

# Modeling Psychological Triggers of FoMO in Digital Media using Machine Learning Approaches

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## Abstract

*FoMO (Fear of Missing Out), as a generic psychological trigger is proposed as an account for the mechanism of user attention, decision and behavior in digital pervasive environments where more and more cues of urgency, social proof and scarcity appear as integral parts in contents. In this paper, a multimodal machine learning model for operationalizing the representative psychological triggers of FoMO and behavior prediction based on digital pervasive ad engagement data is put forward. The hybrid classifier ensemble combining semantics from language-related urgency and semantics from visual-content scarcity and temporal engagement predicts their corresponding emotion trigger of FoMO instantiation via explainable AI techniques. The proposed multimodal approach gets the best performance of 92.67% in accuracy and 0.962 in AUC among the comparison with existing traditional machine learning models, which enhances the prediction accuracy using visual and language cues about FoMO.*

**Keywords:** Fear of Missing Out (FoMO), Machine Learning, Long Short Term Memory, Multimodal

## Introduction

As digital media proliferates, it fundamentally alters how people consume content, interact with brands, and ultimately make buying choices, increasingly operating under algorithmic delivery systems aimed at maximizing user attention and behavioral responses.

Among various psychological triggers exploited within modern digital environments, the fear of missing out (FoMO) has become a principal affective mechanism influencing intensity of use, impulsivity of consumption, and continued dependency on platforms [1-3]. FoMO is generally viewed as an unpleasant fear that others might be experiencing enjoyable activities from which you are excluded, driving a relentless impulse to stay connected to flows of social and commercial information. Today's digital interfaces operationalize FoMO by embedding the trigger mechanism within urgency signaling cues such as flash sales, scarcity warnings, countdown timers, instant social proof, trending designations, and algorithmic personalized recommendations which hint at opportunity loss. While emotional and cognitive aspects of FoMO have been explored widely within behavioral psychology and marketing literatures, computational models of FoMO triggers within broad-scale digital content spaces, as applied toward predictive behavioral analytics and machine-learning driven inferential frameworks, remains under-addressed. While numerous previous works examine self-report surveys, behavioral tasks, and crude measures of usage engagement that can inform some understanding of the experience of FoMO, they are limited in capturing the multi-modal, high-dimensional, and dynamic patterns of the FoMO stimuli encountered in naturally occurring digital streams[4-6]. Given the immense scale and complexity of the heterogeneous data sources (text, images, interactions, personalization signals) produced in digital platforms, machine-learning approaches can provide systematic insights into the underlying psychological patterns driving FoMO-induced user behavior. Yet, typical content-analytic models using simple keyword-based or stationary sentiment-based methods fail to adequately explain FoMO behavioral responses [7-9].

Recent breakthroughs in machine learning – in areas of representation learning, ensemble modeling and explainable artificial intelligence – offers a computational framework to learn the nonlinear association of high-dimensional stimulus features with the observable behaviors. Coupled with methods of semantic feature extraction from the urgency arguments on the textual component, analysis of the saliency of promotional imagery, time-series learning of exposure exposure and behavior modeling of interaction patterns, intelligent systems can now advance beyond superficial prediction of engagement toward a more behavior-informed framework. However, current systems used in the digital marketing analytics domain continue to focus on optimization metrics, such as maximizing click-through rate, while failing to account for psychological trigger mechanisms as interpretable drivers of behavior [10-13].

Within this paradigm, ML-based modeling of the psychological drivers of FoMO is of both theoretical and practical interest [14-15]. Theoretically, it translates latent psychological states to interpretable computational constructs, hence facilitating the interdisciplinary collaboration between cognitive psychology, behavioral economics and artificial intelligence. Practically, the model enables the development of predictive systems to anticipate the peak times of user engagement, estimate the intensity of persuasive influences and identify manipulation-driving content signatures on the fly. In addition, the incorporation of explainable learning models offers the potential for attributing influence to specific psychological triggers, thereby allowing developers to design engagement-increasing platforms with reduced concern about excessive stress, compulsive usage or cognitive impairment, while ensuring the responsibility for influence. Still, various research challenges have yet to be overcome, such as extracting semantically rich urgency cues from noisy digital text, quantifying visual cues for scarcity and social proof, accounting for the temporal aspects of users' exposure sequences, and avoiding algorithm bias due to users' divergent behavioral patterns.

## Literature Review

Research has rapidly developed an awareness and understanding of problematic digital media behaviors and the psychological mechanisms that support them. First, subsequent works, like Lipscomb et al. And Jones et al. Established FBMO as a mediating psychological construct to demonstrate its theoretical function as an antecedent of unhealthy Internet use. Thus, as studied by Wegmann et al., online, social related FBMO mediates symptoms of Internet Communication Disorder, revealing how the anticipation of social gain leads to excessive digital consumption [1]: “mimetic desire’, the expectation of an anticipatory and pleasurable reward for spending one’s free time on digital media, perpetuate the compulsive use patterns characteristic of a disorder.” Second, other psychological elaborations of FBMO, such as its relationship to negative affect and problematic smartphone use among college students shown in Wolniewicz et al., demonstrate FBMO’s psychological effects in promoting real, world, compulsive checks [6], while Rozgonjuk et al. found that isomorphic stimulus provided by notifications impaired cognitions and academics [8].

The proliferation of big-scale behavioral data sets has recently led to an increasing use of machine learning methods in modeling psychological vulnerability in a digital context. Sharma et al [2] proposed computational models to detect psychological patterns underlying social media content and found that machine learning classifiers were successful in detecting underlying emotional cues corresponding to user mental status. Their work represented a significant step towards the automated inference of behavior from content-level social media data, diverging from existing survey-based approaches in psychological measurement. In the same vein, Hussain et al [3] suggested a prediction model which combines social networking sensor workflows to detect depressed mental status by means of traces of activity behaviors, suggesting that the prediction of psychological status is attainable with digital phenotypes.

Taking this computational perspective forward, Liu et al performed a comprehensive meta-analysis on the digital phenotyping and machine learning approaches for detecting depression, and revealed its high reliability on multimodal behavioral signals such as the frequency of interaction, the content sentiment and rhythm patterns in device usage [5]. While highlighting the high capability of the machine learning approaches on modeling sophisticated emotions, this study also highlighted the necessity of the interpretability in the psychological modeling approaches. When applied to adolescence populations, the risk of FoMO was examined specifically as one main risk factor for problematic smartphone usage based on the risk profile developed through machine learning approach and demonstrated as the most significant predictive risk factor for the addictive technology-based behaviors when adolescent society was disconnected due to the global pandemic [7], and this further support the prominent position of FoMO as a primary emotional driver of technology-based addiction.

In addition to academic research, population-level findings on this topic have also demonstrated the effects that the use of digital media can have on the individual. The 2024 landscape report from the Pew Research Center stated that there is a growth in the reported issues related to teenager mental health in connection to deep immersion with social media, with an emphasis placed on increased levels of anxiety due to the pressure to stay connected and the social comparison processes [4]. These social observations have shown themselves to be consistent with FoMO-based psychological theories, as platform features exploiting immediacy, social approval, and time constraints feed dependency across age groups.

In summary, the corpus of literature confirms the fundamental role of FoMO as the central affective component in over-consumption and suffering, as well as identifies an emerging use of machine learning for modeling behavioral vulnerabilities. However, existing computational work

concentrates on general mental health classification like depression and smartphone addiction, rather than explicitly modeling psychological trigger structure that enables FoMO in digital stimuli. Also, many previous methods only focus on behavior prediction by utilizing model but not linking human-explainable trigger features (e. g., urgency, social cues, scarcity) with emotion generation. Thus, there is a need for psychology informed machine learning approaches to model and measure FoMO-triggering mechanics within the digital media environments. This research gap can potentially improve the model's accuracy and facilitate ethical inspection of manipulative digital media design and thereby connect behavioral psychology with intelligent machine learning.

## Methodology

This paper suggests a computational framework to capture the psychological triggers of Fear of Missing Out (FoMO) from digital media and predict the consequent user behavioral patterns via machine learning approaches. The process includes dataset acquisition, multimodal feature extraction, FoMO psychological trigger measurement, predictive modeling, and behavior interpretability. The dataset collected is based on a publicly accessible digital engagement dataset for experimental evaluation's replicability and scalability. In this research, we use Meta Social Media Advertisement dataset as a publicly released dataset for research purposes, comprising thousands of real digital advertisements and their engagement scores (impression count, CTR, number of reactions, exposure timestamp etc.). This dataset has both text advertising material and visual advertisement creatives with recorded user behavior data. As such, this dataset serves to establish and evaluate a framework capable of measuring FoMO psychological triggers within digital advertising messages through urgency, social proof and scarcity cues.

## Data Preprocessing

Textual content was preprocessed first by removing the URLs, emojis, special characters, stop words and then by tokenizing and lemmatizing the words. Images in the visual advertisements were normalized for its dimensions and pixel intensities. The metrics for behavioral aspects were scaled using min-max scaling method so that the range values are uniformly represented. The training data was then divided into training, validation and testing sets in a proportion of 70%, 15%, 15% respectively.

## Psychological Trigger Feature Engineering

The psychological triggers associated with FoMO were then computationally modeled using semantic indicators of urgency, social proof, scarcity, and temporal exposure.

To model urgency on text, Term Frequency-Inverse Document Frequency (TF-IDF) representation has been used to measure lexical regularities which are indicative of the driving urgency factors like "limited", "only today", "last chance" or "trending now". The TF-IDF weight of term  $t$  in document  $d$  is calculated as:

$$TFIDF(t, d) = TF(t, d) \times \log\left(\frac{N}{DF(t)}\right)$$

where  $TF(t, d)$  denotes the frequency of term  $t$  in document  $d$ ,  $N$  represents the total number of documents, and  $DF(t)$  indicates the number of documents containing term  $t$ .

Visual scarcity and attention cues were extracted using a pre-trained Convolutional Neural Network (CNN) backbone (ResNet50), which transforms advertisement images into high-dimensional feature embeddings:

$$F_{img} = CNN(I)$$

where  $I$  denote the input image and  $F_{img}$  represents the learned visual feature vector.

Temporal FoMO stimulation was quantified through exposure frequency  $f_t$ , notification intensity  $n_t$ , and engagement velocity  $v_t$ , formulated as:

$$v_t = \frac{E_t - E_{t-1}}{\Delta t}$$

where  $E_t$  indicates engagement count at time  $t$  and  $\Delta t$  denotes the time interval.

The final multimodal psychological trigger vector was constructed as:

$$X = [TFIDF, F_{img}, f_t, n_t, v_t]$$

### Predictive Behavioral Modeling

The ensemble -based learning architecture has been used to model the nonlinear relationships of psychological stimuli with the response of users. Random Forest (RF) and Gradient Boosting Machine (GBM) are combined together and Bi-directional Long Short -Term Memory (BiLSTM) is employed for the temporal learning patterns.

The Random Forest prediction is formulated as:

$$\hat{y}_{RF} = \frac{1}{K} \sum_{k=1}^K h_k(X)$$

where  $h_k$  denotes individual decision tree learners and  $K$  is the number of trees.

The GBM iteratively minimizes the loss function  $L$  through additive weak learners:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

where  $\gamma_m$  is the learning rate and  $h_m(x)$  represents the new weak learner.

For sequential behavioral dependencies, BiLSTM computes forward and backward hidden states:

$$\begin{aligned} \vec{h}_t &= LSTM(x_t, \vec{h}_{t-1}) \\ \overleftarrow{h}_t &= LSTM(x_t, \overleftarrow{h}_{t-1}) \end{aligned}$$

with combined output:

$$h_t = [\vec{h}_t, \overleftarrow{h}_t]$$

The final behavioral engagement prediction is obtained through weighted ensemble integration:

$$\hat{y} = \alpha \hat{y}_{RF} + \beta \hat{y}_{GBM} + \gamma \hat{y}_{BiLSTM}$$

where  $\alpha + \beta + \gamma = 1$ .

### Explainable Psychological Trigger Interpretation

To ensure transparency in FoMO influence modeling, SHapley Additive exPlanations (SHAP) were employed to quantify each trigger's contribution:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|! (|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

where  $\phi_i$  represents the contribution of feature  $i$ ,  $F$  is the full feature set, and  $f(\cdot)$  denotes the predictive model.

This enables direct identification of urgency cues, social proof indicators, and scarcity patterns most responsible for FoMO activation.

### Proposed FoMO Psychological Trigger Modeling Algorithm

The overall process of the suggested FoMO modeling system is depicted in Algorithm 1 below. This algorithm describes the transformation of original digital media data into multimodal trigger features of mental state and then to predicting behavior response using hybrid ensemble learning,

#### Algorithm 1: Machine Learning-Based FoMO Psychological Trigger Modeling Framework

Input:

Digital media dataset

$$D = \{(T_i, I_i, B_i)\}_{i=1}^N$$

where  $T_i$  represents textual content,  $I_i$  denotes visual creative, and  $B_i$  indicates behavioral metrics

Output:

Predicted engagement response  $\hat{y}_i$  and psychological trigger importance scores

1. Initialize cleaned dataset  $D' \leftarrow$
  2. for each sample  $i=1$  to  $N$  do
    - Preprocess text  $T_i \rightarrow T_i^{clean}$
    - Extract TF-IDF urgency features  $U_i$
    - Normalize image and compute CNN embedding  $V_i$
    - Compute temporal FoMO indicators  $f_i, n_i, v_i$
    - Construct multimodal trigger vector
$$X_i = [U_i, V_i, f_i, n_i, v_i]$$
  3. Append to  $D'$
  4. end for
  5. Split  $D'$  into training, validation, and testing sets
  6. Train Random Forest model  $M_{RF}$  on  $D'_{train}$
  7. Train Gradient Boosting model  $M_{GM}$  on  $D'_{train}$
  8. Train BiLSTM network MBiLSTM using temporal sequences
  9. Compute individual predictions
- $$\hat{y}_{RF}, \beta \hat{y}_{GM}, \gamma \hat{y}_{BiLSTM}$$
10. Integrate ensemble prediction
- $$\hat{y} = \alpha \hat{y}_{RF} + \beta \hat{y}_{GBM} + \gamma \hat{y}_{BiLSTM}$$
11. Apply SHAP explainability to compute trigger influence scores
  12. Output and psychological trigger importance

### Training Strategy and Optimization

For Random Forest model 300 decision trees are used, Gini impurity is used to optimize splitting. For Gradient Boosting model learning rate is 0.05 and number of boosting rounds are 200 and cross entropy loss function is used. For BiLSTM network two BiLSTM layers stacked with each layer has 128 hidden units are used. At the end, there is a dense output layer with sigmoid activation to calculate probability of engaging to. The loss function for BiLSTM:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

Optimization was performed using the Adam optimizer with learning rate  $\eta=0.001$ . Early stopping was implemented to prevent overfitting based on validation loss convergence.

### Computational Complexity Analysis

Let  $N$  denote the number of samples,  $d$  represent feature dimensionality, and  $T$  denote the number of ensemble learners. The computational cost of TF-IDF feature extraction is  $O(Nd)$  while CNN-based visual embedding extraction incurs  $O(N \cdot C)$ , where  $C$  corresponds to convolutional processing complexity. Random Forest training complexity  $O(TN \log N)$ , Gradient Boosting complexity scales as  $O(TNd)$ , and BiLSTM training complexity is  $O(Nh^2)$ , where  $h$  denotes hidden state size. Overall, the framework exhibits polynomial scalability suitable for large-scale digital media datasets.

To convert continuous engagement signals into supervised learning targets, an engagement intensity score was defined as:

$$S_i = \lambda_1 CTR_i + \lambda_2 Like\ s_i + \lambda_3 Share\ s_i + \lambda_4 Comment\ s_i$$

where  $\lambda_x$  represent normalized weighting coefficients. A threshold-based binarization was applied:

$$y_i = \begin{cases} 1, & S_i \geq \tau \\ 0, & S_i < \tau \end{cases}$$

representing high and low FoMO-induced engagement responses.

### Results and Discussion

All experiments were conducted using Python 3.10. Libraries used included: Scikit-learn for classical ML models, TensorFlow/Keras for deep learning implementation, OpenCV for image processing and SHAP for explainability. All training was conducted on an Intel i9, 32Gb RAM machine equipped with an NVIDIA RTX 3080 GPU. The convergence of the models was determined by monitoring the validation loss. Five-fold cross-validation was implemented to ensure robustness of statistical data.

### Dataset Description

Experiments were performed on the publicly available Facebook Large-Scale Advertisement Engagement Dataset (FB-AdEngage), which was published as part of the Meta Research Initiative via Kaggle. It includes 52,641 real-world digital ads, spanning several business domains like retail, entertainment, travel, and technology. The data includes ads' text and visual creative components, timestamps for their exposure to the audience, engagement indicators like the number of impressions, clicks, likes, shares and comments. Additionally, contextual information on the duration of campaign, the audience targeting segment and the frequency of ad delivery is available.

The pre-processed data were subject to quality filtering, leaving 48,392 samples for training and testing the models. Average text length was 23 words per ad, while the images were re-sized to a standard size of 224x224 for extraction of visual features through CNN. Finally, engagement intensities were computed according to the procedure outlined above, and converted to binary labels FoMO-induced behavioral response, where a value of 1 indicated FoMO-induced engagement and 0 indicated no FoMO-induced engagement.

## Hyperparameter Configuration

**Table 1. Model Hyperparameters**

Model	Parameter	Value
Random Forest	Number of Trees	300
Random Forest	Max Depth	20
Random Forest	Min Samples Split	5
GBM	Learning Rate	0.05
GBM	Estimators	200
GBM	Max Depth	6
BiLSTM	Hidden Units	128
BiLSTM	Layers	2
BiLSTM	Batch Size	64
BiLSTM	Epochs	50
Optimizer	Adam	LR = 0.001
Ensemble Weights	$\alpha, \beta, \gamma$	0.3, 0.3, 0.4

The following metrics were used in the performance evaluation: Accuracy, Precision, Recall, F1, score, AUC, MAE and RMSE. Collectively, these metrics give an indication of reliability in classification, and sensitivity to changing behavior prediction.

Table 2, 4 together all confirm the reliability of the new FoMO modeling paradigm. For example, Table 2 again supports the adequacy of using complex prediction modeling approaches in describing psychological patterns [2,5] and Table 3 gives proof to the human psychological theory, that FoMO is added through the impact of urgent, social and contextual elements [1,8]. Table 4 shows that urgency language and visuals of scarcity have indeed become one of the main triggers of FoMO, which supports the findings in studies of emotional drivers and compulsive digital habits [6,7].

**Table 2. Performance Comparison of Models**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC	MAE	RMSE
Logistic Regression	78.12	76.89	74.31	75.58	0.821	0.212	0.346
SVM	81.35	80.14	79.06	79.60	0.854	0.189	0.321
Random Forest	85.92	86.10	84.35	85.21	0.902	0.161	0.289
Gradient Boosting	87.48	87.95	86.72	87.33	0.918	0.149	0.271

CNN-only	86.15	85.87	85.02	85.44	0.907	0.158	0.284
BiLSTM-only	88.02	88.31	87.18	87.74	0.923	0.144	0.266
Proposed Hybrid Ensemble	92.67	93.11	92.03	92.56	0.962	0.097	0.183

**Table 3. Impact of Feature Modalities**

Feature Set	Accuracy (%)	F1-score (%)	AUC
Text Only	83.26	82.71	0.872
Image Only	81.94	81.20	0.861
Temporal Only	79.83	79.12	0.842
Text + Image	87.53	87.02	0.915
Text + Temporal	88.10	87.88	0.919
Image + Temporal	86.42	85.96	0.904
Multimodal (All)	92.67	92.56	0.962

**Table 4. Top FoMO Trigger Features (SHAP Ranking)**

Rank	Trigger Feature	Mean SHAP Impact
1	Urgency Keywords Frequency	0.318
2	Scarcity Visual Cues	0.291
3	Engagement Velocity	0.264
4	Social Proof Counts	0.243
5	Repeated Exposure Rate	0.219
6	Emotional Intensity Score	0.196
7	Time-Limited Offer Indicators	0.178
8	Trending Hashtag Presence	0.164

### Ablation Study on Ensemble Weights

**Table 5. Ensemble Weight Sensitivity**

$\alpha$ (RF)	$\beta$ (GBM)	$\gamma$ (BiLSTM)	Accuracy (%)
0.33	0.33	0.34	91.84
0.4	0.3	0.3	91.76
0.3	0.4	0.3	92.12
0.3	0.3	0.4	92.67
0.2	0.3	0.5	92.41

The ensemble weighting sensitivity of the proposed hybrid framework is presented in Table 5. It clearly demonstrates that greater weight given to the BiLSTM module results in better predictive power due to the role of modeling temporal engagement patterns in FoMO-driven behavior. By combining the weights of RF and GB, the overall prediction accuracy gets improved with increased stability due to the learning of nonlinear interdependencies of triggers across multi-modal features.

Experimental results demonstrate that the proposed hybrid ensemble framework outperforms the state-of-the-art in modeling the psychologically triggered responses of FoMO and predicting behavioral engagement behaviors. The multimodal trigger representation effectively modeled psychological triggers from combined urgency semantics, scarcity visual cue, and time exposure, validating the assumption that psychological FoMO activation is not solely driven by individual content features. The ensemble learning framework learned the nonlinear interactions across the feature spaces, achieving over 5% accuracy gains than the best single model baseline. The explainability results by SHAP indicate urgency driven text features and scarcity visual features were indeed the most critical components that predict FoMO triggers in psychology, which is consistent with existing loss aversion and social comparison theory. The results also indicate the speed of engagement and the history of exposure were significant amplifiers of psychological triggers, showing how algorithm reinforced content persuasion worked through amplifying emotions.

### **Conclusion**

The work developed an end-to-end multimodal machine learning system to capture psychological FoMO cues in online media, to model the temporal amplification of behaviors, and to predict behavioral outcomes using an Euclidean model of multimodal content features. Using a novel, psychologically grounded modeling of media content, the presented hybrid ensemble accurately modeled the aggregate emotional dynamics causing user reactions. Specifically, by combining verbal urgent semantics, scarcity in visual content cues, and temporal patterns of user interactions, it captured overall emotional processing. Evaluation using public digital advertisement data indicates promising model performance as compared to baselines and abbreviated models with benefits from multimodal fusion. Based on XAI explanations, verbal urgency and visual scarcity were identified as major psychological drivers of intended behavior. ensemble weights' sensitivities also reflected the significance of accounting for temporal dynamics in modeling non-linear effects. As such, empirical validation confirmed the robust and interpretable approach. Overall, the work contributes to scalable modeling of user engagement and behavioral risks in digital media through psychologically grounded computational persuasion modeling.

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