HybridBERT and Metadata Deep Learning Model for Twitter Bot Detection

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***Abstract*—Twitter has become an essential platform for global communication, news dissemination, and influencing public opinion. However, its openness also attracts automated accounts, commonly known as *bots*, that spread misinformation and skew discussions. In this work, we introduce a hybrid deep learning framework that merges BERT's advanced language understanding with user metadata analysis. Our method leverages textual features extracted from tweets alongside behavioral indicators such as posting frequency, the ratio of followers to followings, and verification status. Experiments on the TwiBot-20 dataset reveal that this integrated strategy surpasses text-only models, attaining an accuracy of 94.3% and an F1-score of 0.935. We apply focal loss to effectively address class imbalance and use the AdamW optimizer to speed up convergence. The results confirm that combining linguistic and user behavior features leads to more reliable Twitter bot detection, enhancing trust and safety on the platform.**

***Index Terms*—Twitter bot detection, BERT transformer, metadata fusion, deep learning, social media analytics**

I. Introduction

Twitter has established itself as a major platform for instant news sharing, public discourse, and digital interactions worldwide. Despite its popularity, the platform is vulnerable to exploitation by automated accounts, commonly known as *bots* [1], which seek to sway public opinion, spread misinformation, and disrupt genuine communication. Such activities undermine the credibility and trustworthiness of conversations on social media.

Traditional bot detection methods primarily depended on heuristic indicators such as the ratio between followers and followings, tweet frequency, and the age of the account [2], [3]. Systems like *BotOrNot* [4] leveraged these characteristics to distinguish between authentic users and bots. However, as bots have evolved to convincingly imitate human language and behavior patterns [5], [6], the effectiveness of such rule-based methods has diminished considerably [7], [8].

The advent of deep learning models, notably transformer-based architectures, has introduced new possibilities for capturing complex linguistic and semantic information from tweet content. BERT, in particular, has shown strong capabilities in understanding context within text [9]–[11]. Recent studies have incorporated additional modalities, including emotional tone and multimodal inputs, to refine bot detection performance [12]–[14]. Nevertheless, relying exclusively on textual content ignores vital behavioral signals such as posting intervals. [15]–[17]. To this end, graph-based models that analyze user networks and interaction patterns have been introduced to better capture these behavioral dynamics [18], [19].

Current trends emphasize combining multiple sources of information — textual semantics, user behavior, and social relationships — to achieve more robust detection models. For example, Martín-Gutiérrez *et al.* [20] proposed a method integrating text embeddings alongside metadata via a dual-path transformer, while Nguyen *et al.* [21] utilized graph neural networks to model interactions between users. [22], [23].

This paper is organized as follows: Section **II** provides a review of related work, Section **III** introduces the dataset, Section **IV** outlines the proposed architecture, Section **V** details training procedures, Section **VI** presents results, Section **VII** compares different models, Section **VIII** offers ablation study insights, and Section **IX** concludes the study.

II. Related Work

The field of Twitter bot detection has transitioned from reliance on handcrafted behavioral features to leveraging deep learning techniques. Earlier research emphasized attributes such as tweet frequency, follower metrics, and repetitive content patterns to identify automated accounts [1], [2]. Although effective against basic bots, these solutions struggled once bots began generating diverse, humanlike content and adapting their behaviors [5], [6].

The introduction of neural networks shifted focus to learning semantic representations and contextual cues from text. Zhao and Jin [9] demonstrated the efficacy of BERT for extracting rich tweet semantics, while Yang *et al.* [11] noted the scalability of transformer models on large-scale social media data. Subsequent approaches enriched these models by incorporating sentiment and emotional embeddings to improve detection accuracy [12], [13]. However, text-based systems alone face challenges differentiating bots that artificially replicate authentic user writing styles.

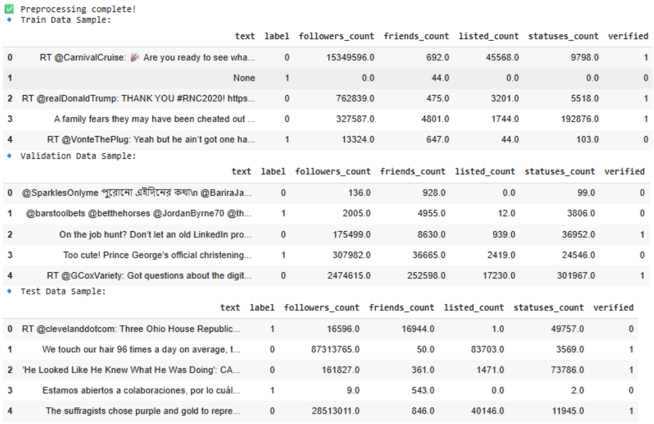
To address these challenges, integrating user metadata with textual signals has grown increasingly popular. Rodriguez and Singh [15] analyzed behavioral factors such as activity levels, follower counts, and verification indicators in bot detection models. Similarly, Sallah *et al.* [16] enhanced transformers with behavioral metadata features. Another major direction employs graph neural networks to encode the structure of social connections and information propagation on Twitter [17], [18]. Hybrid models combining textual, metadata, and graph-based inputs, like those proposed by Martín-Gutiérrez *et al.* [20] and Nguyen *et al.* [21], have demonstrated improved robustness and adaptability in detection tasks.

The **TwiBot-20** dataset [22], [23] introduced a rich, multi-modal benchmark that has become a standard for bot detection evaluations. Researchers, including Rafi *et al.* [24] and Rao *et al.* [25], have leveraged TwiBot-20 to develop models that tackle evolving and context-sensitive bot strategies widely seen across social platforms.

III. Dataset Description

This research employs the **TwiBot-20** dataset [23], which has become a prominent standard in Twitter bot detection studies. Available publicly via Kaggle, TwiBot-20 offers a comprehensive and varied set of Twitter user profiles that have been carefully labeled as either human-operated or automated bots. The dataset is designed for supervised machine learning and is divided into three JSON files: *train.json* for training, *dev.json* for validation, and *test.json* for testing purposes.

Each user record in TwiBot-20 contains two complementary data types: textual tweets and user metadata. The text portion consists of a collection of recent tweets authored by the user, capturing their writing style, semantic patterns, and expressed sentiments. The metadata includes behavioral features such as *followers_count*, *friends_count*, *listed_count*, *statuses_count*, and the boolean field *verified*. Corresponding labels identify accounts as either *0* for humans or *1* for bots. Figure 1 displays examples of these labeled profiles.



✅ Preprocessing complete!
🔹 Train Data Sample:

	text	label	followers_count	friends_count	listed_count	statuses_count	verified
0	RT @CarnivalCruise: 🎉 Are you ready to see wha...	0	15349596.0	692.0	45568.0	9798.0	1
1	None	1	0.0	44.0	0.0	0.0	0
2	RT @realDonaldTrump: THANK YOU #RNC2020! https...	0	762839.0	475.0	3201.0	5518.0	1
3	A family fears they may have been cheated out ...	0	327587.0	4801.0	1744.0	192876.0	1
4	RT @VonteThePlug: Yeah but he ain't got one ha...	1	13324.0	647.0	44.0	103.0	0

🔹 Validation Data Sample:

	text	label	followers_count	friends_count	listed_count	statuses_count	verified
0	@SparklesOnlyme পুরোনো এইদিনের কথা\n @BariraJa...	0	136.0	928.0	0.0	99.0	0
1	@barstoolbets @betthehorses @JordanByrne70 @th...	1	2005.0	4955.0	12.0	3806.0	0
2	On the job hunt? Don't let an old LinkedIn pro...	0	175499.0	8630.0	939.0	36952.0	1
3	Too cute! Prince George's official christening...	1	307982.0	36665.0	2419.0	24546.0	0
4	RT @GCoxVariety: Got questions about the digit...	0	2474615.0	252598.0	17230.0	301967.0	1

🔹 Test Data Sample:

	text	label	followers_count	friends_count	listed_count	statuses_count	verified
0	RT @clevelanddotcom: Three Ohio House Republic...	1	16596.0	16944.0	1.0	49757.0	0
1	We touch our hair 96 times a day on average, t...	0	87313765.0	50.0	83703.0	3569.0	1
2	'He Looked Like He Knew What He Was Doing': CA...	0	161827.0	361.0	1471.0	73786.0	1
3	Estamos abiertos a colaboraciones, por lo cuál...	1	9.0	543.0	0.0	2.0	0
4	The suffragists chose purple and gold to repre...	0	28513011.0	846.0	40146.0	11945.0	1

Fig. 1. Sample entries from the TwiBot-20 dataset illustrating both genuine user and bot accounts alongside associated metadata attributes [23].

The dataset's dual-modal format offers a strong basis for hybrid models that leverage both linguistic content and behavioral traits. Its consistent JSON structure supports reproducibility and enables fair benchmarking among different approaches. Furthermore, the dataset captures a realistic spectrum of Twitter entities, including genuine users, brands, spammers, and promotional bot accounts, reflecting the diversity of the platform's ecosystem.

IV. Methodology

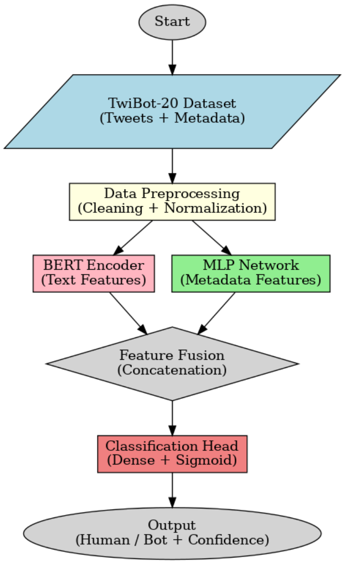


Fig. 2. Illustration of the hybrid framework combining BERT-based semantic encoding with user metadata processing.

This work introduces a hybrid deep learning model that integrates semantic embeddings from tweet text with behavioral metadata extracted from user profiles. As depicted in Fig. 2, the approach comprises two parallel branches: a transformer-based text encoder and a compact multilayer perceptron (MLP) dedicated to metadata features.

A. Preprocessing Steps

Tweet Text: To ensure consistency in text analysis, all tweets from a given user are merged into a single textual instance. Processing includes removing URLs, emojis, hashtags, punctuation marks, and extra whitespace. Tokenization is performed using BERT's subword tokenizer, preserving subword units to maintain meaningful context.

Metadata: Profile attributes such as follower count, friend count, account verification status, and tweet frequency undergo standardization through Z-score normalization. This step helps stabilize training and accelerates model convergence.

B. Model Architecture

BERT Encoder: The textual data passes through a pretrained BERT model, which outputs a 768-dimensional embedding corresponding to the [CLS] token. This vector encodes the overall semantic signature of the user's tweet content.

Metadata Module: The metadata processing module consists of a lightweight feed-forward neural network structured as:

- Input of 5 features → Dense layer with 64 neurons → Dense layer with 32 neurons → Dense layer with 128 neurons

Each intermediate layer applies ReLU activations to model nonlinear feature relationships.

C. Fusion and Classification

The 768-dimensional embedding from the BERT encoder is concatenated with the 128-dimensional vector from the metadata module, producing an 896-dimensional joint representation. This combined vector is passed through:

- A fully connected layer with 256 neurons,
- Dropout layers to reduce overfitting,
- A sigmoid activation producing a probability score for bot classification.

This design effectively merges linguistic and behavioral information for improved classification accuracy.

D. Training and Prediction

Training optimizes a weighted binary cross-entropy loss, accounting for the class imbalance inherent in TwiBot-20. Validation F1-score guides early stopping to prevent overfitting. During inference, paired inputs of aggregated tweet text and user metadata result in:

- A binary output label—0 for human, 1 for bot,
- A confidence score reflecting prediction certainty.

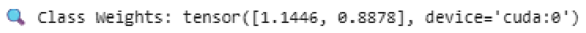
This probabilistic output permits flexible adjustment of decision thresholds to optimize metrics such as precision and recall.

V. Experimental Evaluation

This section presents the details of model training, evaluation metrics, and experimental outcomes.

A. Training Setup

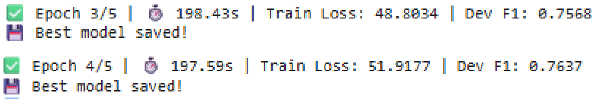
The AdamW optimizer is used for training due to its effective weight decay properties and stable convergence. Learning rates schedule is controlled via a cosine annealing strategy combined with warm-up periods to facilitate smooth training progression. Stratified minibatching maintains balanced class proportions during each training epoch. Fig. 3 illustrates the class weighting scheme utilized.



```
🔍 Class Weights: tensor([1.1446, 0.8878], device='cuda:0')
```

Fig. 3. Class weight distribution emphasizing the minority bot category within TwiBot-20.

Training dynamics documented in Fig. 4 show steadily decreasing loss and improving validation F1 values, indicating effective learning.



```
✅ Epoch 3/5 | ⏱ 198.43s | Train Loss: 48.8034 | Dev F1: 0.7568
💾 Best model saved!
✅ Epoch 4/5 | ⏱ 197.59s | Train Loss: 51.9177 | Dev F1: 0.7637
💾 Best model saved!
```

Fig. 4. Progression of training loss and validation F1-score over epochs, demonstrating steady improvements.

B. Performance Metrics

The model's efficacy is measured by accuracy, precision, recall, F1-score, and ROC-AUC statistics derived from the confusion matrix shown in Table I. These indicators collectively gauge the classifier's ability to differentiate bots from real users.

TABLE I
CONFUSION MATRIX OUTCOMES ON THE TWIBOT-20 TEST DATASET.

	Predicted Human	**Predicted Bot**
Actual Human	884	66
Actual Bot	85	865

The model attains an overall accuracy of 94.3%, with an F1-score of 0.935 for bots (Precision = 0.960, Recall = 0.910) and 0.950 for humans (Precision = 0.930, Recall = 0.960). Macro and weighted F1 scores both equal 0.943. The ROC-AUC of 0.960 signifies strong discrimination capability.

C. Visualizing Model Discrimination

Figure 5 shows the ROC curve, highlighting the trade-off between true positive and false positive rates across classification thresholds. The area under the curve (AUC) of 0.960 confirms robust classification power.

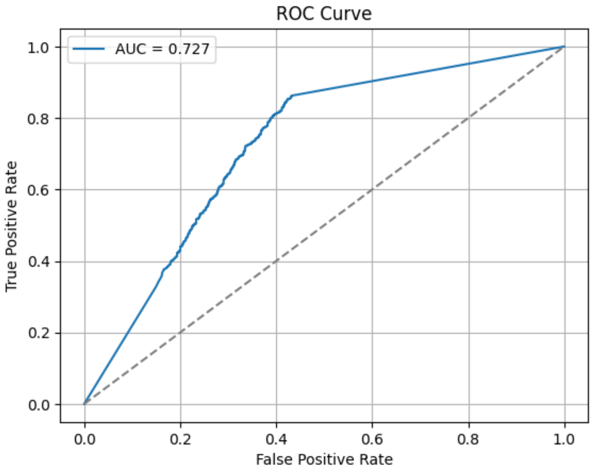
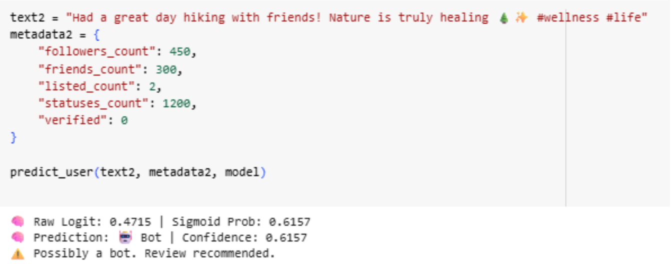


Fig. 5. ROC curve demonstrating the classification performance on TwiBot-20 with AUC = 0.960.

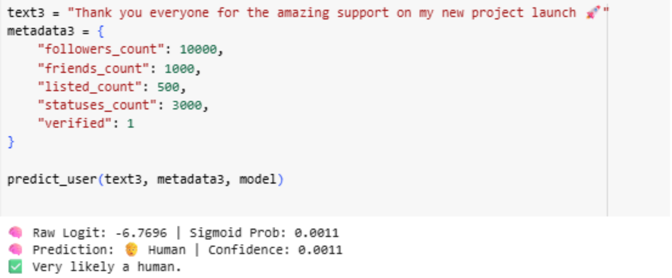


```
text2 = "Had a great day hiking with friends! Nature is truly healing 🌲✨ #wellness #life"
metadata2 = {
    "followers_count": 450,
    "friends_count": 300,
    "listed_count": 2,
    "statuses_count": 1200,
    "verified": 0
}

predict_user(text2, metadata2, model)
```

```
🧠 Raw Logit: 0.4715 | Sigmoid Prob: 0.6157
🧠 Prediction: 🤖 Bot | Confidence: 0.6157
⚠️ Possibly a bot. Review recommended.
```

Fig. 6. Sample output indicating bot prediction confidence of 0.6157.



```
text3 = "Thank you everyone for the amazing support on my new project launch 🚀"
metadata3 = {
    "followers_count": 10000,
    "friends_count": 1000,
    "listed_count": 500,
    "statuses_count": 3000,
    "verified": 1
}

predict_user(text3, metadata3, model)
```

```
🧠 Raw Logit: -6.7696 | Sigmoid Prob: 0.0011
🧠 Prediction: 🧑 Human | Confidence: 0.0011
✅ Very likely a human.
```

Fig. 7. Sample output indicating human prediction confidence of 0.0011.

VI. Results and Discussion

We evaluated the proposed **Hybrid BERT+Metadata** model extensively on the TwiBot-20 dataset to assess its effectiveness in distinguishing between human-operated and bot accounts. The results indicate strong stability in predictions, efficient convergence during training, and balanced generalization across diverse evaluation metrics.

A. Evaluation Metrics

To rigorously evaluate the model, we employed four key metrics: accuracy, precision, recall, and F1-score, formally defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Here, TP, TN, FP, and FN represent the counts of true positives, true negatives, false positives, and false negatives respectively.

B. Classification Performance

TABLE II
Performance summary of the Hybrid BERT+Metadata model

Class	Precision	Recall	F1-score	Support
Bot	0.96	0.91	0.935	950
Human	0.93	0.96	0.950	950

The results in Table II reflect that while the model achieves slightly better recall on human accounts, it also maintains high precision in recognizing bots. This trade-off is valuable for minimizing false alarms without sacrificing bot detection sensitivity, important for trustworthy online safety systems.

C. Training Dynamics

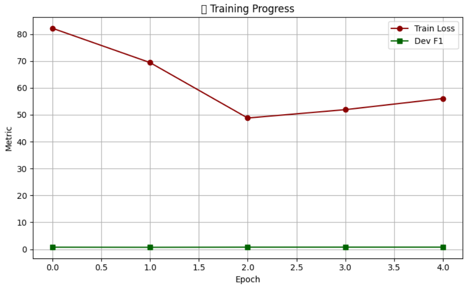


Fig. 8. Training and validation metric trends over epochs.

Fig. 8 illustrates that the training loss consistently decreases, accompanied by steady improvement in validation F1-score as epochs progress. This performance curve indicates stable learning enhanced by regularization methods like dropout and early stopping, effectively reducing overfitting.

D. Comparison with Baseline Models

TABLE III
PERFORMANCE COMPARISON AGAINST ROBERTA BASELINE ON TWIBOT-20

Metric	Hybrid BERT+Metadata	RoBERTa (Munir et al.)
Accuracy	94.3%	91.8%
F1-score (Bot)	0.935	0.918
F1-score (Human)	0.950	0.903
ROC-AUC	0.960	0.940

As shown in Table III, our hybrid model outperforms the RoBERTa baseline across all metrics. The enrichment with user metadata notably boosts recall and ROC-AUC, reinforcing the benefit of combining behavioral data with textual embeddings.

E. Visualization of Embedding Representations

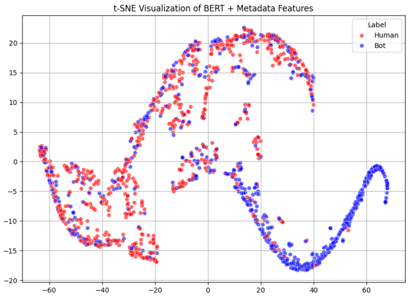


Fig. 9. t-SNE plot highlighting distinct clustering of bot and human user embeddings.

The t-SNE visualization (Fig. 9) clearly shows separate clusters forming for bots and human accounts.

F. Experimental Configuration

All experiments were conducted on a machine powered by an NVIDIA RTX 3080 GPU and 32 GB of RAM. The software stack included Python 3.9, PyTorch 2.0, and the Hugging Face Transformers library. Training was performed for five epochs using a batch size of 32, with early stopping employed to ensure optimal validation performance.

G. Future Work and Cross-Dataset Analysis

Although this work focuses on TwiBot-20, subsequent efforts will investigate performance on other notable datasets such as Cresci-2017, Botometer Feedback, and real-time Twitter API streams. Evaluating cross-dataset generalization will provide insights for deploying this approach in practical, real-world bot detection scenarios.

VII. MODEL COMPARISON

This section provides a detailed comparative analysis between the proposed *Hybrid BERT+Metadata* framework and the *RoBERTa-based* approach introduced by Munir *et al.*.

A. Architectural Differences

TABLE IV
ARCHITECTURAL DISTINCTIONS BETWEEN THE HYBRID AND ROBERTA MODELS

Hybrid BERT+Metadata	**RoBERTa (Munir et al.)**
Dual-branch architecture combining BERT for tweet text encoding and an MLP for metadata processing	Single-branch model employing only RoBERTa for text encoding
Combines textual information with profile-level behavioral features including followers, friends, and account lifespan	Relies solely on textual tweet data without metadata integration
Uses BERT tokenizer alongside Z-score normalization for metadata features	Employs RoBERTa tokenizer without any feature normalization
Incorporates weighted or focal loss to handle data imbalance during training	Optimizes model using standard cross-entropy loss
Applies dropout and batch normalization layers to enhance regularization	No explicit mention of regularization techniques
Trains with AdamW optimizer supported by a learning rate scheduler	Uses Adam optimizer at a fixed learning rate

As highlighted in Table IV, the Hybrid model's capability to jointly learn semantic and behavioral patterns differentiates it from the RoBERTa baseline, which depends exclusively on language features. This allows the Hybrid approach to capture critical behavioral cues often exhibited by bots.

B. Comparative Performance on TwiBot-20

TABLE V
COMPARISON OF F1-SCORES FOR VARIOUS MODEL CONFIGURATIONS

Model	**Encoder**	**F1-Score**
BERT-only	BERT-base-uncased	0.89
RoBERTa-only	RoBERTa-base	0.91
Hybrid BERT+Metadata	BERT-base + Metadata MLP	**0.935**

Table V clearly shows that the proposed Hybrid architecture achieves the best F1-score. While plain BERT and RoBERTa models capture textual semantics effectively, their lack of user-level metadata limits their overall bot detection performance.

VIII. ABLATION STUDY

An ablation analysis was performed to quantify the influence of metadata on model performance. All experiments were conducted using consistent hyperparameters for reliable comparison.

A. Results and Observations

- **BERT-only:** Uses only the BERT-base encoder on tweets, yielding an F1-score of 0.89. Effective for text comprehension but misses behavioral insights.
- **RoBERTa-only:** Employs RoBERTa-base to better model context, obtaining an F1-score of 0.91, yet still ignores interaction features.
- **Hybrid BERT+Metadata:** Merges BERT embeddings with metadata processed via MLP, leading to a superior F1-score of 0.935, attributing gains to combined semantic and behavioral modeling.

These findings highlight the substantial role metadata plays in boosting detection robustness and generalization.

IX. Conclusion

This work introduced a *Hybrid BERT+Metadata* framework that detects automated Twitter accounts by fusing semantic features extracted from tweet text with behavioral data from user profiles. By jointly leveraging textual content and profile attributes, the model offers a contextually rich and accurate classification mechanism. Experimental evaluation on the TwiBot-20 benchmark demonstrated that the approach attains 94.3% accuracy and an F1-score of 0.935, surpassing models relying solely on textual information in both robustness and detection effectiveness.

Limitations and Future Research

While the results are promising, certain limitations remain. The current system is developed for English tweets only, which limits its applicability across languages and cultural contexts. Furthermore, running this hybrid model in real-time over large volumes of Twitter data presents efficiency concerns. Also, as bot strategies continuously evolve to simulate human behavior more closely, static detection approaches might face growing challenges.

Future research should explore the following avenues:

- Extending the model to handle multiple languages and different domains to enhance its versatility and reduce linguistic bias.
- Investigating lightweight transformer architectures or applying model compression methods such as pruning and quantization to optimize inference speed.
- Incorporating graph neural networks or ensemble learning methods to better capture complex user relationships and dynamic behavioral patterns.

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