HGNN-ICFA: A Deep Learning-Based News Recommendation System Using Hybrid Graph Neural Networks and Improved Collaborative Filtering

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People rely increasingly on the internet to obtain news from a variety of sources due to the quick expansion of online information. However, this abundance leads to information overload, making it difficult for users to identify content that matches their interests. News Recommender Systems (NRS) aims to mitigate this issue by delivering personalized suggestions. An online data-mining, Deep Learning (DL)-based NRS is presented as a solution to the performance issues caused by ignoring user preferences in the recommendation process. This research proposes a hybrid architecture combining an Improved Collaborative Filtering Algorithm (ICFA) with a Hybrid Graph Neural Network (HGNN). The system module's core components are network function, database, user administration, and news recommendation. Experimental research was conducted using the News Click Behavior and Engagement Dataset from Kaggle, which contains user interaction logs including clicks, impressions, and engagement patterns across users and news articles. The data was preprocessed using normalization to scale features uniformly and enhance training stability. Additionally, Linear Discriminant Analysis (LDA) was employed for feature extraction to identify hidden topics within the news articles. The efficiency of the proposed model was evaluated based on ICFA-driven news recommendations tailored for both new and old users. The experimental findings show that the suggested method considerably enhances the metrics compared to the traditional methods on a practical dataset. The proposed model achieves 85.29% precision, 77.25% recall, and 81.87% F1 score, outperforming the robust baseline. These results confirm that the proposed HGNN-ICFA model delivers robust and personalized news recommendations across diverse user segments.

Povzetek: Predlagan je sistem HGNN-ICFA za priporočanje novic, ki združuje izboljšan algoritem skupnostnega filtriranja (ICFA) s hibridno grafično nevronsko mrežo (HGNN). Sistem rešuje problem preobremenitve z informacijami, saj upošteva časovno občutljivost in priljubljenost novic ter dinamične odnose med uporabniki in novicami.

1 Introduction

1.1 Background

The gathering of information techniques has undergone substantial modifications due to the internet's revolutionary impact on information transmission. People can access information more quickly and stay up to date with the news due to simultaneous improvements in smartphones and smart devices. Given the importance of news timeliness in today's Internet-driven environment, online news communication has become even more vital [1]. News recommendation systems (NRS) are a subject of interest in the field of recommendation algorithms. Newspapers, radio, and television were common means of suggestion before the internet. In the early days of the internet's growth, posting information on a prominent website, such as Yahoo, was the most common way to recommend anything [2]. As a result, it was urgently necessary to classify, mine, and send a lot of information to various users. Recommendation algorithms were created to deal with this online information overload issue. It effectively manages irrelevant information by filtering internet data, learning user preferences, and delivering comparable content to users. The mechanism and pace of information transmission have significantly changed due to the internet's ongoing development, which has greatly impacted how individuals obtain information. Smartphones and smart devices have expanded so swiftly, people might easily access news information. The news is useful because it is communicated in real-time, which is especially important given the development of the internet [3].

1.2 Personalization and challenges

Personalized and non-personalized recommendation systems were the two types. A non-customized recommendation system that provides the same suggestions to every user without considering their individual preferences. By adjusting recommendations according to each user's interests and preferences, the customized recommendation system would be able to accommodate thousands of users and their wide range of preferences. User clustering can also be used to put people with similar interests in one group. Individualized recommendations were frequently employed in numerous internet products and are extremely effective. Several research investigations have been conducted on NRS to increase their effectiveness in recommending news articles [4].

1.3 Enhancing collaborative filtering for personalization

Conventional recommendation systems face several limitations, such as the frosty beginning, limited information, missing concepts, and poor suggestion precision. To address these, the research explores a personalized news recommendation approach based on event ontology inspired by recent works that organize news items into event-based networks [5]. The news corpus and the news filtering structure were combined to form the event ontology. User browsing data was taken out with the intent to build a user interest model. While the user interest model identifies comparable user interests, occurring ontology's categorization structure determines the similarity between news events. The nonhierarchical event ontology structure's semantic radius was used to determine which news events were pertinent. Personalized news suggestions were produced by taking into account user interests, nonhierarchical structure, and event ontology commonalities. This method implements collaborative filtering techniques as well as content-based recommendation algorithms based on the results of this research. The drawback is that it might offer more irrelevant information because it disregards the user's particular choices. To address this issue, a second hybrid recommendation system that blends progressive collaborative filtering with latent semantic analysis was proposed. This method dynamically modifies the list of suggestions by progressively updating item similarities. The experimental findings demonstrate that the suggested algorithm outperforms traditional recommendation systems in a variety of assessment criteria. It does not give as much priority to brief news recommendations and has significant limits [6].

1.4 Deep learning-based hybrid framework

Use collaborative filtering to create a personalized NRS. The system comprises various modules that classify news, analyze user interests, cluster users, and produce recommendations. User ratings and item popularity were considered to improve the collaborative filtering algorithm. A DL-based hybrid recommendation system termed DNNRec effectively integrates collaborative and content-based filtering techniques with neural networks to increase recommendation accuracy and customization [7]. To suggest a new hybrid personalized news recommendation framework (HYPNER) for personalized news recommendations. For session-based news recommendations, researchers suggest a DL-based approach that incorporates context mixing and might make use of a variety of information kinds [8].

1.5 Objective

However, the main challenges were described in the NRS, and the cutting-edge solutions to address them. To overcome performance issues caused by neglecting user preferences, an online data-mining, deep-learning-based NRS is proposed. The NRS for news organizations is constructed using this method, which also forecasts subclass popularity and makes use of a hybrid graph neural network. The experimental results show how successful and advantageous the suggested strategies are.

1.6 Contribution of this research

- NRS was developed to address performance limitations in existing models by clearly integrating user preferences and reading behavior throughout the recommendation process.
- To capture evolving user interests and relational dynamics between users and news items, the system employs an HGNN. The model integrates user-item interaction data with temporal features and structural embeddings, allowing it to dynamically adapt to changing news consumption patterns.
- The proposed ICFA-HGNN-based method exhibits prominent improvements in the significant metrics when evaluated on a real-world dataset, outperforming multiple baseline models and confirming its capability to generate accurate and personalized news recommendations.

As online news grows exponentially, timely and personalized recommendations are the main challenge of contemporary news recommender systems (NRS). The conventional implementations of collaborative filtering do not engage in considerations of time and structure interplays between consumer finales and the news, which restrains its responses. HGNN based on ICFA was suggested in this research, which adds temporal-based as well as a popularity-based mechanism. The proposed model aims to enhance personalization and reflect the complex patterns of interaction between users and news.

The research explores the following research questions based on its objective.

RQ1: Does the capability of integrating HGNN into ICFA help improve recommendation accuracy and F1 score when compared to the usual collaborative filtering models?

RQ2: Does the inclusion of temporal and popularity-awareness mechanics into the ICFA improve the accuracy of the recommendations or their recalls?

Acronyms

NRS - News Recommender Systems

HGNN - Hybrid Graph Neural Network

GNN - Graph Neural Network

HYPNER - Hybrid Personalized News Recommendation Framework

DAN - Deep Attention Neural Network

RNNs - Recurrent Neural Networks

GCNs - Multiview Graph Convolutional Networks

NRMG - News Recommendation with Multiview Graph Convolutional Networks

LDA - Linear Discriminant Analysis

IUCFA - Improved User Collaborative Filtering Algorithm

KSR - Knowledge-based Sequential Recommendation

CF - Collaborative Filtering Algorithm

2 Literature survey

This section discusses the findings of several researchers, technical reports, and research papers. Other writers provide solutions to the issues raised by integrated and dispersed systems. To analyze the advanced progress of personalized recommendation systems, particularly in the context of application in collaborative filtering, the use of hybrid systems, and the incorporation of DL, the various techniques are compared. The implemented articles address the variability of methods, such as mobile-based recommendation, AI-based clustering, semantic analysis, or ensemble learning methods. Table 1 provides a comparative overview of this literature with respect to its objectives, methodology, outcomes, and limitations.

Table 1: Literature survey

Reference	Objective	Approach	Key Findings	Limitations
[9]	Enhance news personalization by considering temporal and taxonomic features.	Temporal dynamics + news taxonomy	Improved accuracy and user satisfaction by accounting for time-sensitive articles	Lacks adaptability to rapidly evolving news features
[10]	Boost user engagement through utility-based recommendations	Utility-based recommendation model	Significantly improved recommendation accuracy and handled new user scenarios.	Does not address filter bubbles or recommendation bias
[11]	Improve news variety and precision via topic relationships	Knowledge graphs using semantic/topic links	Outperformed standard methods with better diversity	Ignores user preferences and temporal relevance
[12]	Leverage deep attention for personalized recommendations	Deep Attention Neural Network (DAN)	Achieved higher accuracy by capturing relevant news parts	Scalability and deployment issues not addressed
[13]	Solve the cold-start problem using user history	Knowledge embedding + user behavior modeling	Successfully personalized cold-start recommendations	Scalability and system efficiency are not detailed
[14]	Combine long- and short-term interests in recommendations	Graph Neural Network (GNN)	GNN integration boosted recommendation precision	Limited to a single dataset; real-world

				generalizability untested
[15]	Explore political filter bubbles in NRS	Algorithm audit + user attitude modeling	Found increased polarization from personalized recommendations	Results context-dependent (region, user group)
[16]	Enhance hybrid recommendation accuracy	Personalized + content-based (TextCorpus)	Produced highly relevant personalized suggestions	Model specifics and scalability not fully explored
[17]	Improve recommendation precision through contextual modeling	RNN + session-based + content & CF hybrid	Captured sequential patterns, boosting personalization	Evaluation metrics might not reflect full user satisfaction
[18]	Capture user preference evolution in graph structure	Heterogeneous Graph Neural Network	Tracked dynamic interests and improved precision	Generalizability in real-world settings not validated
[19]	Improve personalization via complex relationship modeling	Graph Neural Network with user/news content	Enhanced effectiveness through deep structure learning	Dataset-specific results; applicability remains narrow
[20]	Increase precision using multiview representation	Multiview Graph Convolutional Network (NRMG)	Effectively modeled article dependencies; improved suggestions	Few user studies; real-world performance not tested
[21]	Detect fake news via classification	Ensemble ML with feature extraction	Achieved high classification accuracy	Focused on fake news, not a general recommendation
[22]	Personalize news via neural attention	Neural networks + attention mechanisms	Accurate and scalable recommendations	Lacks empirical proof for large-scale settings
[23]	Improve accuracy with multiple RS techniques	Hybrid RNN + CF + content + modified NRS	Effective and accurate recommendations with better interaction	Unclear performance on other types of recommendation
[24]	Personalize news via user-collaborative filtering	User behavior + CF	Personalized suggestions improved satisfaction	Limited scalability and computational cost concerns
[25]	Improve personalized news recommendation using an enhanced CF algorithm	Improved Collaborative Filtering with simulation	Enhanced recommendation accuracy and relevance by integrating user behavior patterns	Limited evaluation on dynamic user profiles and real-time adaptability
[26]	Improve generalization using meta-learning	Sequential meta-learning + RNN + CF	Delivered targeted recommendations with adaptability	Not easily applied to non-sequential domains
[27]	Personalized recommendations in tourism	Item–item & user–user CF, mobile app UI	High user satisfaction in live deployment	Lacks integration with content-based features or DL techniques

[28]	E-commerce personalized recommendation strategy	AI-enhanced CF with clustering and optimization	Improved clustering, better accuracy	Limited evaluation on small or diverse datasets; lacks time-awareness
[29]	Hybrid intelligent RS design	Meta-learning metaphor + hybrid ML	Demonstrates hybrid frameworks enhance personalization	A conceptual framework with minimal empirical benchmarking
[30]	Review usefulness prediction for recommendations	Semantic ML over reviews	Increases relevance of recommendations	Focuses on static textual features; lacks dynamic or user preference adaptation.
[31]	Mobile recommender integration in tourism	CF + UI architectural design	Effective real-time personalized suggestions	Limited scalability; no temporal or contextual modeling included

With these constraints, the proposed solution incorporates the combination of both ICFA and HGNN, performing multichannel solutions to simultaneously capture historical information on user interactions and their dynamic content relationships, while taking into consideration time-sensitivity and popularity biases in the recommendations.

3 Material and methods

This section presents the dataset for the NRS, preprocessing, and feature extraction. The collaborative filtering algorithm and hybrid graph neural network for the NRS were also discussed.

3.1 Dataset

The News Click Behavior and Engagement Dataset was collected from the open-source called Kaggle: https://www.kaggle.com/datasets/zoya77/news-click-behavior-and-engagement-dataset. This dataset records detailed user interactions with news material seen online. User demographics like age, gender, location, and access device are integrated with behavioral results like clicking on a news item. By connecting a user to a particular news story, each record reflects a singular interaction and enables the investigation of engagement trends. 3,000 records make up the dataset, which is balanced for predictive modeling tasks with a class distribution of 45% clicks and 55% non-clicks. It is shared by public and accurately depicts behavior in the actual world. This dataset is perfect for creating and evaluating recommendation systems since it includes moderate interaction sparsity and temporal activity spanning a year. Table 2 summarizes the description detail of the dataset.

Table 2: Dataset's description

Component	Purpose
User_Id	Used to uniquely identify users and build user profiles
Category_Id	Helps classify news for content filtering
Title	Provides textual content for semantic/news relevance modeling
Time	Captures user interaction time for temporal behavior analysis
Click	Indicates user interest and supports feedback learning
Click_Count	Measures engagement level for ranking and personalization

3.2 Preprocessing

Data Preprocessing involves transforming raw data into a clean and structured format suitable for model training. In this research, preprocessing ensures data consistency, removes noise, and scales feature values to enhance the performance and stability of the news recommendation model.

3.2.1 Min-Max normalization

A data preprocessing method called min-max normalization was applied to scale the values of a numerical dataset to a particular range, usually between 0 and 1. Ensuring all features are on the same scale is a typical practice in data preprocessing for machine learning and statistical analysis. When the dataset's features have varying ranges, this scaling was especially crucial because it aids in the accuracy and convergence of several machine learning methods.

The min-max normalization formula is as follows:

$$X_{normalization} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:

X was the data point's initial value.

$X_{normalization}$ was the normalized value of the data point.

X_{min} denotes the feature's dataset minimum value.

X_{max} represented the feature's greatest value in the dataset.

The minimum value of the feature must be subtracted from each data point before being divided by the range, which was the range's maximum and minimum values. After min-max normalization, the dataset's values can be scaled between 0 and 1. The formula can adjust in accordance if the initial values fall within a different desirable range (for example, between -1 and 1) by indicating the intended minimum and maximum values throughout the normalization procedure.

Although min-max normalization was a simple and widely used technique, some datasets might have better options. Depending on the properties of the data and the particular needs of the machine learning algorithm being used, various scaling strategies, such as Z-score normalization or resilient scaling could be more suitable in some circumstances.

3.3 Feature extraction

Feature extraction transforms unprocessed, highly dimensional data into representations in a lower dimension while preserving the most crucial aspects.

3.3.1 Linear discriminants analysis (LDA)

Machine learning and statistics use the dimensionality-reduction and classification technique known as linear discriminant analysis (LDA). It was especially helpful for resolving classification issues when the classes were clearly defined and evenly distributed. LDA's objective was to identify a linear combination of traits that maximizes class separation while minimizing variation in each category. The main aim of LDA was to preserve class-discriminatory information while projecting the original data onto a lower-dimensional space. This was accomplished by raising the ratio of the within-class scatter matrix to the between-class scatter matrix.

Let's step-by-step describe linear discriminant analysis (LDA) using equations:

Calculating the mean vectors:

Assume that there are C classes and that each class c contains data points. The average of all feature vectors in class c was estimated to be the mean vector for class c, which was denoted as m_c

$$m_c = \frac{1}{n_c} \sum_{X \in \, classc} X \quad (2)$$

Calculate the scatter matrix within the class (S_w).

The expansion or distribution of the data within every type is measured by the within-class scatter matrix S_w. It was calculated by adding the scattered values from each class individually. The covariance matrix of the data points in class c serves as the scatter matrix for that class. The equation for "S_w" is

$$S_w = \sum_{c=1}^{c} \sum_{X \in \, classc} (m_{c-m})(m_{c-m})^T \quad (3)$$

Calculate the S_b between-class scatter matrix:

The spread or distribution of the class mean values was determined using the between-class scatter matrix S_b. The difference between the overall mean across all data points and the class means was calculated using the weighted sum of the outer products. The equation for "S_b" is as follows:

$$S_{b=} \sum_{c=1}^{c} n_c (m_{c-m})(m_{c-m})^T \quad (4)$$

Where the total mean vector of all the data points in the dataset was represented by the average of all mc vectors divided by the sum of the data points in each class.

$$\mathrm{m} = \frac{1}{N} \sum_{c=1}^{c} n_c m_c \quad (5)$$

Determine the (S_w^{-1}, S_b) eigenvalues and eigenvectors.

The product (S_w^{-1}'S_b) was computed, which is the inverse of (S_w), denoted as (S_w^{-1}, S_b). The eigenvalues λ and related eigenvectors v of the product (S_w^{-1}'S_b) were discovered.

Determine the highest (k) eigenvectors:

Select the top k eigenvectors corresponding to the top k greatest eigenvalues by placing the eigenvalues λ in ascending order. These "k" eigenvectors would comprise the transformation matrix W, which can project the data into a lower-dimensional space.

Inject the information into the fresh subspace:

To create a new feature space with a lower dimensionality, multiply the original data X by a conversion matrix W generated in the previous step.

$$[X_{new}] = X \cdot W \quad (6)$$

Each data point in the transformed subspace was represented by a k-dimensional vector, where k is the number of chosen eigenvectors (dimensionality reduction). Because it makes it possible to identify a linear combination of features that maximizes the separation between classes while minimizing the variation in each category, linear discriminant analysis is useful for classification and dimensionality reduction issues.

3.4 Collaborative filtering algorithm (CF)

The CF method primarily leverages behavioral similarity to determine interest-related similarity. Given two users, t and s, equation (7) is used to determine how much their interests are similar. $M(t)$ stands for the News Set (NS)that user s has read as well as $M(s)$ stands for the NS that user t has searched.

$$W_{ts} = \frac{|M(t) \cap M(s)|}{\sqrt{|M(t)||M(s)|}} \quad (7)$$

User s has read news items c and a, while User t has read items d, b, and a. The similarity between user'st and s was calculated using formula (7), and W_{ts} might be rebuilt using the news firms$d, b, and\ a$, which were represented in the formula below:

$$W_{ts} = \frac{|\{d,b,a\} \cap \{c,a\}|}{\sqrt{|\{d,b,a\}|.\{c,a\}|}} \quad (8)$$

3.5 improved collaborative filtering algorithm (ICFA) with hybrid graph neural network (HGNN)

The hybrid model provided the integration of ICFA and HGNN to use the history of interaction between the user and the item, as well as all relations in the news graph. The initial accuracy of recommendation is improved because ICFA has captured personalized user preference using collaborative similarity. HGNN improves these recommendations through modeling the linkages between users and news articles. This hybrid design enhances individualization, adaptability and prediction stability around user behaviors that are dynamic in nature. Figure 1 visually represents the integration of the hybrid model.

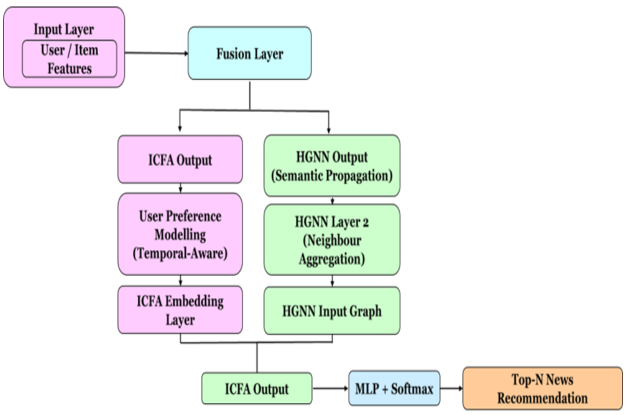

Figure 1: Graphical illustration of the CF and GNN integration model.

3.5.1 Improved collaborative filtering algorithm (ICFA)

The user's reading history can lead to limited predictive power because news recommendations have a substantial timeliness component. The similarity formula was modified based on the attributes of news suggestions. The result of breaking news and news understanding duration on resemblance was also measured. The Harry Potter effect was avoided by downgrading the popular news to penalize its impact on the similarity between users s and t's common interests list. The time attenuation factor is taken into account in the calculation formula to avoid the similarity between users t and s who enjoy news from becoming too tiny over a predetermined time. Equation (7) solely takes into account the user's reading history, not the amount of time spent reading. The following procedure shows how equation (9) was enhanced by taking into account the qualities of news recommendation:

$$\frac{\sum_{j \in M(t) \cap M(s)} n^*(To-Tc/To-Ta) + (1-n)1/1+M(j)}{\sqrt{|M(t)||M(s)|}} \quad (9)$$

Where M(t) denotes the reading set of user t, M(s) denotes the reading set of user s, and M(j) is the recurrence count of news item j. Torepresent the current time,Tc is the time the user consumed the news article, and Ta is the publication time of the article. This formulation ensures that the time attenuation factor reflects the freshness of the user's interaction relative to the article's age, giving higher weight to recent interactions with recently published content. To reduce the overexposure of frequently recommended items, highly popular news articles were penalized by applying an inverse popularity weighting: $1/1 + M(j)$. This encourages recommendation diversity and promotes less-viewed content. The variables considered in the recommendation process, the larger the value of n, ranging from 0 to 1, balances time sensitivity and popularity. To reduce popularity bias, n is selected to highlight temporal recency, ensuring that less frequently consumed but more recent articles remain highly ranked in similarity assessments.

i. Flow of algorithm

After determining how similarity between two users, the user-based CF algorithm offers k articles that the target user hasn't read but those similar users have shown interested in. The user CF algorithm uses a formula (10) to determine the demand of user s in news j:

$$p(j,s) = \sum_{S \in v(k,u) \cap M(j)} W_{bu} R_{it} \quad (10)$$

Where M(j) denotes the user set that has read news j, $S \in v(k,u)$ denotes the k NN sets that were most likely to the user's demand, and User s has read news item j, and R_{it} is 1. W_{bu} indicates the interesting relationship among user s as well as user s, which might be determined using the formula (9). R_{it}indicates the user's news predilection level or attain. The news that user s has not previously read is recommended. The user demand in the news algorithm was explained as follows.

Algorithm: Improved Collaborative Algorithm (ICFA)

Step 1: To find the k nearest neighbor sets S (k, u) that most closely match the user u's interests, sort all W_{vu} .

Step 2: Identify the news items $M(j)$ recently viewed by users in $S(k,u)$.

Step 3: For each neighbor v in $S(k,u)$, compute the predicted interest score $P(i,u)$ for user u and news item i using: Let R_{iv} denote user v's interest level in news i. Multiply R_{iv} by the similarity weight W_{bu} to represent how much neighbor v influences the prediction for u.

Step 4: Initialize $P(i,u) = 0$. Then update it as:$P(i,u) = P\ (i,u) + W_{vu} * R_{iv}, sort\ P(i,u)$to determine the news that k of your neighboursbethe bulk enthusiastic about as well asadvise user u.

A new user can select from a variety of interest categories when signing up. These groups were shown vigorously using word segmentation outcomes from news items in the record, which were not static. The elements of the website's back end that users would probably be interested in are displayed before their selections. This recommendation method's main objective is to address the cold start problem. Tag recommendations are used to solve the issue when the recommendation system lacks the data required for recommendation analysis before the recommendation data are formed. The news headlines are read again. Figure 2 illustrates the recommendation procedure.

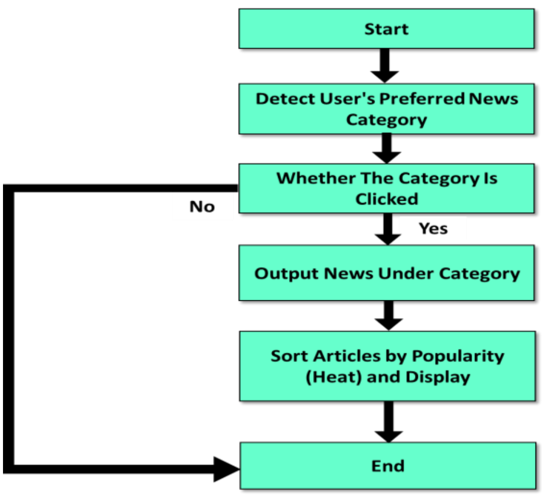

Figure 2: User interaction flow for category-based news selection

ii. Cold start handling

An interest initialization mechanism using tags was applied during the registration phase to determine the recommendation process for incoming users. The categories of interest extracted were dynamic and based on the segmentation of keywords in the current news headlines. Using their choice of preferences, the system constructs the initial profile of a user and provides the appropriate content about news even in the absence of past interactions. This enables the recommender engine to make meaningful suggestions based on the initial session, whereas collaborative filtering slowly gains traction cumulatively with the user activity. The synergistic approach is a proper remedy against the cold-start problem and improves the initial user involvement.

3.5.2 Hybrid graph neural network

A Hybrid Graph Neural Network (HGNN) can be a powerful tool for building a news recommendation engine when the relationships between news articles and viewers can be visualized as a graph. Each node in this system corresponds to a news story or a person, and the edges between nodes record any interactions or connections between them. The HGNN learns to propagate information around the network, enabling it to provide users with individualized recommendations based on their tastes and the relationships between articles.

There are two primary parts to the hybrid GNN. Collaborative Filtering (CF) Component and Graph Neural Network (GNN) Component. The CF method was discussed earlier.

To construct the collaborative filtering embedding V_{CF}, a user-specific embedding vector was computed based on the top-k weighted news items the user has interacted with. These interaction scores $p(i,u)$are used to form a weighted sum of item embeddings:

$$V_{CF}(u) = \sum_{i\epsilon N_u} p(i,u)\, .\, e_i \quad (11)$$

Where N_u is the set of top-k news items rated or clicked by user u, $p(i,u)$ is the predicted interest score from ICFA, and $e_i \in R_d$ is a learnable embedding for item iii. This produces a dense user embedding that can be concatenated with v_{GNN}(u) for final prediction.

The HGNN component improves the starting recommendations from the CF component by utilizing the graph structure and extra node and edge information. Through message transmission and aggregation processes, the GNN updates node representations iteratively. A standard GNN update operation at iteration $t+1$ is expressed as:

$$v_{GNN}^{(t+1)} = \sigma\left(W.AGGREGATE\left(\left\{v_{GNN}^{(t)}\right\} \cup \{v_{CF}\}\right)\right)$$

$v_{GNN}^{(t)}$- Provides the node embeddings for the GNN component at iteration t.

σ- An activation function applied element-by-element to the output, similar to ReLU or Sigmoid.

W– A weight matrix that might be learned to alter the combined representations.

$AGGREGATE$– A function aggregating the node embeddings from the most recent iteration$v_{GNN}^{(t)}$ and CF. components.

The GNN component repeats multiple iterations of the update procedure to gather higher-order dependencies in the graph. The final recommendation was the CF and GNN components are combined, typically by concatenation or element-wise addition, to produce the final recommendation embeddings v_{rec}.

$$v_{rec} = CONCATENATE\left(v_{CF}, v_{GNN}^{(T)}\right) \qquad (13)$$

The total count of GNN iterations, in this case, is T.The hybrid graph neural network technique efficiently captures complicated graph interactions with the GNN component and user preferences with the CF component. This makes it possible for the algorithm to provide users with news recommendations that are more precise and engaging. The model is trained from beginning to end using the proper loss functions and optimization approaches on a sizable dataset of user interactions and news items.

The HGNN used has two Graph Convolutional Network (GCN) layers that comprise 128 hidden units each. Between every GCN layer, the model applies the ReLU activation function to perform non-linearity. A mean aggregation strategy is used to aggregate the neighborhood. To avoid overfitting, the dropout of 0.5 between layers is used. The results of the two branches, the collaborative filtering branch and the GNN branch are concatenated into the final layer, which is fully connected. The recommendation scores are subsequently returned.

4 Result

The effectiveness of the suggested and current methods was assessed in this section. The parameters were accuracy, precision, recall, and F1 score. IUCFA [22], Hybrid Recommendation comprising content-based recommendation algorithm and collaborative filtering [23], KSR [32] and the proposed ICFA-HGNN method. were existing processes. This experimental setup was explicitly intended to test hypotheses H1 and H2 by comparing the proposed model against traditional and state-of-the-art baselines across several evaluation metrics.

4.1 Experimental setup

The proposed approach was executed in a python to analyze the user based NRS. All baseline models and the proposed HGNN model were trained and compared on the same validation to guarantee that there were no unfair comparisons of the models. The hyperparameter optimization was accomplished with grid search by using validation accuracy. The final settings are given in Table 3. A Similar software was used to implement all the models and compute them in similar conditions.

Table 3: Hyperparameter summary table

Model	Learning Rate	Batch Size	Hidden Layers	Other Parameters
IUCFA [22]	0.01	64	—	Similarity metric: cosine
Hybrid Recommendation [23]	0.005	64	—	Combines content + CF
KSR [32]	0.001	64	2 layers, attention mechanism	Embedding dim = 128, sequential encoder used
ICFA-HGNN (Proposed)	0.001	64	2 layers, 128 units	Dropout = 0.5, GCN layers = 2

The evaluation data portions were same for all the models to provide an impartial comparison. Hyperparameters are optimized either with a grid search on the validation set or the values taken from original publications. Such a configuration allows duplicating the result and maintaining a steady assessment.

4.2 Model efficiency and scalability

To assess real-time responsiveness in the proposed ICFA-HGNN-based NRS, latency between article publication and user interaction was estimated. Since the dataset lacked clear click timestamps, simulated click delays were presented by applying randomized time offsets to the publish time of clicked articles. This simulation approaches real-world user interaction behavior in time-sensitive recommendation scenarios. The resulting distribution delivers insight into the system's aptness for handling engagement latency in practical applications. Figure 3 represents the graphical representation of latency distribution.

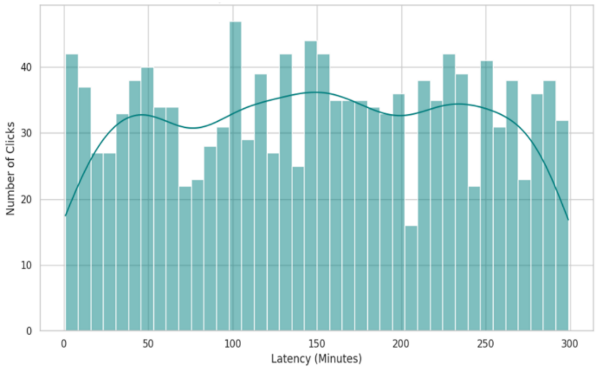

Figure 3: Simulated latency distribution showing the number of user clicks relative to time delay

Empirical results show that most engagements within user-generated sources are within 30-270 minutes of the publication of the articles, hence validating prior theories of delays in content consumption. This temporal dynamic makes it possible to exert influence on recommendation systems nearly in real time. Despite its internally demonstrated robustness, the system scaling to populations of millions of users and articles require optimization efforts, including graph processing distributed over nodes to maintain inference latency.

4.3 Evaluation metric analysis

The effectiveness of the proposed technique conceptual model was evaluated based on three predetermined evaluation measures, including Precision, Recall, and F1-score. The combination of these metrics brings a depiction of the potential of the model in terms of proposing the most significant news articles, as well as the user preferences. Table 4 presents a comparative analysis of the metrics across the various methods.

Table 4: Performance comparison of the metrics over methods.

Metrics	**Precision**	**Recall**	**F1-score**
IUCFA [22]	80.02	70.05	73.05
Hybrid Recommendation [23]	84.25	76.71	80.30
ICFA-HGNN [proposed]	85.29	77.25	81.87

To better visualize the comparative performance, Figure 4 illustrates the model-wise differences across the three metrics. The proposed ICFA-HGNN model consistently outperforms the baselines in all categories, particularly in the F1-score, indicating a better balance between Precision and Recall.

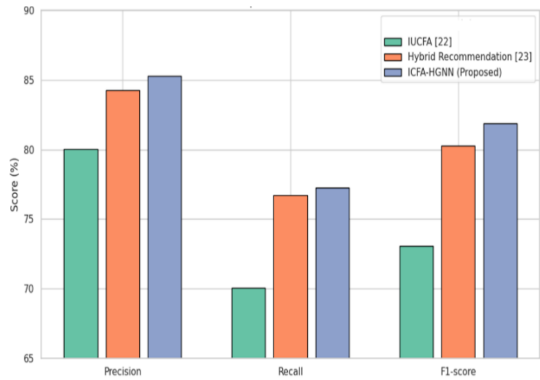

Figure 4: Visual representation of the key metrics over various techniques

As shown in Figure 4, the proposed ICFA-HGNN achieves the highest Precision (85.29%), Recall (77.25%), and F1-score (81.87%) among the models evaluated. These improvements validate the hybrid model's capability to capture complex user-news interactions while minimizing false positives and negatives. The increase in F1-score reflects a more robust and balanced recommendation quality, making the system more suitable for real-world news delivery scenarios.

4.4 Mean squared error (MSE)

To evaluate the predictive performance of the recommendation models, Mean Squared Error (MSE) was used as an error-based metric. MSE reflects the average of the squares of the errors between predicted and actual relevance scores. Lower MSE values indicate better model precision in capturing user preferences. Table 5 summarizes the MSE scores of the baseline KSR [32] and the proposed ICFA-HGNN model.

Table 5: Error-based performance comparison of the methods**.**

Metrics	**MSE**
KSR [32]	0.2406
ICFA-HGNN [proposed]	0.2387

The MSE values shown in Table 5 are further visualized in Figure 5 to highlight the difference between the baseline and proposed methods. Each model is represented with a distinct color for clarity. The slight drop in MSE achieved by the proposed ICFA-HGNN indicates better accuracy in predicting user-item relevance.

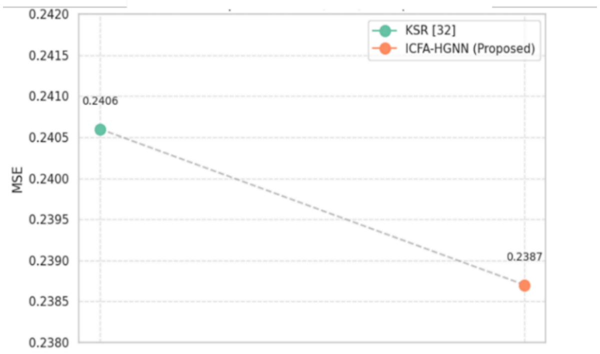

Figure 5: Graphical representation of MSE comparison

The graph in Figure 5 illustrates that the ICFA-HGNN model yields a lower MSE than the KSR baseline. This suggests that the hybrid graph-based approach provides a more accurate prediction of user preferences. While the improvement might appear small numerically, such reductions are impactful in large-scale recommender systems, where minor gains can translate to significant improvements in user experience.

4.5 Comparative evaluation of cold-start handling in user-based news recommendation systems

Personalized content delivery is facing a serious issue of controlling cold-start problems, i.e., NRS cannot effectively apply the recommendations to first-time users. This section involves comparative research of two collaborative filtering algorithms, the traditional CFA as well as the proposed ICFA. The proposed approach combines improved feature mapping and user profiling techniques that aim to generalize on unobserved users' data. The merits of the model efficiency in both old and new user groups are examined with the help of such performance measures as accuracy, precision, recall, and F1-score. In this examination, it is noted that ICFA can address the cold-start problem and ensure good performance among existing users. Table 6 represents a comparison of methods based on user recommendations. Figure 6 depicts the visual representation of the user-based performance.

Table 6: Performance metrics of CFA and ICFA for old and new users

User Type/Method	**Old User**		**New User**	
	CFA	**ICFA**	**CFA**	**ICFA**
Accuracy	85.3	91.6	78.7	82.4
Precision	83.2	90.2	76.5	84.1
Recall	82.5	89.4	75.9	80.8
F1-Score	83.9	87.9	79.8	83.8

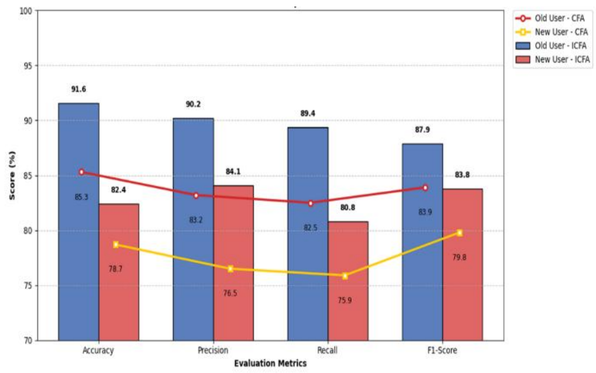

Figure 6: Bar-Line Comparison for Cold-start and existing users

4.6 Sensitivity analysis on time decay factor (n)

To assess the effect of the time decay factor n in Equation 9, ICFA was evaluated under varying values of n = {0.2, 0.4, 0.6, 0.8, 1.0} while keeping other parameters fixed. As shown in Table 7, performance peaked around n = 0.6, balancing the recency and popularity aspects effectively. Extremely low or high values of n degraded performance due to under-weighting or over-weighting temporal freshness. Figure 7 indicates the influence of the parameter n on the CC of the ICFA- HGNN model regarding the varying values of this parameter.

Table 7: Effect of different n values on HGNN-ICFA performance metrics

n Value	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
0.2	90.1	66.5	68.2	71.2
0.4	91.3	68.1	70.4	72.6
0.6	92.8	70.2	71.5	74.5
0.8	91.6	68.5	69.2	72.1
1.0	90.9	67.2	68.0	70.5

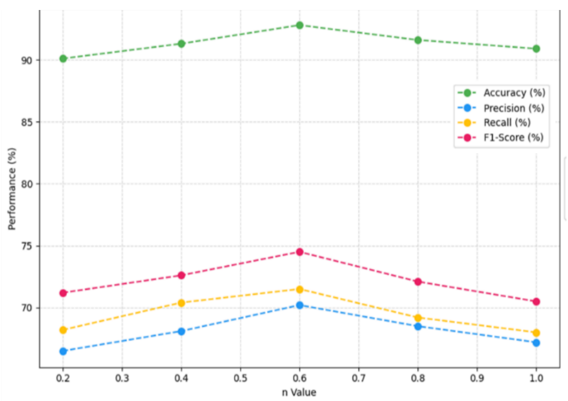

Figure 7: Graphical representation of the impact of n value on key metrics.

As represented in the above figure, the maximum F1 and accuracy are recorded at n = 0.6, which means the best balance between precision and recall. The performance declines a little after this, indicating overfitting to the max, efficiency diminishing, or some combination. It is shown in these trends that n should be tuned to be maximally effective in the model.

4.7 Statistical validation of ICFA-HGNN model performance

To ensure the robustness and consistency of the proposed HGNN-ICFA model, five independent runs were conducted using different random seeds. The key evaluation metrics were evaluated for each run. The results were then averaged, and standard deviations (SD) were calculated. This statistical reporting provides insight into the model's stability and reliability. Table 8 summarizes the mean and SD for each performance metric.

Table 8: Performance of proposed HGNN-ICFA model (5 runs)

Metric	**ICFA-HGNN (Mean ± SD)**
Accuracy (%)	96.00 ± 0.35
Precision (%)	85.29 ± 0.42
Recall (%)	77.25 ± 0.50
F1-Score (%)	81.87 ± 0.39

The recurrent runs were conducted to evaluate the consistency of the model under different initialization conditions. A paired t-test was applied to assess the statistical significance of the improvements observed over baseline methods. This analysis confirms that the reported gains are not due to random variation. The low standard deviations further demonstrate the reliability of the ICFA-HGNN model across runs.

5 Discussion

The development of NRS should adjust to fulfill the requirements of the changing digital news environment through accurate scale, personalization, and adaptability. The proposed ICFA-HGNN-based NRS proves to be more efficient since it incorporates structural embedding with collaborative filtering successfully. While HGNN captures high-order semantic relationships between users and news articles, enabling deeper contextual understanding, the ICFA component enhances personalization by modeling both short- and long-term user preferences, including effective handling of cold-start scenarios. These modules enable a system that delivers consistently high performance across key evaluation metrics. The results of the proposed model consistently outperformed baselines and exposed higher values with temporal-aware collaborative filtering enhancements. The user interest model also makes the recommendations more personalized by being dynamically connected to the changing user behavior. Moreover, the dynamic interest modeling capability of ICFA makes the recommendations responsive to evolving user behavior. However, a notable limitation lies in the computational complexity introduced by HGNN, which might affect scalability in real-time or large-scale deployments.

6 Conclusion

Deep Learning is used in this research to design a NRS based on data mining. It was presented to address the issue of personalized demand, which contributes to the underwhelming performance of NRS. The functionality of this structure must satisfy the needs for acquiring and storing news data, documenting user behavior, displaying news material, etc. The experimental findings demonstrate the proposed method was greatly effective and had several benefits. Our method, based on ICFA-HGNN, has demonstrated strong experimental performance. However, with the rapid advancements in DL, future enhancements can further improve scalability and personalization in NRS. The outcomes demonstrate that the ICFA-HGNN methodology performed better in the NRS than cutting-edge methods. The value of performance metrics of precision is 85.29%, recall is 77.25%, and F1 score is 81.87%. This technique helps to design a NRS effectively. Due to the complexity of DL models, the NRS might experience issues with high computing requirements, possible overfitting to user behaviors, and problems in explaining recommendations. Future research could focus on improving the system's computing efficiency, integrating interpretability techniques to increase transparency, and implementing hybrid systems that combine DL with various recommendation techniques.

Ethical consideration

All datasets used in this study, including those sourced from Kaggle (any open source mentioned in manuscript), are publicly available and come with licenses that grant permission for research use.

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