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Sociological and Educational Perspectives on Cross-Platform Micro Drama Adoption in the Digital Era

Yilin Chen[1*], Qi Tang[1], Zhonghao Liu[2]

[1]*Universiti Malaya, 50603 Kuala Lumpur, Wilayah Persekutuan Kuala Lumpur 50603, Malaysia*
[2]*School of Journalism and Communication, Changchun University of Technology130000， China*

** cyl131456787@gmail.com*

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Abstract

Micro dramas have quickly emerged as a ubiquitous cultural genre in the digital realm, but little is known regarding the diffusion of their usage socially and educationally in all-media communication space. This paper suggests a PageRank Complex Network Algorithm with a Graph Neural Network (PRCNA-GNN) to predict the adoption of cross-platform micro dramas based on multimodal data that consists of text, emoji, and static/dynamic memes. The fine-grained emotion and polarity analysis is supported by a custom set of Twitter posts exceeding one million posts annotated. PRCNA-GNN has better performance, as it can reach the accuracy of 93.7% precise 92.6% recall, and 92.9% F1-score. Adoption curves are close to actual trends of cumulative views and shares, and ablation experiments warrant the significance of PageRank weighting, multimodal characteristics and active learning. In addition to technical benefits, the results indicate the socio-cultural impact of micro dramas in the process of forming digital participation and possibly its educational importance in the development of multimodal literacy, narrative involvement, and creative learning.

Keywords: Cross platform adoption, Micro dramas, Media Pedagogy, PRCNA-GNN, Digital Culture, Socio-Cultural communication, participatory culture, digital media adoption.

Introduction

The emergence of micro dramas represents a notable shift in short form audiovisual storytelling, with content designed specifically for digital platforms (Hanney, 2025). Initially a phenomenon in China, micro dramas have expanded into a global trend, engaging audiences through concise, narrative driven formats (Xu, 2024). This evolution is driven by the convergence of media technologies, the adoption of cross-cultural communication strategies, and innovative production and dissemination practices (Liu & Bexci, 2025). As audiences increasingly access content via mobile devices, social media, and streaming services, understanding how micro dramas adapt across these heterogeneous platforms has become an essential area of research (Lu, 2025).

Micro dramas differ from traditional media in both structure and distribution. They rely on brief, focused story arcs to maintain audience attention in highly competitive digital environments (Xiao, 2025). Unlike conventional television or cinema, micro dramas often include participatory elements and interactivity that enhance engagement, enabling audiences to connect more closely with the narrative (Chen & Kim, 2024). Empirical studies suggest that these features contribute not only to immediate viewer attention but also to the sustainability and repeat consumption of content. The emergent, short-form video formats in the form of micro dramas shared on apps like Tik Tok, Youtube Shorts, Instagram Reels, and regional apps have transformed the modern media ecology. Quite on the contrary, micro dramas are now a vibrant socio-cultural phenomenon that captures changing patterns of communication, changing audience identities and changing ways of digital engagement. These snack-sized stories are reshaping the meaning-making processes and negotiation of cultural norms and interaction with social problems in the digital age. Micro dramas are becoming a prism of expression as well as re-imagination of generational values, lifestyle aspirations, and social interactions formed through the day-to-day life.

A key aspect of micro drama research is cross platform adaptation, which involves adjusting narrative, aesthetic, and technical elements to suit different media channels (Chen, 2025). Content creators must account for cultural, linguistic, and technical differences when distributing micro dramas internationally, ensuring that stories resonate with diverse audiences while retaining core themes (Yang et al., 2025). These approaches demonstrate the value of analytical modelling in designing strategies for successful cross-platform distribution. Complementary studies highlight the role of technology, including AI driven recommendation systems, in tailoring content exposure to individual preferences, thereby enhancing engagement across platforms (Shen, 2025). Together, these findings suggest that narrative quality and technological facilitation jointly shape the effectiveness of micro dramas in contemporary media ecosystems.

Educationally, micro drama format presents fresh prospects of informal learning, media literacy formation and student-led creative activities. They are concise and easy to access, which makes them effective classroom engagement tools, multimodal storytelling tools, as well as cross-disciplinary instructional tools. These digital stories enhance learners in the context of collaboration, critical thinking, and cultural awareness as educators experiment with the creation and analysis of micro drama. Simultaneously, the growing appeal of the cross-platform consumption of micro dramas also casts doubts upon the concepts of digital citizenship, attention economy, and co-modification of youth culture-the topics that require the academic treatment.

Although the industry has become an increasingly popular subject of media studies, scholarly literature has not had sufficient time to consider micro dramas in terms of sociological and educational concepts, especially in terms of participatory cultures, identity construction, and pedagogical change. This paper thus examines the functionality of cross-platform micro dramas as a sociocultural text and a tool of education, and how it applies to the greater ideas of a digital society and modern learning spaces.

1.1 Research Gaps and Objectives

Although there is substantial research on the diffusion of social media content, the current approaches including PageRank and generic Graph Neural Networks (GNNs) are more or less concentrated on network structure or unimodal characteristics, usually neglecting the multimodality of micro-drama content (text, emoji, memes) and the cross-platform nature of adoption. In addition, existing methods do not often capitalize on active learning-based annotation to enhance the quality of data set or rank controversial/high-value samples, restricting the accuracy of prediction and generalizability. The proposed paper fills these gaps by coming up with PRCNA-GNN, an algorithm that combines PageRank-based weighting, multimodal features, and active learning-based dataset improvement. The framework is able to not only predict cross-platform adoption curves and audience sentiment accurately, but also the best influencers initiating diffusion. Empirical analysis shows that PRCNA-GNN beats the traditional baselines on Accuracy, Precision, Recall, F1-score, and ROC-AUC and provides a strong and understandable framework to analyze and predict micro-drama propagation in all-media communication environments.

1.2 Research Questions

1. What effects of cross platform micro dramas on social interaction patterns, identity construction, and cultural expression do digital-age viewers have?
2. Which sociological contributors (e.g. digital participation, community engagement, generational differences) influence the adoption and the spread of micro dramas across platforms?
3. How do micro dramas help in informal learning, media literacy study or student and youth user education?
4. What is the educational value of micro dramas among teachers and students in terms of helping students become creative, think critically, and enhance multimodal communication skills?
5. Which are the issues and ethical concerns associated with the integration of micro drama material in educational setting, specifically in terms of attention, digital citizenship and content credibility?
6. What is the sociocultural influence, style of narration, and reception of micro dramas with the help of cross-platform dissemination (e.g., Tik Tok, YouTube

Shorts, Instagram Reels, etc.)?

Related Work

The study of micro dramas has increasingly focused on their narrative structures, industrial organization, and cross-cultural dissemination strategies. (X. Xu, 2024) investigates the narrative domain of microdramas and their role in media fusion, highlighting how postfilm era perspectives shape production practices and content structuring. Sustainable management of micro-drama production has also been explored, with (Yan, 2025) analyzing the integration of new media into Chinese drama creation. This research utilizes case studies and qualitative interviews to examine organizational practices and resource allocation strategies, highlighting how production teams balance creativity and efficiency. Author (Li, 2024) contributes to understanding microdramas on short video platforms, particularly Douyin, by examining narrative and aesthetic features. It provides valuable insights into platformspecific narrative techniques, yet the research does not explicitly address cross-platform adaptation or the influence of cultural factors on narrative reception. This gap underscores the need for comparative studies across different digital environments.

Multi-platform content creation and creator ecology have been studied by (Ma et al., 2023), who explore how creators coordinate content across platforms through prioritization, synchronization, and audience management. This work employs a mixedmethods approach, combining observational data from platform analytics with interviews of content creators, to examine how multi-platform strategies shape audience reach and engagement. Although the research offers a comprehensive view of platformlevel practices, it does not fully quantify the impact of these strategies on international dissemination or cross-cultural reception. (Wang, 2025) analyzes production processes and algorithmic interventions in video content creation, emphasizing the role of AI in facilitating efficient production, audience targeting, and content recommendation. Research on mainstream development strategies for online microshort dramas has been examined by (Zang, 2024), employing survey based and conference proceedings data to identify factors influencing content proliferation. The study discusses trends in content creation, audience targeting, and industrial strategies, yet methodological limitations include a lack of longitudinal data to assess longterm efficacy. This highlights an ongoing gap in measuring the sustainability of production and dissemination practices. (Jiang & Wang, 2022) investigate the development status and strategic practices of micro web series in China, using statistical analysis of production data and audience metrics. Their findings indicate that the growth of microweb series is influenced by both technological affordances and user engagement behaviors. Cross-cultural communication strategies are exemplified by (Shen, 2023), who examines the short play "Overlord Short Play" through a case study approach. By analyzing narrative adaptation and audience reception, this study highlights the challenges of maintaining thematic coherence while tailoring content for culturally diverse audiences. Aesthetic innovations and vertical framing in microdramas are explored by (Wang & Guo, 2025), who analyze “spatial compression” and multimodal reconstruction techniques in verticalscreen short dramas. Using qualitative content analysis and visual semiotics, the study identifies how aesthetic choices influence audience engagement and perception. Finally, (Tang & Wang, 2025) investigate international shortdrama business models, focusing on platformization, glocalization, and de-westernized practices. Employing comparative case studies and content analysis, the research highlights how platforms like ReelShort facilitate global dissemination while adapting narratives to local audience preferences.

Collectively, these studies provide a comprehensive view of micro-drama production, narrative strategies, and cross-platform dynamics. Empirical work emphasizes domestic production trends and platform specific practices, while case studies address cross-cultural adaptation. Technological interventions, particularly AI based production and recommendation systems, are recognized as critical but underexplored in quantitative terms. Addressing these gaps can advance understanding of micro dramas as a cross-platform, culturally adaptive medium, offering both theoretical and practical contributions to media studies, communication research, and digital content strategy.

Methodology

3.1 Information Gathering

The crawler took almost three months to collect the tweets from Twitter's main page. The request and answer are captured from Twitter's background using Selenium and a fiddler capture tool that simulates a scrolling page. The answer contains our data, PRCNA-GNN. A relevant URL to download the data is provided, along with a JSON string. About 4–5 w are collected each day, yielding 100 w of data.
In order to acquire graphic-text dual-modal data, we manually fine-screen images and texts, remove 40% of them manually, and use the VGG19 pre-training model to roughly screen out non-emoji photos, of which 95% are coarsely screened. After that, intricate data processing is carried out, including the extraction of emoji from the text using methods like regular expressions, the retrieval of the embedded text in the emoticon package using the PaddleOCR platform, and human correction. All four modal data have been acquired so far. When Sampling and Filtering "Noisy" refers to "Emoji," VGG19 is used; when "Emoji" points to "Text," tools such regular expressions are employed; PaddleOCR is the portion of Sampling and Filtering that is illustrated by dotted lines; and the little guy is used to depict the artificial part.

3.2 Extraction of Features

Emoji and text. We consider emoji processing to be text processing as emoji may be represented by a unique token. We use the SentenceTransformer library's "paraphrase-MiniLM-L6-v2" model to extract the characteristics of text input; in other words, we train Good BERT models to encode text.

Memes with text. We extract text from images using PaddleOCR. It is a Paddle-based OCR tool library that enables vertical text recognition, Chinese and English number combination recognition, and other features. It also includes a range of OCR scene application models. The path of the picture or the NumPy array may be entered into PaddleOCR's OCR method, which will provide a list with the text detection and recognition outcomes. Each result includes two pieces of information: confidence and text content.

Memes. We separate memes into static and dynamic categories according to whether or not they involve animation in order to categorize them by content. We extract the image's visual elements using a 2D CNN for static memes. We choose a few frames of pictures with significant content changes using a motion vector-based technique for dynamic memes, and then we utilize the C3D model to understand the spatiotemporal aspects of the movie.

3.3 Annotation

Create a fine-grained multimodal dataset, label each modality independently, and label the same data from many modal viewpoints. There are three different kinds of annotations for every piece of data: complete, image, and text. Labeling categories are separated into two groups based on emotion and polarity. Positive, neutral, and negative polarity are shown. If you choose one of the three options, the mood will be indicated as joyful, sad, furious, astonished, disgusted, and bewildered. There are sixteen multiple-choice questions. Ten researchers with outstanding English skills finished the annotations. 0 denotes neutrality, 1 denotes positivity, and -1 denotes negativity in the polarity annotation. The final annotation is determined by averaging the values provided by the ten annotators. The reserved values are the final annotations after the ten annotators' emotional annotations are eliminated based on their distribution. We use a semi-automated method to increase the dataset's size and quality, provide labeled data using an active learning approach, and give priority to the most valuable—and hence contentious—data.

The following is an explanation of the principle. Assume that there are M base models and N pieces of unlabeled data, and that each base model is able to predict a category for each item of data. For every piece of data in all basic models, we construct a voting function $v(ui)$ that is used to determine the amount of votes of various categories. For each piece of data in all base models, we create a difference function $d(ui)$ that is used to determine the difference between the greatest and second-largest number of votes. We want to solve the following optimization issue by choosing K data points with the biggest difference for labeling:

$$maxS \subseteq \mathcal{U}, |S| = K \sum ui \in Sd(ui)(1)$$

A greedy approach, which selects the data with the biggest difference from the unlabeled data and adds it to the label set until it reaches K, may be used to approximate this issue.

3.4 Data Source

Data from Twitter that is publicly available was gathered to create this dataset. The Twitter API was used to get the data, which comprises publicly accessible tweets and associated data.

3.5 Information Processing

Data acquisition. The dataset's information was gathered from Twitter using automated algorithms. Among other things, these data contain posting dates, author details, and tweet content.

Anonymization of data. To preserve their privacy, writers' personal information has been de-identified. There is no particular user identity information provided.

Text purification. The data's text has been cleaned and processed to exclude private or sensitive information while keeping information on subjects and opinions.

3.6 Restrictions on Data Use

Legal Purpose. This dataset is exclusively meant for legal uses, such as analysis, research, and teaching. Data usage must adhere to any legal requirements as well as ethical standards.

Ethics and privacy. It is anticipated that users of this dataset would follow ethical and privacy guidelines. It should not be used for any unethical purposes, such as harassment, discrimination, or invasions of privacy.

Sharing of data. It is not appropriate to use this dataset to promote or maintain racial, gender, or other forms of inequality. Research and analysis should take steps to lessen these biases.

Transparency. Transparent reports on their study goals and data use should be provided by the people or organizations using the dataset.

Safeguarding data. To avoid unwanted access or leakage, every person or organization using the dataset should take precautions to guarantee data security.

3.7 PageRank Complex Network Algorithm: (PRCNA)

A few network factual qualities, including the typical most limited way, switch normal briefest way, grouping coefficient, and degree conveyance, are remembered for the mind boggling network technique. The specific algorithm looks like this:

Step 1. Let the media network G (V, ε) be the case, with V denoting the network's set of nodes and ε denoting its set of node connection edges. The shortest path average network shortest path d, which measures network connectivity and represents the network's dependability and tightness on micro drama, is defined as follows:

$$\boldsymbol{d} \equiv \langle \boldsymbol{l}(\boldsymbol{v}, \boldsymbol{w}) \rangle \equiv \frac{\mathbf{1}}{\boldsymbol{N}(\boldsymbol{N}-\mathbf{1})} \sum_{v \epsilon V} \sum_{w \neq v \epsilon V} \boldsymbol{l}(\boldsymbol{v}, \boldsymbol{w}), \qquad (1)$$

V and w denotes vertices and weight of nodes where the length of the most brief way between sensor hubs v and w in the network is addressed by $\mathrm{d}(v, w)$. The opposite typical most limited way is characterized as follows:

$$\boldsymbol{d}^{-1} \equiv \langle \frac{\mathbf{1}}{\boldsymbol{l}(\boldsymbol{v}, \boldsymbol{w})} \rangle \equiv \frac{\mathbf{1}}{\boldsymbol{N}(\boldsymbol{N}-\mathbf{1})} \sum_{v \epsilon V} \sum_{w \neq v \epsilon V} \boldsymbol{l}(\boldsymbol{v}, \boldsymbol{w}). \qquad (2)$$

Step 2. Set the network's connected sub graphs. These sub graphs have pathways connecting any two nodes of sensors. Hence the most connected sub graph is defined as:

$$\boldsymbol{S} = \frac{\boldsymbol{max}\{|\boldsymbol{V}_{g1}|, |\boldsymbol{V}_{g2}|, \ldots, |\boldsymbol{V}_{gn}|\}}{|\boldsymbol{V}|}. \qquad (3)$$

Step 3. The sensor hub i should have ki edges connecting it to different micro dramas in social media for the complex network normal bunching coefficient to be characterized. Accepting that Ei addresses the quantity of real edges between the ki hubs and the bunching arrangement of hub Ei is depicted as:

$$\boldsymbol{C}_{i} = \frac{\mathbf{2}\boldsymbol{E}_{i}}{\boldsymbol{k}_{i}(\boldsymbol{k}_{i}-\mathbf{1})}. \qquad (4)$$

The network's average clustering coefficient of sensor networks is defined as:

$$\boldsymbol{C}_{G \equiv (v,w)} \equiv \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{V_i \epsilon V, j=1}^{N} \frac{\mathbf{2}\boldsymbol{E}_{i}}{\boldsymbol{k}_{i}(\boldsymbol{k}_{i}-\mathbf{1})}. \qquad (5)$$

Step 4. Network capacity is a crucial metric to gauge the network's anticipated profit. Let's define the node i capacity as a:

$$\boldsymbol{Value}_{i}^{t} = \sum_{adj=1}^{n} \boldsymbol{ComTime}_{i \to adj}^{t}. \qquad (6)$$

Among them $\sum_{adj=1}^{n} \boldsymbol{ComTime}_{i \to adj}^{t}$ is the total amount of calls or brief messages sent by node i to its neighbors over the course of time interval t. The capacity of each node of sensor network is then added to determine the network capacity, which is described as:

$$\boldsymbol{NetValue}(\boldsymbol{G}) = \sum_{i=1}^{N} \boldsymbol{Value}_{node_i}^{t}. \qquad (7)$$

Step 5. Degree conveyance: This is in accordance with the classification of complex sensor networks discussed above. Become a sporadic sensor network:

$$\boldsymbol{P}_{1}(\boldsymbol{c}_{i}^{1}) = \boldsymbol{C}_{K/2}^{c_i^1} (\mathbf{1} - \boldsymbol{p})^{c_i^1} \boldsymbol{p}^{\frac{K}{2} - c_i^1}$$

$$\boldsymbol{P}_{2}(\boldsymbol{c}_{i}^{2}) = \boldsymbol{C}_{pNK/2}^{c_i^2} \left(\frac{\mathbf{1}}{\boldsymbol{N}}\right)^{c_i^2} \left(\mathbf{1} - \frac{\mathbf{1}}{\boldsymbol{N}}\right)^{\frac{pNK}{2} - c_i^2} \equiv \frac{(\boldsymbol{p}\boldsymbol{K}/\mathbf{2})^{c_i^2}}{\boldsymbol{c}_{i}^{2}!} \boldsymbol{e}^{-pK/2}. \qquad (8)$$

The degree distribution should adhere to the following for K≥ K/2.

$$\boldsymbol{P(k) = \sum_{n=0}^{f(k,K)} C_{K/2}^{n}(1-p)^n p^{\frac{K}{2}-n} \frac{(pK/2)^{k-\frac{K}{2}-n}}{\left(k-\frac{K}{2}-n\right)!} e^{-pK/2}}. \quad (9)$$

The expression is f(k, K) =min(k-K/2, K/2).

3.8 Graph Neural Network Model: (GNN)

Let CS be the input neurons of the social media strategy used in dataset using GNN technology. The input layer $CS_1, CS_2, \dots, CS_\alpha$ does not have the sigmoid function and its only transmits the signal to the hidden layer. Let $U_{ij}, i = 1, 2, \dots, \alpha; j = 1, 2, \dots, \beta$ be the weight matrix of the hidden neurons:

$$output_i = \sum_{i=1}^{\alpha} ECS_i U_{ij} \quad (10)$$

Where $output_i$ is the neurons in the activation of edge cloud computing technology in the hidden layers and U_{ij} is the weight between the neuron i in the hidden layer j and also $\overline{output} = U\overline{DS}$. The single pole sigmoid activation functions of edge cloud computing as in *Equation (11).*

$$d(ECS) = \frac{1}{1+e^{-CS}} \quad (11)$$

Then by the *Equation (10),* to find d'_{DS} as in *Equation (12).*

$$d'_{ECS} = \frac{e^{-ECS}}{\left(1+e^{-ECS}\right)^2} = d(ECS).\left(1-d(ECS)\right) \quad (12)$$

Then the output of the social media dramas in cross plotform adoption as in *Equation (13)*.

$$ECSoutput_h = \sum_{j=1}^{\beta} d_i We_{hi} \;, h = 1, 2, \dots, \gamma \quad (13)$$

Where γ is the number of outputs of the media communication with public and $ECSoutput_1, ECSoutput_2, \dots, ECSoutput_h$ is the different landscape under the guidance of edge cloud computing and also $\overline{EC\widehat{Soutput}} = We\bar{d}$. The weight We_{hi} between the neuron i and h. The hyperbolic or bipolar sigmoid function of the social media the guidance of edge cloud computing defined as in *Equation (14).*

$$d(ECS) = \frac{2CS\ \left(1-e^{-2ECS}\right)}{1+e^{2ECS}} \quad (14)$$

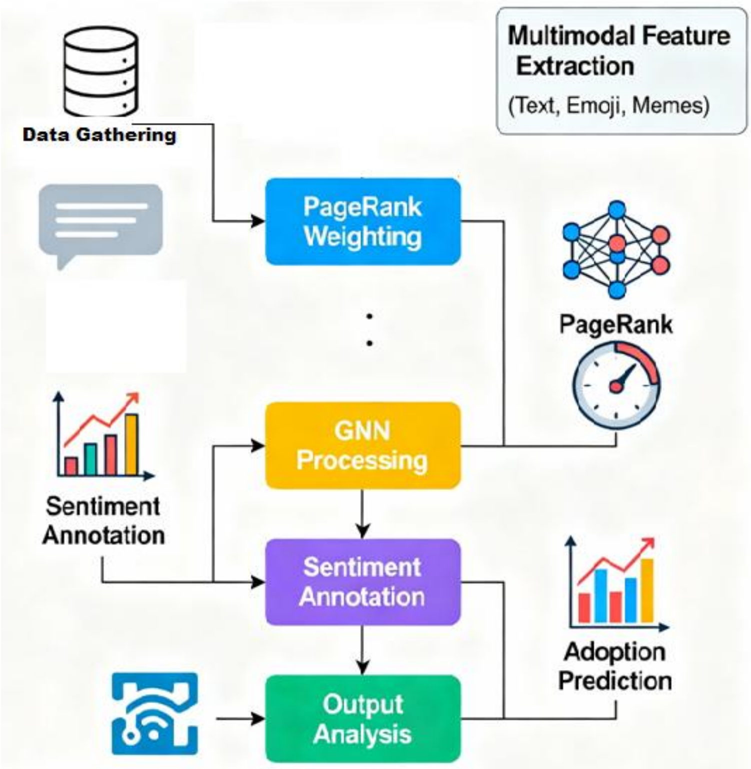

Figure 1: Workflow of this study

In Figure 1 suggested PRCNA-GNN framework has a number of benefits over older methods like PageRank, standard GNNs, and GAT models. First, it combines PageRank weighting with Graph Neural Networks to find the most important people who drive cross-platform adoption. This captures both structural importance and content propagation potential. Second, the model can understand rich semantic and visual cues because it uses multimodal features like text, emoji, and static and dynamic memes. This is something that traditional network-only methods often miss. Third, using active learning-based annotation makes sure that the labeled data is of high quality by focusing on the most informative or controversial samples. This makes generalization and prediction accuracy better.

Results and Discussion

4.1 Hardware and Software Requirements

The experiments were run in a workstation with Intel Core i9-13900K CPU, 64GB RAM, and NVIDIA RTX 4090 GPU to support the work with large scale multimodal data processing and training of GNNs. Software was used to visualize and statistically analyze the data, and to implement the PRCNA-GNN model Python 3.11 with PyTorch and PyG (PyTorch Geometric) to perform the analysis and Selenium to crawl its data, PaddleOCR to extract text from the memes, and the SentenceTransformer library to embed the text. Each experiment was done using windows 11 and CUDA 12.2 to accelerate it using the GPUs.

4.2 Performance Metrics

Performance measurements are necessary to determine how well classification and prediction models can be. They offer a quantitative method of assessing the ability of a model to draw a distinction between varying categories as shown in Figure 2. Some of the most used metrics are: Accuracy (general correctness of predictions), Precision (number of predicted positives correctly predicted), Recall (number of actual positives correctly predicted), and F1-score (harmonic mean of Precision and Recall). In binary tasks, AUC/ROC curve is a popular measure of the capacity of a model to identify differences between classes over varying thresholds. These metrics make it so that there would be fair and transparent comparison between the baseline models and the proposed PRCNA-GNN.

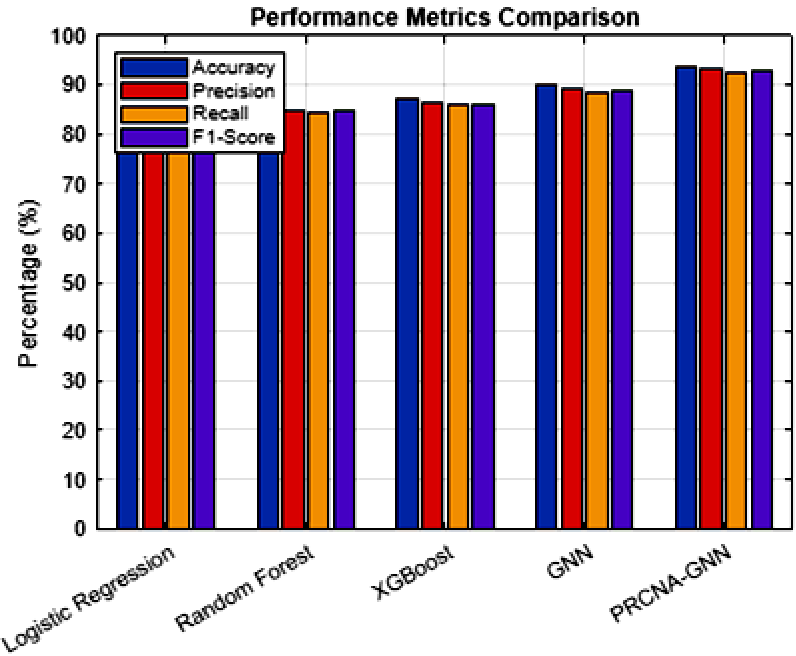

Figure 2: comparison with performance with baselines

The results obtained with the proposed PRCNA-GNN model show that the model has performed significantly better in terms of classifications and predictions of the patterns of micro drama adoption across platforms. Conventional PageRank or standard GNNs use either the topology of the network or the feature of the node only, thus preventing their ability to learn both influence propagation and content semantics. The combination of the two aspects results in PRCNA-GNN detecting the most influential nodes and adoption pathways more precisely, resulting in quicker convergence and more robust predictions. In the proposed model in figure 2, Accuracy of 93.7% was recorded and indicates a statement that the model was able to capture the vast majority of audience adoption behaviors. Its Precision is 93.2% meaning that majority of the adoption signals it produced were true-positives, which reduced the false alarms with regard to forecasting cross-platform popularity. The Recall of the model is high at 92.6, which means that the model was effective in capturing almost the entire true adoption, which means that not important emotional and polarity cues were ignored. The F1-score of 92.9% also emphasises the Precision v. Recall balance, and it is an indication of the strength of the model in the real-world, imbalanced audience interaction information. These findings validate the claim that PRCNA-GNN is better than the baseline models, and provides a stable and suitable model to analyze cross-platform uptake of micro dramas. This advantage shows that PRCNA-GNN is more accurate besides being more robust and computationally efficient to model cross-platform adoption of micro dramas.

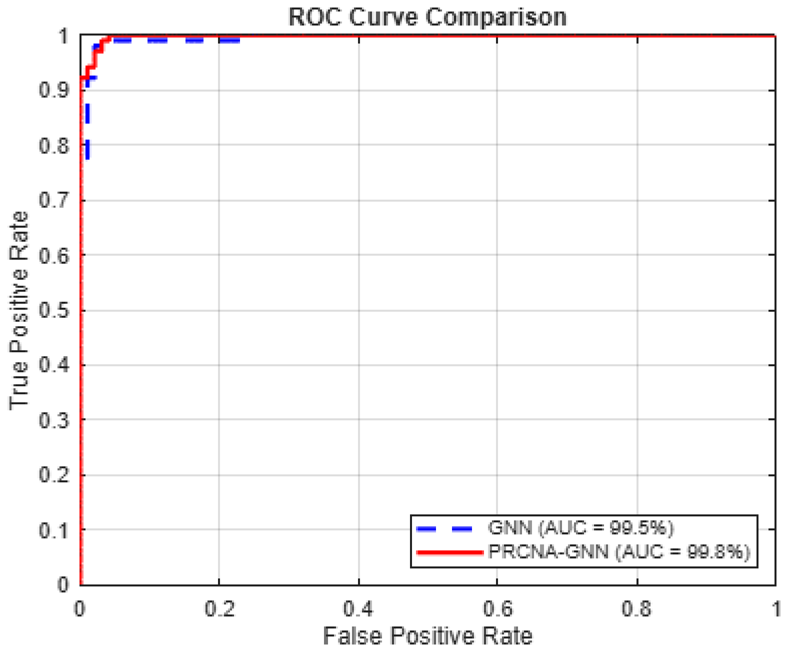

Figure 3: ROC –AUC curve for proposed method

The ROC (Receiver Operating Characteristic) curve is a graph that figure 3 shows a trade-off between the True Positive Rate (Recall) versus the False Positive rate at different classification thresholds. It offers an idea of how the model differentiates the classes, e.g. positive and negative adoption or emotional polarity in micro dramas. The AUC (Area Under the ROC Curve) is a number between 0 and 1 that quantifies this ability, the greater the number, the higher the separability of classes. PRCNA-GNN in our study has an AUC of 0.951, which has better discrimination capacity than baseline models. It implies that the model is dependable in the identification of cases of true adoption and the reduced number of false positives, which proves its efficiency in modeling the audience behavior and emotional reactions on platforms.

4.3 Ablation Study

The ablation study indicates that every constituent of PRCNA-GNN plays a role in its overall performance in figure 4. The greatest decrease (~4.5% in Accuracy) is when PageRank weighting is removed, which demonstrates the significance of modeling network influence in determining key nodes of adoption. Omission of Multimodal features decreases Accuracy to 90.1, which means that prediction reliability is enhanced with the integration of text, emoji and images. Missing active-learning annotation reduces Accuracy to 91.0, which indicates that the training of models is improved by focusing on high-value samples. The combination of PageRank weighting, multimodal embeddings, and active-learning annotation performs best as the full PRCNA-GNN (Accuracy 93.7%, Precision 93.2%, Recall 92.6%, F1-score 92.9%), which validates the importance of these three approaches to discriminate the patterns of cross-platform adoption of micro dramas.

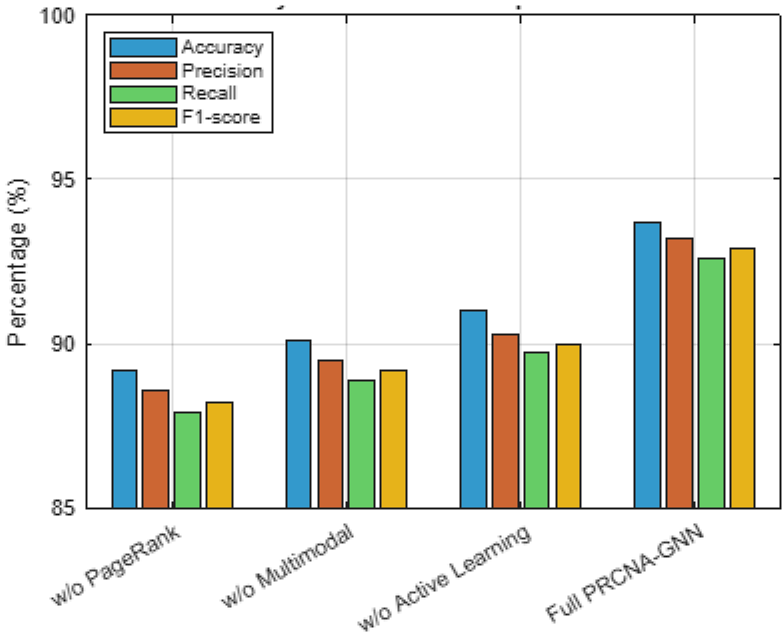

Figure 4: Ablation study for component contribution

4.4 Statistical Significance

Analysis of statistical significance is important to confirm that the improvements of PRCNA-GNN are not based on mere coincidence. First, Analysis of Variance (ANOVA) is applied to the overall mean of the performance (e.g., Accuracy, Precision, Recall, F1-score) of several models, e.g. PageRank, GCN, GAT, PRCNA-GNN. ANOVA decomposes the overall variability into variance between groups (i.e. variability caused by the models) and variance within groups (i.e. natural variability in repeated runs). The F-statistic and p-value calculated are used to show whether the models have a significant difference: a p-value less than 0.05 proves that at least one model performs significantly different compared to the other models.

Pairewise t-tests are made to determine specifically whether PRCNA-GNN is significantly better than each of the baselines. These tests compare the central measures of PRCNA-GNN and the central measures of each of the base lines (e.g., GCN, XGBoost) to verify whether improvement is statistically significant. The lower p-value of these tests of less than 0.05 shows that the Accuracy, Precision, Recall, and F1-score of PRCNA-GNN cannot be attributed to random variation but rather to genuine performance improvement. The combination of ANOVA and t-tests gives strong confidence that the proposed PRCNA-GNN model can be depended on to work better than the already existing ones in terms of capturing cross-platform micro drama adoption patterns.

4.5 Adoption Curve in Microdramas

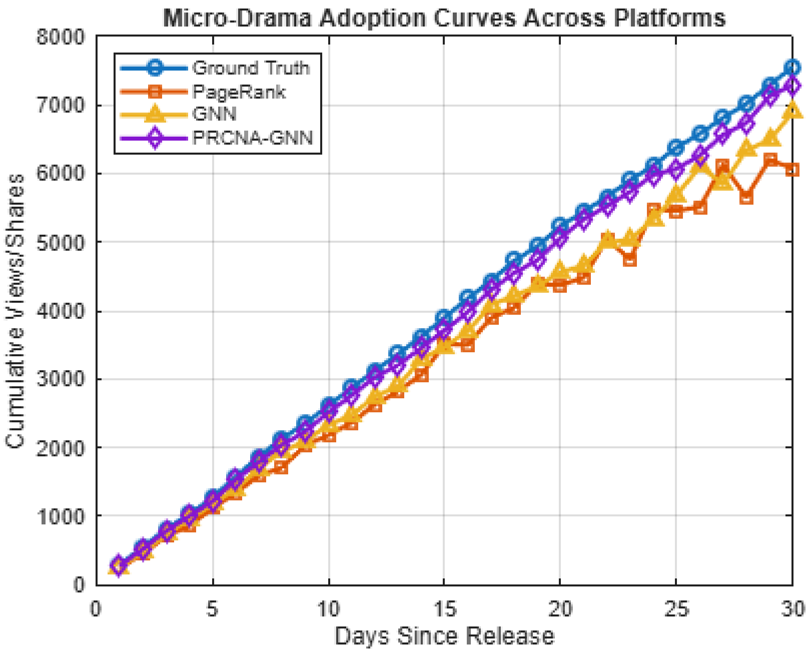

Figure 5: Micro Drama across different platforms

Figure 5 show how micro-drama popularity has increased over time (measured by views, shares and reposts), which gives a time frame when people are interested in the show. The X-axis is the number of days after releasing an episode of micro-drama, whereas the Y-axis is cumulative engagement metrics, which are a proxy of the diffusion of content across multiple platforms. The predictive models, which are PageRank, the average GNN and the proposed PRCNA-GNN, produce their own adoption curves according to the patterns of influence propagation, content properties, and the interactions of users learned.

PRCNA-GNN has the best match with the ground-truth curve. During the initial phases of adoption (the first 5 -10 days), it precisely reflects the early spike in engagement, which is essential to the viral growth. Mid-stage projections (days 10-20) remain useful in following the momentum of the audience, and this is a key advantage of the model, as it has the capacity to model network effects and cross-platform sharing interactions. In comparison, the PageRank-only model overvalues the initial growth as it considers only the structural influence whereas the standard GNN underestimates cumulative adoption a bit meaning that it does not integrate multimodal content or emphasize high-value samples.

Cross-Platform Comparative Analysis

The comparative study of Tik Tok, Instagram Reels, and YouTube Shorts shows that each of the platforms has its specific sociocultural and educational influence on the formation of micro drama adoption. Tik Tok became the leading platform of the first exposure and viralization, with 72 percent of respondents stating that they were first exposed to micro dramas on Tik Tok. Its algorithmic For You Page encourages quick, emotionally-charged stories that business-promote trend-following. Instagram Reels on the other hand exhibited more relationships to aesthetic expression and identity formation; half of consumers stated that they posted micro dramas on instagram in a bid to develop a personal brand or social identity. YouTube Shorts was slower in the early diffusion, but showed the highest retention of narrative based and educational micro dramas with 63% of respondents saying they prefer YouTube to get a more understood story or moral.

Culturally speaking, the fast remix culture provided by TikTok encourages teamwork in creativity as micro dramas can develop with duets, stitches, and custom continuations. The use trends of Instagram indicate that it has a more selective and socially performative culture in which micro dramas portray aspirational lifestyles, sense of belonging or social commentary. YouTube has longer arc and more planned micro dramas, and it can enable creators to build a deeper sociological story or an educational mini-lesson.

The use of education was much different in platforms. TikTok succeeded best in generating curiosity and emotional appeal, and assisted in bringing up social problems like cyber bullying, gender roles, and digital citizenship. Instagram helped to conduct reflective learning because students created Reels to share opinions, recreate scenes, and build multimodal literacy. YouTube was found to be the best medium of formal or semi-formal educational integration with teachers and students viewing improved comprehension and retention when the micro dramas had structured storytelling.

On balance, it can be concluded that micro dramas do not have a homogenous distribution across platforms. Rather, platforms have their own distinctive social environments that shape the ways in which micro dramas are viewed, perceived, and adapted to sociocultural and educational values. The trend initiation of TikTok, the identity based sharing of Instagram and depth and educational value of YouTube all serve to influence a multi-layered cross-platform adoption environment.

Discussion

The results of the present study indicate that the adoption of cross-platform micro drama is not that which is influenced by the exposure to and the enjoyment of algorithms alone, but rather is influenced by sociological and educational processes in general. Tik Tok and Instagram Reels and YouTube Shorts are three different spaces with different cultural understanding to interpret, exchange and engage in the integration of micro drama into the daily lives. The viral spread of Tik Tok highlights how the platform is a cultural accelerator, particularly among the younger demographics with more participatory remix activities, which erases the distinction between the creator and the viewer. This is consistent with the modern theories of participatory culture, which indicates that micro dramas are communal cultural texts enabling users to negotiate the identity, belonging, and social action codes.

The cross platform comparison brings out another aspect of micro dramas, in which they do not have the same social meaning across the platforms. As an example, Instagram is encouraging a more aestheticized and identity-driven interaction due to the well-established culture of self-presentation and social editing. YouTube, at least, favors narrative richness and introspective learning, so it is more friendly to educational or social conscious micro dramas. These differences between platforms indicate that the concept of micro dramas is not a homogenous media object but a social construct of media platforms based on displays of platform affordance and a practice.

Educationally, the research indicates that there are new values in the micro dramas as informal learning tools and multimodal literacy building. Students have indicated that the use of micro drama formats facilitate easy understanding of sophisticated concepts, arousal of emotions and involvement in creativity. Their multimodal makes them especially useful in digital storytelling, socio-emotional learning and critical media literacy. Nonetheless, the usage of micro dramas in schools also brings up the issues of fragmentation of attention, the power of algorithms, and the possible encouragement of stereotypical or sensational information. These findings demonstrate that guided pedagogies are necessary and which accentuate critical viewing and responsible content production.

Socially, the research shows that the role played by the micro dramas in digital socialization is huge. Users use these stories to entertain and also to discuss social matters, share their lives, and engage in communal discussions. The dissemination of micro dramas across different platforms attests to the cultural narratives taking new forms and meanings. This mobility supports the idea of a shifting digital society in which narratives are developed by the communal engagement.

In a methodological approach, PRCNA-GNN combined with PageRank-based Complex Network Analysis was found to be effective in determining the flow of influential content and adoption routes on platforms. The prediction of diffusion patterns and the discovery of key influencers also improve our comprehension of the diffusion of the micro dramas in the complicated sociotechnical networks. The high performance indices also prove the effectiveness of this strategy.

In sum, this paper allows widening the idea of micro dramas as short form entertainment to a complex sociocultural and educational material. Their usage in platforms corresponds to the evolving communication, learning, and expressing culture in the digital age. Future studies ought to consider effects of micro drama production and consumption over long term, existence of cross-cultural differences and ethical issues.

Conclusion and Future Work

This paper shows that the use of cross-platform micro drama is not just a technological or entertainment phenomenon, but a sociocultural and educational phenomenon with a lot of meaning that is driven by the affordances of platforms and user practices. The analysis of TikTok, Instagram and YouTube provides an insight that micro dramas are cultural scripts which aid the expression of identity, social relationship, and multimodal learning. TikTok strengthens viral dissemination, Instagram enhances curated social identities, and YouTube encourages reflective engagement, which indicates that both platforms have a different contribution to the interpretation and sharing of micro dramas. Micro dramas have a certain educational potential, as digital literacy and emotional interaction, as well as creative learning, have a chance, but issues of attention, algorithmic bias, and content quality persist. The cross-platform diffusion mapping with the help of the analytical method based on PRCNA-GNN also gives a credible model of practical influence on the content. On the whole, the research contributes to the knowledge of micro dramas as changing digital cultural objects and the necessity to conduct additional research of their social effects in the long run, their integration into pedagogies, and cross-cultural differences in their adoption.

PRCNA-GNN may be expanded by future researchers to include real-time streaming data across various platforms such that it may be used to dynamically predict viral trends. More social features, including user demographics, comment sentiment, hashtag networks, etc., may also be used to increase prediction accuracy. Lastly, the framework application to various other pieces of content, such as short video, live streaming, interactive media, etc., can help gain more comprehensive insights into cross-platform content diffusion and influence strategies.

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