 NRC (%) Comparison Across Datasets Using Different Recommendation Methods

E. Comparative analysis

The comparative evaluation across all metrics clearly demonstrates the superiority of the Proposed Strategy (PS) in both immediate prediction accuracy and long-term user retention. In terms of precision and recall, PS consistently achieved higher BLEU and ROUGE scores than DT4Rec and the baseline, indicating its ability to generate recommendation sequences that are both accurate and comprehensive. Moreover, the improved NDCG@10 and HR@10

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values confirm that PS not only recommends relevant items but also ranks them more effectively, ensuring that users are presented with the most engaging content early in their interaction. Moving to retention-oriented metrics, PS outperformed DT4Rec in both MB-URS and SB-URS, signifying that its recommendations align more closely with patterns historically associated with sustained engagement. Most notably, PS achieved the highest IUR, reflecting a substantial boost in user retention compared to prior behaviors, while also attaining the lowest NRC, meaning fewer users disengaged after receiving recommendations. DT4Rec, while strong in sequence modeling, showed moderate gains in retention metrics and lacked the behavioral nuance offered by PS's fuzzy logic and multi-factor task modeling. The baseline model consistently lagged in all areas, underlining the advantage of personalized, data-driven strategies. Overall, PS presents a robust, behavior-aware solution that not only anticipates user needs more accurately but also intervenes effectively to prolong user engagement—a critical outcome for telecom environments focused on reducing churn and enhancing customer loyalty.

IV. CONCLUSION

This paper proposed PRISM (Personalized Retention-Integrated Strategy Model), a retention-oriented and behavior-aware framework designed to address the limitations of traditional churn prediction systems in cold-start scenarios. PRISM integrates multiple complementary modules—ROIM, RAEM, FRPM, ROBE, and PFER—to model user influence, estimate task engagement likelihood, forecast behavioral patterns, and generate personalized task recommendations that promote long-term user retention. Unlike conventional models that focus solely on dropout prediction, PRISM offers a holistic approach by combining predictive analytics with actionable recommendation strategies, all underpinned by fuzzy logic and contextual user data. The model was evaluated using multiple datasets across domains, demonstrating superior performance on both engagement and retention metrics compared to existing baselines. By framing user retention as a multi-dimensional, data-driven optimization problem, this work contributes a modular and domain-agnostic architecture that can be extended across diverse digital ecosystems. The findings underscore the importance of integrating influence modeling and personalized task allocation in the design of intelligent user engagement systems. Future research may explore real-time feedback mechanisms, adaptive learning policies, and hybrid architectures to further improve dynamic retention outcomes in large-scale environments.

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