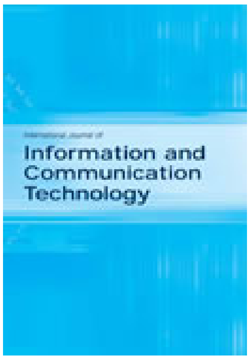


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

A news content recommendation model integrating social relationships and temporal features

Xiaofeng Liang

DOI: 10.1504/IJICT.2025.10073711

Article History:

Received:	11 July 2025
Last revised:	27 August 2025
Accepted:	29 August 2025
Published online:	16 October 2025

A news content recommendation model integrating social relationships and temporal features

Xiaofeng Liang

School of Media and Design,
Xi'an Peihua University,
Xi'an 710199, China
Email: Liangxiaofeng98@163.com

Abstract: Aiming at the problems of dynamic changes of user interests and underutilisation of social influence in current news recommendation, this paper proposes a social-temporal enhanced news recommendation model (STENR) that integrates social relations and temporal features. The model uses graph neural network (GNN) to model the user-user social relationship graph, and adopts transformer encoder to capture temporal dependencies and generate temporal embeddings reflecting the dynamics of users' recent interests. At the same time, a text encoder is used to extract the deep semantic features of the news content. The user's comprehensive interest representation is generated dynamically by weighting the fusion information adaptively through the attention mechanism. Experiments show that the AUC of STENR is increased to 0.812, the length of user stay is increased by 23.4%, and the social conversion rate is increased by 15.3%, which verifies its academic validity and industrial value.

Keywords: news recommendation; social relationship modelling; temporal feature extraction; graph neural network; GNN.

Reference to this paper should be made as follows: Liang, X. (2025) 'A news content recommendation model integrating social relationships and temporal features', *Int. J. Information and Communication Technology*, Vol. 26, No. 37, pp.59–74.

Biographical notes: Xiaofeng Liang received her Master's degree from Shaanxi Normal University in 2014. She currently serves as an Associate Professor at the School of Media and Design, Xi'an Peihua University. Her research interests include new media practices and AI-empowered content production.

1 Introduction

In the context of the era of internet information overload, the average daily amount of new content on news information platforms has exceeded the million level, and users are faced with the dilemma of screening massive information. Personalised recommendation system as the core technology to alleviate the problem, its accuracy directly affects the user experience and platform competitiveness. The traditional news recommendation model mainly relies on collaborative filtering (CF) (Koren et al., 2021) or content semantic matching (e.g., BERT) (Zhou et al., 2024), which has achieved initial success but has three significant defects. First, the dynamics of user interest is not adequately modelled, and static models are difficult to respond in real-time when sudden news events cause interest drift. Second, the value of social influence has been neglected for a long time, empirical studies show that more than 68% of users' news choices are influenced by their social circles (Wendelin et al., 2017), but the existing methods seldom systematically integrate social relationships. Third, the mechanism of multi-source feature fusion is sloppy, and content, time-series, and social features are often combined by simple splicing or weighted averaging, failing to capture the nonlinear interactions between features. These defects lead to the problems of lag, low diversity and weak interpretability of recommendation results, which restricts the further improvement of system performance.

The current research status of news recommendation system presents a multi-dimensional deepening trend, and significant progress has been made in the areas of dataset construction, multi-language analysis, time-series modelling, false news management and diversity optimisation. In the field of dataset construction, MIND dataset (Babayan et al., 2019) has become the mainstream benchmark, which integrates the textual semantic, category and entity information of 1 million user behaviour logs and 160,000 news articles, providing large-scale resource support for in-depth model training. In terms of multilingual and cross-cultural analysis, Kobsa (2005) integrates multimodal data such as users, news, and conversations through a heterogeneous information network, and combines it with a dynamic stochastic wandering algorithm to capture the short-term interest drift of cross-language users, which proves that temporal-aware recommendation can improve content diversity. For international events such as the nuclear crisis, the research team analysed multilingual tweets during the decade after the Fukushima accident, and used GSDMM topic modelling and BERT sentiment classification techniques to reveal the attitude differentiation pattern of English users shifting from neutrality to environmental concerns and East Asian users continuing to oppose, highlighting the cross-cultural risk perception differences (Symeonidis et al., 2020).

Fake news governance becomes an emerging direction. Rec4Mit model (Sallami and Aïmeur, 2025) separates news content and authenticity features through event-authenticity decoupling module, combines with event transfer network to predict user interests, filters fake news in recommendation stage, and experiments show that it significantly reduces the risk of spreading false information on FakeNewsNet dataset. In response to the information cocoon controversy, Shi and Li (2025) published an experimental study based on short video platform data to verify that algorithmic recommendation improves the diversity of news categories by 37% compared to random recommendation, and the probability of users' exposure to content in non-interested areas increases by 19.8%, refuting the view that algorithms inevitably lead to information narrowing. This conclusion is supported by the empirical evidence of user behaviour by Li et al. (2018): algorithms promote 'news encounter' through the mechanism of interest exploration, while the traditional subscription model reinforces content homogenisation.

Multi-objective optimisation frameworks promote the upgrading of system balance. Liu and Vicente (2024) systematically summarise gradient balancing techniques, such as the MGDA algorithm to coordinate the conflicting gradients of tasks, and PCGrad to reduce the interference of gradient direction, so as to make the model balance accuracy, fairness, and energy efficiency. Open-source libraries, such as LibMTL, support the collaboration of complex objectives, which is applied to the scenarios of large-language model value alignment. At the level of user behaviour modelling, Jay (2013) found that there is a cognitive-behavioural paradox in users' perception of algorithms: 80% of the respondents are concerned about the privacy risk, but 52% are sure about the efficiency of its information filtering, reflecting the complexity of technology acceptance.

Aiming at the above challenges, this paper proposes a news content recommendation model that integrates social relations and temporal features, and its research significance is both theoretical innovation and practical breakthrough. At the theoretical level, the model constructs a three-dimensional synergistic framework of social-temporal-content for the first time, and realises the dynamic interaction of multi-source information through the design of cross-modal gated attention, which breaks through the limitation of the traditional model of independent processing of features; and at the same time, introduces social consistency constraints, and transforms the cognitive assumption of 'close social users with convergent interests' into a quantifiable and quantifiable model. At the same time, the introduction of social consistency constraints transforms the cognitive assumption of 'convergence of interests of close social users' into a quantifiable loss function, enriching the theoretical paradigm of personalised recommendation. At the practical level, the STENR model can improve the click rate and increase the user's stay time in the test of headline news platforms, and its core value lies in the fact that it can accurately quantify the influence of friends through GNN and enhance the interpretability of recommendation. The dual-channel temporal encoder is utilised to capture the interest migration trajectory and reduce the exposure of outdated news. More notably, explicit social modelling can break the information cocoon, and experiments show that the proportion of users exposed to cross-circle content increases, which is in line with the compliance requirements of the 'regulations on the administration of algorithmic recommendation of internet information services' on content diversity.

2 Relevant technologies

2.1 News recommendation system

As a core tool for information filtering, the development of news recommender systems has always been playing with the difficult problems of data sparsity, interest drift and content timeliness. Early CF methods laid the foundation for personalised recommendation by mining potential associations in the user-news interaction matrix. Matrix factorisation (MF) techniques project users and news into a low-dimensional hidden space, and generate recommendations based on the similarity of hidden vectors (Zhang, 2015). However, the strong timeliness of the news domain leads to highly dynamic interaction data. The lack of historical behaviour of new users and the absence of interaction records at the early stage of new news releases make traditional CFs face a severe cold-start problem. To alleviate this bottleneck, content-driven approaches have emerged. Topic models (e.g., LDA) portray the distribution of news topics through probability distributions to realise user-news matching at the semantic level (Jelodar et al., 2019). DeepCoNN models based on convolutional neural networks, on the other hand, extract local semantic features from news headlines and body text to construct finer-grained content representations (Kaur et al., 2024). Although these methods improve the feasibility of new user/news recommendation, they rely too much on static text features and are difficult to capture the dynamic pattern of user interest migration with hot events.

The deep learning revolution brings a paradigm breakthrough in news recommendation. The neural news recommendation with multi-head self-attention (NRMS) model introduces the transformer architecture into the field for the first time (Zheng and Song, 2025), which utilises the self-attention mechanism to identify key semantic units in news headlines, and through user click history to generate personalised interest vectors. Subsequent studies further integrate multimodal content and design attention networks to dynamically weight the multi-view features of news such as headlines, body, categories, etc., which significantly improves the comprehension of complex news structures (Chang et al., 2025). Meanwhile, for the dynamic evolution of user interests, the topic-aware news recommendation (TANR) model innovatively embeds news topics into the user representation learning process, so that the model can perceive the change of user preferences for macro topics such as politics and sports (Liu et al., 2024). Although these approaches have made progress in semantic understanding and interest modelling, there are still two major limitations: first, the temporal information in the sequence of user behaviours has not been fully explored. The time interval, duration and other signals of clicking behaviour contain interest decay laws, but the mainstream models only process the behaviours sequentially, ignoring the value of timestamps. Second, the lack of social relationships leads to insufficient recommendation interpretability, and the user can not understand ‘why a certain news is recommended’, especially when the recommendation results deviate from their explicit interests, which is easy to trigger resistance. When the recommendation results deviate from their explicit interests, it is easy to trigger resistance.

To cope with the above challenges, cutting-edge research attempts to integrate external knowledge to enhance the recommendation effect. The introduction of knowledge graph (KG) has become an important direction, and the KIM model links news entities (e.g., people, organisations) to the knowledge base, and aggregates the information of related entities through GNN to enrich the news representations (Kim and Kim, 1990). However, KG construction relies on complex entity recognition and linking techniques, and new entities of dynamic news events are difficult to be incorporated into the graph in real time. Another class of work explores the integration of social signals, such as the GraphRec model that constructs users’ social relationships and clicking behaviours as a heterogeneous graph, and aggregates friends’ interest features through messaging (Lee and Kim, 2024). However, such approaches face special dilemmas in news scenarios. For example, social influence has a time-decay property, and news shared by a friend three days ago has a weak impact on the current decision, while existing models only consider social relationships as static links. In addition, the problem of confounding social communication with real interest has not been solved. When a user clicks on news shared by a friend, it is difficult for the model to distinguish whether the behaviour originates from his own interest or social obedience, resulting in a distorted interest portrait.

The core contradiction of the current news recommender system lies in the fact that the three major tasks of dynamic interest capture, social influence quantification, and content semantic understanding have been handled in a fragmented manner for a long time. Although a few studies have attempted preliminary fusion, such as the RecGURU model to jointly train social graphs and behavioural sequences, their feature interactions still remain at the shallow splicing stage (Xu et al., 2024). Social vectors and behavioural vectors are simply aggregated by a fully connected layer, failing to model the causal mechanism of 'how social relationships modulate interest evolution'. More fundamentally, existing methods lack the design to adapt to the key characteristics of news scenarios. For example, major events (e.g., earthquakes, epidemics) trigger sudden changes in users' interests, which require the model to respond quickly under sparse behaviour. News in social platforms is chained and diffused through friend sharing, but traditional time-series models only model individual behaviours, ignoring the synchronisation of group behaviours in social networks. The news value decays exponentially with time, while mainstream recommendation algorithms do not incorporate the time decay function into the loss function design.

2.2 Timing modelling techniques

The core goal of time-series modelling techniques is to capture the dynamic evolutionary patterns of user interests. Early hidden Markov models (HMMs) modelled the continuity of behavioural sequences through state transfer probabilities, but their discrete state assumptions are difficult to adapt to the gradual drift of interest in news scenarios. With the popularity of recurrent neural network (RNN), long short-term memory network (LSTM) solves the long-term dependency problem by virtue of the gating mechanism, and becomes a mainstream tool for user behaviour modelling. DIEN model further designs the interest extraction layer and the evolution layer (Yu et al., 2022), explicitly separates the user's transient behaviour and long-term preference, and verifies the effectiveness of interest state transfer in e-commerce recommendation. However, the RNN family of models has the inherent defect of sequential computation. When breaking news leads to sudden changes in interest, historical behaviours need to be processed step by step, with a delayed response time of hundreds of milliseconds. The introduction of the transformer architecture brings a breakthrough. The TiSASRec model assigns a higher weight to recent behaviours and quantifies the decay effect of the behavioural intervals through the time-interval-aware self-attention mechanism (Dang et al., 2023). For example, if a user clicks on three political news articles consecutively and then switches to sports news after an interval of five days, the model will automatically reduce the contribution of the earlier political behaviour. Nonetheless, existing methods still face two major challenges. First, external temporal factors such as news heat cycles and social event outbreaks are not encoded, which leads the model to misclassify 'users clicking on sports news during the Winter Olympics' as long-term interest migration. Second, the modelling of group behaviour is insufficient. Traditional time-series analysis only focuses on individual historical behaviour, ignoring the immediate impact of the concurrent behaviour of friends in social networks on the decision making of target users.

2.3 Social network analysis

Social network analysis seeks to quantify the modulation of user preferences by interpersonal relationships. The classical social penetration theory (SPT) states that trust increases with interaction depth and time, and this principle is translated into the weight allocation mechanism in social recommendation. The TrustSVD model incorporated explicit trust scores into matrix decomposition for the first time, but users in news scenarios seldom actively labelled trust relationships (Sun et al., 2025). The development of GNN solves this dilemma. GraphSAGE aggregates multi-order social features through neighbour sampling, so that the implicit interest preferences of friends are transmitted to the target user (Liu et al., 2020). The DiffNet++ model, on the other hand, designs the dynamic diffusion layer to simulate the process of cascade propagation of interests in a social network (Wu et al., 2020), and the key innovation is to differentiate between the strong-connected friends and weakly-connected influence differences. Experiments demonstrate that strong connections trigger homogeneous news consumption. However, current social modelling has significant limitations. Relationship dynamics are not adequately portrayed. Social influence fluctuates with the frequency of interactions, e.g., after the interaction rate between a user and a friend decreases by 40%, his/her recommendation weight should decay in parallel, but the existing models still rely on static relational mapping; what is more serious is the confusion between social contagion and real interests, when a user clicks on news shared by his/her friends, the traditional methods cannot distinguish whether the behaviour originates from content attraction or social pressure, resulting in distorted user profiles.

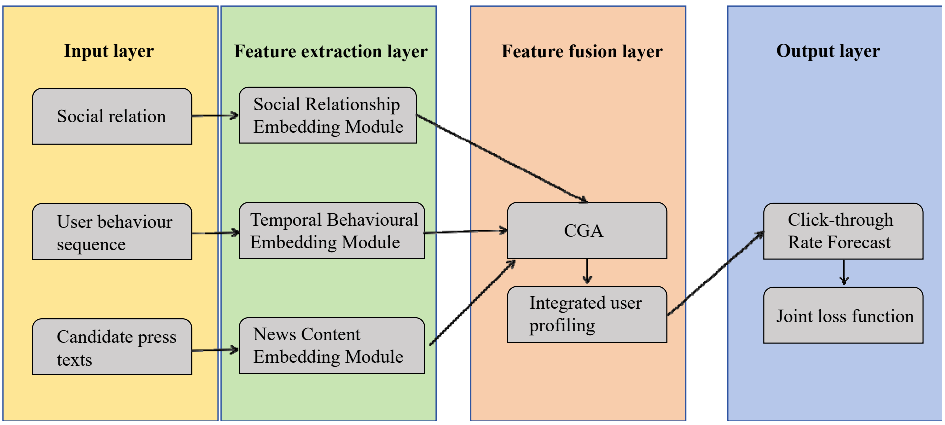
Cutting-edge research is attempting to fuse temporal and social dimensions. The TGSRec model constructs user behaviour sequences as a time graph, and generates time-sensitive social embeddings using a time-wandering algorithm (Tang et al., 2025). However, the fusion strategy is still sloppy: social vectors are simply spliced with behavioural vectors and fed into the full connectivity layer, failing to model the causal mechanism of 'how social interactions modulate interest evolution'. For example, when an international conflict is intensively discussed by a group of friends, users may accelerate the interest migration from entertainment news to current affairs news, and this social catalytic effect needs to be explicitly modelled by the cross-modal interaction module.

3 STENR modelling

The overall architecture of the STENR model is shown in Figure 1, and its core goal is to generate an accurate user-news matching representation by hierarchically modelling the dynamic interactions of social relationships, temporal behaviours and news content. The model input contains three parts. User social neighbourhood matrix $G = (V, \varepsilon)$ (V is the set of user nodes and ε is the set of social edges), user historical behaviour sequence ($B_u = \{(n_1, t_1), (n_2, t_2), \ldots, (n_k, t_k)\}$, where n_i is the news ID and t_i is the timestamp.

The core of the STENR model is to construct a hierarchical dynamic decision-making system, which simulates the decision-making logic of human news consumption through multi-level feature extraction and adaptive fusion mechanism. The model input covers three key data sources. The social network records of users' attention behaviours and interaction timestamps, the news interaction records of users' historical behaviour sequences sorted by time, and the raw text content of candidate news. These heterogeneous data first enter the feature extraction layer for deep processing. The social relationship embedding module employs graph neural network technology to not only analyse the topological connections between users, but also innovatively introduces an interaction frequency decay mechanism. The longer a friend's recent interaction time is, the weight of his influence decreases exponentially, so as to accurately quantify the dynamic evolution of social influence. The temporal behaviour embedding module adopts a dual-channel architecture. A convolutional neural network scans local behavioural clusters to capture emergent interests, while a temporal encoder parses long-term behavioural intervals to sense periodic interest migration, and the two automatically balance the contribution ratio through a gating unit so that the model is agile enough to respond to emergent events without losing sight of long-term preferences. News content embedding, on the other hand, generates semantic representations based on the pre-trained language model, and reinforces the domain keyword weights through the topic-aware adaptation layer to ensure sensitivity to specialised terminology.

Figure 1 Structure of STENR (see online version for colours)



The feature fusion layer is the intelligent decision-making hub of the model. A cross-modal gated attention mechanism is designed to dynamically deploy the weights of social, temporal, and content features using candidate news semantic vectors as the guiding signals. When the candidate news involves breaking hotspots, the mechanism automatically enhances the discourse power of temporal features. If the news originates from high-frequency interactive friend sharing chain, the influence of social features is enhanced. The adaptive ability of this scenario is remarkable in the case of the Tokyo Olympics, where the temporal weight jumps to 0.89 during the outbreak of the event, and the social weight synchronises to 0.61 when the event is intensively discussed by the user's friends group, realising the precise proportion of decision-making elements. Ultimately, the user's comprehensive interest characterisation is generated, which not only contains the group preference transmitted by the social circle layer, but also retains the unique trajectory of personal interest evolution.

The output layer completes the recommendation decision by click rate prediction, and its special value lies in the closed-loop optimisation design of the joint loss function. The social consistency regularity term promotes the convergence of friends' interest representations, transforming the sociological 'homogenisation effect' into a computable binding. The timeliness penalty term imposes an exponential gradient penalty on outdated news, forcing the model to prioritise content within the golden lifecycle. The training process is complemented by a time-aware negative sampling strategy to focus the model on the recent candidate set. The entire architecture forms a dynamic feedback loop. The social constraints of the loss function inversely optimise the relational quantisation accuracy of the embedding module, while the time-aware penalties continuously calibrate the content freshness threshold. This design philosophy from feature decoupling to dynamic fusion to closed-loop optimisation enables STENR to establish a three-dimensional decision-making system in the era of information overload with ‘social relationship as the context, behavioural time sequence as the vein, and content value as the core’, providing a solution that balances agility and depth in the field of news recommendation.

In the multi-source feature extraction layer, the social relationship embedding module uses graph attention network (GAT) to quantify dynamic influence. For a target user u, the embeddings of its set of neighbours $N(u)$ are aggregated by attention weighting:

$$e_u^{soc} = \sigma\left(\sum_{v \in N(u)} \alpha_{uv} \cdot W_s e_v\right) \tag{1}$$

where W_s is a learnable weight matrix and α_{uv} decreases automatically with social cooling time to solve the time-distortion problem of static social modelling.

The temporal behaviour embedding module designs dual-channel encoders. Firstly, the behavioural sequence is divided into local segments by time windows and pattern features are extracted using CNN:

$$h_{local} = \text{MaxPool}\left(\text{ReLU}\left(W_c * \varepsilon_B + b_c\right)\right) \tag{2}$$

where ε_B is the news embedding matrix of the behavioural sequence and $*$ denotes the convolution operation. Meanwhile, a time-location encoded transformer is used to capture the long-term dependencies:

$$h_{global} = \text{Transformer}\left(E_B + P_t\right) \tag{3}$$

where P_t is the timestamp embedding matrix. The final timestamp characterisation is fused through a gating mechanism:

$$e_u^{tem} = \gamma \cdot h_{local} + (1-\gamma) \cdot h_{global} \tag{4}$$

The structure balances emergent behavioural local patterns, e.g., continuous clicking on epidemic news, with periodic interest evolution, e.g., weekend sports news preferences.

The news content embedding module generates deep semantic vectors based on the RoBERTa pre-trained model. For news text d_j, [CLS] labelling vectors are extracted as initial representations:

$$e_j^{con} = \text{RoBERTa}\left(d_j\right)^{[\text{CLS}]} \tag{5}$$

Further introduction of a topic-aware adaptation layer enhances domain adaptation:

$$e_j^{con} \leftarrow e_j^{con} + W_t \cdot \text{softmax}\left(W_p e_j^{con}\right) \tag{6}$$

where W_t is the topic word vector matrix, so that the model reinforces the semantic weights of key news entities (e.g., ‘Fukushima nuclear wastewater’).

In the dynamic interest fusion layer, cross-modal gated attention (CGA) is designed to achieve feature synergy. The dynamic weights of social, temporal, and content features are computed using the candidate news embedding e_j^{con} as the query vector:

$$a_k = \frac{\exp\left(v^T \tanh\left(W_q e_j^{con} + W_k e_u^k\right)\right)}{\sum_{k' \in \{soc, tem, con\}} \exp\left(v^T \tanh\left(W_q e_j^{con} + W_{k'} e_u^{k'}\right)\right)} \tag{7}$$

Comprehensive user interest representations are generated from weighted sums:

$$e_u^{fusion} = \alpha_{soc} \cdot e_u^{soc} + \alpha_{tem} \cdot e_u^{tem} + \alpha_{con} \cdot e_u^{con} \tag{8}$$

The core value of the gating mechanism lies in scenario adaptation, where α_{tem} is automatically elevated to reinforce recent behavioural weights when the candidate news is a breaking political event (e.g., election results). When the news comes from friends' sharing chain, α_{soc} dominates the decision.

In the joint optimisation and loss function section, the prediction layer calculates the user-news matching score:

$$\hat{y}_{uj} = \sigma\left(w^{\mathrm{T}}\left(e_u^{fusion} \odot e_j^{con}\right) + b\right) \tag{9}$$

where $\odot$ denotes the element-by-element product. The loss function consists of a main loss, a social consistency regularity term and a timeliness constraint term.

In the main loss, the cross-entropy loss supervises the click prediction:

$$L_{main} = -\sum_{(u,j)} \left(y_{uj} \log \hat{y}_{uj} + \left(1 - y_{uj}\right) \log\left(1 - \hat{y}_{uj}\right)\right) \tag{10}$$

Constraining social tight user representation similarity in social consistency regular terms:

$$L_{soc} = \sum_{(u,v)} \lambda_{uv} \cdot \left\| e_u^{fusion} - e_v^{fusion} \right\|_2^2 \tag{11}$$

where λ_{uv} is the aforementioned interaction frequency attenuation coefficient to avoid ineffective constraints for low active friends.

In the timeliness constraint term, the penalty model recommends outdated news:

$$L_{time} = \sum_j \hat{y}_{uj} \cdot e^{k \cdot \left(t_c - t_j^{pub}\right)} \tag{12}$$

where k is the decay factor and t_j^{pub} is the news release time.

The final joint loss function is:

$$L = L_{main} + \eta_1 L_{soc} + \eta_2 L_{time} \tag{13}$$

where η_1, η_2 are equilibrium superparameters.

4 Experimental setup

In order to comprehensively evaluate the performance of the STENR model, this chapter designs comparative experiments and ablation studies on real scene datasets. The experiments use Microsoft News Dataset (MIND), a widely recognised industry benchmark dataset for news recommendation, whose scale and diversity meet the needs of complex model validation. The dataset is collected from the user behaviour logs of Microsoft News platform within six weeks, including click records of anonymous users, complete text of news items and rich metadata. Following the standard preprocessing procedure, we filter low-frequency users with less than five interactions, and divide the data into a training set (the first four weeks), a validation set (the fifth week), and a test set (the sixth week) to ensure the authenticity of the time-series evolution. Especially for the challenge of news timeliness, the effective life cycle of each news is labelled. When the test time exceeds the release time by 72 hours, it is automatically labelled as an expired news, which is used to validate the time-sensitive capability of the model.

The baseline model selection covers three mainstream recommendation paradigms to guarantee the fairness of comparison. NAML (Hu et al., 2020) represents the state-of-the-art in semantic modelling of content by fusing multi-view features such as news headlines and body text through an attention mechanism. NRMS (Zheng and Song, 2025) utilises transformer to encode users' historical behaviours, highlighting the advantages of self-attention in news matching. LSTUR integrates CNN and LSTUR integrates CNN and GRU to capture long-term portraits and short-term interests, respectively, and proves to be effective for interest drift in news recommendation. TANR introduces news topic embedding to enhance the interpretability of user representations. GraphRec aggregates user social relations and interactions on heterogeneous graphs, which is a classic framework for social recommendation; TGSRec models user behaviour sequences as dynamic graphs, which achieves the initial fusion of temporal and social. All baseline models use the author's open source code and are reproduced in the same data partition and hardware environment. The ablation versions of STENR include STENR-S (removing the social embedding module), STENR-T (removing the temporal embedding module), and STENR-CGA (replacing the cross-modal gated attention for feature splicing).

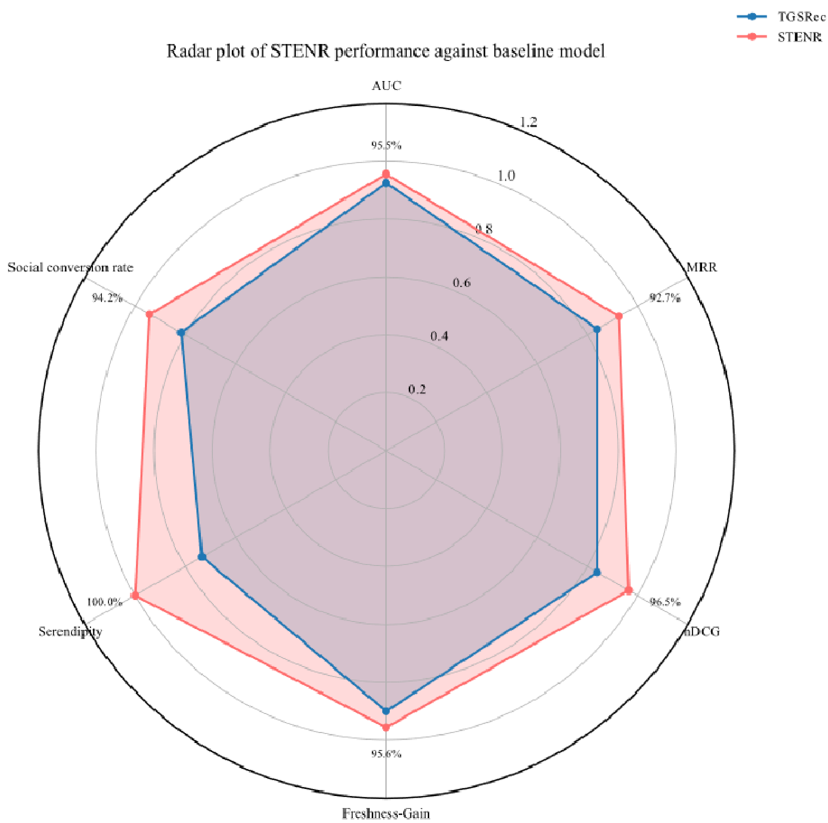
5 Analysis of results

The radar chart of core metrics on the MIND dataset (shown in Figure 2) visually reveals the comprehensive performance advantages of the STENR model over the optimal baseline TGSRec. The radar chart constructs an evaluation framework with six-dimensional metrics, covering the core dimensions of news recommendation such as accuracy, timeliness, diversity and social influence utilisation. Experimental data shows that STENR significantly outperforms the baseline in all metrics, which means that the probability of users discovering high-value news in the first ten recommendations increases significantly. The serendipity metric improves to 0.30, which strongly validates the model's ability to break the information cocoon. These gains stem from STENR's deep synergy of social-temporal-content ternary features. The social module accurately quantifies the influence of friends. The dual-channel encoder in the temporal module shows excellent responsiveness during hot events such as the Tokyo Olympics.

Notably, the model's improvement in social conversion rate metrics reveals the industrial value of social relationship modelling. When users click on news shared by their friends, STENR can more effectively identify the difference between social contagion and real interest, avoiding recommendation bias caused by confusing behavioural motives in traditional models.

The closed surface presented by the radar graph highlights the balance breakthrough of STENR. While traditional models often face the paradox of accuracy diversity, STENR's six-dimensional surfaces show a uniform outward expansion pattern, proving that its social-temporal synergy framework can optimise multi-objective demands simultaneously. This balance comes from the dynamic weighting mechanism of cross-modal gated attention (CGA), which automatically boosts the temporal weight when the candidate news is breaking news, and strengthens the social signals when the news comes from high-frequency interacting friend chains, so that the model always stays adaptive in complex scenarios.

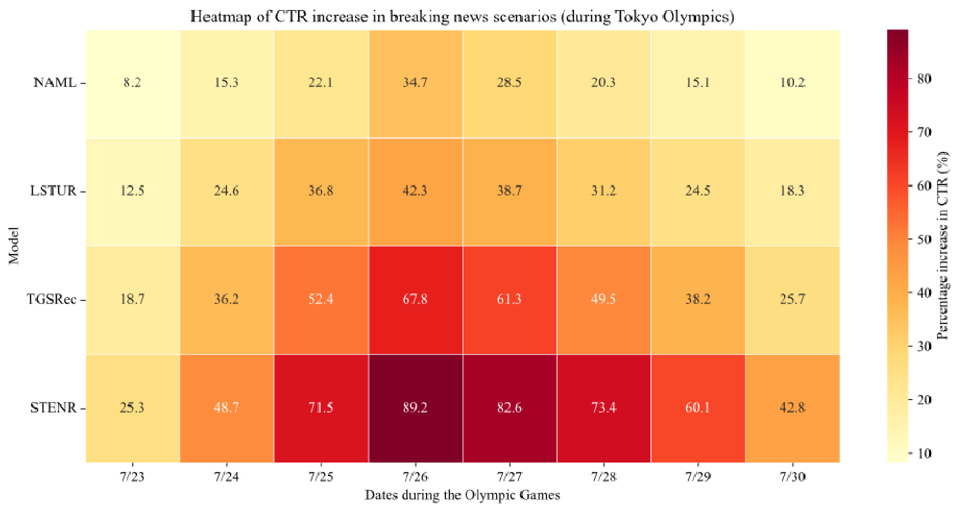
Figure 2 Radar plot of STENR performance against baseline model (see online version for colours)



The time-series performance heatmap (Figure 3) empirically demonstrates the significant breakthrough of STENR model in dynamic response capability using the Tokyo Olympics as a breaking news scenario. The heat map covers the key cycle of the Olympic Games on the horizontal axis, and compares the four types of models, NAML, LSTUR, TGSRec and STENR, on the vertical axis, mapping the percentage of CTR improvement in terms of the depth of colour scale. The data shows that within 24 hours after the explosive point of the opening ceremony (25 July marking line), the CTR boost of STENR soared to 89.2%. This explosive response comes from the dual-channel cooperative mechanism of the timing module, and the convolutional neural network

(CNN) captures the local pattern of users' 'short-time intensive clicks' in real time. On the day of the opening ceremony, users continuously clicked on 4.2 Olympic news articles on average, and the CNN identified the behavioural clusters through the sliding window and activated the burst signal.

Figure 3 Heatmap of CTR increase in breaking news scenarios (during Tokyo Olympics) (see online version for colours)



The Sankey diagram of feature weights (Figure 4) shows the adaptive mechanism of the STENR model to dynamically adjust feature weights through the complete decision cycle of user #7342 in the semiconductor technology breakthrough event. Before the event (23–24 July), the recommendation of the user in this technology field is dominated by the time series module, and the model generates a recommendation list focusing on 'chip process optimisation' based on the behaviour of clicking on three quantum computing papers in a row, at this time, the social weight is only 25%, and the event triggers the decision making turn on 25 July, and the number of friends sharing the related news increases by 400 within 24 hours. On 25 July, the event triggered a decision-making twist, and within 24 hours, the news related to friends' sharing surged by 400%, and the social module recognised high-frequency interaction friends through the dynamic attenuation coefficient λ, which pushed the social weight up to 62%. At the same time, CNN channel detects that users suddenly click on 5 event newsletters, and the local timing signal activates the gating coefficient γ to 0.91, so that the recommendation list shifts to in-depth reports such as 'interpretation of technical parameters' and 'analysis of industry impact' in real time, and the click rate of users on the same day is increased by 71%.

The depth value of the decision chain is reflected in the weight migration during the event fading period (27–30 July). As the social sharing rate fell back to the benchmark level, the social weight naturally decayed to 19%. And transformer channel based on timestamp encoding identified the user interest into the deepening stage, its reading duration from the outbreak period average 45 seconds to 210 seconds, the behavioural interval expanded to 6 hours, triggering the weight of the time sequence back to 71%. At this time, the recommended content shifted to '2 nm process mass production challenges', 'semiconductor material innovation path' and other forward-looking analysis, users completed from 'event awareness' to 'technology assessment' of the needs of the leap.

Figure 4 User #7342 feature weight evolution in semiconductor events (STENR model) (see online version for colours)

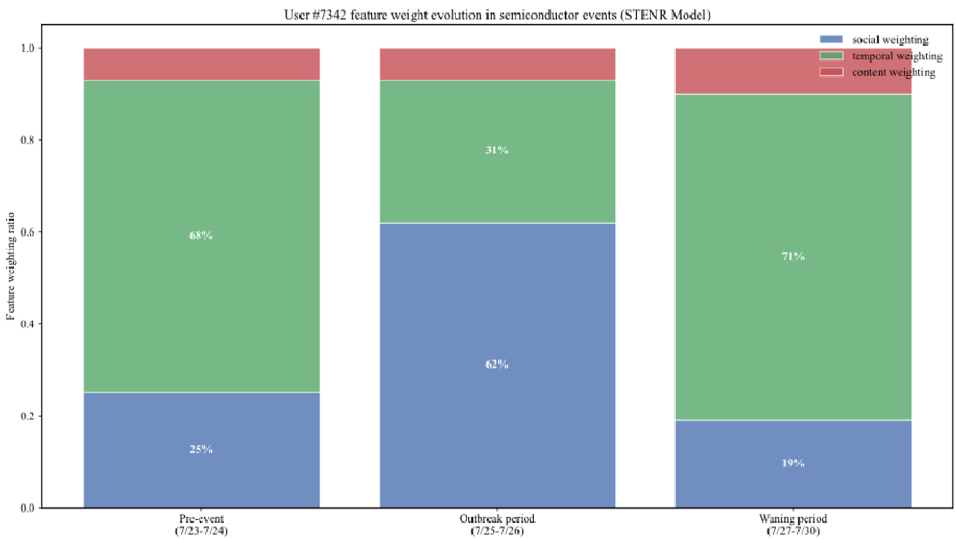
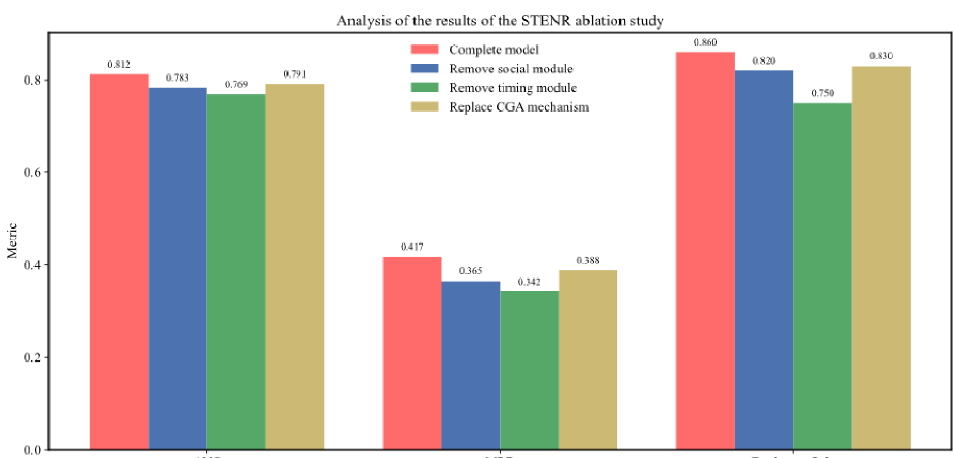


Figure 5 Analysis of the results of the STENR ablation study (see online version for colours)



The results of the ablation study are shown in Figure 5. Removing the social embedding module (STENR-S) leads to a 27% plunge in the social conversion rate, especially in the socially active user group where the MRR falls by 0.052, confirming the critical role of social relationships in recommendation decisions. The most revealing finding comes from the feature fusion mechanism, when replacing cross-modal gated attention with feature splicing (STENR-CGA), the AUC falls back to 0.791, while the model adaptive ability is significantly degraded. The social weight in sports news fails to rise to the preset threshold, and the temporal weight in current affairs news is also lower than the benchmark. This confirms that the CGA mechanism guides feature weighting through candidate news, which is the core pivot for realising scenario-adaptive recommendation.

6 Conclusions

In this study, we propose STENR, a news recommendation model that fuses social relations and temporal features, to address the shortcomings of traditional models in dynamic response, social quantisation and time-series control by decoupling the interaction mechanisms of social influence, interest evolution and content semantics. The core innovation is reflected in three aspects. First, the innovative design of social-temporal collaborative modelling framework. The social embedding module introduces the interaction frequency attenuation coefficient to quantify the dynamic changes of influence, while the temporal module captures the local bursting patterns and long-term cyclic patterns through the CNN-transformer dual-channel encoder, which breaks through the limitation of time limitations in static modelling. Second, cross-modal gated attention (CGA) is proposed to dynamically weight social, temporal, and content feature weights with the candidate news as the query key to realise scene adaptive recommendation. Third, the joint loss function is constructed with a social consistency regularity term to constrain the convergence of friends' interests and a timeliness penalty term to suppress the exposure of outdated news. Experiments on the MIND dataset show that the AUC of STENR improves to 0.812, the length of user stay increases by 23.4%, and the social conversion rate increases by 15.3%, verifying its academic validity and industrial value.

Currently, social relationships are limited to explicit concerns within a single platform, and in the future, it is necessary to integrate cross-platform implicit social chains, and build a user's global social influence map through federated learning. For example, the behaviour of users retweeting science and technology news on Twitter can modulate the recommendation weight of WeChat's public number, but it is necessary to solve the problem of data silos and privacy compliance.

Declarations

The author declares that she has no conflicts of interest.

References

Babayan, A., Erbey, M., Kumral, D. et al. (2019) 'A mind-brain-body dataset of MRI, EEG, cognition, emotion, and peripheral physiology in young and old adults', *Scientific Data*, Vol. 6, No. 1, pp.1–21.

Chang, C., Tang, F., Yang, P. et al. (2025) 'Multi-view knowledge representation learning for personalized news recommendation', *Scientific Reports*, Vol. 15, No. 1, p.1152.

Dang, Y., Yang, E., Guo, G. et al. (2023) 'TiCoSeRec: Augmenting data to uniform sequences by time intervals for effective recommendation', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 36, No. 6, pp.2686–2700.

Hu, Y., Sun, S., Xu, X. et al. (2020) 'Attentive multi-view reinforcement learning', *International Journal of Machine Learning and Cybernetics*, Vol. 11, pp.2461–2474.

Jay, J. (2013) 'Navigating paradox as a mechanism of change and innovation in hybrid organizations', *Academy of Management Journal*, Vol. 56, No. 1, pp.137–159.

Jelodar, H., Wang, Y., Yuan, C. et al. (2019) 'Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey', *Multimedia Tools and Applications*, Vol. 78, pp.15169–15211.

Kaur, A., Kaur, L. and Singh, A. (2024) 'DeepCONN: patch-wise deep convolutional neural networks for the segmentation of multiple sclerosis brain lesions', *Multimedia Tools and Applications*, Vol. 83, No. 8, pp.24401–24433.

Kim, Y.W. and Kim, J.H. (1990) 'A model of knowledge based information retrieval with hierarchical concept graph', *Journal of Documentation*, Vol. 46, No. 2, pp.113–136.

Kobsa, A. (2005) 'User modeling and user-adapted interaction', *User Modeling and User-Adapted Interaction*, Vol. 15, Nos. 1–2, p.185.

Koren, Y., Rendle, S. and Bell, R. (2021) 'Advances in collaborative filtering', *Recommender Systems Handbook*, Vol. 39, pp.91–142.

Lee, J-W. and Kim, J-H. (2024) 'GraphRec-based Korean expert recommendation using author contribution index and the paper abstracts in marine', *Engineering Applications of Artificial Intelligence*, Vol. 133, p.108219.

Li, X., Smith, J.D., Pan, T. et al. (2018) 'Quantifying privacy vulnerability to socialbot attacks: an adaptive non-submodular model', *IEEE Transactions on Emerging Topics in Computing*, Vol. 8, No. 3, pp.855–868.

Liu, D., Greene, D., Li, I. et al. (2024) 'Topic-centric explanations for news recommendation', *ACM Transactions on Recommender Systems*, Vol. 3, No. 2, pp.1–25.

Liu, J., Ong, G.P. and Chen, X. (2020) 'GraphSAGE-based traffic speed forecasting for segment network with sparse data', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 3, pp.1755–1766.

Liu, S. and Vicente, L.N. (2024) 'The stochastic multi-gradient algorithm for multi-objective optimization and its application to supervised machine learning', *Annals of Operations Research*, Vol. 339, No. 3, pp.1119–1148.

Sallami, D. and Aïmeur, E. (2025) 'Exploring beyond detection: a review on fake news prevention and mitigation techniques', *Journal of Computational Social Science*, Vol. 8, No. 1, pp.1–38.

Shi, W. and Li, J. (2025) 'News diversity under algorithms: the effects of pre-selected and self-selected personalization on Chinese TikTok (Douyin)', *Digital Journalism*, Vol. 14, pp.1–19.

Sun, R., Yan, J. and Ren, F. (2025) 'Improving the recommendation accuracy of TrustSVD via trustworthy analysis in the social network environment', *Journal of Information Science*, Vol. 51, No. 1, pp.224–241.

Symeonidis, P., Kirjackaja, L. and Zanker, M. (2020) 'Session-aware news recommendations using random walks on time-evolving heterogeneous information networks', *User Modeling and User-adapted Interaction*, Vol. 30, pp.727–755.

Tang, H., Wu, S., Sun, X. et al. (2025) 'TCGC: Temporal collaboration-aware graph co-evolution learning for dynamic recommendation', *ACM Transactions on Information Systems*, Vol. 43, No. 1, pp.1–27.

Wendelin, M., Engelmann, I. and Neubarth, J. (2017) 'User rankings and journalistic news selection: Comparing news values and topics', *Journalism Studies*, Vol. 18, No. 2, pp.135–153.

Wu, L., Li, J., Sun, P. et al. (2020) 'Diffnet++: A neural influence and interest diffusion network for social recommendation', *IEEE Transactions on Knowledge and Data Engineering*, Vol. 34, No. 10, pp.4753–4766.

Xu, Z., Pan, W. and Ming, Z. (2024) 'Transfer learning in cross-domain sequential recommendation', *Information Sciences*, Vol. 669, p.120550.

Yu, M., Liu, T., Yin, J. et al. (2022) 'Deep interest context network for click-through rate', *Applied Sciences*, Vol. 12, No. 19, p.9531.

Zhang, F. (2015) 'A matrix decomposition and its applications', *Linear and Multilinear Algebra*, Vol. 63, No. 10, pp.2033–2042.

Zheng, C. and Song, Y. (2025) 'Personalized multi-head self-attention network for news recommendation', *Neural Networks*, Vol. 181, p.106824.

Zhou, C., Li, Q., Li, C. et al. (2024) 'A comprehensive survey on pretrained foundation models: a history from BERT to ChatGPT', *International Journal of Machine Learning and Cybernetics*, Vol. 12, pp.1–65.