RESEARCH ARTICLE OPEN ACCESS

Artificial Intelligence Based Prediction of Social Media Engagement among Young Adults: A Literature Review

Mr. Kiran Abasaheb Shejul[1], Dr. Manisha Patil[2]

[1] Research Scholar, School of Information Technology, Indira University, Pune, India & Assistant Professor, Rajarshi Shahu College of Engineering, Pune, India
[2] Associate professor, School of Information Technology, Indira University, Pune, India
[1]Kiran.shejul7@gmail.com

Abstract - Social media has become an important part of everyday communication, information sharing, entertainment, and social interaction among young adults. At the same time, artificial intelligence (AI) is increasingly used by social media platforms to recommend content, personalize feeds, rank posts, and influence what users see and interact with. AI and machine-learning methods are also being used by researchers to understand and predict user engagement. However, the available research is spread across different areas. Some studies focus on psychological and behavioral factors among young adults, while others concentrate on prediction models, temporal patterns, recommendation algorithms, or explainable AI. This integrative review brings these research streams together. Analysis was performed on twenty-four studies from 2017 to 2026. The studies have been compared based on their population, platforms, data, engagement indicators, behavioral indicators, predictive variables, methodology, machine learning models, results, and limitations. The literature was organized into six themes: the meaning and measurement of social media engagement; behavioral and psychological factors among young adults; AI and machine-learning methods for engagement prediction; temporal, contextual, content, and multimodal features; the influence of AI recommendation systems; and explainability, privacy, and responsible AI. The review shows that engagement is not a single behavior. Passive viewing, liking, commenting, sharing, and content creation have different characteristics and may require different prediction strategies. Studies also show that personality, boredom, information overload, emotion regulation, social influence, previous activity, content characteristics, posting time, and algorithmic recommendations can affect engagement. Machine learning algorithms such as Random Forest and Gradient Boosting are appropriate for structured data whereas LSTMs and other deep learning algorithms are appropriate for sequential data. Recently, there has also been some attention paid to the usage of Transformers and other graph-based algorithms. Regardless of these advancements, not many studies have been carried out which integrate specific behaviors of young adults with multidimensional engagement, temporal and contextual data, AI predictions, and explainability. Moreover, cross platform validation, privacy, fairness, and explainability of the models is yet to be taken into consideration. Thus, this review suggests a framework for the use of AI from young adult-centric and context-aware perspective.

Keywords - Artificial Intelligence; Social Media Engagement; Young Adults; Machine Learning; Engagement Prediction; User Behavior; Explainable AI; Recommendation Systems; Predictive Analytics

1. Introduction

From a communication technology, social media has transformed into an algorithmic ecology in which the user receives information, produces and distributes content, makes connections, engages in community, and interacts with filtered information continually. Social media platforms like Instagram, TikTok, YouTube, Facebook, Snapchat, and X have become integral to young adults' daily online lives. As a result, understanding the engagement of young adults with these platforms is of interest to multiple disciplines, including computer science, information systems, communication, psychology, and behavioral sciences.

Engagement on social media is a multi-dimensional construct. It involves passive activities, such as browsing and viewing, as well as active activities, like liking, commenting, sharing, posting, producing content, and engaging with communities. According to Trunfio and Rossi (2021), engagement was operationalized in varied ways, whereas empirical research demonstrates differentiating between passive, participative, and contributive social media uses (Chen et al., 2026). Also, Youth adult engagement with social media is shaped by not only stable factors but also dynamic psychological states. Personality traits, age, and gender have been associated with multiplatform social-media activity (Vaid & Harari, 2021), along with boredom, information overload, social-media fatigue, social anxiety, life satisfaction, emotion regulation, motivations, and awareness of algorithms (Brown et al., 2026; Kamble et al., 2026; Santoro et al., 2026).

AI becomes increasingly prominent in the process, adding another dimension. The influence of AI takes place at the platform level via ranking, personalization, and recommendation and also at the level of analytics predicting user engagement. Human-AI interaction research indicates that people not only react to recommendations but also actively form them, thus affecting content consumption and production, networking, and further engagement (Kang & Lou, 2022). Young adults may also adapt their digital self-presentation and communication practices to perceived recommendation patterns (Arkhipova & Janssen, 2024).

AI-based engagement prediction has progressed from conventional machine learning into sequential and hybrid forms. Large-scale studies that use LSTM models show that behavioral history is able to predict both active and passive engagement while contextual information provides extra prediction value (Peters et al., 2024). Other studies employ Random Forest, Gradient Boosting, LSTM, RF-LSTM hybrids, sentiment and emotional information along with explainability tools like SHAP (Al-Quraishi et al., 2025; Chaudhary & Punit, 2024; Madnure & Kadam, 2025).

However, high predictive power does not explain why the person is expected to become engaged. That is the reason for the employment of XAI (explainable AI) and increased transparency on part of users. According to Haque et al. (2024), users especially appreciate explanation of unknown AI suggestions and want more information about the data privacy and security. The same topics of fairness, manipulation, trust, accountability, and privacy are raised by the academic literature as important issues in the field of AI-SM (Saheb et al., 2024).

Thus, the literature continues to be divided between human-centered behavior research, computational prediction, recommendation system investigation, and responsible AI research. This review attempts to connect all these aspects to show current state-of-the-art in order

1.1 Objectives of the Review

- To learn about how social media engagement is currently measured in the literature.
- To understand the determinants of engagement amongst youth: behavioral, psychological, demographic, social, content-related, temporal, contextual, and algorithmic factors.
- To examine how AI and machine learning techniques can be used for predicting engagement.
- To analyze the data sets, features, platforms, and measures of engagement studied in engagement prediction.
- To examine the role of recommendation engines and algorithmic awareness in engagement.
- To investigate the aspects of explainability, privacy, transparency, fairness, and ethics of AI-enabled engagement.
- To determine the gaps in literature and suggest future directions for further research.

1.2 Research Questions

RQ1: How is social media engagement defined and operationalized in previous literature?

RQ2: What behavioral, psychological, demographic, social, content-based, temporal, contextual and algorithmic factors have been found to be related to the phenomenon of social media engagement in young adults?

RQ3: What are the AI and machine learning techniques that have been applied for analysis of social media engagement?

RQ4: What features, sources of data, platforms, and effects on engagement and evaluation techniques are utilized?

RQ5: How do AI-driven recommendations and algorithms affect social media engagement of young adults?

RQ6: How well explainability, privacy, transparency, fairness and other ethical questions are considered?

RQ7: What gaps are there in the area and which directions can be further investigated?

2. Review Methodology

2.1 Review Design

This study applies an integrative literature review because the data sources used in this paper involve different techniques like machine learning experiments, psychometrics, and the overall meaning thereof. The paper aims at integrating the results of these studies without conducting any meta-analysis of the statistics.

2.2 Study Corpus and Selection Approach

There were initially 43 articles on the use of social media, social media engagement, user activities, artificial intelligence, predictive analysis, recommendation systems, and young adults. Every paper was screened to ensure its relevance to the research. There were 24 studies which were published between 2017 to 2026, and were retained due to their relevance either direct or indirect to measure social-media engagement, young-adult behavior, AI/ML prediction, and contextualization, impact of recommendation system, explainability, privacy or ethics of AI.

2.3 Eligibility Criteria

Selection criteria for the papers included the following:

- Papers deal with social media and social networking.
- Papers focusing on engagement, usage, participation, and behaviors of users.
- Papers refer to AI, machine learning, deep learning, predictive analytics or factors (behavioral, psychological and algorithmic) influencing social media engagement.
- Preferably these are papers on young adults, though general population papers can be considered too if they contribute to prediction of engagement.
- Studies providing sufficient methodological or conceptual information for analysis and comparison.

Papers that were less relevant in relation to the subject of the research, did not have sufficient methodological information or had repeating results from other relevant papers were given secondary priority or excluded from consideration

2.4 Data Extraction

An evidence matrix for the structured literature review was prepared, extracting information from author/year, title/source, population/platform, objectives, theory/framework, method/model, sample/dataset, variables / features, results, weaknesses/limitations, knowledge gaps, and relevance to the present review. This table enables comparison between computational and behavioral research in light of the difference in methodology used.

(1) definition and Measurement of Social Media Engagement; (2) behavior and psychological factor among young adults; (3) AI/ML approaches for predicting engagement; (4) predictors across temporal, contextual, content, and multimodal (5) AI recommendation systems and algorithm-mediated engagement; and (6) privacy, explainability, ethics, and responsible AI.

2.6 Methodological Scope and Limitation

This study is an integrative literature review. The studies included in this review were selected from an existing collection of research papers. Complete records of database searches, duplicate removal, and title and abstract screening were not available. Therefore, this review does not cover all published studies in this area. Instead, it focuses on a selected set of highly relevant studies and provides a detailed comparison and thematic analysis of computational and human-centered research.

3. Results and Thematic Synthesis

The 24 studies reveal a gradual movement from general social-media forecasting and engagement conceptualization toward more sophisticated AI-based behavioral modeling, while recent research increasingly addresses recommendation algorithms, young-adult psychological factors, and explainability. The six themes below summarize the main evidence.

3.1 definition and Measurement of Social Media Engagement

Studies have shown that there are different types of social media engagement. Trunfio and Rossi (2021) describe engagement as consumption, contribution, and creation. Similarly, Chen et al. (2026) describe various TikTok engagement profiles, including passive viewing, participation, contribution, and problematic use tendencies. Peters et al. (2024) distinguish between active and passive usage in their analysis, and Kim and Hwang (2025) find that likes and comments have different predictability. The findings suggest that a single measure of screen time or overall engagement may not capture differential types of social media engagement. Thus, predictive studies should clearly specify the type of engagement being predicted and, when possible, examine different types of engagement separately.

3.2 Behavioral and Psychological Determinants among Young Adults

regulation, motivations, self-presentation, social comparison, parasocial relationships, and algorithmic awareness. Vaid and Harari (2021) provide strong evidence from two large samples linking individual differences to multiplatform use. Algorithmic media-content awareness as a buffer of boredom-driven overload and fatigue. Kamble et al., 2026. Find that. Chen et al. (2026) associate psychological traits with unique TikTok engagement styles. Network analysis also shows the connected motivational pathways (Santoro et al., 2026). A major limitation is that such human-oriented variables are rarely used in AI engagement-prediction models.

3.3 AI/ML approaches for predicting engagement

The computational literature uses different prediction methods, including supervised machine learning, ensemble methods, deep learning, and hybrid models. Selvakumar et al. (2025) apply several machine learning algorithms using demographic and behavioral features. Al-Quraishi et al. (2025) combine Random Forest, SMOTE, and SHAP in their approach. Peters et al. (2024) use deep LSTM models to study more than 100 million Snapchat sessions. Chaudhary and Punit (2024) propose a hybrid model that combines Random Forest and LSTM, while Madnure and Kadam (2025) compare tabular and sequential prediction methods. Recent studies also discuss the use of Transformers, GNNs, and agent-based models (Singh et al., 2025). Overall, the research shows a shift from traditional tabular models toward temporal, relational, and hybrid approaches. However, as these models become more complex, proper validation and clear interpretation of their results become more important.

3.4 predictors across temporal, contextual, content, and multimodal

Past user behavior, posting time, seasonal patterns, content type, sentiment, emotional features, hashtags, popularity, device and connectivity information, and social relationships can all be useful for predicting social media engagement. Peters et al. (2024) provide strong evidence that contextual information can improve prediction beyond the use of behavioral history alone. Kim and Hwang (2025) show that emotional and temporal factors may influence simple reactions differently from more active forms of engagement, such as conversations. Overall, the literature suggests that useful features can be grouped into user, behavioral, content, temporal and contextual, and social or network-

3.5 AI recommendation systems and algorithm-mediated engagement

AI is not only used to predict social media engagement but also influences how engagement takes place on social media platforms. Kang and Lou (2022) show that TikTok users and recommendation algorithms affect each other during content consumption, content creation, and social networking. Arkhipova and Janssen (2024) also report that young adults change their online representation and social practices based on how they understand recommendation patterns. Therefore, awareness of algorithms may influence user behavior and may also affect the relationship between other factors and engagement. Prediction studies that do not consider recommendation exposure may explain engagement mainly through user characteristics, even though some of this behavior may also be influenced by the platform's recommendation system.

3.6 privacy, explainability, ethics, and responsible AI.

Explainability and responsible data management have significant importance in AI literature pertaining to social media analysis. According to Haque et al. (2024), users seek transparency and simplicity in the explanation of recommendations that they are unfamiliar with. Moreover, users are interested in the way their private data are managed and how their privacy is secured. Al-Quraishi et al. (2025) use SHAP technique to present an explanation of the predictions made by their model. Several works also emphasize privacy, bias, manipulation, trust, and accountability concerns related to AI applications in social media (Saheb et al., 2024; Singh et al., 2025). Therefore, taking into account these findings, one can conclude that privacy and explainability should be taken into consideration at an early stage in developing any AI models, especially those which use multiple types of information (demographic, psychological, contextual, social network information).

4. Comparative Analysis

The available literature may be classified into two distinct domains. The first domain is concerned with human-centered research and aims at explaining the reasons for which people use social media considering psychological, motivational, social, and algorithmic factors. Yet these works do not offer any predictions using AI methods. Conversely, computational approaches demonstrate that social media engagement may be predicted using different factors such as digital activity, content, time, and context. Still, in their turn, to be researched together.

Approach	Strengths	Limitations	Potential role
Linear/logistic models	Simple; interpretable; strong baseline	Limited nonlinear/temporal capacity	Baseline and hypothesis-oriented modeling
Random Forest	Handles nonlinear mixed features; robust; feature importance	Weak explicit sequence modeling	Behavioral/content feature modeling
Gradient Boosting	Strong on structured/tabular data	Tuning and interpretability challenges	High-performance benchmark
SVM	Useful in moderate-dimensional spaces	Scaling and interpretation challenges	Comparative baseline
LSTM	Captures sequential dependencies	Training complexity; limited transparency	Temporal engagement trajectories
Hybrid RF-LSTM	Combines structured and temporal learning	Higher complexity; validation burden	Integrated behavioral-temporal prediction
Transformers	Long-range sequence and multimodal potential	Data/compute requirements	Advanced content/sequence representation
GNNs	Represents peer/community relationships	Graph data and privacy requirements	Social influence and network structure

	ns	causality	AI layer

5. Research Gaps

Gap	Synthesis	Future direction
G1. Young-adult-specific AI models	Studies on young-adult behavior and studies on AI-based engagement prediction are mostly conducted separately.	Build models explicitly designed and validated for young adults.
G2. Fragmented engagement measures	Studies measure engagement in different ways, such as likes, comments, passive viewing, content creation, and time spent on social media.	Model multiple engagement dimensions rather than a single aggregate target.
G3. Limited multimodal integration	Psychological, behavioral, content, temporal, contextual, and network features are rarely fused.	Develop heterogeneous feature-fusion architectures with ablation testing.
G4. Limited explainability	Performance is often prioritized over interpretable reasoning.	Integrate XAI and evaluate explanation usefulness.
G5. Algorithmic influence under-modeled	Recommendation exposure and algorithmic awareness shape behavior but are seldom predictive features.	Represent algorithm awareness/personalization exposure where ethically feasible.
G6. Weak cross-platform generalization	Many studies are single-platform.	Use cross-platform or platform-stratified validation.
G7. Limited causal interpretation	Most evidence is cross-sectional or observational.	Separate prediction from causality and use longitudinal/counterfactual methods where appropriate.

s not fully integrated	discussed but not operationalized.	assessment, transparency, and governance.
G9. Inconsistent evaluation/reporting	Some applied papers under-document datasets, splits, baselines, and external validation.	Use reproducible preprocessing, strong baselines, multiple metrics, and transparent reporting.

6. Proposed Future Research Framework

The synthesis highlights the need for an AI model that focuses on the youth, multidimensional, and explainable nature of the AI system. The engagement process in the system should be modeled in a manner where the effects of individual, behavior, content, context, social, and algorithmic elements interact to produce engagement.

Component	Dimension	Illustrative variables / function
Layer 1	Individual characteristics	Age range, personality, motivations, psychological characteristics, algorithmic awareness
Layer 2	Behavioral history	Sessions, passive/active use, likes, comments, shares, posting patterns, trajectories
Layer 3	Content/emotional features	Text, sentiment, topics, media type, hashtags, emotional cues, visual/text representations
Layer 4	Temporal/contextual/social factors	Time, session context, peer activity, influencer/community relationships, network structure
Layer 5	AI prediction	Strong tabular baselines plus LSTM/Transformer/GNN/hybrid models as justified by the data
Layer 6	Explainability & responsible AI	SHAP/counterfactual explanations, fairness checks, privacy safeguards, transparent reporting
Outputs	Multidimensional engagement	Passive consumption → reaction/like → comment → share → creation/contribution

The evidence shows that social media engagement is influenced by many factors. These include user behavior, psychological factors, technology, time, social relationships, and recommendation algorithms. Studies that focus on only one type of factor may not fully explain social media engagement. Human-centered studies help explain why young adults use and engage with social media. Computational studies show that past behavior, content, posting time, and context can help predict engagement. Research on recommendation systems also shows that algorithms can influence what users see and how they behave. At the same time, explainable AI (XAI) research shows the importance of making AI predictions clear and understandable.

The findings suggest that simply developing more complex AI models may not be enough. Different types of information need to be considered together. Knowledge about user behavior can help researcher's select meaningful features and understand model results. AI models can then be used to examine whether these factors improve engagement prediction beyond basic platform data. However, an important feature in a prediction model does not necessarily mean that it causes engagement. Long-term studies and suitable causal methods are needed when researchers want to study cause-and-effect relationships.

Advanced AI models should also be compared with simpler models. Random Forest and Gradient Boosting are helpful techniques for structured data. However, techniques like LSTM, Transformers, and GNNs could be better choices if the data have any time-series, text, heterogeneous, or social relationships. Therefore, researchers should select a model based on the research problem and the type of available data rather than choosing a model only because it is new or advanced.

Proper AI usage is also vital in social media engagement analysis. Merging the behavior of the users with their psychological, contextual, and social network data can raise issues of privacy and fairness. Researchers should therefore collect and use only the data that are necessary, protect user privacy, check models for unfair results, and clearly explain how the data and AI models are used. The possible use and limitations of the model should also be clearly stated.

8. Conclusion

explainable AI. The findings indicate that the engagement phenomenon is multi-faceted and driven by individual differences, psychological factors, past behaviors, contents, times, contexts, social connections, and algorithmic factors. AI/ML techniques have good promise; however, the existing literature still lacks coherence. The key gap is the lack of synthesis between young adult behavior factors, multi-dimensional engagement, contextual data, prediction using AI/ML techniques, the role of algorithms, and explainability. Future work must focus on developing interpretable, cross-platform, context-based, and responsible AI technologies, which can provide explanations for why and how young adults engage.

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