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A Conceptual AI-Based Framework for Understanding and Predicting Social Media Engagement among Young Adults

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Abstract – Among the young adults social media has become an important part of everyday communication, information sharing, entertainment, and social interaction. At the same time to recommend content, personalize feeds, rank posts, and influence what users see and interact with artificial intelligence (AI) is increasingly used by social media platforms. 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

Young adults use social media for many purposes. They get information, communicate, express themselves and join communities. Their activities include viewing, liking, commenting, sharing and creating content. These activities need different levels of effort. They also differ in public visibility. Therefore, they should not be combined into one total engagement score without a clear reason (Trunfio & Rossi, 2021; Chen et al., 2026). A prediction study must first define the behaviour to be predicted. It must also define the future time period. AI can learn from user profiles, activity records, text, images and social networks. A large platform study found that context can improve prediction beyond past behaviour (Peters et al., 2024). Other studies have used ensemble, sequential and explainable models (Al-Quraishi et al., 2025; Chaudhary & Punit, 2024; Madnure & Kadam, 2025). However, an accurate prediction does not always explain why the behaviour occurred.

Another group of studies examines why young adults engage. Important factors include personality, emotion control, boredom, fatigue, anxiety and motivation. Self-presentation and awareness of algorithms may also matter (Vaid & Harari, 2021; Arkhipova & Janssen, 2024; Brown et al., 2026; Kamble et al., 2026). Surveys often examine these factors. However, prediction models rarely include them. At the same time, many prediction studies use platform activity but give little attention to psychological or algorithmic effects.

This separation creates a practical and research problem. Human-centred studies may explain engagement but may not predict it. Computational studies may predict engagement but may not explain the prediction. Shejul and Patil (2026) identified this gap in an earlier review. That paper reviewed the literature. It did not develop or test a complete framework. The present paper extends that work. It converts the research gaps into variables, data flows, model-selection rules and safeguards. It also provides nine propositions and an evaluation process. Thus, this paper offers a testable framework. It does not repeat the earlier literature review.

2. Aim and Research Questions

This paper aims to develop a testable framework. It combines human, content, context, relationship and algorithm-related information. It uses this information for AI-based prediction and explanation.

- RQ1. Which multidimensional factors should be represented when modelling social-media engagement among young adults?
- RQ2. How can heterogeneous information be integrated into an AI pipeline without assuming one universal model?
- RQ3. How can predictive performance and behavioural understanding be evaluated together?
- RQ4. How should explainability, privacy, fairness and transparency be embedded across the framework?

3. Conceptual Foundations

3.1 Engagement as a multidimensional construct

Engagement has several related but different forms. Passive use includes viewing, browsing and watch time. Simple reactions include likes, saves and emojis. Active participation includes comments, shares and discussions. Creation means posting original content or starting an interaction. Different factors may predict each form (Kim & Hwang, 2025). Therefore, a study may predict several outcomes together. It may also use a separate model for each outcome.

3.2 Person–content–context interaction

Young-adult engagement may result from an interaction between the person, the content and the situation. Personal traits may shape preferences. Past behaviour may show habits. Content features may affect attention and interest. Time and device conditions may affect the chance to engage. Social relationships may affect trust and participation. These areas should not be studied only in isolation. Their combined effect may provide better information.

3.3 Human–algorithm interaction

Recommendation systems influence what users encounter, while user actions supply signals that influence later recommendations. This reciprocal relationship means that platform exposure is not merely background context. It can shape both observed behaviour and the data used to train predictive models (Kang & Lou, 2022). Young adults may also adjust self-presentation and participation based on their understanding of algorithmic curation (Arkhipova & Janssen, 2024). The framework therefore includes algorithmic exposure and awareness when such information can be collected lawfully and reliably.

3.4 Prediction and explanation as complementary objectives

Prediction estimates a future outcome. Explanation shows which information influenced that estimate. Feature importance does not prove cause and effect. SHAP shows how each feature contributes to a prediction (Lundberg & Lee, 2017). LIME builds a simple local explanation for one prediction (Ribeiro et al., 2016). These methods can help researchers check and compare models. They can also support group analysis and new hypotheses. However, their accuracy and stability must be tested (Barredo Arrieta et al., 2020). Explanations for users should be clear and useful. This is especially important when a system uses recommendations or sensitive data (Haque et al., 2024).

3.5 Framework-development approach and novelty boundary

The authors developed the framework in five steps. First, they used the areas and gaps found in their earlier review (Shejul & Patil, 2026). They did not repeat the earlier selection process or results. Second, they grouped the ideas into inputs, data forms, analysis stages, controls and outcomes. Third, they converted the expected relationships into testable propositions. Fourth, they linked each idea with possible measures and evaluation stages. Finally, they checked whether the framework supports different models, useful explanations and responsible data use. This paper does not reuse any table, figure, abstract or results section from the published review. Its new contribution is the framework, propositions, measurement plan and validation process.

4. Theoretical Foundation

Three theories support the framework. Uses and Gratifications Theory (UGT) explains why people choose and use media. The Stimulus–Organism–Response (S–O–R) framework explains how content and platform conditions affect users. It also explains how these effects lead to engagement. Social Cognitive Theory (SCT) explains the links between the person, past behaviour and the social environment. Together, these theories explain why the selected factors belong in the framework.

Theory	Core mechanism	Framework constructs	Explanatory role
UGT	Needs and gratifications	Motivation, preferences, information seeking, entertainment, belonging, self-expression	Explains why engagement is initiated or continued
S–O–R	Stimulus → internal state → response	Content, context and recommendations → emotion/cognition → engagement	Organises the principal predictive pathway
SCT	Reciprocal person–behaviour–environment influence	Prior behaviour, observation, peer feedback, self-efficacy, social ties	Explains learning, reinforcement and repeated engagement

Table 1. Theoretical foundations and their roles in the proposed framework.

4.1 Uses and Gratifications Theory

UGT views people as active media users. They choose media to meet social and psychological needs (Katz et al., 1973). Young adults may use social media for information, entertainment or social contact. They may also use it for self-expression, belonging or relief from boredom. Expected benefits can affect platform and content choices. Benefits received may encourage later use. UGT therefore supports the motivational, emotional and preference-related factors in the framework. It also explains why the same content may produce different responses from different users.

4.2 Stimulus–Organism–Response framework

The S–O–R framework starts with an external stimulus. The stimulus affects a person's thoughts and feelings. These internal changes then shape behaviour (Mehrabian & Russell, 1974). In this paper, content, recommendations and notifications are stimuli. Posting time and social cues are also stimuli. Motivation, perception, emotion, fatigue and awareness are internal states. Viewing, liking, commenting, sharing and creating are responses. This theory provides the main path from platform conditions to engagement.

4.3 Social Cognitive Theory

SCT explains behaviour through the interaction of the person, past behaviour and the social environment (Bandura, 1986). Young adults may learn by watching peers, creators and influencers. Likes and comments may encourage or reduce certain actions. Confidence may affect whether a user comments, creates content or participates in public. SCT therefore supports the use of past behaviour, social networks, communities and feedback in the framework. It also supports the feedback loop. A user's engagement changes the social and algorithmic environment. That changed environment may affect the user's next action.

4.4 Integrated theoretical logic

The three theories have different roles. UGT explains why a person uses social media and what benefit the person expects. S–O–R explains how content or platform stimuli affect internal states and lead to a response. SCT explains how observation and feedback shape behaviour over time. AI does not replace these theories. It tests the relationships between theory-based variables and future engagement.

5. Proposed Conceptual Framework

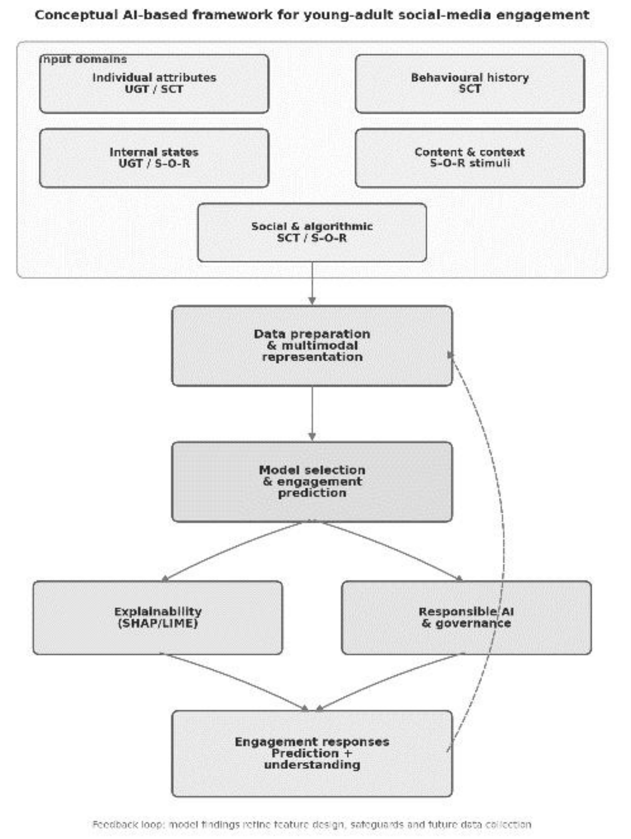

Figure 1. Proposed conceptual AI-based framework grounded in UGT, S-O-R and SCT.

Figure 1 shows the full process. It does not require one fixed algorithm. Five types of information enter the data-preparation stage. The prepared data then enter a suitable prediction model. The task and data structure guide model selection. Explainability helps researchers understand the results. Responsible-AI rules guide model development and use. The framework produces predictions and useful explanations. Feedback from error, fairness and stakeholder reviews helps improve the next version.

5.1 Input domains

Individual attributes. Age, education, occupation and digital skills may explain differences between users. Gender may be included when there is a valid and ethical reason. Personality and stable preferences may also be useful. Sensitive information should be collected only when the research or fairness check truly needs it.

Behavioural history. Past views, likes, comments and shares show earlier engagement. Session frequency, duration and posting activity add more detail. The order and timing of actions may show habits and changing interests.

Emotional and psychological factors. Motivation, boredom, fatigue and social anxiety may affect engagement. Emotion control and life satisfaction may also matter. Researchers should use valid survey tools or carefully designed short reports. They should not guess these factors without consent.

Content and context. Text, topic, emotion and media type may affect attention. Posting time, device, internet access and the situation may affect the chance to engage. Content analysis should consider language, platform style and local culture.

Social and algorithmic environment. Links between users, content and communities may affect engagement. Recommendations and personalisation may also shape what users see. Awareness of the algorithm may influence how they respond.

5.2 Data preparation and representation

The preparation stage places the data in one common form. A record may represent a user and post, a user and session, or a user and day. This stage manages consent and removes personal identity. It also checks quality and handles missing values. The process aligns time, prepares text and media, creates features and prevents data leakage. The study must define the record type, prediction target and future period before modelling. A multi-platform study should keep platform-specific features. Otherwise, hidden platform differences may produce misleading results.

5.3 Model-selection and prediction layer

The framework does not claim that one model is always best. Logistic and linear models provide simple baselines. Decision trees, Random Forest and Gradient Boosting can work well with structured data. Recurrent, temporal or transformer models may suit time-based activity records. Language and multimodal models can study text, images and videos. Graph Neural Networks can study clear relationships between users and content. A study should use a hybrid or ensemble model only when it gives a useful improvement over simpler models. The comparison must also be free from data leakage.

The prediction task may take different forms. Classification can predict whether a user will engage. Regression can predict the expected number of interactions. Forecasting can predict engagement over time. Ranking can order content by likely engagement. Survival analysis can estimate the time until a user stops engaging. The evaluation measures must match the task. Results should also show uncertainty and performance for relevant groups.

5.4 Explainability layer

Global explanations show patterns across the whole model. Local explanations explain one prediction. SHAP shows how each feature contributes to a prediction (Lundberg & Lee, 2017). LIME builds a simple model near the selected case (Ribeiro et al., 2016). Other useful methods include attention maps, partial-dependence plots and counterfactual explanations. Graph models may need graph-specific explanation methods. Each method answers a different question. Researchers should explain why they selected a method (Barredo Arrieta et al., 2020). They should also test whether the explanation is accurate, stable and useful. An explanation must not reveal private information. It must not support manipulation.

5.5 Responsible-AI governance

Responsible-AI rules apply to the full process. Data minimisation means collecting only the information needed for the research questions. Privacy controls include informed consent and removal of personal identity. They also include access limits, retention rules and safe reporting. Fairness checks compare errors and calibration across suitable groups. Transparency records the data source, model purpose, limits and intended users. A person must review important interpretations and decisions. These controls address bias, privacy, trust and accountability (Saheb et al., 2024; Singh et al., 2025).

6. Theory-Linked Research Propositions

ID	Theoretical basis	Proposition
P1	UGT; S–O–R	Separate engagement measures will provide more useful results than one combined engagement score.
P2	S–O–R	Models that combine past behaviour, content and context will predict engagement better than models based only on past behaviour.
P3	UGT; S–O–R	Emotional, motivational and psychological factors will explain engagement beyond demographic and behavioural factors.
P4	SCT; S–O–R	Time-based models will perform better when engagement depends on recent actions, repeated patterns or reinforcement.
P5	SCT	Relationship-based models will add value when reliable links between users, content or communities are available.
P6	S–O–R; SCT	Recommendation exposure and algorithm awareness will directly affect engagement and change selected user–content relationships.
P7	UGT; S–O–R	Passive viewing, reactions, participation and creation will have partly different motivational and contextual predictors.
P8	Methodological	Explainability checks will improve the usefulness and auditability of the framework without necessarily reducing prediction accuracy.
P9	Responsible AI	Privacy and fairness controls will reduce risk and support responsible research use.

Table 2. Research propositions and their theoretical bases.

7. Applying and Measuring the Framework

Table 3 shows possible measures and data sources for each area. A study does not need to collect every variable. The research questions and theories should guide the final choice. Participant consent and platform access must also be considered. Researchers should collect only the data they need.

Domain	Illustrative indicators	Possible source	Role
ndividual	Age band, education, digital literacy, stable preferences	Consent-based survey	Control / explanatory
ehavioura	Views, likes, comments, shares, sessions, duration, recency	Platform export, diary or approved log	Predictor
motional / sychologic l	Motivation, boredom, fatigue, anxiety, emotion regulation	Validated scales / experience sampling	Explanatory / moderator
ontent	Topic, sentiment, emotion, format, novelty, hashtags	Post metadata and content analysis	Predictor
emporal / ontextual	Time, day, sequence, device, connectivity, situation	Timestamped logs and survey	Predictor / moderator
ocial / elational	Interaction frequency, tie strength, centrality, community	Ethically constructed graph	Relational predictor
lgorithmi	Recommendation exposure, perceived personalisation, awareness	Exposure record / survey	Predictor / moderator
utcomes	Passive viewing, reaction, contribution, creation, retention	Defined behavioural target	Dependent variable

Table 3. Candidate constructs, indicators, sources and analytical roles.

8. Proposed Empirical Evaluation Plan

8.1 Study design and sampling

A future study may combine a consent-based survey with behaviour or platform data. The study must clearly define young adulthood. It must also explain the selected age range. The sample should include varied genders, education levels and social backgrounds. It should also include different locations and patterns of platform use. A pilot study should check whether the questions are clear. It should also check whether survey and behaviour data can be linked safely.

8.2 Validation strategy

Training and testing data must be separated carefully. Information from the same participant must not leak between them. Future information must not enter the training data. A forecasting study should usually split data by time. This is better than a random split. Repeated records from one participant should remain in the same cross-validation group. If possible, the model should also be tested on a later period, institution, region or platform.

8.3 Comparative modelling

Evaluation should begin with simple baseline models. More information and more complex models can then be added step by step. An ablation study can test the value of each feature group. These groups include behaviour, psychology, content, context, relationships and algorithms. All models must use the same outcome, training data and test split. Confidence intervals or repeated tests should show the uncertainty in the results.

8.4 Performance, explanation and fairness measures

Classification models may use precision, recall, F1-score and curve-based measures. Calibration should also be checked. Regression and forecasting models may use mean absolute error, root mean squared error and R^2. Other measures may be added when they suit the scale. Explanation quality can be checked through accuracy, stability, consistency and usefulness. Fairness checks should compare performance across suitable groups. However, equal statistical results across all groups may not always be the correct goal.

8.5 Robustness and practical usefulness

Robustness tests should examine missing data and class imbalance. They should also examine changes over time, platform differences and different prediction periods. Relevant stakeholders should review the practical value of the framework. They may include researchers, educators, mental-health professionals or platform designers. The selected group should match the intended use. The framework must not encourage compulsive use. It must not manipulate vulnerable users.

10. Discussion

The earlier paper by Kiran Abasaheb Shejul and Dr. Manisha Patil (2026) reviewed existing research. The present paper makes a different contribution. It turns the research gaps into a practical and testable AI framework. It asks more than which algorithm gives the best prediction. It also asks which variables, data and models produce valid and responsible knowledge. A model may be technically accurate but scientifically weak. This can happen when the outcome is unclear or important variables are missing. It can also happen when future data leak into training. Model explanations must not be treated as proof of cause and effect.

The framework separates the overall design from the final model. Tree-based models may suit structured survey and post data. They can balance accuracy and explanation. Sequential models may suit repeated observations over time. Graph models may suit reliable network links. A study may combine these models. However, a complex model should be used only when it gives better results or clearer answers.

For young-adult research, responsible data use is especially important. Psychological measures, location, relationships and platform histories can become sensitive when linked. Data minimisation and purpose limitation should therefore shape feature selection before modelling begins. Fairness and explanation checks should be planned in the protocol rather than added only after model development.

11. Limitations and Future Research

This paper proposes a framework. It does not test the framework with real data. Future studies must test the propositions. Access to platform data may be limited. Platform rules and interfaces may also change. Self-reported data may contain memory or social-desirability bias. Platform activity may not explain a user's thoughts or feelings. Cross-sectional data cannot show the direction of change or prove cause and effect. Future studies should collect data over time when possible. They should test measures in different cultural settings. They should also compare results across platforms. Finally, they should check whether the explanations are clear and useful to intended users.

12. Conclusion

This paper presents an AI-based framework for understanding and predicting social-media engagement among young adults. The framework treats engagement as a group of different behaviours. It combines personal, behavioural, emotional, content, context, relationship and algorithm-related information. Researchers can select models that match their data. Explainability and responsible-AI rules are central parts of the framework. The propositions, measurement table and evaluation plan make future testing possible. The framework connects human behaviour with AI prediction. It supports research that is accurate, clear, transparent and responsible.

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