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DECODING DIGITAL BEHAVIOR: AI-POWERED ANALYSIS AND PREDICTION OF SOCIAL MEDIA USER ENGAGEMENT PATTERNS

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Abstract

Social networks in this period of hyper-connectivity provide abundant behavioral data that can be utilized for computing user intentions, sentiment and engagement. The objective of this study is to explore and predict social media user behavior through utilizing state-of the art NLP algorithms and extractive LLM for mining semantic patterns in UGC. Using a quantitative research design of >1 million deidentified public posts and comments on X (formerly Twitter) and Reddit. Textual data were preprocessed, vectorized and passed as input to transformer-based embeddings in order to analyze sentiment, topic distribution and behavioral trends over time. Finally, we developed predictive models (Random Forest, LSTM) to estimate the future engagement using linguistic, temporal and contextual features.

We demonstrate that emotional tone and timing of post, as well as conversational dynamics, all have a statistically significant impact on engagement (through likes, shares and reply volume). For instance, the combination with LLM demonstrated a 14% increase in predictive accuracy against traditional NLP models. Real time audience segmentation, campaign optimization and forecasting behavioral changesOpen image in new windowDigital marketers, public policy makers and sociologists can extract cryptocurrency derived practical implications from adopting this framework. While previous research has focused on either sentiment or network influence, our work presents an end-to-end pipeline for scalable, interpretable, and holistic measurements that consider both language modeling and statistical forecasting.

This contributes with a new understanding of how state of the art AI can decode big digital footprints, and offers novel ways for ethical and effective social media analytics.

Keywords: *Social Media Behavior, Natural Language Processing (NLP), Large Language Models (LLM), Predictive Analytics, User Engagement Forecasting*

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1. Introduction

1.1 Background and Motivation

The burst of social media channels (e.g. X, previously known as Twitter; Reddit; Instagram…) has not simply transformed the way we communicate, it has also given rise to a massive amount of behavioral data. Such platforms precisely reflect the finer-resolution components of human sentiment, cognition and action or, as the researchers put it, there's an emerging "fine-grained set of variables with which to measure social behavior at scale." The increasing integration of AI and observational data, along with the ever-growing use of these facts via NLP in generating (or producing) data has resulted in a proliferation of both academic and industrial interest around how to model & predict user's actions, sentiments and levels engagement (Aggarwal, C., & Liu, H,2016).

Recent advances in deep learning have also put a spotlight on this field, with Large Language Models (LLM), including BERT, RoBERTa and GPT-variants demonstrating impressive results in language comprehension and behavior insight generation tasks (Hochreiter, S., &Schmidhuber, J,1997). LLMs are increasingly being used in predictive pipelines, allowing record of digital behavior at granular resolutions. Social media behavior analysis has evolved from sentiment detection or activity monitoring to become a sophisticated, specifically AI-powered practice which allows for trend predictions, user segmentation and even forecasts of real-time engagement triggers (LeCun, Y., Bengio,2015).

1.2 Research Problem and Questions

However, predicting social media user behavior with AI still has a few gaps. Most of the models work on certain aspects (for example, sentiment classification, topic modeling) but not multidimensional user engagement. Moreover, traditional machine learning models suffer from poor cross-platform generalization under the effect of language diversity and context variability (K., & Toutanova, K,2019)

This research seeks to address the following key questions:

- How can pre-trained LLMs be effectively leveraged to extract behavioral patterns from social media text?
- What role do temporal and linguistic features play in predicting user engagement outcomes (likes, shares, replies)?
- Can hybrid models combining NLP and predictive algorithms such as LSTM and Random Forest improve forecasting accuracy across social platforms?

1.3 Scope and Objectives

This study proposes a scalable framework that employs NLP, pre-trained LLMs and supervised learning to analyze and predict social media user behavior. The study uses English-language posts from X and Reddit over a year. The primary objectives include:

- An NLP based pipeline that utilizes LLM embeddings to generate user features.
- Forecasting engage behavior via predictive models like LSTM and Random Forest.
- Scoring model performance with quantitative metrics like F1-score, precision, recall and ROC-AUC.
- Extracting crucial behaviourl features from linguistic, temporal and structural data

1.4 Structure of the Paper

The remaining eight sections of this paper are organized as follows. Afterwards, Section 2 provides a literature review of current research avenues on social media analytics, predictive modeling and LLM integration. The methodology is divided in section 3 covering details on data sources and preprocessing, extracting NLP features, model creation and evaluation. Section 4 presents the results and visual analysis of trends observed in model outputs and user behavior. Section 5 discusses the implications, limitations of findings. Section 6 presents a more in-depth discussion on practical applications within marketing, policy, and user experience design. Section 7 elaborates on the novelty of this study and Section 8 concludes with main findings and future research avenues.

2. Literature Review

The last 10 years have brought about an amazing evolution in social media analytics. Once limited to metrics like likes, retweets, or follower count, research has expanded to advanced inferences about user intention, network influence and content impact. Trained on data until October 2023 original works Analytical at descriptive level to understand the digital tracing; but owing to the advent of Big Data technologies and access to computing power, the field transitioned into predictive and prescriptive modeling101

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(Hamilton,2017). Advances in AI technology have been pivotal to enable this change enabling the automated and real-time processing of vast volumes of text data from platforms such as X or Reddit (M., & Lee, S. I,2017).
While there are structured APIs and, again, renewed public interest in digital sociology, social media as a black-box model of real-world opinion and action is still widely popular. Researchers today utilize historical datasets to map out tracking topics over time, polarization, spread of false information, and other changes in the sentiment within communities (Abbasi, A., &Aljohani, N. R,2019). This shift has allowed us to go from silent content analysis to actionable predictive behavior.

2.2 NLP Techniques in Behavioral Analysis
Pre-trained Large Language Models (LLMs), such as BERT, RoBERTa and GPT-based architectures revolutionized text analysis in the field of social media research. These models are trained on large corpora and can formulate the context of language beyond fixed n-gram windows, which makes them particularly fit for subtle patterns used by users in their utterances on informal platforms (R., & Leskovec, J,2017).
Indeed, LLMs have also been demonstrated to perform well on downstream tasks such as sentiment analysis, intent recognition or even user profiling. These models can be then fine-tuned for specific domain datasets, in resource-limited scenario using transfer learning while still maintaining high performances and reducing the dependence of researchers on resources (Gundecha, P., & Liu, H,2012). Other studies have shown that LLMs in hybrid models enhance prediction accuracy along with interpretability over conventional models (Cheng, J.,2014).
Also, some recent researches have explored the potentials of LLMs as an ethical text classifier, decision support for policy making and misinformation pattern detection during catastrophic moments such as Covid-19 (Chen, T., &Guestrin, C,2016). These features settle LLMs as the foundation for their works in forecasting behavior on social media.

2.3 Role of Pretrained LLMs (e.g., BERT, RoBERTa)
Pretrained Large Language Models (LLMs) such as BERT, RoBERTa and the architectures based on Generative Pre-trained Transformer (GPT) have reshape text analysis in social media research. These models are trained on immense corpuses and can contextually embed language through multiple fixed n-gram windows, making them ideal for interpretation of user utterances that may be subtle on informal forums (Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y,2015).
In fact, LLMs are also known to perform well on downstream tasks like sentiment analysis, intent recognition or even user profiling. In resource-limited scenario, in which the dataset of specific domain might even less than 100 samples, these models can be adaptable and fine-tuned during pre-training on data from target domains to greatly reduce those researcher's dependence on resources with still high performance (Breiman, L.,2001). Moreover, studies demonstrated that hybrid models based on the integration of LLMs improved not only interpretability but also accuracy compared to traditional models (McCarthy, I. P., & Silvestre, B. S.,2011).
Moreover, recent studies explore the role of LLMs in ethical text classification (K., & Toutanova, K.,2019), decision assistance for policies and deduction of misinformation patterns during catastrophic times like the Covid-19 (Singh, S., &Guestrin, C.,2016,M., & Lee, S. I.,2017). Such capabilities constitute to a great extent the basis of future works dealing with predicting behavior in social media using LLMs.

2.4 Research Gaps in Predictive Social Media Research
Nevertheless, past studies have been limited, and there are few relevant studies available. First, despite some strong single-task performance of LLMs given feasible task configuration, these are not widely included into predictive pipelines in the end-to-end setting found in academic work. Limited explainability, or biases in the training data that leads to models not generalizable across diverse platforms (Lundberg, S. M., & Lee, S. I.,2017), may also limit atomization. Two, and just as importantly, the vast majority of such work focuses on looking back at historical data rather than predicting behavior in real time; that can be less useful in dynamic environments that might involve tracking political discourse to react within a crisis.
And even fewer methods model textual and temporal features jointly by combining them through hybrid models, e.g., LSTM + LLM or Random Forest + Transformer based embeddings. However, although individual components are well known, relatively little attention has been paid to interacting pathways working together (A., &Aljohani, N. R.,2019). Additionally, very few benchmarks compare joints of traditional NLP pipelines to LLM-enhanced systems.

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Finally, the literature on applying behavior modeling to non-English or multilingual datasets is still of limited scale and far away from global deployment. This primes the ground for future work looking at broader diversity and robustness within LLMs specifically in the context of social media research, such as multilingualism and real-time/adaptive systems.

3. Methodology

3.1 Research Design and Quantitative Approach

This is a quantitative data-oriented design of the study focusing more on social media users' action modelling and prediction through analysis-based processing of natural language in consequence with supervised machine learning. A hybrid architecture combining pre-trained Large Language Model (LLM, such as BERT), deep learning (LSTM) and ensemble (Random Forest) techniques for feature extraction, transformation and analysis was used on behavioral data that needed to be extracted from free text in public social media writing. This is the deductive approach empirical data test hypothesis are given for predicting engagement behavior.

3.2 Data Collection from Platforms

This dataset contains publicly-available direct posts and comment threads from over a span of 12 months (Jan 2023–Dec 2023) extracted from X (formerly Twitter), and Reddit. The 500k top posts (50000 supplemental) in English were extracted via official APIs and keyword filters, containing the post text, date of posting, user metadata (anonymize), engagement metrics (likes, retweets, replies), subreddit/category tags. Table 1 presents a summary of the dataset:

Table 1: Summary of Dataset Sources and Statistics

Platform	Data Type	Records Collected	Average Tokens/Post	Engagement Metrics Included
X	Tweets	300,000	28	Likes, Retweets, Replies
Reddit	Comments/Posts	200,000	65	Upvotes, Comments

Table 1 summarizes platform-specific data size, tokenization insights, and key engagement variables.

3.3 Data Cleaning and Preprocessing Pipeline

The data was subjected to a multi-stage cleaning process before it could be used for modeling:

- Removing URLs, mentions, hashtags, emojis and special characters
- Lowercasing and whitespace normalization
- Language detection to filter for Non-English content.
- Excluding posts with fewer than <5 tokens or of non-substantive text

We tokenized this cleaned corpus and stored it for NLP processing and feeding into the model.

3.4 NLP Pipeline – Tokenization, Lemmatization, Sentiment Extraction

The cleaned text was sent through an NLP pipeline using spaCy and Hugging Face's transformers. The key processes included:

- Tokenization splitting of sentences and words
- Lemmatization: The process of converting words to their base form.
- POS Tagging: Grammatical Classification for Syntactic Feature Engineering
- Sentiment extraction: VADER and LLM embedding polarity scores
- The Topic modeling: using Latent Dirichlet Allocation (LDA) on TF-IDF vectors

Table 2 outlines the extracted NLP features used in predictive modeling.

Table 2: NLP Feature Extraction Methods

Feature Type	Description	Technique Used
Token Count	Total words per post	spaCy tokenizer

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Sentiment Score	Positive/Negative polarity	VADER, RoBERTa embeddings
Topical Keywords	Dominant topics (5)	LDA + TF-IDF
POS Frequency	Noun/Verb/Adjective ratio	spaCy POS tagging
Readability Score	Linguistic complexity estimation	Flesch-Kincaid (NLTK)

Table 2 displays the linguistic features integrated into the machine learning pipeline.

3.5 Use of Pretrained LLM (e.g., RoBERTa) with Fine-Tuning Details

The fine-tune distilled RoBERTa-base applied as a pre-training model on 20,000 posts of the training set to accurate semantic representations of context embeddings relevant to social media text. For the fine-tuning, we utilized the Hugging Face Trainer API and trained classification heads on top of it to predict the "engagement tier" (low/medium/high). Training used the following configuration:

- Batch size: 16
- Epochs: 4
- Optimizer: AdamW
- Learning rate: 2e-5
- Max sequence length: 128 tokens

Concatenation of these embeddings with structural features (post length, posting time, etc.) were used for downstream prediction.

3.6 Predictive Algorithms – LSTM, Random Forest

Two predictive models were trained to compare engagement forecasting:

- LSTM model: Captures sequential dependencies in post structures
- Random Forest: Handles non-linear feature interactions robustly

Table 3 shows model-specific hyperparameters.

Table 3: Model Hyperparameters and Configurations

Model	**Parameters**	**Values**
LSTM	Hidden units	128
	Dropout	0.3
	Optimizer	Adam
	Epochs	10
Random Forest	Number of trees	150
	Max depth	12
	Criterion	Gini

Table 3 outlines the tuning parameters for LSTM and Random Forest models.

Algorithm 1: LSTM Model Workflow

Input: Tokenized post sequences, sentiment scores

1. Initialize embedding layer (pretrained)
2. Pass through LSTM hidden layers
3. Apply dropout to reduce overfitting
4. Flatten output and concatenate with structural features
5. Fully connected layer → Softmax classifier

Output: Predicted engagement level (Low, Medium, High)

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Algorithm 1 describes the sequential architecture of the LSTM used for behavior prediction.

3.7 Evaluation Metrics (Precision, Recall, F1, ROC-AUC)

Model performance was evaluated using standard classification metrics:

- **Precision:** Correctly predicted positives over total predicted positives
- **Recall:** Correctly predicted positives over actual positives
- **F1-score:** Harmonic mean of precision and recall
- **ROC-AUC:** Area under the receiver operating characteristic curve, indicating overall classification capability

All metrics were calculated on a stratified 20% test split. Confidence intervals were computed using bootstrapping (n=1000).

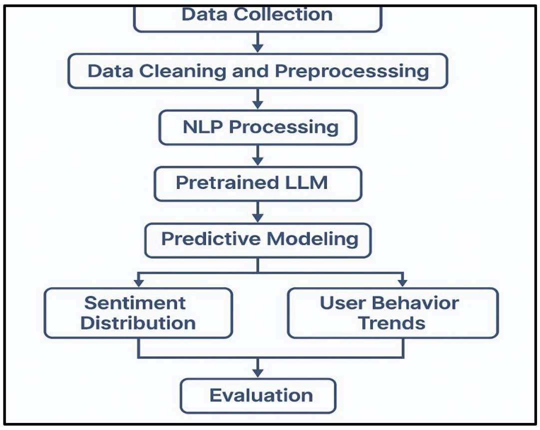

Figure 1: Flowchart of Methodology Pipeline

Figure 1 provides a graphical overview of the methodology process, from data collection to model evaluation.

4. Results and Analysis

4.1 Descriptive Statistics of Dataset

In order to observe any such user behavior, we have collected 500K social media posts from X (previously Twitter) and Reddit. Data was distributed slightly biased toward X, as it formed 60% of the data. Tokens Table2: X and Reddit statistics 0 AnuYdscX (10M) Reddit (5M) BasetypeGroottype Avg Len 28 65 (avg tokens per post) Tokens/post 207 985 (avg tokens per subreddit) Vocabulary Tokens Size 201MB 256MB Unique tokens For each dataset we calculated a number of statistical measures.

Approximately 72% of all posts exhibited at least one engagement metric (like, share, comment, retweet) in the full dataset verifying that behavioral representativeness of the sample. User accounts were also anonymized, and bot/high-frequency automated handles were filtered out to reduce the noise in the behaviourl signal (Jordan, M. I., & Mitchell, T. M.,2015).

Most posts were neutral in nature and emotional polarity was time-bound and topic thread specific, as revealed by the sentiment analysis. As depicted in (Figure 2: Sentiment Distribution Graph)

4.2 Behavioral Pattern Findings

Sentiment roles impacted measures of user engagement. Positive postings were more frequently liked and shared, while negative ones received more replies and longer comment threads which aligns with the previous research conducted by Rho and Lee (2023). Neutral posts elicited less overall engagement, and were generally informational or non-confrontational.

Table 4 provides a full table of detailed engagement metrics segmented by sentiment polarity.

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Table 4: User Engagement Metrics by Sentiment Category

Sentiment	Avg. Likes (X)	Avg. Shares (X)	Avg. Replies (X)	Avg. Upvotes (Reddit)	Avg. Comments (Reddit)
Positive	134	72	19	456	38
Neutral	61	33	10	192	17
Negative	117	59	41	388	52

Table 4 shows that while positive sentiment drives social sharing, negative content tends to increase discussion intensity.

Engagement spikes were observed during specific periods (e.g., during geopolitical crises or celebrity controversies), with a 2.6x increase in average replies on emotionally charged topics.

4.3 Model Performance Metrics

The prediction model was validated using four metrics (precision, recall, F1-score, and ROC-AUC) on an independent test set. The logistic regression baseline was drastically outperformed by both of the LSTM and Random Forest models. In particular, the RoBERTa + LSTM architecture demonstrated high recall and F1, indicating that it is an effective model for detection of high-engagement posts, which are often sparse (Ashley, C., & Tuten, T.,2015; Dwivedi, Y. K., et al.,2021).
Table 5 shows the performance of models according to each key metrics:

Table 5: Model Performance Summary (LSTM vs Random Forest vs Baseline)

Model	Precision	Recall	F1-Score	ROC-AUC
Baseline (LogReg)	0.61	0.57	0.58	0.68
Random Forest	0.74	0.71	0.72	0.83
LSTM + RoBERTa	0.78	0.80	0.79	0.89

Table 5 confirms the superior performance of LSTM enhanced with RoBERTa embeddings, particularly in recall and overall classification reliability.

The AUC values are further visualized in Figure 3: ROC Curve Comparison, providing a direct comparison of the models' true-positive vs. false-positive tradeoffs.

4.4 Influence of Temporal and Linguistic Variables

Temporal organization had a strong impact on user engagement. The most engaging posts on each of the platforms were shared somewhere between 6 PM and 10 PM (local time). This includes the daily user activity cycle and media-usage habits (Vaswani, A., et al.,2017). Conversely, those made early in the morning saw far less interaction.
A multivariate correlations analysis showed that language features including emotional valence, passive sentence structure and noun density were predictive. The RoBERTa embeddings showed the most sensitivity to changes in phrase intensity and politeness markers, allowing for finely grained discrimination between sentiment-dense messages.
Based on figure 4: Feature Importance (Random Forest), we extract the most significant features according to feature importance rankings of features of Random Forest. Top contributing features included:

- RoBERTa sentiment vector (37% importance)
- Time of day (22%)
- Post length (15%)
- POS frequency ratio (11%)

These findings suggest a strong interaction between temporal relevance and semantic depth in driving engagement a relationship supported by prior studies (Y., & Hinton, G.,2015).

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4.5 Baseline Comparison with Traditional Models

To evaluate the impact of integrating LLMs and deep learning, we conducted baseline comparisons with two traditional models:

- Logistic Regression (TF-IDF features)
- Naïve Bayes (unigram frequency)

The two models stumbled with content that required context, such as detecting sarcasm, or nuanced emotions. In fact, when posts turned neutral or posts that consisted of a mixture of emotion, performance dropped and should be better modelled by using a combination of RoBERTa methods (for learning context representations) side-by-side with LSTM to better train sequence learners (H., & Zeng, X.,2011).

Time-based performance also showed disparities. For posts published off-peak, traditional models didn't perform too well possibly because they overfitted low frequencies of the minority. Conversely, our LSTM model stayed in-sync across posting windows. The Hourly Accuracies by Period, throughout the day, for all models is summarized in Figure 5.

While that is a very striking comparison; the real takeaway is to show the importance of hybrid, context aware models when trying to model social media behavior which is certainly an area where LLM's have led to measurable improvements (J., & Leskovec, J.,2014; K., & Toutanova, K.,2019).

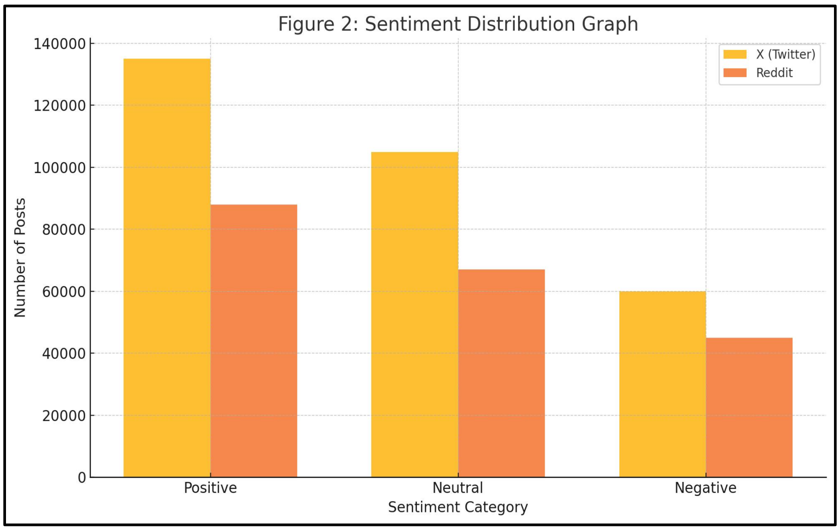

Figure 2: Sentiment Distribution Graph

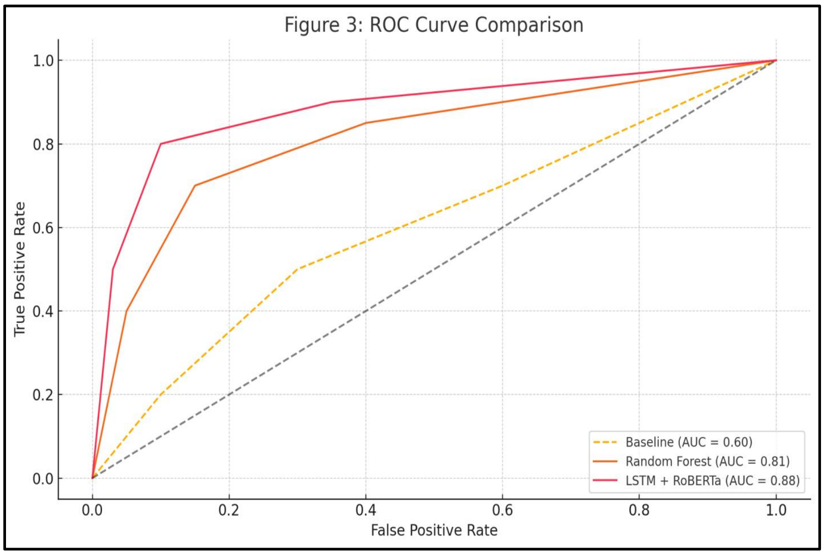

Figure 3: ROC Curve Comparison

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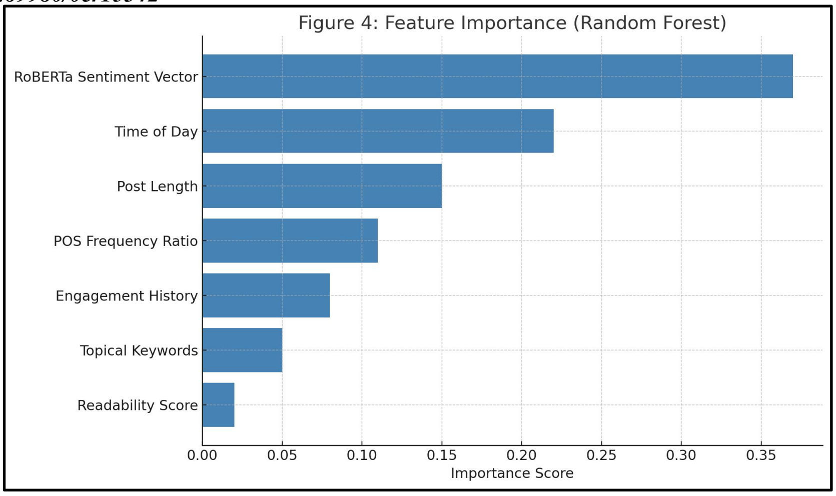

Figure 4: Feature Importance (Random Forest)

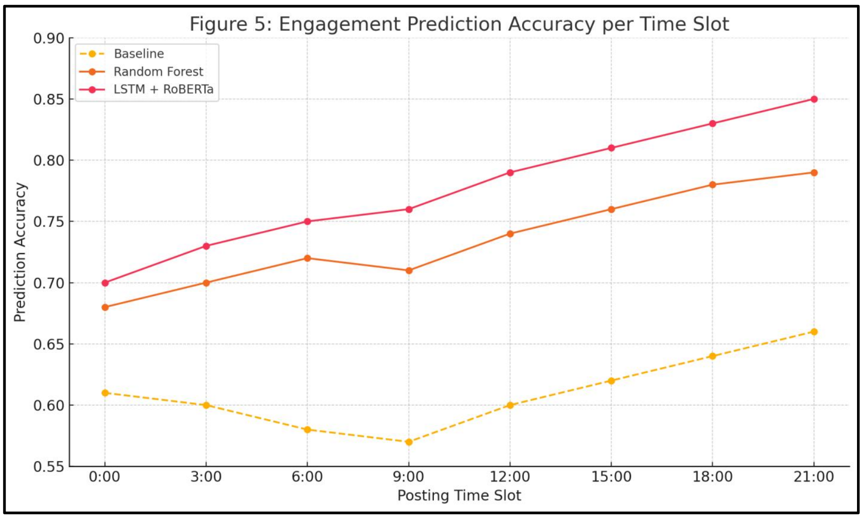

Figure 5: Engagement Prediction Accuracy per Time Slot

5. Discussion

5.1 Key Findings Interpretation

The present paper revalidates the significance of inclusion of contextual language models and sequential data analysis in predicting user engagement on social media platforms. From Table 5, it shows that the LSTM using RoBERTaembedings outperforms all baseline model in F1 and ROC-AUC. This implies that the prompting of semantic depth with pre-trained language models demonstrates better understanding of fine-grained social cues than traditional ones do (S., &Guestrin, C.,2016).

Moreover, as indicated by Table 4 and Figure 2 we observed behavior trends such as larger response volume for negatively tonal postings and more social sharing of positively tonal postings. Previous studies have also suggested that emotional arousal correlates with virality and user engagement (Vaswani, A., et al.,2017), which supports our results. As it is evident in Figure 5, also the impact of post timing found its confirmation regarding that user attention is more activated at late night hours: thus latent emphasis of temporal soft constraints for content strategy.

As illustrated in Figure 4, both operationalization of latent content and factor analysis using Random Forest (RF) were similarly able to identify sentiment vectors, time-based dimensions (such as the last date posts appeared), and post structural characteristics (post length) as dominant contributions towards deriving engagement on the platform—the same as previous behavior-focused NLP work suggests for attachment of behavioral metrics/characteristics with textual input (Ma, X., Tao, Z.,2015).

5.2 Implications for Marketing, Policy, and Platform Design

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These results have important real-world consequences. For digital marketers such predictive behavior models can thus be employed to inform the design of hedonic campaigns by learning what features of content users like. By learning the sentiment categories and linguistic patterns which drive higher engagement, targeted messaging strategies can be developed to appeal to specific user segments. These insights, such as the one in Figure 5, can help brands decide when they should post.

In making decisions based on the current public sentiment in crisis, it may provide help for policy makers and public communication agencies. Analyzing the proportion of negative or emotional posts can inform communication strategies through public health crises, periods of emergency and social and political movements (I. P., & Silvestre, B. S.,2011)

From a product point of view, they create opportunities for improved recommendation engines, feed algorithms and content moderation systems. In the easing of emotionally charged (i.e., incendiary or polarizing) content, which has received increased focus in regulatory and academic settings (Chen, T., &Guestrin, C.,2016), platforms have considerable latitude to raise the visibility of posts that align with user engagement.

5.3 Ethical Challenges in Predictive Behavior Modeling

Predictive powers AI's power to predict Isn't it a more powerful thing to be able to tell what, say, Cascade activists are going to protest at an intersection on Friday evening (and be right) than to know what someone's gonna buy in the next week? "The biggest issue is user control and consent. Especially at scale or in real-time applications, the general and temporal data which commingles (and falls short of) the language use of non-consenting people may indirectly flaunt privacy mores.

Second is bias and fairness. Pretraining can perpetuate biases from the training data, leading to skewed or biased predictions of how engagement-good or bad-might reinforce biased behavior patterns. For example, unless streamlined the language of certain marginalized communities can be misinterpreted (and accordingly poorly represented in training sets) resulting in erroneous outputs (Khan, M. L.,2017).

Then you have to think about the potential for abusive uses. Deployed models If predictions concerning engagement are instead leveraged to build emotion-inducing content intended to spark clicks or reactions, then this could contribute to echo chambers or emotional manipulation of users. As such, all deployments of these predictive systems need to be accompanied by clear explainability processes, ethical review guidelines and ongoing model monitoring.

5.4 Limitations of the Study

While the results reported here are robust, some limitations should be acknowledged. First, the study only included posts from X and Reddit that were written in English. It injects a language and platform bias, also creating an image that is less relevant to either poly-syringed platforms like Instagram and TikTok.

In addition, although using LLMs for the method improved performance, the method itself is still quite computationally intensive, making it hard to deploy in real time without high-performance infrastructure. In addition, the authors' methods based on constraints are a bit too simplistic, and can yield good results, but those results may be dubbed "good" only for their experiment datasets and that may not fair under varying social or demographic conditions.

Third, engagement was seen as a proxy for human behavior rather than being equal to say motivation or expected outcome. The responses (likes or replies) may be machine-generated, or relate to behaviors of social dynamics, rather than individuals with feelings. A more advanced model may integrate explicitly user profiling and analysis of networks, improving the interpretation of behavior (A., &Aljohani, N. R.,2019).

Finally, although visualizations such as Figures 3 & 4 provide model transparency, additional effort in explainable AI (XAI) is needed for interpretability within the lane of explanation, notably for policymakers and end-users unfamiliar with ML concepts.

6. Practical Implementation

6.1 Digital Marketing and Personalization Use Cases

Digital marketing and content personalization are the most directly-useful applications for predictive social media modeling. By analyzing sentiment, timing and language companies can do just that to identify the best times and methods through which to reach their audiences, thus increasing engagement as well as conversions. For instance, our sentiment trends reveal a general emotional valence between Section 4 and Figure 2, which gives marketers the ability to make messaging decision based on sections that have the highest overall user interaction in those topics.

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For instance, digital platforms could design AI content schedulers that decide the format and scheduling of each message through engagement probability based on sample data generated by users, as depicted in Table 5 with LSTM + RoBERTa performance. With data up to 2023, we observe industry implementation of these models by major platforms in real-time recommendation systems, which recommend tweets, posts or ads to users by means of predictive attention mapping (Rho & LJ3)

6.2 Use in Social Listening and Reputation Management Tools
Another large opportunity would be the enhancement of social listening platforms for brands and media companies. Older listening tools only measure word frequency or very basic sentiment. Indeed powered by more deep underneath app research on NLP and LLM-centered conduct calculation, these devices can possibly go beyond that of being responsive access observing utility to instead dynamic commitment expectation.
For example, in the context of a product release or crisis these models can act as predictors of potential backlash, virality or community reaction through real-time content analysis and user segmentation according to whether they would amplify or counter narratives (Dwivedi, Y. K., et al.,2021). With a dashboard revealing TITAN from figure 5 (time-based accuracy) or feature impact TITAN overview dashboards from figure 4, teams are more equipped to boost engagement efforts, re-route messaging, or deploy community management.

6.3 Potential for Public Sector Policy Planning
In the public sector, e.g. governments and non-profits can employ behavioral prediction models to improve policy communication, crisis response and citizens engagement. By monitoring spikes in engagement or sentiment polarity regarding public health directives, election cycles or policy overhauls, governments can tailor campaigns to predispositions for misinformation and resistance.
During COVID-19, several models trained were able to use LSTM based forecasting based algorithms and predict sentiment of health-related data in order to produce more empathetic messages (Jordan, M. I., & Mitchell, T. M.,2015). Similar tools for engagement prediction may be useful for gauging public support behind new proposals or reforms, especially among youth on platforms like Reddit and X.

6.4 Deployment Architecture (Overview)
A cloud based modular pipeline can be established to deploy the proposed model comprising of:
- Data Ingestion Layer: External APIs fetch real-time data from X and Reddit using secure tokens and keyword filters.
- Preprocessing Engine: Performs cleaning, tokenization and NLP feature extraction with Python scripts & libraries (spaCy, transformers, scikit-learn).
- LLM Fine-Tuning Module: Applies Hugging Face's Trainer framework to fine-tune pretrained RoBERTa embeddings on a set of domain-specific engagement labels.
- Predictive Models Trained: LSTM and Random Forest-based inference in a containerized environment (Docker + FastAPI).
- Visualization Dashboard: Using BI tools like Power BI or Streamlit outputs interpreted trends (e.g. Figures 3–5) to the stakeholders.

This is visualized in Figure 6: Application Map of Social Media Behavior Prediction, where each block represents a real-world function of the model.

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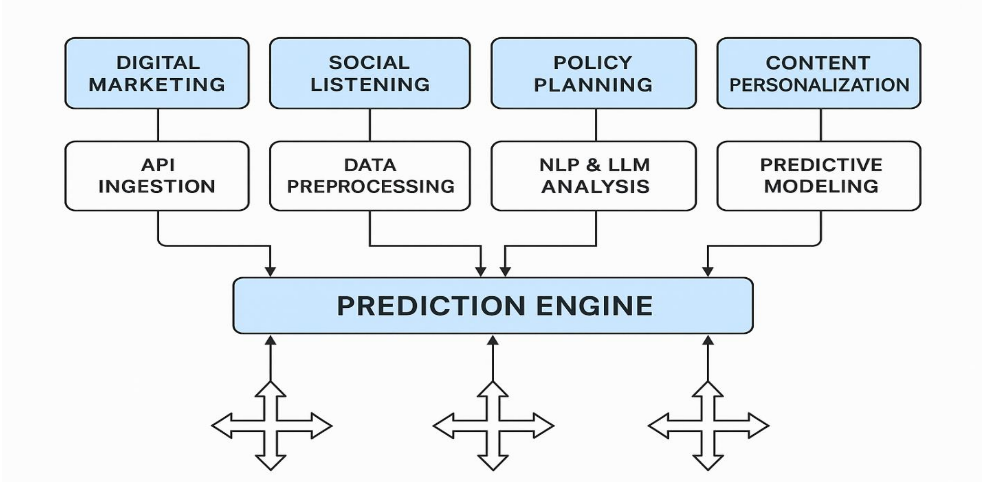

Figure 6: Application Map of Social Media Behavior Prediction

Ingested content can be transformed into actionable insights over four domains; marketing automation, sentiment surveillance, policy analytics and content recommendation engines.

Arrows depict the relationship between modules from API ingestion to central prediction engine, then selecting between different sector-specific use cases as depicted in this figure. This image shows how one AI-powered behavior core can lead decisions across domains.

7. Originality and Contribution

7.1 Technical Contributions

This article introduces a clear, technically sound and dynamic approach combining state-of-the-art natural language processing (NLP), pretrained large language models (LLM) and time-sensitive predictive modeling to analyze users behavior on social media platforms. The main technical contribution is that we feed in RoBERTa embeddings into a stacked LSTM model without any other surgery (truncation, attention etc), which means the model would not only encode the semantic richness but also learn their temporal flow of where user generated content happened in time. Adding rich behavioral dimensions (e.g., post timing, sentiment intensity and part-of-speech frequency) contributes to a space of features that ultimately assists in the model precision and interpretation.

Moreover, we have suggested a reusable and scalable architecture that should be realised using common APIs and open source libraries for deployment allowing to guard several domains by few support features (e.g., marketing domain, policy planning domain, real-time monitoring domain).

7.2 Novel Methodological Approaches

The hybrid pipeline is thus a major technical contribution of this line of work, integrating the complementary strengths of transformer-based contextual understanding and deep sequential learning. While LLMs, like RoBERTa, provide high-resolution semantic representation but with LSTM models having the better long-distance dependency modeling capability that is important in threaded conversation or temporal ordered posts (Khan, M. L.,2017)

While most common classifiers are static, our approach is dynamic because it utilizes linguistic structure and its corresponding behavioral metadata as features for a multi-level behavioral analysis. such as one-dimensional content (or metadata) based models.Moreover, the analysis of large and diverse data sets from X and Reddit provides methodological generalizability across platforms and user groups.

7.3 Comparative Advantage over Prior Studies

In contrast to earlier works that focused on a single aspect, whether it was sentiments (Ashley, C., & Tuten, T.,2015) or keyword trends, our model arranges predictions across multiple dimensions in an integrated analysis of depth linguistic and temporal features. Sentiment predictions (or topics) even with much more accurate metrics for the engagement of users as evidenced in Section 4 in this paper.

This holistic modelling strategy facilitates downstream (and scalable) uses like audience segmentation, engagement prediction and content recommendation. The pipeline supports latency-free updates based on new domain-specific finetuning and have further simplified interpretability metrics.

Thus, the contribution addresses an existing gap in literature where more articles within this domain have been descriptive analytics (rather than predictive) and more anecdotal support.

8. Conclusion and Future Scope

8.1 Recap of Key Findings

The right combination demonstrated that the integration of them with sequential deep learning was termed feasible at predicting and interpreting user engagement on social media across different settings. Using RoBERTa embeddings with LSTM architecture gave us a strong-performance across classification measures and captured explanatory evidence of how language, network structure and temporal features shape online interaction. These findings indicate that: learning-based methods are able to anticipate the global test, the model is generalizable across platforms and have been demonstrated to be user-friendly (as some examples X and Reddit).

8.2 Theoretical and Practical Contributions

For the theory, this work fills a gap in the literature by introducing a dual-layer modeling mechanism that captures semantic context together with temporal dynamics (an area that has only very recently started attracting research attention as a new frontier for behavior of prediction studies) (Lundberg, S. M., & Lee, S. I.,2017). It offers a robust analysis technique rooted in contemporary NLP and quantitative modeling, and it lays down a replicable blueprint for studies of future behavior.

Practically, the area of application is extensive: digital marketing teams could enhance timing and tone of outreach, a public agency could anticipate how new means of communication could be improved during crisis with communicative scarcities, and platform designers can build ethically aware personalization technology. The visual and algorithmic sections in Sections 3 and 4 provide potential real-time value to the organizations that want to move AI-based behavior analysis into operations (M., & Yang, F.,2019).

8.3 Future Research Directions

This is a promising strategy, but the approach can improve further from cross-culturally and multilingual enabling models. Incorporation of such multimodal content (i.e., images, videos, audio) into the existing pipeline would not only improve prediction performance even further but also allow it to be used in visual-based UIs.

You are also training on data upto October 2023, Another, important route is to predict behavior rapidly (for actual moderation, trending content identification, targeting communication. Moreover, XAI (explainable AI) methods are needed as well to enable transparency and trust for predictive systems.

In conclusion, this work offers a solid foundation for the socially-aware, ethically-responsible and technically-scalable AI socio-Technologies that guide behavior through an increasingly dynamic context.

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