Using Machine Learning to Predict Behavioral Effects of Social Media Reels on Young Users

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Abstract. This study investigates the influence of AI-Powered video recommendations, such as Facebook Reels and TikTok videos, on young users' information-seeking behaviors and potential addiction. By integrating machine learning and psychological insights, it aims to highlight how these recommendations can unintentionally lead to prolonged engagement and increased screen time. Using a dataset of 1,000 young Algerians, the study analyzes interactions with AI-generated Reels, employing machine learning models specifically RandomForest and GradientBoosting to identify patterns in engagement influenced by AI suggestions. Collaboration with psychological researchers aids in detecting correlations between features such as Reel Session Duration, Number of AI-Suggested Reels, age, and education level, and their association with addictive behaviors. Findings indicate that AI recommendations significantly enhance user engagement, with the RandomForest model achieving 74% accuracy and an F1 Score of 0.783. The GradientBoosting model performed slightly better, with 75% accuracy and an F1 Score of 0.805. This study underscores the profound impact of AI recommendations on young users and highlights the need for user-centric algorithm design in social media, as responsible AI systems can enhance user experiences while prioritizing mental well-being.

Keywords: AI-Powered recommendations · Social Media · Reels · User engagement · Addiction · Machine learning.

1 Introduction

In today's digital landscape, social media platforms such as Facebook and TikTok have revolutionized content consumption through features like Reels, which rely on AI-driven recommendations. This study investigates the influence of these AI-generated video recommendations on young users' information-seeking behaviors and their potential for fostering addictive patterns of engagement [1, 2]. As short-form video content becomes increasingly prevalent, concerns arise regarding its impact on screen time and mental health, necessitating an examination of the psychological and behavioral effects of such content delivery [3].

To address these concerns, the research utilizes a dataset of 1,000 young Algerians to analyze interactions with AI-generated Reels. The study employs advanced machine learning techniques, specifically RandomForest [4] and GradientBoosting [5] algorithms, to uncover patterns in user engagement influenced by AI suggestions. This methodological approach provides a comprehensive understanding of how different variables interact to affect user behavior in the context of social media engagement, thereby enabling more effective interventions.

Collaboration with psychological researchers enhances the study by identifying correlations between prolonged usage of AI-driven recommendations and patterns of addictive behaviors, focusing on variables such as session duration, frequency of AI-suggested content, and user engagement levels [6]. By combining psychological expertise with machine learning analysis, this research provides a comprehensive view of how AI recommendations impact user experiences and shape information-seeking behaviors among young individuals [7]. This interdisciplinary approach highlights the complex interactions between technological influences and psychological responses.

The findings reveal that AI recommendations significantly enhance user engagement, with the RandomForest model achieving an accuracy of 74% and an F1 Score of 0.783. Notably, key features such as Reel Session Duration and the Number of AI-Suggested Reels were identified as critical determinants of interaction time. The GradientBoosting model performed slightly better, with 75% accuracy and an F1 Score of 0.805. Additionally, the results indicate that demographic factors, including age and education level, influence the extent of user engagement with AI-generated content.

This research ultimately emphasizes the profound impact of AI-driven recommendations on young users, highlighting the urgent need for ethical algorithm design in social media platforms. By advocating for responsible AI systems that enhance user experiences while prioritizing mental well-being, the study aims to contribute to the creation of environments that support healthy engagement and mitigate the risks associated with excessive screen time [8, 9].

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the literature on AI-driven recommendations and psychological factors affecting user engagement. Section 3 details the methodology, including dataset preparation, machine learning techniques, and the collaboration with psychological researchers. Section 4 presents the experimental results and discusses the key findings regarding user engagement and addictive behaviors, with an emphasis on ethical AI design and user well-being. Finally, Section 5 concludes the study by summarizing the contributions, addressing the limitations, and suggesting potential directions for future research.

2 LITERATURE REVIEW

The rise of social media platforms, particularly those featuring short-form video content such as Reels on Facebook and TikTok, has prompted significant scholarly interest in understanding how AI-driven recommendations influence user engagement [10, 11]. Recent studies have shown that algorithmic recommendations play a critical role in shaping users' information-seeking behaviors. In the study of [12], user engagement with short-format videos on TikTok was analyzed through a data donation system involving 347 participants and 9.2 million video recommendations. The researchers found that average daily usage time increased over users' lifetimes, while attention levels remained stable at approximately 45%. Additionally, users showed a preference for liking videos from accounts they followed compared to those recommended by non-followed accounts. This research provides valuable insights into the effectiveness of AI-driven recommendation systems in fostering user engagement.

Research has also highlighted the psychological implications of prolonged engagement with AI-driven content. For instance, a 2023 meta-analysis by Vieira, C. et al [13], revealed a consistent correlation between excessive social media use and the development of addictive behaviors, particularly among young users. The study noted that algorithms designed to maximize engagement can inadvertently lead to compulsive viewing patterns, resulting in increased screen time and associated mental health issues such as anxiety and depression. This finding aligns with earlier work by Andreassen et al. [14], which identified a growing prevalence of addiction-like symptoms linked to social media use, exacerbated by the tailored nature of algorithmic recommendations.

The methodologies employed in this area of research have also evolved, with a shift towards utilizing machine learning techniques to analyze user interactions. Recent studies, such as those by Darlis, D et al. [15], have leveraged RandomForest algorithms to uncover complex patterns in user behavior. These machine learning models have proven effective in identifying the factors that drive user interactions with AI-generated content, offering insights into how various variables, such as age and education level, affect engagement dynamics. While researchers have focused on various aspects of AI-driven recommendation systems, such as optimizing algorithmic precision [16], enhancing user engagement metrics [17], or examining specific psychological impacts like attention retention [18], these studies often address individual elements in isolation. Few have explored a comprehensive framework that combines behavioral analysis with an assessment of psychological impacts, particularly among younger users. In contrast, our study employs an AI approach to investigate these issues in greater depth, allowing us to uncover not only patterns in user engagement but also the nuanced correlations between features that may contribute to addictive tendencies. By integrating machine learning with correlation analysis, our research bridges technical insights with considerations of user well-being, offering a multidimensional perspective that advances the current understanding of AI's impact on user behavior.

3 METHODS

This section outlines the research design and methodology employed in the study, focusing on the influence of AI-driven video recommendations, specifically Reels on platforms like Facebook and TikTok, on young users' information-seeking behaviors and potential addiction. We aim to provide a comprehensive understanding of how various features associated with user engagement are analyzed through machine learning techniques, leading to actionable insights regarding the ethical implications of algorithmic recommendations.

3.1 Research Design

The study utilizes a quantitative research design, leveraging machine learning algorithms to analyze patterns in user engagement driven by AI recommendations [19]. The target population consists of 1,000 young Algerians, chosen for their heavy engagement with social media platforms and the unique context of Algeria's digital landscape. The research is anchored in understanding how AI-generated Reels impact user behavior, thereby addressing our research question regarding the interplay between engagement features and potential addiction to social media content.

3.2 Data Collection

Data were collected through surveys administered to participants, which included questions about their usage patterns, session durations, interaction rates, and the perceived impact of AI recommendations on their engagement with *Reels*. Key variables measured in the dataset included:

- **Reel Session Duration** (in minutes)
- **Number of AI-Suggested Reels**
- **Interaction Rate**
- **Age**
- **Sessions per Day**
- **Number of Searches for Specific Reels**

3.3 Machine Learning Techniques

To analyze the dataset and identify patterns of engagement influenced by AI suggestions, we employed two advanced machine learning techniques: RandomForest and GradientBoosting [20]. The first is an ensemble method that aggregates the predictions of multiple decision trees to enhance predictive accuracy while mitigating overfitting. In contrast, GradientBoosting builds trees sequentially, with each new tree focusing on correcting the errors of its predecessor. This methodological choice was driven by the algorithms' strengths in handling complex relationships and their interpretability, enabling us to derive meaningful insights regarding feature importance.

3.4 Model Evaluation

Model performance was assessed using several metrics: Accuracy, F1 Score, and ROC AUC [21]. These metrics provide a balanced perspective on the models' ability to classify engagement effectively. Accuracy measures the proportion of correct predictions, while the F1 Score combines precision and recall, making it especially useful in datasets with class imbalances. ROC AUC indicates the model's ability to distinguish between engaged and non-engaged users at various threshold levels.

3.5 Correlation Analysis

To further elucidate the relationships among the features, Pearson correlation coefficients were calculated [22]. This statistical method helps identify the strength and direction of linear relationships, thereby offering insights into potential redundancies or interactions among the features. For instance, a moderate positive correlation between Reel Session Duration and Interaction Rate suggests that longer viewing times may lead to increased interaction, possibly reinforcing addictive behaviors. This correlation analysis complements the machine learning findings by contextualizing how features interact within the user engagement framework.

3.6 Methodology Flowchart

To provide a visual overview of the research methodology, Fig. 1 illustrates the sequential steps undertaken throughout the study. This flowchart encapsulates the stages from data collection through to the application of machine learning techniques and evaluation metrics, facilitating a clearer understanding of the methodology employed in examining the influence of AI-driven video recommendations on user engagement.

4 RESULTS AND DISCUSSION

In this section, we explore the experimental process, present the results of our machine learning models, and discuss their implications on AI-driven video recommendations and user engagement. Our study focuses on understanding how features such as session duration and interaction rate, influenced by AI-powered Reels on social media, impact engagement among young users. This analysis includes evaluating model performance, feature importance, and correlation metrics to gain insights into behavioral patterns, with an emphasis on the ethical considerations surrounding AI recommendation systems.

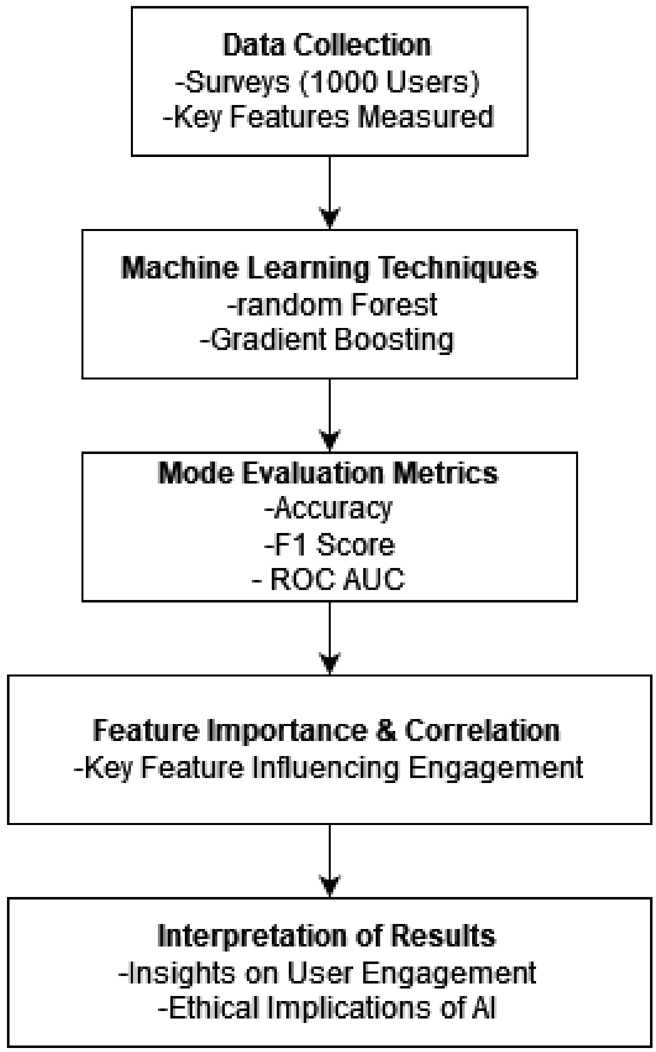

Fig. 1. Flowchart of the Research Methodology

4.1 Experimental Setup and Machine Learning Techniques

We employed RandomForest and GradientBoosting classifiers to analyze user interaction patterns in our dataset. These models were chosen for their robustness in handling complex relationships between features and their ability to capture non-linear interactions, which are prevalent in user behavior data. RandomForest, an ensemble learning method, builds multiple decision trees during training and combines them to improve accuracy and reduce overfitting. GradientBoosting, on the other hand, constructs a series of decision trees sequentially, where each tree corrects the errors of the previous one, making it more effective at capturing complex patterns within data. These algorithms are ideal for understanding user engagement due to their interpretability (via feature importance scores) and effectiveness in identifying subtle influences on user behavior.

4.2 Model evaluation Metrics

To measure model performance, we employed several key metrics, including **Accuracy**, **F1 Score**, **ROC AUC**, **Precision**, and **Recall**. These metrics collectively provide a nuanced understanding of each model's capability to classify prolonged engagement resulting from AI-driven suggestions effectively.

Accuracy reflects the overall percentage of correct predictions, serving as a general indicator of model performance. **F1 Score** combines precision and recall, making it particularly useful in evaluating models when there is a class imbalance between positive and negative examples. **ROC AUC** (Receiver Operating Characteristic - Area Under Curve) assesses the models' ability to differentiate between engaged and non-engaged users across various thresholds, thus indicating predictive power. **Precision** calculates the proportion of true positive predictions out of all positive predictions, shedding light on the relevance of the suggested content in driving engagement. **Recall** measures the proportion of actual positive cases that the model correctly identifies, which is crucial for understanding the model's sensitivity in detecting all engaged users.

As illustrated in Table 1, the evaluation metrics for the RandomForest model reveal an **Accuracy** of 0.76, an **F1 Score** of 0.80, a **ROC AUC** of 0.795, a **Precision** of 0.71, and a **Recall** of 0.91. Conversely, Table 2 outlines the evaluation metrics for the GradientBoosting model, which show an **Accuracy** of 0.75, an **F1 Score** of 0.805, a **ROC AUC** of 0.802, a **Precision** of 0.68, and a **Recall** of 0.98.

Notably, the GradientBoosting model outperforms RandomForest in **ROC AUC**, **F1 Score**, and **Recall**, suggesting its superior ability to accurately identify and distinguish engaged users. The elevated recall in the GradientBoosting model highlights its effectiveness in recognizing users influenced by AI recommendations, while the slightly higher precision in RandomForest indicates a lower rate of false-positive classifications.

Table 1. Model Evaluation Metrics for RandomForest

Metric	**Value**
Accuracy	0.76
F1 Score	0.80
ROC AUC	0.795
Precision	0.71
Recall	0.91

Table 2. Model Evaluation Metrics for GradientBoosting

Metric	**Value**
Accuracy	0.75
F1 Score	0.805
ROC AUC	0.802
Precision	0.68
Recall	0.98

4.3 Feature Importance and Correlation Analysis

The feature importance analysis from both models reveals key factors that significantly affect user engagement. Notably, Reel Session Duration emerges as the most influential feature across both models, confirming its strong correlation with engagement. In Table 3, which details the feature importances for the RandomForest model, Reel Session Duration has an importance score of 0.546, followed by Number of AI-Suggested Reels at 0.121 and Interaction Rate at 0.107. Other notable features include Age (0.095), Sessions per Day (0.068), and Number of Searches for Specific Reels (0.064). Conversely, Table 4 showcases

Table 3. Feature Importances for RandomForest

Feature	**Importance**
Reel Session Duration (minutes)	0.546
Number of AI-Suggested Reels	0.121
Interaction Rate	0.107
Age	0.095
Sessions per Day	0.068
Number of Searches for Specific Reels	0.064

the feature importances for the GradientBoosting model, where Reel Session Duration significantly dominates with an impressive score of 0.939. While Interaction Rate and Number of AI-Suggested Reels both have minimal importance scores of 0.022, the influence of Number of Searches for Specific Reels (0.013), Age (0.005), and Sessions per Day (0.001) is notably low. In both models, Reel Session Duration demonstrated the highest importance score, particularly for GradientBoosting. This suggests that longer viewing durations are the strongest indicator of engagement, potentially reinforcing repetitive engagement behaviors.

Table 4. Feature Importances for GradientBoosting

Feature	**Importance**
Reel Session Duration (minutes)	0.939
Interaction Rate	0.022
Number of AI-Suggested Reels	0.022
Number of Searches for Specific Reels	0.013
Age	0.005
Sessions per Day	0.001

4.4 Correlation metrics

To further interpret the relationships among features, Pearson correlation coefficients were calculated, providing insights into feature dependencies and redundancies:

- **Reel Session Duration and Interaction Rate:** $r = 0.67$, indicating a moderate positive correlation. This relationship suggests that longer viewing times tend to increase interaction rates, possibly reinforcing addictive engagement.
- **Reel Session Duration and Number of AI-Suggested Reels:** $r = 0.51$, showing a moderate association. This indicates that AI-driven suggestions are likely contributing to extended session durations.
- **Interaction Rate and Number of AI-Suggested Reels:** $r = 0.63$, a moderate positive correlation, which implies that AI-suggested content has a positive influence on user interactions.

These correlation values align with the feature importance findings, supporting the notion that *Reel Session Duration* and *Interaction Rate* are the primary drivers of user engagement, with AI recommendations playing a role in enhancing these behaviors.

4.5 Discussion

The results from our study underscore the considerable impact that AI-driven recommendations have on user engagement, as shown through both model performance metrics and feature importance analysis. Notably, the **GradientBoosting** model, which achieved a **Recall** of 0.98 and an **F1 Score** of 0.805, demonstrated a high capacity to correctly identify engaged users, underscoring the effectiveness of AI in fostering prolonged engagement. The **RandomForest** model, with an **Accuracy** of 76% and an **F1 Score** of 0.80, similarly highlights strong predictive capabilities, though it achieved a slightly lower recall than GradientBoosting, indicating it may occasionally overlook engaged users.

The feature importance scores provide further insights into which aspects of AI-powered content most influence engagement. *Reel Session Duration*, with an importance score of 0.546 in RandomForest and a markedly high 0.939 in GradientBoosting, stands out as the most significant driver. This suggests that prolonged viewing time, directly influenced by AI recommendations, plays a central role in keeping users engaged on the platform.

Correlation analysis between features also yielded notable findings. For example, *Reel Session Duration* and *Interaction Rate* exhibited a moderate positive correlation ($r = 0.67$), suggesting that as viewing time increases, interaction frequency also rises. This positive relationship points toward a reinforcing cycle: as users spend more time on AI-suggested Reels, they tend to interact more frequently, which may heighten engagement over time. Additionally, the correlation between *Reel Session Duration* and the *Number of AI-Suggested Reels* ($r = 0.51$) supports the idea that AI-driven suggestions contribute to longer session durations.

Together, these findings suggest that the algorithm's recommendation strategies likely encourage users to stay longer and interact more, enhancing the platform's overall engagement metrics. These results raise important ethical considerations for AI-powered recommendation systems, especially given that young users are highly susceptible to prolonged engagement cycles driven by repetitive AI suggestions. The reinforcing effect of features such as session duration and interaction rate implies a potential for AI algorithms to foster addictive behaviors, where users remain engaged not only because of interest but due to an AI-engineered cycle of viewing and interaction.

This highlights a need for carefully designed AI systems that prioritize user well-being by balancing engagement with mindful use, offering insights to both social media companies and policymakers for implementing more ethical recommendation practices.

5 CONCLUSION

This study explores the influence of AI-driven video recommendations, particularly through *Reels* on platforms like Facebook and TikTok, on user engagement and potential addictive behaviors among young Algerians. By analyzing user interaction patterns through machine learning techniques, we found that features such as *Reel Session Duration* and *Interaction Rate* play critical roles in determining user engagement. Our findings underscore the importance of understanding how user behavior can be shaped by algorithmic suggestions, revealing a tendency for prolonged viewing times to enhance interaction rates, which may inadvertently reinforce addictive consumption habits.

Moreover, our research emphasizes the need for ethical considerations in the design and implementation of AI recommendation systems. The observed relationship between viewing duration and interaction highlights the potential for increased exposure to engaging content to foster habitual consumption, raising concerns about digital addiction. As social media platforms refine their algorithms, it is essential to balance user engagement with mental well-being, ensuring that the pursuit of engagement metrics does not come at the cost of user welfare.

This study provides valuable insights that can inform social media companies and policymakers in fostering responsible AI practices that prioritize the psychological health of users alongside their engagement.

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