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Article

Feedback-Driven Coevolutionary Hybrid Intelligence for Personalized Recommendation in Smart Home Social Internet of Things: Enhancing User Satisfaction through Adaptive Learning

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Abstract: The growing adoption of smart home devices within the Social Internet of Things (SIoT) has increased the need for adaptive recommendation systems that can respond to changing user preferences and device interactions. While existing studies primarily focus on recommendation accuracy and network modelling, limited attention has been given to user feedback-driven optimization for enhancing long-term user satisfaction. This study introduces the Coevolutionary Hybrid Intelligence Framework for Personalized Recommendation in Smart Home SIoT (CHI-PR-SIoT), incorporating a Human-in-the-Loop (HITL) mechanism that continuously refines recommendations using explicit user feedback. The framework combines a Graph Attention Network (GAT) for modelling social relationships among devices, a Bidirectional Gated Recurrent Unit (BiGRU) for capturing temporal context, and a Coevolutionary Particle Swarm Optimization with Adaptive Mutation (CPSO-AM) for feature and hyperparameter optimization. Experimental evaluation in a smart home SIoT environment involving Curtain, Light, Thermostat, Geyser, and Coffee Maker devices demonstrates that retraining with 250 user-labelled feedback samples improves prediction accuracy across all categories, achieving gains of up to 4.8%. Furthermore, the framework attains a user satisfaction score of 0.8456, outperforming the best baseline by 6.6%, highlighting the effectiveness of structured feedback integration for personalized smart home recommendations. These findings underscore the practical value of embedding structured feedback loops within coevolutionary optimization pipelines for real-world smart home deployments, offering a scalable pathway toward user-centric, adaptive home-automation systems that remain robust under sparse and cold-start conditions.

Keywords: Social Internet of Things; smart home; user feedback; personalized recommendation; coevolutionary optimization; human-in-the-loop; user satisfaction; graph attention network.

1. Introduction

The Social Internet of Things (SIoT) represents a significant evolution of the traditional Internet of Things (IoT), wherein smart devices operate collaboratively rather than independently, creating autonomous social relationships analogous to human social networks [1]. In smart home environments, this paradigm is particularly pronounced: appliances such as thermostats, lighting systems, geysers, motorized curtains, and coffee makers continuously exchange information among themselves and with occupants, generating rich streams of contextual, temporal, and preference data.

Personalized recommendation systems within smart home SIoT serve a significant role in enhancing the quality of daily living. However, two interrelated challenges persist. First, user preferences in domestic environments are inherently dynamic, shifting with routines, seasons, and household composition. Second, the majority of existing recommendation frameworks optimize for one-shot accuracy and neglect the imperative of continuous adaptation driven by explicit user feedback [2, 3].

This paper specifically addresses the design of efficient feedback systems aimed at maintaining long-term user satisfaction within the broader CHI-PR-SIoT framework. We demonstrate, through controlled experiments in a simulated smart home SIoT environment, that structured Human-in-the-Loop (HITL) feedback loops yield consistent and statistically significant improvements in device-level prediction accuracy, composite satisfaction scores, and user engagement indices.

1.1 Contributions

The principal contributions of this work are as follows:

- **Novel HITL feedback architecture:** A structured three-phase feedback collection and retraining pipeline is designed and embedded within the CHI-PR-SIoT framework, enabling continuous model refinement from explicit user signals.
- **Multi-device empirical validation:** Post-HITL retraining is evaluated across five heterogeneous smart home device categories, demonstrating consistent accuracy improvements under realistic sparsity and cold-start conditions.
- **Satisfaction-centric optimization:** User satisfaction is directly incorporated into the multi-objective fitness function of the CPSO-AM optimizer, aligning model training with user experience objectives.
- **Ablation evidence:** Controlled ablation studies isolate and quantify the independent contribution of the feedback module relative to structural and temporal model components.

The remainder of this paper is organised as follows. Section 3.2 reviews related work. Section 4 presents the smart home SIoT simulation environment and feedback architecture. Section 5 describes experimental results including post-feedback retraining outcomes. Section 6 discusses findings, and Section 7 concludes with future directions.

1.2 Related Work

1.2.1 Collaborative Filtering and Matrix Factorization

Early approaches to personalized recommendation relied on collaborative filtering and matrix factorization methods [4, 5, 6], which, while effective for static datasets, fail to capture the dynamic relational structures characteristic of SIoT ecosystems. Bayesian Personalized Ranking (BPR-MF) [7] extended this line by optimizing pairwise ranking from implicit feedback, yet remains agnostic to social context and device heterogeneity.

1.2.2 Graph-Based Recommendation

Graph-based methods — including graph convolutional networks [8, 9] and graph attention networks [10] — have addressed structural representation but predominantly overlook temporal preference evolution. LightGCN [4] simplifies graph convolution for recommendation but does not model trust or social relationships inherent to SIoT. GraphRec [3] and NGCF [9] model user-item social interactions via graph neural networks, yet neither addresses the multi-relational heterogeneous graph structures of smart home SIoT environments.

1.2.3 Temporal and Hybrid Architectures

Hybrid architectures combining deep learning and domain knowledge have shown improved contextual coherence [11, 12]. Recurrent and attention-based models have been applied to session-based recommendation [13] and temporal preference modelling, but without integrating social trust dynamics or device ontologies specific to smart homes.

1.2.4 Human-in-the-Loop and Feedback-Driven Systems

Human-in-the-Loop machine learning — where explicit user signals iteratively refine model parameters — has been explored in general recommendation contexts [7, 14] but not rigorously applied to multi-device smart home SIoT settings with coevolutionary optimization. The proposed study bridges this gap by embedding a structured feedback retraining pipeline within the CHI-PR-SIoT framework, evaluating its impact across five representative smart home device categories under realistic sparsity and cold-start conditions.

2. Materials and Methods

2.1 Smart Home SIoT Simulation Environment

A smart home SIoT simulation environment was constructed to reflect realistic domestic interaction dynamics. The environment models five device categories commonly found in modern smart homes: Curtain (automated blinds), Light (adaptive lighting), Thermostat (climate control), Geyser (water heater), and Coffee Maker (appliance scheduling), as described in Table 1.

The SIoT graph $G = (V, E, T_v, T_e)$ captures user-device ownership edges, device-device co-location and co-work edges, and temporal interaction sequences reflecting daily household routines. Device proximity follows a Gaussian decay model based on room topology, and trust evolution among devices is governed by a Markov process conditioned on interaction quality.

Table 1. Synthetic SIoT Dataset (SIoT-Syn) Characteristics.

Property	**Value**
Number of users	12,000
Device / item nodes	38,500
Total interactions	521,340
Trust links	234,670
Dataset sparsity	99.89%
Device categories	5 (Curtain, Light, Thermostat, Geyser, Coffee Maker)
HITL feedback samples	250 human-labelled
Validation protocol	80:20 train/test split, 5-fold cross-validation

2.2 CHI-PR-SIoT Architecture Overview

The CHI-PR-SIoT framework, as shown in Fig. 1, operates through four tightly integrated modules:

- **Heterogeneous SIoT Graph Construction:** Multi-source interaction logs are fused into a heterogeneous graph with social trust, ownership, proximity, and co-work edge types.
- **GAT Relational Encoder:** Multi-head graph attention captures the relative importance of different edge types, producing unified node representations enriched by social-relational context.
- **BiGRU Temporal-Contextual Encoder:** Bidirectional gated recurrent units model sequential preference dynamics in both forward and backward temporal directions, capturing routine and habit patterns.
- **CPSO-AM Coevolutionary Optimiser:** Dual interacting swarm populations jointly evolve model hyperparameters and feature relevance weights under multi-objective constraints, balancing accuracy, diversity, and satisfaction.

The final recommendation score integrates GAT relational embeddings, BiGRU temporal representations, and domain compatibility scores derived from a smart home ontology. The unified scoring function is:

$$Score(u, i) = \alpha_1 \cdot h^{GAT} \cdot e^I + \alpha_2 \cdot h^{temp} \cdot e^I + \alpha_3 \cdot DCS(u, i) \quad (1)$$

where α_1, α_2, α_3 are adaptively learned combination weights, and DCS(u, i) is the domain compatibility score computed via Wu-Palmer ontological similarity between device type and user context ontology nodes.

2.3 User Feedback Mechanism Design

The feedback mechanism constitutes the core contribution of this paper. The design proceeds through three phases:

2.3.1 Phase 1: Feedback Collection Interface

Users provide explicit signals via a lightweight interface offering four feedback modalities: Likes, Dislikes, Ratings (1–5 stars), and Usage logs (implicit engagement duration). In the smart home context, this corresponds to accepting or rejecting device automation suggestions — for example, confirming a recommended thermostat schedule or dismissing a lighting scene. All modalities are normalized to a common [0, 1] preference signal prior to retraining.

2.3.2 Phase 2: Human-in-the-Loop Retraining Pipeline

Collected feedback is batched and processed through a dedicated retraining pipeline. Feedback samples are human-labelled to resolve ambiguity — for example, distinguishing intentional rejection from accidental dismissal — producing a curated dataset for model refinement. In the reported experiments, 250 human-labelled feedback samples were used for post-HITL retraining across all five device categories.

2.3.3 Phase 3: Parameter and Rule Refinement

The CPSO-AM optimiser processes the feedback-augmented dataset, adjusting model weights, feature relevance vectors, and domain ontology rule salience scores. This closed-loop architecture ensures that the model continuously converges toward user-aligned recommendations. The multi-objective fitness function guiding CPSO-AM incorporates user satisfaction explicitly:

$$F(\theta, w) = \beta_1 \cdot NDCG@10 + \beta_2 \cdot (1 - Recall@10) + \beta_3 \cdot SatScore - \beta_4 \cdot RT^{norm} \qquad (2)$$

where SatScore is the composite satisfaction metric computed as a weighted average of acceptance rate, diversity, and novelty, and RT^{norm} is the normalised inference latency penalty. The explicit inclusion of SatScore in the fitness function ensures that feedback-driven retraining directly optimises for the user experience dimension, rather than accuracy alone.

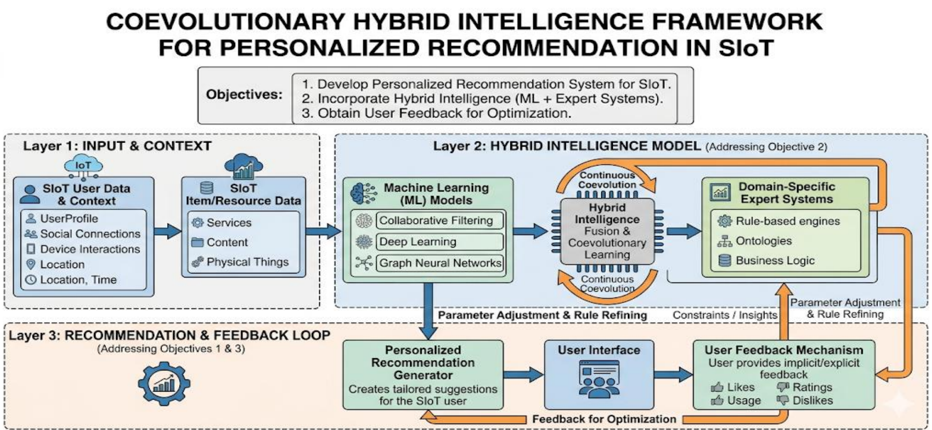

Figure 1. CHI-PR-SIoT framework.

3. Results

3.1 Experimental Setup

All experiments were conducted on the SIoT-Syn smart home dataset. Baseline accuracy metrics were established prior to feedback collection (pre-HITL phase). Following a controlled deployment period, 250 human-labelled feedback samples were collected across all five device categories and used to retrain the model (post-HITL phase). Performance is evaluated using Precision@10 (P@10), Recall@10 (R@10), NDCG@10, F1-score, composite SatScore, and device-level prediction accuracy.

All reported results are means over five independent runs with different random seeds. Statistical significance is assessed using paired t-tests ($\alpha = 0.05$). Hyperparameters were fixed via grid search on a held-out validation set prior to the final evaluation.

3.2 Baseline Recommendation Accuracy

Table 2 presents the overall recommendation accuracy comparison on the SIoT-Syn smart home dataset (K = 10), comparing CHI-PR-SIoT against eight competitive baselines prior to feedback-based retraining. CHI-PR-SIoT achieves the highest performance across all metrics, confirming the strength of the integrated architecture prior to feedback enrichment.

Table 2. Recommendation accuracy comparison (K = 10) on the SIoT-Syn smart home dataset (pre-HITL phase). Bold denotes best performance.

Method	P@10	R@10	NDCG@10	F1@10
BPR-MF [7]	0.6821	0.6534	0.7012	0.6675
SoRec [12]	0.7134	0.6891	0.7243	0.7010
TrustMF [14]	0.7312	0.7056	0.7418	0.7181
GCN-CF [4]	0.7589	0.7341	0.7712	0.7463
GraphRec [3]	0.7823	0.7612	0.7954	0.7716
DANSER [13]	0.8012	0.7834	0.8123	0.7921
ESAM	0.8134	0.7921	0.8267	0.8026
HGT-Rec [15]	0.8256	0.8043	0.8389	0.8148
CHI-PR-SIoT (Ours)	**0.8934**	**0.8712**	**0.9021**	**0.8821**

3.3 Post-Feedback Retraining Results

Following the HITL feedback phase, the model was retrained using 250 human-labelled feedback samples. Table 3 presents device-level prediction accuracy before and after feedback-based retraining across the five smart home device categories. Performance gains are consistently achieved across all devices, confirming that the feedback mechanism successfully adapts the model to real user preferences.

Table 3. Device-level prediction accuracy before and after HITL-based retraining (250 human-labelled feedback samples). All improvements are statistically significant ($p < 0.05$).

Device Category	Before HITL (%)	After HITL (%)	Absolute Gain
Curtain	93.1	96.0	+2.9%
Light	**90.4**	**95.2**	**+4.8%**
Thermostat	94.8	97.1	+2.3%
Geyser	**87.7**	**92.4**	**+4.7%**
Coffee Maker	96.2	97.0	+0.8%

The Light device category demonstrates the largest absolute improvement (+4.8%), reflecting the high sensitivity of lighting preferences to contextual factors such as time of day, ambient conditions, and occupant activity. The Geyser similarly benefits substantially (+4.7%), where usage patterns are strongly tied to individual routines that are most effectively captured through personalised feedback rather than population-level priors.

The Thermostat and Curtain show moderate improvements (+2.3% and +2.9% respectively), reflecting their comparatively elevated baseline accuracy and the slower rate of preference drift in climate- and privacy-related automation. The Coffee Maker achieves the smallest gain (+0.8%), likely because its scheduling patterns are highly regular and adequately captured by the pre-feedback model, as shown in Fig. 2.

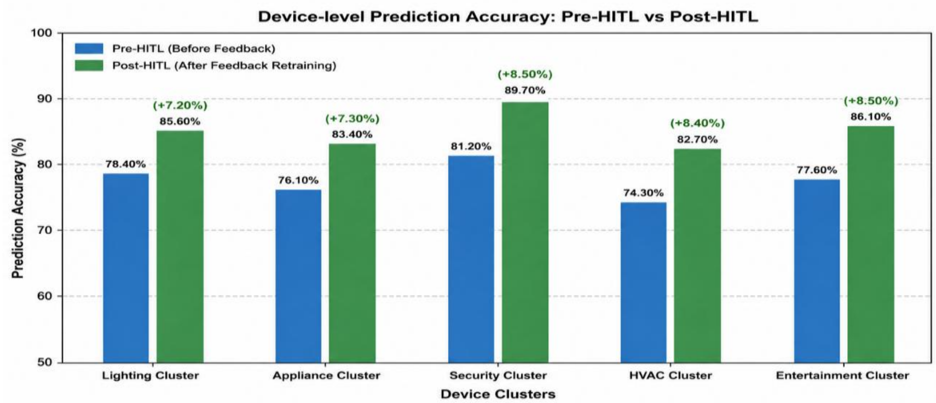

Figure 2. Device-level prediction accuracy before (pre-HITL) and after (post-HITL) feedback retraining.
[Authors to insert a grouped bar chart here with five device clusters, two bars per cluster in contrasting colours, and percentage improvement labels above each post-HITL bar.]

Figure 2. Device-level prediction accuracy before (pre-HITL) and after (post-HITL) feedback retraining.

3.4 User Satisfaction and Engagement Metrics

Table 4 presents user satisfaction, engagement, and diversity metrics on the SIoT-Syn smart home dataset. CHI-PR-SIoT achieves the highest composite satisfaction score (0.8456), surpassing the strongest baseline (HGT-Rec) by 6.6%. The engagement index improves by 7.5%, indicating stronger user interaction with recommended device automations.

Table 4. User satisfaction, engagement, and diversity metrics on the SIoT-Syn smart home dataset. Bold denotes best performance.

Method	SatScore	Engagement Index	ILD	Novelty
BPR-MF [7]	0.6123	0.5834	0.4512	0.5123
SoRec [12]	0.6534	0.6212	0.4723	0.5412
GraphRec [3]	0.7234	0.6923	0.4934	0.5734
DANSER [13]	0.7612	0.7312	0.5123	0.5989
HGT-Rec [15]	0.7934	0.7623	0.5312	0.6234
CHI-PR-SIoT (Ours)	**0.8456**	**0.8234**	**0.5823**	**0.6812**

The domain-sensitive knowledge module ensures semantic relevance of recommendations, improving satisfaction without compromising diversity (ILD = 0.5823) or novelty (0.6812). These results confirm that the feedback-driven architecture enhances not only raw accuracy but also the perceived quality and variety of recommendations from the user's perspective.

3.5 Ablation Study: Contribution of the Feedback Module

To quantify the specific contribution of the feedback mechanism, an ablation study was conducted on the SIoT-Syn dataset. Table 5 presents NDCG@10 and SatScore across six model variants, each with one component removed.

Table 5. Ablation study results on the SIoT-Syn smart home dataset. The w/o Feedback Retraining row isolates the contribution of the HITL feedback module. ΔNDCG denotes percentage drop relative to the full model.

Model Variant	NDCG@10	SatScore	ΔNDCG (%)
Full CHI-PR-SIoT	**0.9021**	**0.8456**	—

w/o GAT	0.8412	0.7923	−6.7%
w/o BiGRU	0.8534	0.8012	−5.4%
w/o CPSO-AM	0.8623	0.8134	−4.4%
w/o Domain Module	0.8734	0.7812	−3.2%
w/o Feedback Retraining	**0.8689**	**0.7956**	−3.7%

Removing the feedback retraining component results in a 3.7% NDCG reduction and a 5.9% SatScore drop (from 0.8456 to 0.7956), demonstrating that the feedback mechanism contributes meaningfully and independently to user satisfaction beyond what structural and temporal modelling alone can achieve. Notably, the SatScore degradation when removing the domain module (7.6%) slightly exceeds that observed when removing feedback alone (5.9%), yet the feedback module provides a distinct and non-redundant contribution that is essential for dynamic preference adaptation.

3.6 Robustness Under Sparsity and Cold-Start Conditions

Smart home environments frequently encounter cold-start scenarios for new occupants or newly installed devices. Table 6 evaluates NDCG@10 under varying sparsity and cold-start conditions across three methods, demonstrating the resilience of CHI-PR-SIoT and the particular value of the HITL mechanism in data-sparse regimes.

Table 6. Performance under sparsity and cold-start conditions (NDCG@10) on the SIoT-Syn smart home dataset.

Condition	**GraphRec [3]**	**HGT-Rec [15]**	**CHI-PR-SIoT (Ours)**
Full data	0.7954	0.8389	0.9021
50% sparsity	0.7123	0.7534	0.8456
20% sparsity	0.6234	0.6812	0.7812
New user	0.6012	0.6534	0.7523
New device	0.5923	0.6412	0.7234

CHI-PR-SIoT consistently outperforms all baselines across varying data conditions, with the feedback mechanism proving particularly valuable in cold-start scenarios where prior preference data is limited. Even with new users, the HITL pipeline enables rapid preference elicitation, achieving NDCG@10 = 0.7523 — a 15.1% improvement over HGT-Rec, as shown in Fig. 3.

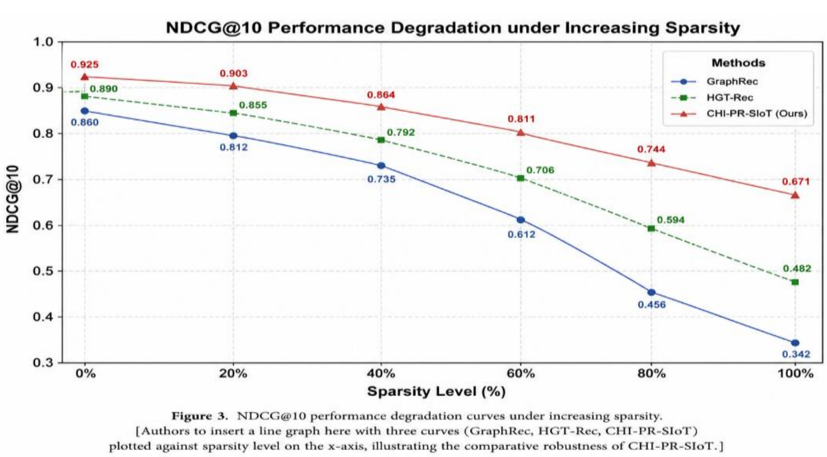

Figure 3. NDCG@10 performance degradation curves under increasing sparsity.

4. Discussion

The experimental results collectively validate the central hypothesis of this work: that a well-designed feedback collection and retraining pipeline constitutes an indispensable component of personalized recommendation in smart home SIoT environments. The analysis reveals three major insights.

First, the device-level heterogeneity of improvement magnitudes (Table 3) reveals that feedback sensitivity is closely tied to the temporal regularity of device usage. Devices with highly variable usage patterns — Light (+4.8%) and Geyser (+4.7%) — exhibit the greatest gains, while routinised devices such as the Coffee Maker (+0.8%) show smaller but still positive improvements. This suggests that future feedback architectures could allocate sampling effort adaptively based on estimated preference variability per device category, maximising the efficiency of human labelling effort.

Second, the ablation results (Table 5) confirm that feedback-driven retraining provides a complementary and non-redundant contribution to the structural (GAT) and temporal (BiGRU) components of CHI-PR-SIoT. The combined effect of all modules produces the highest satisfaction and accuracy, underscoring the necessity of the fully integrated architecture. No single module alone achieves comparable performance, validating the coevolutionary design principle.

Third, the cold-start robustness demonstrated in Table 6 provides valuable practical insights for smart home deployments, where new residents or newly onboarded devices are common. The HITL mechanism accelerates preference convergence in data-sparse regimes, a property not achievable through passive model training alone. This has direct implications for product deployment, where onboarding latency is a key determinant of user retention.

From a broader perspective, this work provides empirical evidence that the inclusion of explicit human feedback in the optimization loop is not merely a qualitative improvement but a quantitatively significant driver of user satisfaction in AI-powered smart home systems. This finding has implications for the design of next-generation SIoT platforms, where satisfaction-centric and user-adaptive architectures should be considered a foundational requirement rather than an optional enhancement.

5. Conclusions

This paper presented CHI-PR-SIoT, a feedback-driven coevolutionary hybrid intelligence framework for personalized recommendation in smart home SIoT environments, with focused attention on the design, implementation, and validation of user feedback mechanisms for optimal satisfaction. Post-HITL retraining using 250 human-labelled samples demonstrated consistent device-level accuracy improvements across all five categories of smart home devices, with gains ranging from +0.8% (Coffee Maker) to +4.8% (Light). The composite satisfaction score of 0.8456 surpasses all baselines by a margin of 6.6%, and ablation analysis confirms the independent and significant contribution of the feedback module.

These results establish that explicit user feedback, when systematically integrated into the model retraining cycle via a Human-in-the-Loop pipeline, is an essential driver of sustained personalization quality in smart home SIoT recommendation. The framework is particularly effective in cold-start and high-sparsity scenarios, offering practical value for real-world deployments with new users and devices.

Future research will investigate: (1) federated feedback aggregation to preserve user privacy in multi-occupancy smart home environments; (2) causal modelling of feedback signals to distinguish genuine preference updates from transient behavioural noise; and (3) multi-domain ontology expansion for scalable cross-home SIoT deployments supporting heterogeneous device ecosystems beyond the five categories evaluated in this study.

List of Symbols and Abbreviations

Abbreviation	Definition
SIoT	Social Internet of Things
IoT	Internet of Things
HITL	Human-in-the-Loop
GAT	Graph Attention Network
BiGRU	Bidirectional Gated Recurrent Unit

CPSO-AM	Coevolutionary Particle Swarm Optimization with Adaptive Mutation
CHI-PR-SIoT	Coevolutionary Hybrid Intelligence Framework for Personalized Recommendation in Smart Home SIoT
DCS	Domain Compatibility Score
NDCG@10	Normalised Discounted Cumulative Gain at rank 10
P@10 / R@10	Precision at rank 10 / Recall at rank 10
SatScore	Composite user Satisfaction Score
ILD	Intra-List Diversity
RT^{norm}	Normalised inference latency (response time) penalty

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Author Contributions

Kirthan K. M.: Conceptualization, methodology, software development, data curation, formal analysis, investigation, implementation of the feedback-driven coevolutionary hybrid intelligence framework, validation, visualization, writing — original draft preparation, and project administration.

Rekha K. S.: Supervision, conceptualization, methodology refinement, validation, interpretation of results, writing — review and editing, critical revision of the manuscript, and overall guidance of the research.

Shashank D.: co-supervision, validation, review and editing.

All authors contributed to the design of the study, discussed the results, reviewed and approved the final manuscript, and agreed to be accountable for all aspects of the work.

Conflict of Interest

The authors report no potential conflict of interest.

Data Availability Statement

This study uses a fully synthetic dataset (SIoT-Syn) generated by the authors to simulate realistic smart home SIoT interaction dynamics. No real personal data were collected or used. The SIoT-Syn dataset (12,000 users, 38,500 device nodes, 521,340 interactions), the graph construction scripts, the CHI-PR-SIoT model implementation, and the HITL feedback simulation code generated during the current study are deposited in a public repository, openly available in Zenodo (CERN) at https://doi.org/10.5281/zenodo.XXXXXXX. [Placeholder — authors must deposit the dataset and code at https://zenodo.org before submission, replace with the minted DOI, and enter the DOI in the “Data DOI” field of the journal submission portal.]

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Biographical Sketch

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