IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 2, May 2025
Impact Factor: 7.67

Cold Start Issue with Federated Recommendation: Distinguishing Item Properties from User Interactions

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Abstract: *Federated recommendation systems typically don't have direct access to users' personal information on their own devices; instead, they train a global model on the server. Nevertheless, the recommendation model's separation and users' private information makes it difficult to deliver high-quality service, especially for new products like cold-start suggestions in federated settings. Item-aligned Federated Aggregation (IFedRec) is an innovative approach to this problem that is presented in this study. This is the first research on federated recommendation to focus on the cold-start scenario. The technique learns two sets of item representations simultaneously by utilising item attributes and interaction records. A federated learning framework includes an item representation alignment mechanism that aligns two item representations and learns the meta-attribute network at the server. IFedRec achieves improved performance in cold-start conditions, as shown by experiments on four benchmark datasets. Additionally, it is confirmed in this work that IFedRec exhibits strong resilience in the face of noise injection and low client involvement, which offers encouraging real-world application potential in privacy-protected enhanced federated recommendation systems. The code for implementation is accessible.*

Keywords: Federated Learning, Recommendation Systems, Cold-start

I. INTRODUCTION

IFedRec tackles federated cold-start challenges by learning dual item representations—server-side via a meta-attribute network and client-side from interactions—while keeping raw attributes private. Its two-phase framework aligns these representations, enabling accurate, private recommendations that outperform existing baselines.

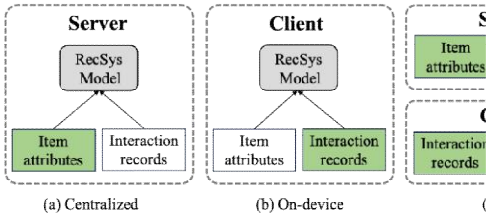

Fig 1. Comparison of three cold-start suggestion systems. While the centralised approach (a) exposes private user interaction information, it saves raw item attributes on the server. Conventional FedRecSys (b) gives customers access to the item properties while protecting the interaction records. Both of these categories of security-sensitive data can be safeguarded by our IFedRec (c). But given the grave societal concerns regarding the exploitation of user privacy [29, 34], there has been a growing interest in creating recommendation models that prevent the leakage of users' private information.

Cold-start scenarios in federated systems remain underdeveloped, and deploying centralized models with raw item attributes poses commercial and security risks. IFedRec addresses this by keeping raw attributes on the server and

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learning dual item representations—server-side via a meta-attribute network, and client-side from interaction data. An alignment module connects both representations through a two-phase framework: clients align embeddings during learning, and use server-generated attributes for inference. This approach preserves privacy and outperforms both federated and centralized baselines across benchmarks.

In conclusion, the following is a list of our primary contributions:

To the best of the authors' knowledge, a unique framework called IFedRec is introduced, which is the first attempt to address the cold-start recommendation in a federated system without any interactions for the new items.

The suggested item semantic alignment mechanism is simple to incorporate into current federated recommendation frameworks for cold-start recommendation performance enhancement; our approach achieves state-of-the-art performance in comprehensive experiments and in-depth analysis validates the importance of cold items recommendation.

II. RELATED WORK

The Cold Start Suggestion

The cold-start recommendation problem aims to suggest new products [46], with solutions including content-based approaches [10, 31], collaborative filtering [36, 46], and hybrid models [4]. Hybrid models combine item attributes with collaborative filtering for better recommendations.

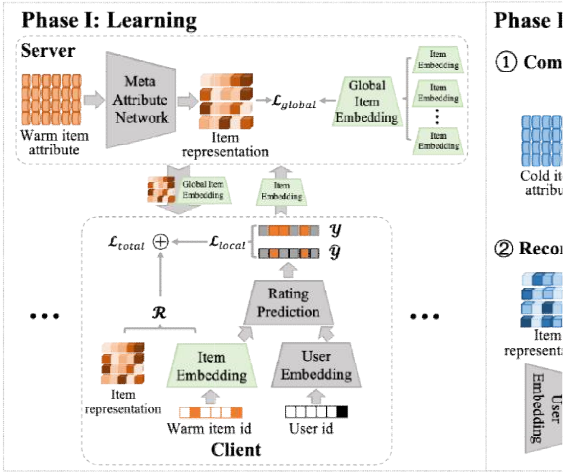

Fig 2. IFedRec's framework.

System of Federated Recommendations

Federated learning frameworks [20, 21, 28, 39] preserve user privacy in recommendation models by having clients train local models and a central server aggregate parameter. While FedRecSys has been adapted for various systems [3, 8, 9, 13, 19, 23, 26, 40, 41, 43, 45], research on cold-start recommendations is limited. This study focuses on recommending new items without user interaction.

PRELIMIARY

Cold-Start Federated Recommendation. Using $n = |U|$ users, let U represent the user set. The warm item set that users have interacted with is represented by I^{warm}, and the cold item set I^{cold} whose items No users have ever interacted with the products. Each user is considered a client under the federated learning framework, and the model $\mathcal{F}_\theta$ is made up of three modules: a rating prediction module $\mathcal{S}$, a user embedding module $\mathcal{Q}$, and an item embedding module $\mathcal{P}$. Considering each user's interaction records $\mathcal{Y}^{warm}$ and the item attribute matrix $\mathcal{X}^{warm}$, federation-based cold-start proposal seeks to understand the optimisation target of a recommendation model $\mathcal{F}_\theta$ as

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$$\min_{\theta} \sum_{i=1}^{n} \mathcal{L}_i(\theta) \quad (1)$$

where $\mathcal{L}_i(\theta)$ represents the loss of the i-th client and $\theta \coloneqq (\mathcal{p}, q, \mathcal{s})$ represents the model parameters. Based on the item property $\mathcal{X}^{cold}$, the system can then suggest cold items to each user. The prediction for cold goods could be expressed mathematically as follows:

$$\hat{y}_u^{cold} = \mathcal{F}_\theta(\mathcal{X}^{cold}) \quad (2)$$

III. METHODOLOGY

The general structure of the approach is outlined, detailing the learning and inference phases, and introduce IFedRec, which incorporates local Differential Privacy to enhance privacy protection.

Overview of the framework

IFedRec separates learning and inference, with the server training a meta-attribute network and clients training local models. It aligns item representations and incorporates local Differential Privacy for secure cold-start recommendations.

Studying the Warm Things

Training starts with warm items, leveraging past user interactions and item attributes. First, the server learns a global meta-attribute network $\mathcal{M}_\phi$. Then, each client u updates its local model $\mathcal{F}_{\theta_u}$ using historical data. An alignment step ensures client embeddings match server-side attributes.

The server coordinates clients to build a shared item embedding module $\mathcal{P}$, while user-specific components stay local. After local training, clients send embeddings to the server, which averages them to form a global item representation, balancing accuracy and efficiency.

$$\mathcal{p} \coloneqq \frac{1}{n} \sum_{i=1}^{n} \mathcal{p}_u \quad (3)$$

Here, n is the number of clients and $\mathcal{p}_u$ is client u's item embedding. Weight-based aggregation methods [16, 22] can enhance performance. Cold item suggestions use attribute data to relate products. Learning a meta-attribute network $\mathcal{M}_\phi$ from item attributes is proposed, then deploying it on the server. The learning process for $\mathcal{M}_\phi$ is defined as:

$$r_v \coloneqq \mathcal{M}_\phi(x_v) \quad (4)$$

where ϕ is the model parameter. The attribute and learnt representation of item v are represented by the x_v and r_v, respectively.

Alignment of the item embedding. To build the link between the item attributes and the user interaction records, item embedding as the intermediary and consider the global item embedding $\mathcal{p}$ as the supervision to train the meta-attribute network $\mathcal{M}_\phi$ are employed. The mean square error is specifically chosen as the loss function, taking into account the characteristics of the regression task, and formulate it as follows:

$$\mathcal{L}(\mathcal{p}; \phi) \coloneqq \frac{1}{m} \sum_{v=1}^{m} \left(r_v - \mathcal{p}(v)\right)^2 \quad (5)$$

where m is the number of warm items. The learnt attribute representation and global item embedding of item v are represented by r_v and $\mathcal{p}(v)$.

The stochastic gradient descent approach is used to update the meta-attribute network parameter ϕ based on the loss $\mathcal{L}$ in Eq. (5). The t-th update step is as follows:

$$\phi^t \coloneqq \phi^{t-1} - \gamma \partial_{\phi^{t-1}} \mathcal{L}(\mathcal{p}; \phi) \quad (6)$$

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where γ is the parameter update learning rate.

Update of the local recommendation model

The model prediction of user u regarding item v is formulated as follows, based on the recommendation model $\mathcal{F}_\theta$, where $\theta := (p, q, s)$.

$$\hat{y}_{uv} := \mathcal{S}(\mathcal{P}_v, \mathcal{Q}_u) \tag{7}$$

$\mathcal{P}_v$ and $\mathcal{Q}_u$ indicate the embedding of item v and user u, respectively. The common implicit feedback recommendation task is specifically mentioned, where $y_{uv} = 1$ in the event that user$u$ and item v interact, and $y_{uv} = 1$ otherwise. Given that implicit feedback is binary-value, the recommendation loss of user u as the binary cross-entropy loss is defined as,

$$\mathcal{L}(y_{uv}; \theta_u) := -\sum_{(u,v)\in D_u} log\, \hat{y}_{uv} - \sum_{(u,v')\in D_u^-} log(1 - \hat{y}_{uv'}) \tag{8}$$

where $\mathcal{D}_u^-$ is the user u negative samples set. The binary cross-entropy loss is used as an example here; however, it is important to note that alternative loss metrics can also be used. Initially it is counted on all of user u's uninteracted objects as follows in order to generate $\mathcal{D}_u^-$ efficiently:

$$I_u^- := I^{warm} / I_u \tag{9}$$

where I_u is the user u's set of interacted heated things. Next, by adjusting the sampling ratio according to the user's interacted item amount, negative items from I_u^- are evenly sampled.

Alignment of item attribute representation. Each local model learns a unique item embedding, while the server uses raw item attributes to learn a latent representation. To enhance training, the server's global item representation with the client's local embedding is aligned by updating the training loss accordingly.

$$\mathcal{L}_{total} := \mathcal{L}_u(y_{uv}; \theta_u) + \lambda \mathcal{R}(p_u, r) \tag{10}$$

where pu is the item embedding module parameter of user u and r indicates the item attribute representation learnt by raw item attributes on the server. The stochastic gradient descent approach can be used to update the recommendation model parameter θ_u based on the local training loss $\mathcal{L}_{total}$.

Interestingly, an alternative update method is used to update various modules. That is, the rating prediction module $\mathcal{S}$ and the locally preserved user embedding module $\mathcal{Q}$ are updated first to modify the recommendation model using the global item embedding, and then the local item embedding $\mathcal{P}$ using the adjusted $\mathcal{Q}$ and $\mathcal{S}$ are updated. The formula for the t-th update step is as follows:

$$\begin{aligned} (q_u^t, s_u^t) &:= (q_u^{t-1}, s_u^{t-1}) - \eta_1 \partial_{(q_u^{t-1}, s_u^{t-1})} \mathcal{L}_{total} \\ p_u^t &:= p_u^{t-1} - \eta_2 \partial_{p_u^{t-1}} \mathcal{L}_{total} \end{aligned} \tag{11}$$

where the parameter update learning rate for modules $\mathcal{Q}$ and $\mathcal{S}$ is represented by η_1, and for module $\mathcal{P}$ by η_2.

Overall goal of optimisation

Each user is treated as a client u in the FL setup, and they use the private dataset $\mathcal{D}_u$ to train a local recommendation model $\mathcal{F}_\theta$. In summary, the proposed IFedRec as the bi-level optimisation problem is constructed as,

$$\begin{aligned} &\min_{\{p_u, q_u, s_u\}_{u=1}^n} \sum_{u=1}^{n} \mathcal{L}_u(y_u; p_u, q_u, s_u) + \lambda \mathcal{R}(p_u, r) \\ &s.t.\, r := \mathcal{M}_\phi(X^{warm}) \end{aligned} \tag{12}$$

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Here n is the number of clients, with $\mathcal{L}_u$ as the client's loss. Parameters for item, user, and rating prediction are $\mathcal{p}_u$, $\mathcal{q}_u$, and $\mathcal{s}_u$. Regularization is $\mathcal{R}(\cdot;\cdot)$ with coefficient λ. The meta-attribute network $\mathcal{M}_\phi$ learns item representation $\mathcal{r}$ from warm item attributes. Client embeddings are aggregated to optimize the network on the server.

Conclusion Regarding the Cold Items

Warm items are employed to optimise the system during the learning phase, and cold item recommendations can be inferred using the learnt model. The server first uses the meta-attribute network to find the item attribute representation $\mathcal{r}_{cold}$ when new items I^{cold} arrive. The clients can then create customised suggestions by combining the locally maintained user embedding Q and rating prediction module $\mathcal{S}$ with $\mathcal{r}_{cold}$.

Local Differential Privacy Enhanced IFedRec for Privacy Protection

The goal is to prevent the server from inferring client data through shared model parameters. To enhance privacy, techniques like Differential Privacy [7] and Homomorphic Encryption [2] are integrated into the FL framework. Our improved IFedRec applies local Differential Privacy when clients upload item embeddings, protecting against potential data leakage. Specifically, before uploading the item embedding to the server, each client u adds a zero-mean Laplacian noise, which can be expressed as follows:

$$\mathcal{p}_u = \mathcal{p}_u + Laplace(0, \delta) \tag{13}$$

where δ is the noise strength.

IV. EXPERIMENT

Datasets

The proposed IFedRec is evaluated on two cold-start recommendation benchmark datasets, CiteULike [33] and XING [1]. The XING dataset is divided into three subsets based on user count: XING-5000, XING-10000, and XING-20000. For CiteULike, 80% of the items are considered as warm for training, with the remaining cold items used for testing, and 30% sampled as a validation set. The training set is split, validation, and test sets in a 6:1:3 ratio for the XING datasets. Table 1 summarizes dataset statistics. The datasets are presented here, and Table 1 provides a summary of the specific statistics.

	Training				**Validation**			**Test**		
	#users	#items	#interactions	sparsity	#users	#items	#interactions	#users	#items	#interactions
CiteULike	5,551	13,584	164,210	0.22\%	5,551	1,018	13,037	5,551	2,378	27,739
XING-5000	5,000	11,261	117,608	0.21\%	5,000	1,878	56,465	5,000	5,630	17,530
XING-10000	10,000	12,153	230,765	0.19\%	10,000	2,027	110,731	10,000	6,076	41,660
XING-20000	20,000	12,306	444,199	0.18\%	20,000	2,051	251,735	20,000	6,153	72,537

Table 1. Four cold-start suggestion dataset's statistics. Three subsets of the objects are created, with some things in the training set being warm and others being cold.

CiteULike consists of 16,980 articles, 5,551 users, and 204,986 interactions. Item attributes are derived from the article's title and abstract using tf-idf to produce an 8,000-dimensional vector, which is then reduced to 300 dimensions via SVD. XING, from the ACM RecSys 2017 Challenge, contains 20,519 items, 106,881 users, and 4,306,183 interactions. The item properties have 2,738 dimensions, and three user subsets (5,000, 10,000, and 20,000) are sampled to form three subsets with varying interaction counts and item numbers.

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Volume 5, Issue 2, May 2025
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Algorithm 1 Item-Guided Federated Aggregation for Cold-Start Recommendation - **Learning on the Warm Items**

ServerExecute:

Initialize item embedding module parameter
Initialize meta-attribute network parameter
for each round t = 1, 2, … **do**
    for e from 1 to E_1 **do**
        Computer $\mathcal{L}(p^t; \phi)$ with Equation (5)
        Update ϕ^t with Equation (6)
    end for
    Compute warm items representation r_{warm}^t with Equation (4)
    $S^t \leftarrow$ (select a client subset randomly from all n clients with sampling ratio α)
    for each client $u \in S^t$ **in parallel do**
        $p_u^{t+1} \leftarrow$ ClientUpdate(t, u, p^t, r_{warm}^t)
    end for
    Aggregate global item embedding p^{t+1} with Equation (3)
end for

ClientUpdate(t, u, p, r):

Initialize p_u with p
if t =1 **then**
    Initialize user embedding module parameter q_u
    Initialize rating prediction module parameter s_u
else
    Initialize q_u and s_u with the latest updates
Count all uninteracted items set I_u^- with Equation (9)
Sample negative feedback D_u^- from I_u^-
$\mathcal{B} \leftarrow$ (Split $D_u \cup D_u^-$ into batches of Size $\mathcal{B}$)
for e from 1 to E_2 **do**
    for batch $b \in \mathcal{B}$ **do**
        Compute L_{total} with Equation (10)
        Update $(p_u,\ q_u,\ s_u)$ with Equation (11)
    end for
end for
Return p_u to server

Metrics for evaluating the experimental setup

To assess model performance, three ranking metrics—Precision@k, Recall@k, and NDCG@k— are utilized that are often employed [6, 12, 47]. In this study, results of k = {20,50,100} are reported in units of 1e-2. Baselines. Two baseline branches are considered for comparison: federated cold-start recommendation methods and centralized cold-start recommendation methods.

For federated approaches, two state-of-the-art FedRecSys models are adapted, CS_FedNCF and CS_PFedRec, and compare them with FedMVMF. Additionally, federated versions of two content-enriched centralized models are built in this work, VBPR and DCN, named FedVBPR and FedDCN. For centralized approaches the latest models, GAR and Heater, are used as baselines, and modify CS_NCF and CS_MF for the cold-start environment.

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Volume 5, Issue 2, May 2025
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	Methods	Metrics	CiteULike			XING-500			XING-10000			XING-20000		
			@20	@50	@100	@20	@50	@100	@20	@50	@100	@20	@50	@100
FedRec	FedMVMF	Recall	6.18	14.34	24.97	1.96	2.70	3.81	0.96	2.61	4.50	0.77	2.42	4.59
		Precision	1.57	1.48	1.30	0.77	0.46	0.36	0.52	0.55	0.48	0.51	0.66	0.62
		NDCG	5.55	10.04	14.42	2.60	1.78	1.98	1.02	1.85	2.43	0.65	1.50	2.39
	CS_FedNCF	Recall	1.49	3.83	7.21	0.22	2.37	3.15	0.44	0.77	1.51	0.16	1.21	1.72
		Precision	0.37	0.39	0.36	0.14	0.41	0.29	0.24	0.17	0.17	0.10	0.33	0.23
		NDCG	1.76	3.16	4.38	0.26	0.96	1.20	0.37	0.42	0.67	0.16	0.67	0.93
	CS_PFedRec	Recall	1.37	2.66	4.67	0.13	0.54	1.54	0.29	2.10	2.42	0.16	1.21	1.72
		Precision	0.33	0.25	0.24	0.09	0.13	0.18	0.19	0.44	0.26	0.19	0.33	0.23
		NDCG	1.40	1.92	2.54	0.15	0.34	0.93	0.35	1.02	0.99	0.16	0.67	0.93
	FedVBPR	Recall	18.73	29.88	39.55	2.03	3.02	3.63	0.42	0.82	1.26	0.40	1.35	1.86
		Precision	3.75	2.46	1.66	0.78	0.56	0.36	0.24	0.19	0.14	0.27	0.36	0.24
		NDCG	13.24	16.07	17.91	0.95	1.37	1.41	0.35	0.48	0.57	0.32	0.74	0.98
	FedDCN	Recall	1.42	3.57	6.59	0.32	0.65	1.14	0.43	0.83	1.52	0.24	0.80	1.43
		Precision	0.35	0.38	0.35	0.17	0.15	0.13	0.22	0.19	0.17	0.14	0.18	0.16
		NDCG	1.10	2.44	3.60	0.27	0.46	0.66	0.51	0.46	0.66	0.21	0.46	0.64
Ours	IFedNCF	Recall	**42.32**	**59.92**	**72.89**	**23.48**	**42.05**	**55.45**	**26.97**	**41.57**	**55.37**	**26.36**	**41.44**	**54.48**
		Precision	**9.70**	5.80	3.65	**13.66**	**9.55**	**6.37**	**14.38**	**9.02**	**6.06**	**16.25**	**10.23**	**6.75**
		NDCG	**34.29**	37.61	38.74	**20.93**	**27.41**	**29.46**	**21.65**	**24.66**	**27.02**	**21.99**	**25.30**	**27.22**
	IPFedRec	Recall	41.51	59.63	72.71	21.77	37.30	53.18	25.92	40.33	54.64	24.67	40.07	53.58
		Precision	9.48	**5.81**	**3.67**	12.75	8.76	6.12	13.84	8.77	5.97	15.29	9.92	6.66
		NDCG	33.48	**37.69**	**39.07**	19.74	24.77	28.34	20.66	23.90	26.52	20.53	24.49	26.91

Table 2. Our technique and the federated baselines' experimental outcomes. "Ours" indicates that we incorporate two cutting-edge federated models into our system, while "FedRec" indicates the federated baselines. The boldest outcomes are the best.

FedVBPR: VBPRmodel [11] is a content enhanced recommendation model that enhances the collaborative filtering framework by incorporating visual item attributes. Fed VBPR is acquired by adapting it to the federated learning architecture.

FedDCN: FedDCN is a deep and cross-network architecture that is capable of capturing intricate relationships between various item features. FedDCN is the result of our adaptation into the federated learning architecture.

Details of implementation. Table 3 shows that IFedRec outperforms centralised baselines on all datasets, with 13.86%, 8.74%, and 9.34% improvements (@20) on CiteULike using Heater. This is due to its use of personalised user embedding and rating prediction modules, unlike shared modules in centralised models.

Baseline Comparison Analysis (Q1)

After comparing the model's performance using centralised and federated baselines, the experimental findings are examined.

In contrast to baselines for federated cold starts. Two observations are presented in Table 2:

First off, our approach consistently outperforms all federated baselines. CS_PFedRec performs worse than FedMVMF, CS_FedNCF, FedVBPR, and FedDCN because these methods use both item attributes and user-item interactions, which are key for cold item recommendations. Our item representation alignment connects embeddings from interactions with attribute representations, improving cold item recommendations. This approach helps the meta-attribute network learn latent item representations based on user preferences.

	Methods	Metrics	CiteULike			XING-500			XING-10000			XING-20000		
			@20	@50	@100	@20	@50	@100	@20	@50	@100	@20	@50	@100
CenRec	Heater	Recall	37.17	55.13	68.52	14.51	16.09	18.16	16.60	19.48	22.48	16.94	19.74	22.55
		Precision	8.92	5.50	3.52	5.70	2.69	1.60	8.73	4.19	2.44	8.86	4.21	2.43
		NDCG	31.36	35.95	37.68	8.97	7.78	7.48	14.00	12.06	11.13	13.18	11.32	10.66
	GAR	Recall	5.45	8.81	13.07	1.44	3.22	5.49	0.74	3.38	6.16	0.85	2.87	6.11
		Precision	1.42	0.91	0.66	0.69	0.55	0.46	0.37	0.67	0.62	0.45	0.51	0.39
		NDCG	3.43	4.42	5.48	0.89	1.57	2.32	0.80	1.86	2.87	0.85	2.02	2.97
	CS_NCF	Recall	29.41	46.43	61.85	18.42	32.03	45.19	21.80	35.26	47.54	19.65	33.00	45.98
		Precision	7.06	4.70	3.18	10.76	7.49	5.28	11.72	7.68	5.22	12.09	8.09	5.65
		NDCG	24.93	30.52	33.71	16.38	20.85	23.88	17.58	20.98	23.32	15.91	19.76	22.72
	CS_MF	Recall	1.01	2.30	4.32	0.48	1.04	1.99	0.36	0.89	1.78	0.41	0.93	1.73
		Precision	0.25	0.24	0.23	0.24	0.22	0.22	0.20	0.32	0.40	0.26	0.24	0.22
		NDCG	0.87	1.62	2.59	0.36	0.59	0.97	0.30	0.54	0.88	0.35	0.58	0.87

DOI: 10.48175/IJARSCT-26257
ISSN 2581-9429 IJARSCT

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Ours	IFedNCF	Recall	**42.32**	**59.92**	**72.89**	**23.48**	**42.05**	**55.45**	**26.97**	**41.57**	**55.37**	**26.36**	**41.44**	**54.48**
		Precision	**9.70**	5.80	3.65	**13.66**	**9.55**	**6.37**	**14.38**	**9.02**	**6.06**	**16.25**	**10.23**	**6.75**
		NDCG	**34.29**	37.61	38.74	**20.93**	**27.41**	**29.46**	**21.65**	**24.66**	**27.02**	**21.99**	**25.30**	**27.22**
	IPFedRec	Recall	41.51	59.63	72.71	21.77	37.30	53.18	25.92	40.33	54.64	24.67	40.07	53.58
		Precision	9.48	**5.81**	**3.67**	12.75	8.76	6.12	13.84	8.77	5.97	15.29	9.92	6.66
		NDCG	33.48	**37.69**	**39.07**	19.74	24.77	28.34	20.66	23.90	26.52	20.53	24.49	26.91

Table 3. Experimental results of the centralized baselines and our method. “CenRec" denotes the centralized baseline and “Ours” represents that we integrate two state-of-the-art federated models into our framework. The best results are bold.

Second, IFedNCF and IPFedRec, our IFedRec framework, deliver exceptional performance improvement in all circumstances by integrating current FedRecSys designs. A general cold-start FedRec framework is proposed in this work that integrates easily with existing FedRecSys systems. Our IFedNCF and IPFedRec add an item embedding regularization term and deploy a meta-attribute network on the server side. ***In Contrast to cold-start baselines that are centralised***. Table 3 shows IFedRec outperforms centralised baselines across all datasets, with improvements of 13.86%, 8.74%, and 9.34% (@20) on CiteULike using Heater, due to personalised user embedding and rating modules.

Ablation Studies (Q2)

To investigate the efficacy of the main components of our approach model variations are created. Experiments are done based on IFedNCF and IPFedRec on four datasets for a comprehensive analysis, and the findings of @20 are presented on three metrics.

Methods	**CiteULike**			**XING-500**			**XING-10000**			**XING-20000**		
	Recall	Precision	NDCG	Recall	Precision	NDCG	Recall	Precision	NDCG	Recall	Precision	NDCG
IFedNCF	**42.32**	**9.70**	**34.29**	**23.48**	**13.66**	**20.93**	**26.97**	**14.38**	**21.65**	**26.36**	**16.25**	**21.99**
w/ LAN	38.73	9.01	31.60	1.59	0.67	0.85	0.86	0.47	0.79	1.54	0.91	1.35
w/o ISAM	0.85	0.22	0.79	0.55	0.17	0.25	0.32	0.19	0.27	0.25	0.15	0.20
IPFedRec	**41.51**	**9.48**	**33.48**	**21.77**	**12.75**	**19.74**	**25.92**	**13.84**	**20.66**	**24.67**	**15.29**	**20.53**
w/ LAN	38.73	8.93	31.27	2.00	0.77	0.95	0.58	0.36	0.53	0.18	0.10	0.12
w/o ISAM	1.05	0.26	1.03	0.27	0.15	0.21	0.42	0.24	0.38	0.46	0.27	0.39

Table 4. Ablation study for IFedRec. “w/ LAN” denotes that we deploy the local attribute network on the client. “w/o IRAM" means to remove the item representation alignment mechanism from our method. We show the results on @20 metrics.

Include the attribute network in the model for local recommendations. A variant is created, "w/ LAN," by placing the attribute network on every client, replacing the item embedding module with item attributes. Table 4 shows that IFedRec outperforms this variant by learning two item representations, improving its ability to distinguish items. This helps IFedRec offer more accurate recommendations while keeping raw item attributes on the server to prevent misuse.

Take away IFedRec's item representation alignment mechanism. Removing the item representation alignment mechanism "w/o IRAM" significantly reduces performance, highlighting its importance in aligning item representations for improved cold item recommendations.

Hyper-parameters’ Effect (Q3)

This section examines the effects of two important IFedRec hyper-parameters: the training epochs $E1$ of the meta-attribute network on the server and the coefficient λ of item attribute representation regularisation on the client. Specifically, experiments are done based on IFedNCF and IPFedRec using the CiteULike dataset as an example.

DOI: 10.48175/IJARSCT-26257
ISSN 2581-9429 IJARSCT

International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Volume 5, Issue 2, May 2025
Impact Factor: 7.67

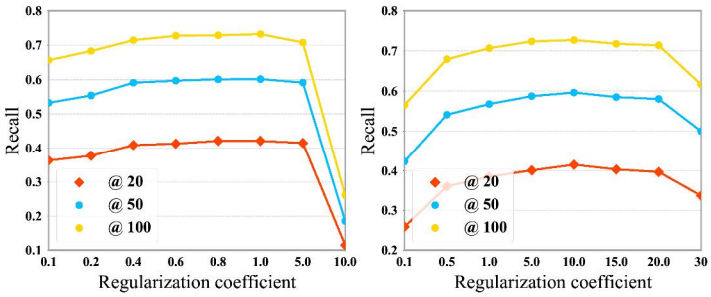


Fig 3. Impact of the regularisation coefficient. The vertical axis is the recall metric, while the horizontal axis is the value of the regularisation coefficient λ.

Training epoch for meta-attribute networks *E*1. As the number of server training epochs increases a minor improvement is observed in IFedNCF performance, as illustrated in Figure 4. The model performs optimally for the IPFedRec when $E1$=1. Therefore, one-step optimisation is sufficient to attain it.

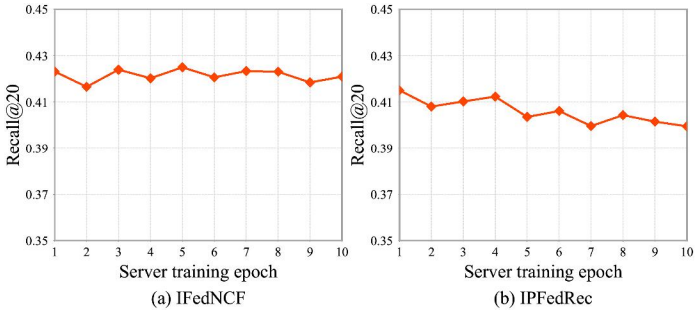


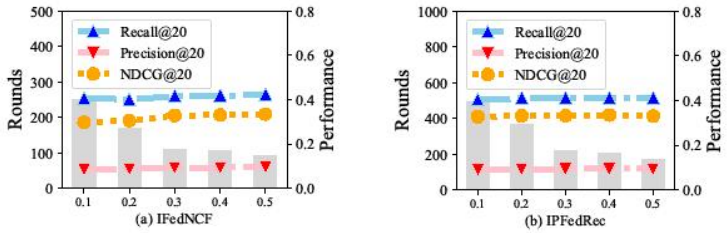
Fig 4. Effects of the Meta-Attribute Training Era.

The vertical axis is the Recall at 20 and the horizontal axis is the value of the meta-attribute network training epoch E1.

Figure 3 illustrates that: IFedNCF and IPFedRec have comparable performance change trajectories, meaning that performance improves initially before declining as the coefficient rises. The local recommendation model is overloaded with globally learnt item attribute representation information when the regularisation coefficient is high, which hinders the local model's ability to learn from user preference. As a result, the model performs worse since the local item embedding is biassed and unable to accurately describe user personalisation. For IFedNCF and IPFedRec, the ideal regularisation coefficient values are 1.0 and 10.0, respectively.

Clients Amount Convergence (Q4)

The convergence of the four IFedRec models is examined using the CiteULike dataset as an example. Federated optimization involves a trade-off between convergence speed and client participation per round. Generally, the model converges faster with more clients sampled during training rounds. However, due to communication costs and client processing constraints, it is challenging to gather enough clients, especially in large-scale recommendation systems, this environment is simulated by varying the client sampling ratio between 0.1 and 0.5 per round.



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Volume 5, Issue 2, May 2025
Impact Factor: 7.67

Fig 5. Convergence analysis about the client's level of participation in each round of communication. The client sampling ratio is on the horizontal axis, the number of communication rounds is on the left vertical axis, and the model performance on three metrics is on the right vertical axis

Figure 5 illustrates how our approach may produce exceptional results at a low sampling ratio, such as IPFedRec gets0.4035 on Recall@20, which also outperforms other baselines. In conclusion, IFedRec helps the FedRec System to optimise with insufficient customer participation, which is typical in real-world situations.

Methods	**Metrics**	**Noise Strength δ**					
		0	0.1	0.2	0.3	0.4	0.5
IFedNCF	Recall	42.32	41.81	41.87	41.23	41.09	40.84
	Precision	9.70	9.66	9.59	9.32	9.08	8.79
	NDCG	34.29	33.83	33.62	33.15	33.16	32.86
IPFedRec	Recall	41.51	41.10	40.84	40.11	40.57	39.52
	Precision	9.48	9.49	9.31	9.49	9.45	9.03
	NDCG	33.48	33.50	33.30	32.68	32.13	31.49

Table 5. Privacy-protection IFedRec results with different Laplacian noise strengths λ.

Enhanced IFedRec(Q5) Privacy-Protection

The performance is evaluated of four IFedRecs with local differential privacy using the CiteULike dataset, varying the Laplacian noise level from 0.1 to 0.5. Results show that while performance decreases as noise strength increases, the drop is modest, with a noise strength of 0.2 offering an optimal trade-off between performance and privacy.

V. CONCLUSION

This paper introduces IFedRec, a federated approach for new item recommendations that preserves user privacy by keeping data on the server. The two-phase learning architecture allows the learning of two item representations, and the item presentation alignment mechanism maintains associations between item features and user preferences. The server uses attribute representations to deduce cold items. Extensive testing shows IFedRec outperforms state-of-the-art models, and its framework can be easily integrated with existing methods for exploring new scenarios like recommendation diversity and fairness.

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International Journal of Advanced Research in Science, Communication and Technology
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Volume 5, Issue 2, May 2025
Impact Factor: 7.67

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DOI: 10.48175/IJARSCT-26257