Derivation Topic Propagation Prediction Model Based on Topic Attractiveness and Dynamic Temporal Perception

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ABSTRACT

An attractive topic is generally associated with a higher potential for dissemination. Considering the comprehensive factors of influence and topicality in the process of topic propagation, a derivation topic propagation prediction model based on topic attractiveness and dynamic temporal perception is proposed. Firstly, to address the complex relationships between derivative topics, a derivative topic co-occurrence network is constructed. Normalized co-occurrence strength, derived from topic tag co-occurrence data, is used as edge weights to characterize the strength of topic associations. At the same time, the Node2vec algorithm is utilized to optimize the low-dimensional spatial embedding of topic nodes, thereby enabling a deeper understanding of the association patterns between derivative topics. Secondly, the role of topic attractiveness in promoting propagation is emphasized, and a multidimensional perspective is introduced to quantify attractiveness by jointly measuring influence and topicality. Finally, the dynamic nature of topic relationships and the timeliness of recent co-occurrences are considered. A time-sensitive attention mechanism is then integrated into the Graph Attention Network to process the occurrence network of derivative topics. Based on this integration, the Dynamic Time-Aware Graph Attention Network model is constructed to effectively predict the propagation trends of these derivative topics. The experimental results demonstrate that the proposed model not only effectively captures the complex associations between derivative topics and quantifies topic attractiveness, but also achieves significant improvements in predicting the propagation trends of derivative topics.

1. Introduction

In the era of social media, the propagation dynamics of derived topics have attracted considerable attention. Platform mechanisms accelerate information diffusion. Some topics spread rapidly, whereas others quickly fade. Such divergence is not only determined by network structure, but is also closely related to users' overall responses and emotional orientations. Accordingly, topic attractiveness can be regarded as an interactive manifestation of collective user sentiment. Positive emotions promote diffusion, while negative or skeptical emotions inhibit it. Their combined effects jointly shape the overall propagation potential of a topic. Therefore, understanding and predicting diffusion trajectories from the perspective of topic attractiveness is of substantial practical significance.

In recent years, the study of the information dissemination dynamics of derivative topics has garnered widespread attention from scholars both domestically and internationally(van der Linden & Kyrychenko, 2024; Li et al., 2024b; Xu et al., 2025b). In the research field of derivative topic information dissemination dynamics, there are currently two main directions. One direction involves researchers improving the SIR model(Wang et al., 2024; Yu et al., 2025; Chen et al., 2025; Ye et al., 2025b) to construct information dissemination models applicable to the Internet for predicting the propagation trends of derivative topics. The other direction focuses on analyzing the actual dissemination dynamics of derivative topics in networks, extracting and summarizing their characteristics, and using deep learning algorithms to predict user forwarding behavior based on these features(Xiaoyang et al., 2024; Xinyu et al., 2023; Yeqing et al., 2023; Hui et al., 2024).

In studies of topic propagation prediction, an interesting phenomenon can be observed. The diffusion of a topic is jointly influenced by its own attractiveness and that of semantically related topics, as illustrated in Fig. 1. Similar

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topics often emerge in parallel and compete with each other under the constraint of limited user attention. Users' positive interests enhance topic attractiveness and accelerate diffusion. In contrast, negative or skeptical emotions weaken attractiveness and inhibit further spread. At the same time, competing topics may divert user attention and thus impose additional constraints on the propagation process. How can topic attractiveness be effectively quantified, and how can such a formulation be leveraged to further improve the prediction accuracy of derived topic propagation trends?

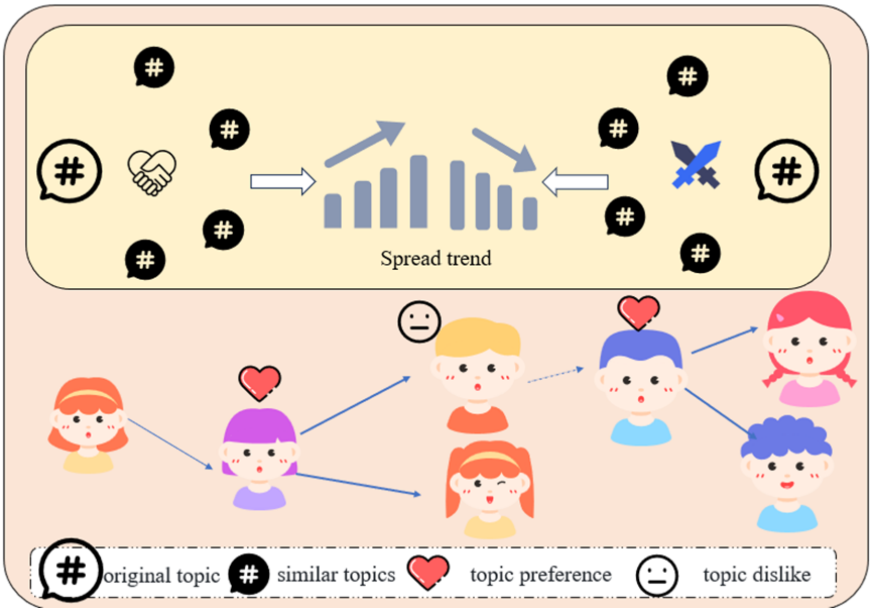


Figure 1: Inspiration Chart

The current challenge is that many existing propagation prediction models, such as SIR-based diffusion models (Wang et al., 2024; Yu et al., 2025) and deep learning–based propagation predictors (Xiaoyang et al., 2024; Yeqing et al., 2023), fail to adequately capture the unique characteristics and dynamic changes of derivative topics. These models often overlook the multidimensional nature of topic attractiveness and the complex relationship networks between different topics. In light of this, the key challenges encountered in the study of derivative topic propagation are examined, with a focus on the following three aspects:

1. The complex relationships between derivative topics. The interrelationships among topics can significantly influence their propagation speed and reach; closely related topics can enhance each other's dissemination.

2. The key role of topic attractiveness in driving topic propagation. Topics with high attractiveness can stimulate users' interest and curiosity, encouraging them to engage in discussions, share, and disseminate the topic.

3. The dynamism of relationships between topics. The relationships among topics are not static; over time, the connections between certain topics may become closer or more distant.

To explore the aforementioned challenges in depth, the analysis of derivative topic co-occurrence networks is conducted. By comprehensively considering the co-occurrence relationships between topic tags and their normalized co-occurrence strength, it reveals long-term stable association patterns between topics. Furthermore, an innovative representation method for topic attractiveness is introduced, which quantitatively integrates multiple dimensions of topic attractiveness, including influence and topicality. At the same time, to capture the dynamic changes in relationships between topics and emphasize the timeliness of co-occurrence, a time-sensitive attention mechanism is incorporated into the Graph Attention Network (GAT)(Veličković et al., 2018) to handle derivative topic co-occurrence networks. On this basis, an innovative derivative topic propagation prediction model is proposed, which is based on topic attractiveness and dynamic time perception. This research not only enriches the theoretical framework of topic propagation but also provides new perspectives and methods for practical applications. The main contributions are as follows:

1. Construct a derivative topic co-occurrence network based on topic tag co-occurrence data. Taking the normalized co-occurrence strength as edge weights, apply the Node2vec(Grover & Leskovec, 2016) algorithm to optimize low-dimensional embedding representations of topic nodes, thereby uncovering long-term and stable association patterns among derivative topics.

2. Propose a multi-dimensional topic attractiveness representation approach. By precisely quantifying topical influence and topicality across multiple dimensions, comprehensively capture the intrinsic attractiveness of topics.

3. Construct the Dynamic Time-Aware Graph Attention Network (DTA-GAT) derivative topic propagation prediction model. The timeliness of recent co-occurrences is emphasized, and a time-sensitive attention mechanism is integrated into the GAT to process the derivative topic co-occurrence network. This integration enables the prediction of propagation trends for derivative topics.

The subsequent arrangement is as follows. Section 2 delves into the current state of work in this research field. Section 3 provides necessary definitions and presents the research questions. Section 4 elaborates in detail on the proposed methods and their associated learning algorithms. Section 5 validates the proposed methods on real datasets. Section 6 summarizes the entire paper.

2. Related Work

Research on topic significant progress in both theory and practice. Researchers are continuously developing new methods and models, including graph neural network–based approaches (Han et al., 2025; Lingwei et al., 2024), hypergraph and temporal modeling methods (Delabays et al., 2025; Qian et al., 2025), and representation learning–based dissemination predictors (Li et al., 2024a; Wang et al., 2025a), to better understand its dynamics on social media, offering valuable insights and decision support. Meanwhile, as social media continues to evolve, new challenges and opportunities will emerge. This section will focus on elaborating and analyzing the achievements of scholars in recent years, centered around the three challenges mentioned in the previous section.

Firstly, addressing the complexity of multi-topic relationships. Bizyaeva et al. (2025) analyzed belief formation across multiple topics on signed social networks, capturing the complexity of multi-topic relationships through bifurcation dynamics. Xuemei et al. (2023) modeled the interactions among rumors, counter-rumors, and promotional content using evolutionary game theory. Gao et al. (2024) developed a Two-Stage Model that incorporates the timing and impact of official rebuttals. Qian et al. (2025) highlighted the complexity of multi-topic relationships by learning temporal dependencies among events. Delabays et al. (2025) proposed a dynamic hypergraph reconstruction method that captures the complexity of multi-topic relationships. Jia et al. (2025) tackled the complexity of multi-topic relationships by modeling correlated topic propagation patterns with group identity–aware representation learning. This approach captures the intertwined influences among multiple topics in complex social networks. Wang et al. (2025b) addressed the complexity of multi-topic relationships by modeling topics in a dynamic heterogeneous graph. By incorporating trajectory-based temporal evolution and semantic-aware aggregation, it captures complex and evolving inter-topic dependencies. Liu et al. (2025) addressed the complexity of multi-topic relationships by modeling high-order and hierarchical interactions in temporal hypergraphs. By leveraging hyperbolic graph learning, it captures intertwined dependencies among multiple topics in information diffusion. The studies mentioned above mainly investigate the effects of competition and cooperation on the information dissemination process, achieving significant results. However, due to the complexity of topic propagation, further research is needed to more accurately capture the intricate relationships between topics.

Secondly, regarding the impact of topic characteristics on dissemination. Yu et al. (2023) proposed a latent space-based method under the independent cascade model to identify multiple negative influence sources. Lingwei et al. (2024) designed Fuzzy Graph Convolutional Network to model uncertain interactions in cascades. Lanting et al. (2023) developed an unsupervised rumor detector with Variational Autoencoder aligning tweet trees. Han et al. (2025) proposed a hypernetwork-based topic dissemination model to capture the high-order interactive characteristics among users and improve topic diffusion prediction. Haonan et al. (2023) proposed a method to maximize effective information dissemination amid expression ambiguity in social networks. Ye et al. (2025a) proposed MVP, which predicts social media video popularity by integrating multimodal features with metadata, demonstrating that content characteristics significantly drive dissemination. Mane et al. (2025) surveyed online aggression on social media. It analyzes behavioral factors and patterns. This reveals how aggressive content characteristics influence dissemination. Wu et al. (2024) proposed Influence-based Social Media Attack. It enhances content dissemination via behavior poisoning. This demonstrates how user behaviors and profile characteristics significantly impact information spread on social media.

Xu et al. (2025a) proposed a retrieval-augmented framework that enhances multimodal UGC popularity prediction, demonstrating the significant impact of content and metadata characteristics on social media dissemination. The above studies mainly explored the impact of topic propagation structure and content on the information dissemination process, achieving notable results. However, how to quantify these topic characteristics remains a subject for further research.

Finally, regarding the study of the dissemination trends of derivative topics. Li et al. (2024a) proposed a derivative topic dissemination model based on representation learning and topic relevance, which encodes semantic associations between derivative topics to forecast dissemination trends and enhances the accuracy of propagation trend prediction. Junchang et al. (2023) developed a method for analyzing and identifying the trends of misinformation propagation based on social context analysis and a multi-level attention network, using a multilayer perceptron to identify propagation volume trends. Wang et al. (2025a) proposed a guided derivative topic dissemination model based on topic identity and transfer learning, exploiting intrinsic topic identity features and transferred knowledge to improve the forecasting precision of derivative topic propagation trends. Wu & Pan (2025) studied dynamic topic evolution by modeling temporal decay and attention mechanisms. The proposed approach captures time-sensitive topic variations and supports the prediction of dissemination trends of derivative topics. Li et al. (2025) proposed a derived topic propagation model based on cognitive accumulation and transfer learning, which improves the prediction of dissemination trends of derivative topics. Zhang et al. (2025) proposed a multi-agent simulation framework to jointly model the co-evolution of topics and stances in online discourse, revealing how emerging subtopics and evolving interactions influence the dissemination trends of derivative topics. The above studies have achieved notable results in predicting the dissemination trends of derivative topics. However, further research is needed to predict these dissemination trends more accurately.

3. Problem Definition and Formalization

3.1. Relevant Definitions

By deeply analyzing the co-occurrence patterns of topics, the dynamic interactions between topics, and topic attractiveness, a more accurate and comprehensive topic propagation prediction model is constructed. The concepts used are defined as follows:

Definition 1. Total Topic Interactions $totalEngage(v)$.

The total topic interactions measure the degree of user interaction and engagement with that topic. It reflects the dynamic interactions between users and the topic, including various forms of participation such as likes, comments, shares, and retweets. These behaviors all constitute direct user responses to a topic and thus convey participation signals at a comparable semantic level. To avoid introducing subjective weighting assumptions that depend on prior experience or specific data distributions, an equal-weight setting is adopted as an unbiased baseline measure. Accordingly, the above interaction behaviors are assigned identical weights and linearly aggregated. The calculation method for the total interactions of a topic is shown in Equation 1.

$$totalEngage(v) = like(v) + comment(v) + share(v) + forward(v) \tag{1}$$

where v represents a specific topic, $like(v)$ represents the total number of likes for that specific topic, $comment(v)$ represents the total number of comments related to that specific topic, $share(v)$ represents the total number of shares for that specific topic, and $forward(v)$ represents the total number of retweets for that specific topic.

Definition 2. Topic Engagement Rate $engageRate(v)$.

The topic engagement rate is used to measure the proportion of users who noticed the topic and actually participated in the interactions. A higher topic engagement rate typically indicates that users have a more positive response to the topic, and their behavior in disseminating the topic is also more active. The calculation method for the topic engagement rate is shown in Equation 2.

$$engageRate(v) = \frac{totalEngage(v)}{totalFollow(v)} \tag{2}$$

where $totalEngage(v)$ represents the total number of interactions users have had with the topic, including likes, comments, shares, and retweets, and $totalFollow(v)$ represents the total number of users who have seen the topic, measured through the topic's view count.

Definition 3. Topic Growth Rate $growthRate(v)$.

The topic growth rate measures the proportion of change in the total number of interactions with a topic over two consecutive time periods of equal length, reflecting short-term variations in user engagement. If the growth rate increases, it indicates that the discussion volume of the topic is rising during the current time period, suggesting that the topic is receiving more attention. Conversely, if the growth rate gradually decreases to zero, it indicates a reduction in discussion volume, which may suggest that the topic is losing interest. The calculation method for the topic growth rate is shown in Equation 3.

$$growthRate(v) = \frac{totalEngage_{cur}(v) - totalEngage_{pre}(v)}{totalEngage_{pre}(v)} \tag{3}$$

where $totalEngage_{cur}(v)$ and $totalEngage_{pre}(v)$ represent the total number of interactions for a specific topic in the current time period and the previous time period, respectively.

Definition 4. Topic Coverage $reach(v)$.

Topic coverage is a metric used to quantify the extent to which a specific topic is seen or exposed on social media. It can be characterized as the sum of two parts. The first is the number of users who directly encounter the topic. The second is the number of users who are indirectly exposed through diffusion behaviors such as reposting and sharing. Together, these components reflect the overall audience size reached by the topic within the observed time window. The calculation method for topic reach is shown in Equation 4.

$$reach(v) = audiCount_{dir}(v) + audiCount_{indir}(v) \tag{4}$$

where $audiCount_{indir}(v)$ refers to the additional audience reached through indirect channels, such as shares, retweets, etc, who obtain information about the topic, and $audiCount_{dir}(v)$ represents the number of users who directly engage with the specific topic.

Definition 5. Initial User Influence Index $influIndex(v)$.

The initial user influence index is specifically used to assess the influence of a particular user in leading a specific topic, where it represents the topic initiator. The Initial User Influence Index quantifies the role of the initiating user in promoting the topic's dissemination and influence, and its calculation method is shown in Equation 5.

$$influIndex(v) = I_f(u) + I_h(u) + I_e(u) \tag{5}$$

where $I_f(u)$ represents the number of followers of the topic's initial user u, $I_h(u)$ denotes the historical average interaction rate of the topic's initial user u, reflecting how much interaction the content generated by the user can elicit from other users, and $I_e(u)$ indicates the content reach rate of the topic's initial user u, reflecting the proportion of non-direct followers that the user's content can reach.

3.2. Problem fo rmalization

In order to clearly describe the research problem, this section formalizes it as follows. Based on the topic co-occurrence data $C = \{(s, h, p) \,|\, p \in P\}$, a derived topic co-occurrence network is constructed within a specific time window t, and the Node2vec algorithm is applied to the network $G = \left\{V, E_V\right\}$ to obtain low-dimensional structural representations of topic nodes. Meanwhile, according to the basic attribute set of derived topics $D = \{(a, v) \,|\, v \in V\}$ and the co-occurrence data C, the attractiveness of each topic is quantitatively characterized from the perspectives of influence and topicality. Furthermore, the weighted average co-occurrence time is computed from C to emphasize recently and frequently co-occurring topic pairs, and this temporal information is incorporated into the attention coefficients of the GAT to model dynamic interaction strength.

Based on the above components, the proposed method can be regarded as a unified mapping function that takes the topic co-occurrence data C, the derived topic graph G, and the topic attribute set D as inputs, and outputs the predicted dissemination trend of derived topics in the next time period. The overall problem formulation is expressed as:

$$\left.\begin{array}{l} C = \{(s, h, p) \mid p \in P\} \\ G = (V, E_V) \\ D = \{(a, v) \mid v \in V\} \end{array}\right\} \Rightarrow \text{Method}() \Rightarrow B \tag{6}$$

3.2.1. Problem Input

According to the definitions and descriptions, the model input is as follows:

(1) Topic co-occurrence data, $C = \{(s, h, p) \,|p \in P\}$, where s represents the set of topic tags in post p, h represents the posting time, and P represents the collection of all posts. This data describes the temporal co-occurrence patterns of multiple topics within the same semantic context, serving as the fundamental evidence of topic-level associations and their dynamic evolution.

(2) The derived topic co-occurrence network, $G = \left\{V, E_V\right\}$, where V represents the set of topics, and E_V represents the co-occurrence status between topics. It is a graph structure constructed from topic co-occurrence data to characterize the structural associations and semantic relationships among derived topics.

(3) Derived topic basic attributes, $D = \{(a, v) \,|v \in V\}$, where a represents the basic information of topic v, such as the number of comments, shares, likes, and so on. These attributes provide quantitative descriptions of the popularity, activity, and influence of each topic, complementing the structural information of the co-occurrence network.

3.2.2. Problem Output

According to the definitions and descriptions, the model's output is as follows:

(1) Topic structural feature representation T_{struct}. A derived topic co-occurrence network is constructed, and Node2vec is used to deeply mine the correlations among multiple derived topics.

(2) Topic attractiveness $T_{attraction}$. By precisely quantifying the influence and topicality of topics, a multidimensional perspective is provided to capture the overall attractiveness of the topics.

(3) Prediction model output B. The weighted average co-occurrence time calculated based on topic co-occurrence data is used to emphasize recently frequently co-occurring topic tags, which are then integrated into the attention coefficients of the GAT. Ultimately, this predicts the user's behavior towards derived topics in the next time period.

4. Model

To address the aforementioned issues, this section proposes a derived topic propagation prediction model based on topic attractiveness and dynamic temporal awareness. This model consists of three parts. The first part involves mining the structural characteristics of topics through the derived topic co-occurrence network. The second part extracts topic attractiveness based on the two attributes of influence and topicality. The third part calculates the weighted average co-occurrence time between nodes in the derived topic co-occurrence network and integrates a time-sensitive attention mechanism into the GAT to construct the derived topic propagation prediction model. The framework of the model is illustrated in Fig. 2.

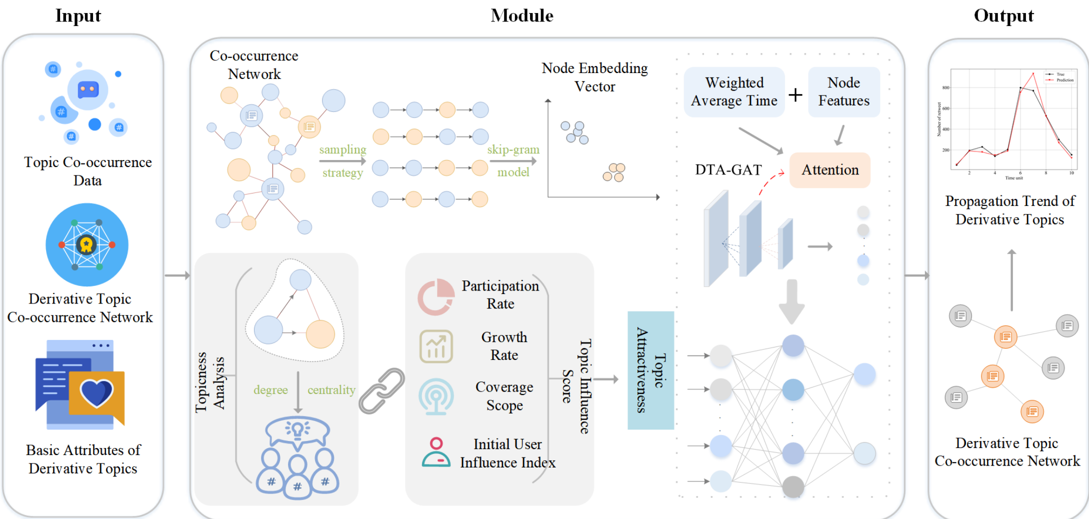


Figure 2: Model Framework

4.1. Model Framework

The traditional topic analysis methods focus on the extraction and description of single topic features, often overlooking the potential connections between different derived topics. To overcome this limitation, an analysis method based on the co-occurrence network of derived topics is introduced. This method constructs a derived topic co-occurrence network by observing the co-occurrence of different topic labels within the same post. Furthermore, the Node2vec algorithm is utilized to encode the derived topic co-occurrence network, aiming to learn the structural feature vector representation of each topic node for a deeper understanding of the relationships between topics.

Based on the topic co-occurrence data $C = \{(s, h, p) \mid p \in P\}$, a derived topic co-occurrence network $G = \{V, E_V\}$ can be formed within a specific time window t , representing the co-occurrence status between topics. Meanwhile, each edge (v, x) is assigned a weight that indicates the co-occurrence strength between topic v and topic x. However, to reduce the excessive influence of high-frequency topics, this section employs a normalization method to quantify this weight. The weight normalization calculation is shown in Equation 7.

$$W_{VX} = \frac{N(v, x)}{max(N)} \tag{7}$$

Where $N(v, x)$ represents the number of co-occurrences of topic v and topic x within a given time window, while $max(N)$ is the maximum value among all co-occurrence counts.

Based on the shared network, random walks are conducted to generate node vectors, and this process is illustrated in Fig. 3.

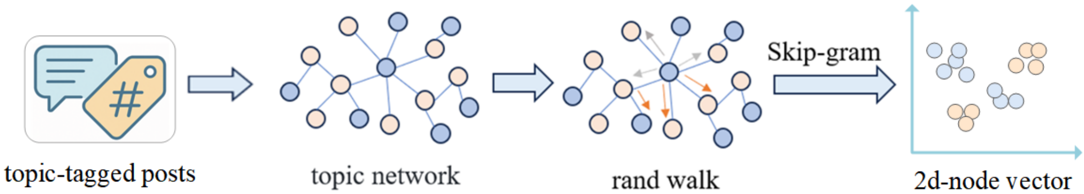


Figure 3: Topic Node Embedding via Node2vec in the Derivative Co-occurrence Network

Node2vec uses a specialized random walk strategy that combines the characteristics of Depth-First Search (DFS) and Breadth-First Search (BFS). This strategy is controlled by two parameters, p and q. The parameter p controls the probability of returning to the previous node, while q controls the tendency to explore away from the source node. In the derived topic co-occurrence network, assuming a random walk starts from a certain derived topic, if the current derived topic at step $i-1$ is v, then the jump probability to the derived topic x at step i is given in Equation 8.

$$P(c_i = x \mid c_{i-1} = v) = \begin{cases} \frac{\pi_{vx}}{Z}, & \text{if}(v, x) \in E_V \\ 0, & \text{else} \end{cases} \tag{8}$$

Where Z is the normalization constant, and π_{vx} represents the probability of the derived topic node v jumping to the next derived topic node x, with the calculation method as shown in Equation 9.

$$\pi_{vx} = \alpha_{pq}(m, x) \cdot w_{vx} \tag{9}$$

Where m represents the previous topic from which the random walk arrived at topic v, w_{vx} is the edge weight between topic v and topic x , and $\alpha_{pq}(m, x)$ is the normalized co-occurrence strength obtained from the above calculations, which is the correction factor. The correction factor is defined as shown in Equation 10.

$$\alpha_{pq}(m, x) = \begin{cases} \frac{1}{p}, & \text{if } (d_{mx} = 0) \\ 1, & \text{if } (d_{mx} = 1) \\ \frac{1}{q}, & \text{if } (d_{mx} = 2) \end{cases} \tag{10}$$

Where d_{mx} represents the shortest path length between topic m and topic x measured in hop distance. When multiple shortest paths exist between two topics, only the minimum hop distance is considered, and the specific path is not distinguished. If there is a direct connection between the two topics, then $d_{mx} = 1$; if the two nodes are the same node, then $d_{mx} = 0$; if the two nodes are not connected, then $d_{mx} = 2$.

Based on the node sequences obtained from the aforementioned random walks, the Skip-gram model is used to learn the topic node embeddings, and the optimization objective function is defined as shown in Equation 11.

$$\max \sum_{v \in V} \log \Pr\left(N_s(v) \mid f(v)\right) \tag{11}$$

Where $N_S(v)$ is the set of neighboring nodes of topic v obtained through random walk sampling, $f(v)$ is the embedding vector of topic v, and $Pr(N_S(v) \mid f(v))$ represents the probability of observing its neighboring node set given the feature vector of topic v.

Finally, the structural feature representation of the derived topic is shown in Equation 12.

$$\mathbf{T}_{struct} \in R^{|V| \times d} \tag{12}$$

Where $|V|$ is the number of nodes in the derived topic co-occurrence network, and d is the dimension of the node embedding vectors.

4.2. Quantification of Topic Attraction

In social media, users' attention to a topic and their interaction tendencies are core factors influencing its dissemination scope. Topic attractiveness may arise from positive engagement and resonance. It may also evolve dynamically under controversy and negative feedback. To quantitatively characterize topic attractiveness, a multivariate linear regression model is employed to capture the promoting or inhibiting effects of different user responses. This formulation enables a multidimensional assessment of the overall dissemination potential from the perspective of topic attractiveness. Topic attractiveness is mainly quantified along two key dimensions: topic influence and topic topicality. The specific quantification process is illustrated in Fig. 4

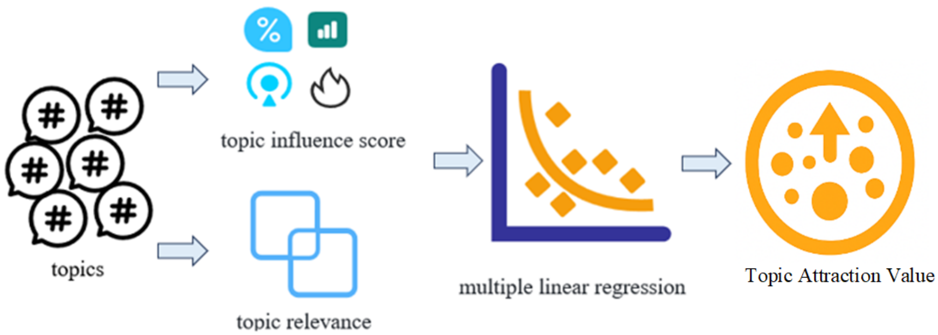


Figure 4: Process of Quantifying Topic Attraction

Topic influence reflects a topic's capability to stimulate user participation and further diffusion on social platforms. In this study, it is comprehensively evaluated from four aspects: participation rate, growth rate, coverage range, and the initial user influence index. To ensure comparability and unified analysis, these indicators so that they range from 0 to 1, as represented in Equation 13.

$$S(y) = \frac{y - min(y)}{max(y) - min(y)} \tag{13}$$

Where y represents the value of the quantified indicator.

The standardized indicators are summed and averaged to obtain a comprehensive topic influence score, as specifically represented in Equation 14.

$$I_{\text{impact}} = \frac{\sum_{i=1}^{\|\mathbf{D}\|_0} S(y_i)}{\|\mathbf{D}\|_0} \tag{14}$$

where I_{impact} denotes the topic influence score, and $S(y_i)$ represents the standardized value of the i-th quantitative indicator. Let $\mathbf{D} = [\text{Participation Rate}, \text{Growth Rate}, \text{Coverage Range}, \text{The Initial User Influence Index}]^\top$ be the feature vector composed of the four influence dimensions, and let $\|\mathbf{D}\|_0$ denote its ℓ_0-norm. This design exploits the discrete counting property of the ℓ_0-norm to characterize the effective number of dimensions, while ensuring that the four dimensions contribute equally to the overall topic influence.

On the other hand, topic relevance is defined as a key dimension for measuring topic attractiveness. It refers to a topic's ability to provoke discussions on related topics and to engage users in further dissemination. Topics with high relevance are more likely to become nodes of dissemination. Based on this definition, this section calculates the degree centrality of each derived topic node v using the derived topic co-occurrence network G to assess the relevance of the derived topics. Its specific definition is represented in Equation 15.

$$I_{relate} = \frac{deg(v)}{|V| - 1} \tag{15}$$

Where $|V|$ represents the number of topic nodes, and $deg(v)$ represents the degree of the topic node v .

Considering the importance of both topic characteristics, multiple linear regression is used to combine topic influence and relevance to quantify topic attractiveness, as specifically represented in Equation 16.

$$T_{attraction} = \lambda_0 + \lambda_1 \cdot I_{impact} + \lambda_2 \cdot I_{relate} + \varepsilon \tag{16}$$

Where λ_0, λ_1 and λ_2 are the regression coefficients, revealing the relative importance of topic influence and relevance on topic attractiveness, and ε is the error term.

4.3. Derived Topic Propagation Prediction Model

Given the rapidly changing nature of the social media environment, solely focusing on long-term co-occurrence patterns may not be sufficient to fully capture the dynamic propagation characteristics of topics. Therefore, this section integrates a time-sensitive attention mechanism into GAT by combining long-term co-occurrence intensity with recent co-occurrences to address the derived topic co-occurrence network.

To this end, this section introduces the concept of weighted average co-occurrence time' to quantify and capture the timeliness of the co-occurrence relationships between topics. The weighted average co-occurrence time is a quantitative method that considers the proximity of co-occurrence event times. For each pair of co-occurring topics on social media, this section not only considers the number of their co-occurrences but also how far these co-occurrence events are from the current time. The calculation method for the weighted average co-occurrence time is shown in Equation 17.

$$W_{vx} = \frac{\sum_{h \in H_{vx}} e^{-\gamma(h_{current} - h)}}{|H_{vx}|} \tag{17}$$

Where W_{vx} represents the weighted co-occurrence time between topics v and x, H_{vx} is the set of all time points at which the two topics co-occur, $h_{current}$ is the current time, h is the time point of the co-occurrence event, and γ is a decay rate used to determine the strength of the temporal influence.

In the standard GAT, the attention coefficients are typically calculated based on the feature vectors between nodes. Here, this is adjusted to simultaneously consider both node features and the weighted average time, specifically defined as shown in Equation 18.

$$\text{Attention}(v, x) = \mathbf{a}^\top [M\mathbf{T}_v \parallel M\mathbf{T}_x] \times W_{vx} \tag{18}$$

Where M is the weight that needs to be trained, $\mathbf{a}$ is used to map the transformed high-dimensional features to a real number, W_{vx} is the weight based on the weighted average time, and $\mathbf{T}_v$ and $\mathbf{T}_x$ are new vector representations obtained by fusing the structural features and attractiveness of topics v and x , respectively. The specific representation is shown in Equation 19.

$$\mathbf{T}_m = [\mathbf{T}_{struct} \parallel \mathbf{T}_{attraction}] \tag{19}$$

Where $\mathbf{T}_{struct}$ is the structural feature vector of topic m, $\mathbf{T}_{attraction}$ is the attractiveness value of topic m, and $\mathbf{T}_m$ is the feature vector obtained after the fusion of the previous two.

Additionally, this section requires the normalization of the obtained attention coefficients to ensure that, for each node, the sum of all attention coefficients equals 1. The specific representation is shown in Equation 20.

$$\alpha_{vx} = \frac{\exp(\mathrm{LeakyReLU}(\mathrm{Attention}(v, x)))}{\sum_{k \in N(v)} \exp(\mathrm{LeakyReLU}(\mathrm{Attention}(v, k)))} \tag{20}$$

Where α_{vx} is the normalized attention coefficient, representing the importance of topic node v to topic node x.

Then, each node aggregates the feature information of its neighboring nodes based on the attention coefficient, forming a new node feature representation. The specific representation is shown in Equation 21.

$$\mathbf{T}_m^{new} = \sigma\left(\sum_{j \in N(m)} \alpha_{mj} M \mathbf{T}_m\right) \tag{21}$$

The output of the prediction model is the propagation trend of derived topics, which can be viewed as a regression task. Let $W^{(L)}$ and $b^{(L)}$ denote the weights and biases of the output layer, where (L) indicates that it corresponds to the L-th layer of the model. Let H' represent the transformed hidden representation obtained after multiple layers of information processing. The model output is shown in Equation 22.

$$B = W^{(L)} H' + b^{(L)} \tag{22}$$

4.4. Modelling algorithms

The derived topic propagation prediction model aims to predict the propagation trend of derived topics. The specific algorithm is shown as Algorithm 1.

The overall time complexity of the algorithm is mainly influenced by the random walks of Node2vec and the processing of the GAT model. Let r be the number of random walks, l be the length of each walk, and $|V|$ be the number of nodes. Then the time complexity of the random walks is $O(r \cdot l \cdot |V|)$. The time complexity of the GAT model is related to the number of nodes $|V|$, the number of edges $|E|$, and the average number of neighbors k considered by each node. Assuming the GAT model has L layers, the time complexity of the GAT is approximately $O(L \cdot |V| \cdot k)$.

5. Experiments and Discussion

5.1. Experimental set-up

This section will introduce the data used in the experiments, the baseline methods for comparing model performance, and the performance evaluation metrics used for the model.

5.1.1. Experimental Data

The data used in this section are sourced from the Weibo dataset (Song et al., 2019), the COVID-19-rumor dataset (Cheng et al., 2021), the Twitter dataset (Arkaitz et al., 2016; Zubiaga et al., 2016), and the PHEME dataset (Kochkina et al., 2018). Prior to conducting the experiments, multiple relevant derived topics were manually identified, and posts associated with these topics were collected to obtain co-occurrence data. The data were then split into 70% for the training set, 20% for the validation set, and 10% for the test set.

One derived topic was selected from each of the four datasets. Derived Topic A is “The Academic Misconduct Scandal of Zhai Tianlin,” Topic B is “The Plandemic Vaccine and Virus Conspiracy Theory,” Topic C is “The July 20 Extreme Rainstorm and Flood Disaster in Zhengzhou, Henan,” and Topic D is “The Lion Air JT610 and Ethiopian Airlines ET302 Air Crash Incidents (Boeing 737 MAX).” Table 2 presents the statistical information for these four derived topics. The subsequent analysis is based on the co-occurrence data of these derived topics and their related

Table 1
Algorithm for Derived Topic Propagation

Derived Topic Propagation Prediction Model
Based on Topic Attractiveness and Dynamic Time Perception

Input: Topic Co-occurrence Data: $C = \{(s, h, p) \mid p \in P\}$;
Derived Topic Co-occurrence Network: $G = (V, E_V)$;
Basic Attributes of Derived Topics: $D = \{(a, v) \mid v \in V\}$.
Output: Topic Structural Feature Representation $\mathbf{T_{struct}}$;
Topic Attractiveness $T_{attraction}$;
Prediction Model Output B.

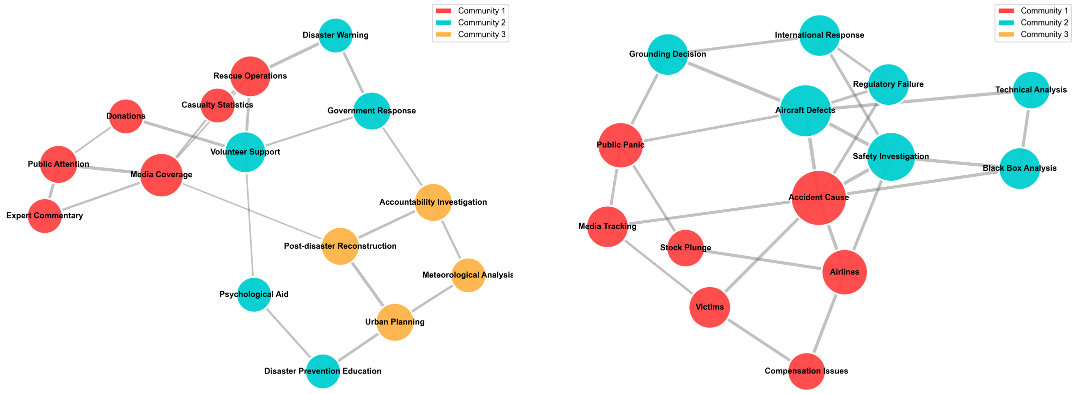
```
for each user node do do
    Calculate the topic structural feature representation based on Equations. 7 - 12 : T_struct;
    Calculate the influence of the topic based on Equations. 1 - 6, C, and Equation. 14: I_impact;
    Calculate the topicality of the topic based on Equation. 15: I_relate;
    The topic attractiveness can be quantified by integrating topic influence
     and topicality using multiple linear regression, as derived from Equation. 16: T_attraction;
end for
for each training data do do
    Calculate the weighted average time based on Equation. 17: W_vx
    Calculate the attention coefficient between two nodes based on Equations. 18-20: α_vx;
end for
repeat
    update W_0, W_1, use Gradient Descent to calculate ∂L/∂W_0, ∂L/∂W_1;
until model convergence
for each testing data do do
    Predict the dissemination trend of derivative topics based on Equation. 2;
end for
```

Table 2
Topic Data

dataset	times interval	number of disseminating users	number of potential users	number of historical actions
Topic A	2019.02.08 - 2019.02.18	4823	812450	1324716
Topic B	2020.05.04 - 2020.05.18	7502	1243892	2197430
Topic C	2021.07.20 - 2021.08.05	9316	1568204	3019885
Topic D	2018.10.29 - 2019.03.20	6945	1025610	2487902

counterparts. It investigates the derived topic co-occurrence network, examines structural characteristics of the topics, and explores how topic attractiveness influences propagation trends.

To further reveal the structural differences among derived topics, the co-occurrence networks of Topic C and Topic D are visualized and analyzed, as shown in Fig. 5. In the graph, nodes represent subtopics, and edges denote normalized co-occurrence relationships. The network of Topic D exhibits a highly centralized and compact topology. Most subtopics are tightly clustered around a few core nodes, forming a strongly coupled global structure with pronounced temporal synchrony. Such a configuration corresponds to a bursty diffusion pattern. Multiple semantically related branches are activated simultaneously within a short time span, which triggers rapid cascade propagation. In contrast, the network of Topic C displays clear modularity and community structure. Subtopics are partitioned into several semantically relatively independent clusters, with sparse connections between clusters. This indicates that its diffusion mainly relies on long-term semantic associations and slow cross-community propagation, rather than instantaneous and globally synchronized outbreaks. These structural discrepancies provide support for constructing models that integrate temporal awareness and multidimensional attractiveness. Such models can accommodate both burst-driven diffusion and sustained-attention diffusion scenarios.



(a) Topic C: Sustained-attention type

(b) Topic D: Burst-driven type

Figure 5: Visualization of Derived Topic Co-occurrence Networks.

5.1.2. Baseline Methods

To comprehensively evaluate the performance of the derived topic propagation prediction model, a comparative analysis is conducted with the following baseline methods:

(1) DBGNN Model(Heeg & Scholtes, 2024): Utilizing time-aware graph neural networks to predict node temporal centrality within dynamic graphs, capturing temporal dependencies across evolving topologies.

(2) PT-GCN Model(Zeng & Xiang, 2023): Using multidimensional cascading graphs to model and analyze the forwarding frequency of topics related to information cascades.

(3) TAG Model(Pan et al., 2025): Using time-aware graph learning with recent-neighbor sampling and contrastive learning to predict link trends in dynamic co-occurrence networks, capturing short-term dynamics and long-term topic associations.

(4) CasDO Model(Cheng et al., 2024): Modeling information cascade popularity as a probabilistic diffusion process, leveraging Neural Ordinary Differential Equations (ODEs) to simulate and predict continuous-time popularity dynamics.

5.1.3. Evaluation indicators

To comprehensively evaluate and compare the prediction accuracy of different models, two key performance metrics in regression tasks are employed, namely Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

(1) MAE refers to the average of the absolute differences between the predicted values and the actual values, calculated as shown in Equation 23.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{23}$$

(2) RMSE is the square root of the average of the squared errors, calculated as shown in Equation 24.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{24}$$

Where n is the number of observation points, $\hat{y}_i$ is the predicted value for the i-th observation, and y_i is the actual value for the i-th observation.

5.1.4. Parameter Sensitivity Analysis

To further examine the robustness and interpretability of the model, a systematic parameter sensitivity analysis is conducted on several key hyperparameters involved in derived topic propagation prediction. These include the time decay rate γ, the Node2vec parameters p and q, and the regression coefficients λ_0, λ_1, and λ_2 in the topic attractiveness modeling.

(1) Impact of Node2vec Parameters p and q.

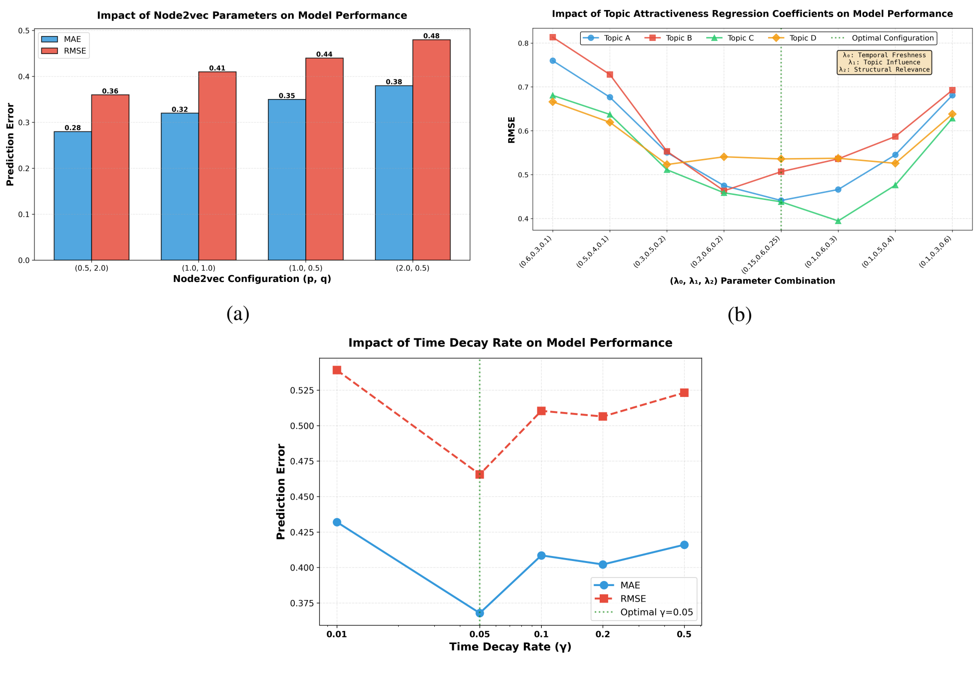
Parameters p and q regulate the random walk strategy in Node2vec and control the trade-off between exploring local neighborhoods and capturing deeper network structures. A smaller q emphasizes local co-occurrence relations and biases the walk toward BFS. A larger q encourages exploration of long-range structural patterns and biases the walk toward DFS. Several representative parameter combinations are evaluated, including $(p, q) = (0.5, 2)$, $(1, 1)$, $(1, 0.5)$, and $(2, 0.5)$. As shown in Fig. 6(a), configurations with a moderate BFS bias achieve clearly better overall predictive performance than those biased toward DFS. This indicates that, for derived topic propagation prediction, local co-occurrence relationships are more discriminative than long-range structural patterns and play a more critical role in modeling diffusion trends.

(2) Analysis of Topic Attractiveness Regression Coefficients.

Fig. 6(b) illustrates the relative importance of different factors in topic attractiveness modeling. Under the constraint $\lambda_0 + \lambda_1 + \lambda_2 = 1$, various coefficient combinations are evaluated through grid search. The optimal performance is obtained when $\lambda_1 = 0.6$, $\lambda_2 = 0.25$, and $\lambda_0 = 0.15$. This result indicates that topic influence is the most critical component in attractiveness modeling. The ordering $\lambda_1 > \lambda_2 > \lambda_0$ is consistently observed. Topic influence contributes the most, followed by structural relevance, while temporal freshness plays a comparatively smaller role. This finding is in accordance with real social media diffusion mechanisms, in which user engagement and interaction intensity constitute the primary driving forces of topic propagation.

(3) Impact of the Time Decay Rate γ.

The time decay rate γ controls the attenuation strength of historical topic co-occurrence information in the DTA-GAT. A larger value amplifies the influence of recent interaction events, whereas a smaller value increases the reliance on long-term historical dependencies. With other parameters fixed, γ is set to 0.01, 0.05, 0.1, 0.2, and 0.5, respectively. The results are shown in Fig. 6(c). When γ is too small, recent topic dynamics are insufficiently captured, leading to degraded predictive performance. When γ is too large, the model becomes overly sensitive to short-term fluctuations, resulting in unstable predictions. The best performance in terms of both MAE and RMSE is achieved at $\gamma = 0.05$. This setting provides a suitable balance between long-term co-occurrence modeling and short-term dynamic perception.



(a) (b) (c)

Figure 6: Parameter Sensitivity Analysis.

5.2. Experimental analyses

This section will provide a comprehensive analysis of the performance of the proposed topic propagation prediction model based on the four selected sets of derived topic co-occurrence networks. The structure of this section is as follows: (1) Effectiveness of topic structural feature representation; (2) Effectiveness analysis of topic attractiveness; (3) Ablation experiments of the DTA-GAT model; (4) Comparative analysis with baseline methods.

5.2.1. Effectiveness of Topic Structural Feature Representation

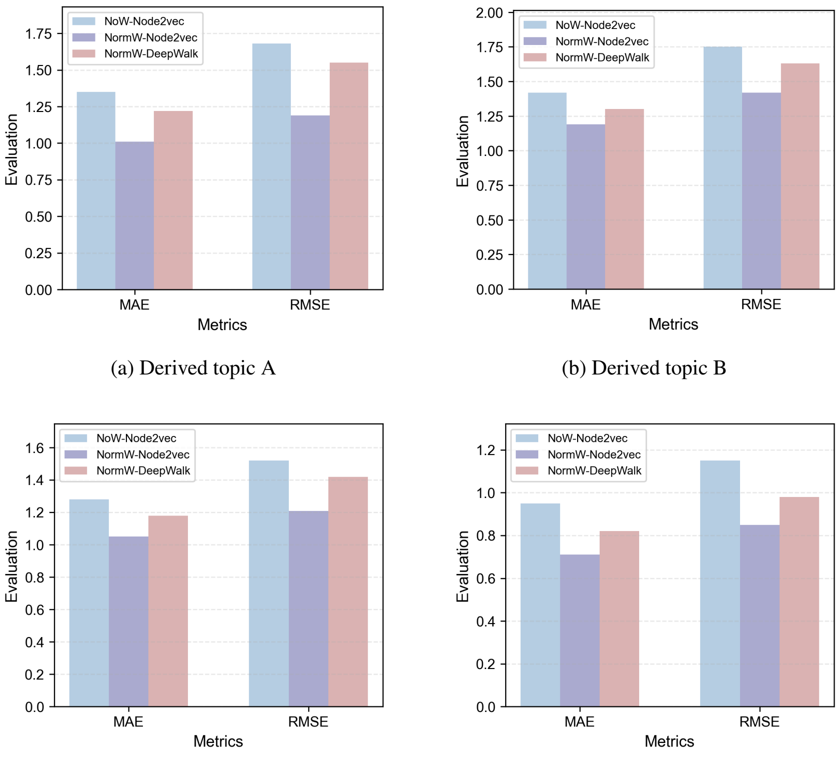
To evaluate the impact of different network construction methods and node embedding techniques on social media topic propagation prediction, the following three groups of experiments were designed for analysis. And the experimental results shown in Fig. 7 were obtained using the MAE and RMSE metrics.

NoW-Node2vec: A basic topic co-occurrence network is used, which does not consider the impact of edge weights, combined with the Node2Vec algorithm for node embedding. This approach focuses on exploring the co-occurrence relationships between nodes but does not address the strength or importance of those co-occurrences.

NormW-Node2vec: A topic co-occurrence network is constructed by adding normalized co-occurrence strength as edge weights, combined with the Node2Vec algorithm for node embedding. This method contrasts with Experiment 1, exploring the excessive influence between high-frequency topics.

NormW-DeepWalk: Building on the topic co-occurrence network that includes normalized co-occurrence strength as edge weights, the DeepWalk algorithm is used for node embedding.

As shown in Fig. 7, based on the four groups of topic co-occurrence networks, NormW-Node2vec performed significantly better across all metrics compared to NoW-Node2vec and NormW-DeepWalk.



(a) Derived topic A

(b) Derived topic B

(c) Derived topic C

(d) Derived topic D

Figure 7: Experimental results of topic structure feature representation.

By comparing NoW-Node2Vec with NormW-Node2Vec, consistent reductions in both MAE and RMSE can be observed across all four topics after incorporating normalized co-occurrence strength. For Topics A and B, MAE decreases by approximately 0.2–0.3, and RMSE by about 0.3–0.4. This indicates that edge-weight modeling effectively suppresses weak and noisy co-occurrence relations, while highlighting dominant semantic association paths. Similar magnitudes of error reduction are also observed for Topics C and D. This demonstrates that weighted structural modeling provides robust performance gains under different diffusion patterns. Under the same weighted network setting, NormW-Node2Vec further reduces the prediction error compared with NormW-DeepWalk. As shown in Fig. 7(c) and Fig. 7(d), both metrics are generally lowered by about 0.1–0.2. This suggests that the biased random walk strategy of Node2Vec is more effective in capturing heterogeneous topic neighborhood structures and multi-scale dependency patterns.

Among all topics, Topic D consistently achieves the lowest prediction error. Under the NormW-Node2Vec configuration, its MAE and RMSE are approximately 0.7 and 0.85, respectively. These values are substantially lower than those of the other topics. This indicates that Topic D is characterized by dense and high-intensity co-occurrence structures, as well as pronounced local clustering properties. When co-occurrence strength modeling is combined with structure-aware embedding, its core diffusion structure can be represented more accurately, leading to the best overall prediction performance.

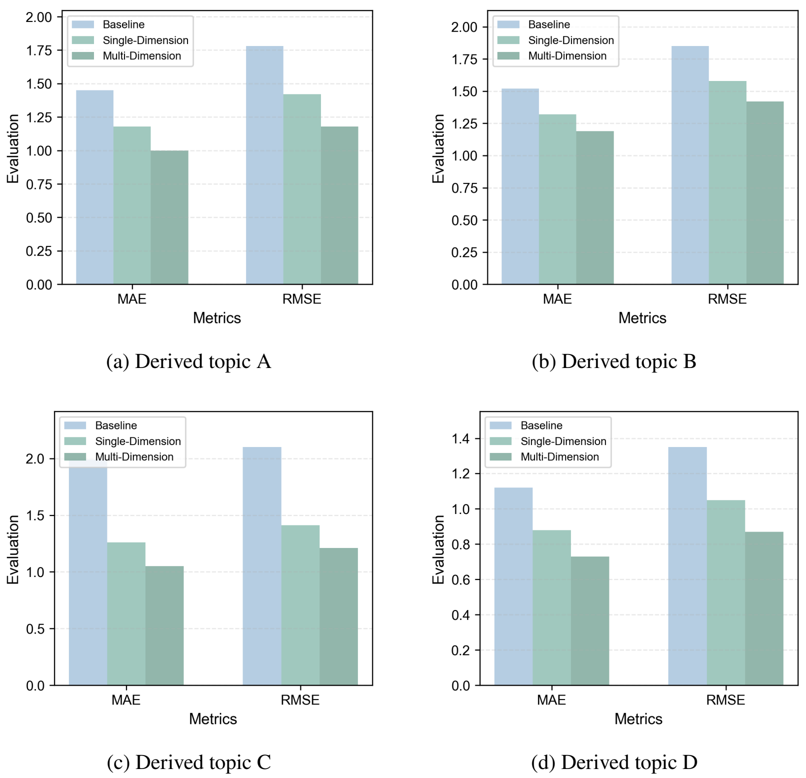
5.2.2. Analysis of the Effectiveness of Topic Attractiveness

To explore the effectiveness of quantifying the topic attraction method in predicting the dissemination dynamics of topics on social media, this section designs three detailed comparative experiments. The MAE and RMSE metrics are used to obtain the experimental results shown in Fig. 8.

Baseline uses the DTA-GAT model to predict the dissemination trend of topics without incorporating information related to topic attractiveness.

Single-Dimension introduces the concept of topic attractiveness but quantifies it only from a single dimension, combined with the DTA-GAT model for prediction.

Multi-Dimension builds on Single-Dimension by further expanding the consideration of topic attractiveness. It incorporates multi-dimensional evaluations combined with the DTA-GAT model for trend prediction.



(a) Derived topic A

(b) Derived topic B

(c) Derived topic C

(d) Derived topic D

Figure 8: Experimental results on quantifying topic attractiveness.

By analyzing the prediction results of different experimental groups, it is evident that the performance of Single-Dimension shows improvement compared to Baseline. Moreover, Multi-Dimension demonstrates a more significant enhancement in performance. This emphasizes the importance of multi-dimensional quantification of attractiveness in improving the performance of topic dissemination prediction models. From Baseline to Single-Dimension, both MAE and RMSE decrease significantly for all topics. Taking Topic C as an example, its MAE drops from about 2.0 to around 1.25. Its RMSE decreases from above 2.1 to approximately 1.4. This indicates that even a single-dimensional attractiveness representation can substantially enhance the explanatory power of user participation motivation, beyond structural and temporal features. On this basis, multi-dimensional attractiveness modeling yields further stable improvements. Compared with the single-dimensional setting, MAE is reduced by about 0.15–0.25 and RMSE by approximately 0.2–0.3 across the four topics. This suggests that topic diffusion is driven by the joint effects of multiple factors. A single scalar intensity indicator is therefore insufficient to fully capture the underlying diffusion mechanisms. In contrast, the joint modeling of semantic, emotional, and cognitive dimensions enables a more discriminative representation of user–topic affinity.

This advantage is particularly evident for Topic C. As shown in Fig. 8(c), its MAE is further reduced from about 1.26 to around 1.05. Its RMSE decreases from approximately 1.41 to about 1.21. This topic exhibits a diffusion pattern dominated by content-driven and long-term attention. Instantaneous popularity alone cannot explain sustained user engagement. Multi-dimensional attractiveness features provide a more stable representational basis and lead to more pronounced and robust performance gains for this topic.

5.2.3. Ablation Experiments of the DTA-GAT Model

To verify the effectiveness of the DTA-GAT model, which incorporates a time-sensitive attention mechanism, this section designs an ablation study, which is particularly crucial. The ablation study evaluates the contribution of specific components by comparing the performance differences between the complete model and models with certain components removed. The following outlines a possible design for the ablation study of the DTA-GAT model. This section aims to clearly present the results of the ablation study, as shown in Table 3.

Table 3: Ablation Experiments of the DTA-GAT Model

Topic	Experimental Setup	MAE	RMSE
A	DTA-GAT-Full	**1.0100**	**1.1900**
A	DTA-GAT-NoTemporal	1.1450	1.3750
B	DTA-GAT-Full	**1.1900**	**1.4200**
B	DTA-GAT-NoTemporal	1.3290	1.5950
C	DTA-GAT-Full	**1.0500**	**1.2100**
C	DTA-GAT-NoTemporal	1.0650	1.2250
D	DTA-GAT-Full	**0.7100**	**0.8500**
D	DTA-GAT-NoTemporal	1.2300	1.4800

DTA-GAT-Full: The complete DTA-GAT model, which integrates the time-sensitive attention mechanism, is used to analyze the dynamic characteristics of the derived topic co-occurrence network.

DTA-GAT-NoTemporal: The time-sensitive attention mechanism is removed from the DTA-GAT model while keeping all other components of the model unchanged.

This table presents a clear performance comparison between DTA-GAT-Full and DTA-GAT-NoTemporal. All four topics exhibit degraded performance in DTA-GAT-NoTemporal. This highlights the overall contribution of the time-sensitive attention mechanism to improving prediction accuracy. Topic C, however, shows only a small performance gap between the two setups. This may be attributed to its diffusion process being less dependent on recent temporal dynamics. Table 3 further compares the complete DTA-GAT model with a variant that removes the time-sensitive attention mechanism. This comparison isolates the role of temporal awareness in propagation prediction. For Topics A, B, and D, the removal of the temporal module leads to clear increases in both MAE and RMSE. This indicates that their diffusion processes strongly depend on recent interaction intensity and temporal ordering. By assigning higher attention weights to recent and rapidly changing interactions, the full model can better capture bursty propagation patterns and the temporal synchrony of user behaviors, thereby achieving higher prediction accuracy.

In contrast, Topic C exhibits only marginal performance degradation after the temporal component is removed. This suggests that its diffusion is less sensitive to short-term temporal fluctuations and is more influenced by long-term accumulated attention. Its relatively flat and long-tailed temporal distribution implies that historical interactions remain informative for prediction. As a result, the marginal contribution of a strictly time-sensitive weighting scheme is reduced.

These ablation results indicate that the time-sensitive attention mechanism yields substantial gains for burst-driven and rapidly spreading topics. For diffusion patterns dominated by sustained attention, its role is primarily complementary rather than decisive.

5.2.4. Comparative Analysis of Baseline Methods

This study focuses on macro-level user behavior and proposes a derivative topic propagation prediction model based on topic attractiveness and dynamic temporal awareness. The model is designed by exploring topic appeal and the complex dynamic relationships among topics, with the goal of accurately forecasting propagation trends of derivative topics. To evaluate its predictive performance, several representative methods in the field of derivative topic diffusion prediction are selected as baselines, and their results are compared with those of the DTA-GAT model. A comparative analysis is conducted on four derivative topics from two perspectives: error magnitude and the ability to fit temporal evolution patterns.

As reported in Table 4, DTA-GAT achieves the lowest MAE and RMSE on all tested topics. This demonstrates its strong generalization capability across different diffusion scenarios. Topic D exhibits the most complex propagation pattern, characterized by multi-peak fluctuations and reactivation behavior. Baseline models often show delayed responses at peak positions or overly smoothed predictions during decay phases. In contrast, DTA-GAT integrates dynamic topic-attractiveness perception with time-dependent modeling. It can accurately capture the nonlinear variations of the diffusion process. For Topic D, MAE and RMSE are reduced by an average of 0.461 and 0.549, respectively, compared with the baselines. This highlights its superior nonlinear fitting ability and temporal robustness.

The source of this performance advantage lies in fundamental differences in model design. DBGNN and PT-GCN mainly emphasize structural diffusion relationships among users or topics. TAG focuses on extracting temporal evolution patterns. CasDO concentrates on modeling cascade diffusion dynamics. By comparison, DTA-GAT explicitly models multidimensional topic attractiveness. It jointly characterizes the driving effects of semantic intensity, emotional resonance, and cognitive attention on diffusion potential. In addition, a dynamic time-aware attention mechanism is introduced to adaptively weight critical historical stages. This design allows the model to closely follow true diffusion dynamics during acceleration phases, peak periods, and multi-peak reactivation stages. As a result, consistently lower MAE and RMSE are obtained across all derivative topics.

Table 4: Comparison of Model Performance with Baseline Methods

Topic	Metrics	DBGNN	PT-GCN	TAG	CasDO	DTA-GAT
Topic A	MAE	1.2598	1.1947	1.2235	1.1130	**1.0006**
	RMSE	1.5823	1.4960	1.5401	1.3106	**1.1871**
Topic B	MAE	1.2458	1.2539	1.2512	1.1513	**1.1000**
	RMSE	1.5507	1.5791	1.5704	1.3934	**1.3200**
Topic C	MAE	1.1177	1.0407	1.1397	1.0200	**0.9500**
	RMSE	1.3267	1.2043	1.3566	1.1800	**1.1200**
Topic D	MAE	1.1112	1.1806	1.1175	1.2751	**0.7103**
	RMSE	1.3046	1.3713	1.3182	1.5904	**0.8467**

6. Summary

A derivative topic propagation prediction model is proposed by integrating topic attractiveness with dynamic temporal perception to capture macro-level dissemination patterns. A co-occurrence network of derivative topics is built using normalized co-occurrence strength, and Node2vec generates low-dimensional topic embeddings. Topic attractiveness is modeled from influence and topicality perspectives. A time-sensitive attention mechanism in GAT forms the DTA-GAT model, enabling more accurate propagation trend prediction. Experiments on multiple public datasets confirm the effectiveness of the structural representation, attractiveness modeling, and the DTA-GAT framework.

Future work will incorporate user-level interaction dynamics and extend the model to cross-lingual topic propagation scenarios, allowing the study of multilingual information diffusion. These extensions aim to further improve the model's generalization ability and its applicability in real-world social media environments.

CRediT authorship contribution statement

Rong Wang: Supervision, Writing - review & editing, Resources. **Runyu Mao:** Conceptualization of this study, Methodology, Software, Writing - Original draft preparation, Writing - review & editing. **Wenyi Xi:** Methodology, Writing - review & editing. **Qian Li:** Methodology, Supervision, Writing - review & editing. **Tun Li:** Methodology, Supervision, Writing - review & editing. **Yunpeng Xiao:** Project administration, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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