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The Effect of YouTube Recommendation Engine: A Study of Visibility and Engagement

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Abstract: YouTube, one of the widely used online video platform which has an excellent algorithm to recommend the users with the customized content which leads them to binge-scrolling. Binge-Scrolling is the habit of continuously scrolling through social media feeds or other digital content for extended periods. This study focuses on what is the relationship between recommendation videos and binge-scrolling. To find out, BWESQ (Binge-Watching Engagement and Symptoms Questionnaire) is used with the selected variables such as Engagement, Binge-Watching, Dependency and Loss of control. The random sampling approach is employed to get samples from prominent locations around the metropolitan metropolis in India. 389 (N=389) samples collected through online data collection platform (Microsoft Forms) and the Multiple linear regression is used to analyse the linear relationship between those variables in Binge-scrolling. The statistics are employed with SPSS software. The study results with that prominent statistical significance are found between YouTube Recommendation videos and Binge- Scrolling.

Keywords: Binge- Scrolling, YouTube, Recommendation, BWESQ

1. INTRODUCTION

1.1 YouTube and YouTube Shorts

YouTube is a widely used online video platform that allows users to create, share, and watch videos. It has a staggering global user base of over 2.7 billion individuals (23 Essential YouTube Statistics You Need to Know in 2024, 2024). Featuring a diverse range of material including instructional videos, documentaries, music videos, and more, YouTube is a universally accessible platform. Daily, individuals consume 1 billion hours of video content on YouTube, resulting in billions of views (Mohsin, 2023).

The rapid progress of the internet and the extensive use of mobile devices have resulted in a new era of consuming information, results in short-form video platforms (Zhang, 2022). This brief transformation in content occurred with the rise of a social media network known as Vine, which emerged as one of the most rapidly expanding social media platforms in 2013 (Herald, 2023). Soon, many giant platforms like as TikTok, Instagram, and Snapchat have also embraced this content culture. YouTube also joined as a key player in this landscape in the year 2020, challenging the dominance of traditional long-form video content on the platform as a YouTube Shorts. YouTube videos that were 60 seconds or shorter earned 27% more views in 2023 compared to videos that were longer than 60 seconds (Adobe Express, n.d.). The vertical aspect ratio satisfies as most of the users are using YouTube in mobile (The Latest YouTube Stats on When, Where, and What People Watch, n.d.).

The personalization part of the YouTube algorithm plays a significant role in ensuring viewer engagement. Both YouTube and YouTube shorts Algorithm is crucial in deciding the visibility and recommendations of content on the platform. The algorithm considers several criteria such as watch time, user engagement, history, location, relevance etc. to determine which videos should be suggested to viewers (Adisa, 2023). Users encounter videos in numerous places, including search results, home page, notifications etc.

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1.2 Video Recommendations

The primary goal of recommendation system is to make the users to spend more time on the platform. YouTube Chief Product Officer Neal Mohan state that YouTube Recommendation Engine is responsible for more than 70% of user's time watching video on the Platform (Solsman, 2018). The YouTube video recommendation systems have seen significant advancements over the years. Initially, videos were ranked primarily on their popularity. However, the current system has grown to utilize over 80 billion signals to facilitate individuals in discovering and connecting with videos that align with their interests and preferences (Goodrow, 2021). The YouTube recommendation algorithm primarily operates on two sections, the home page, and the up-next panel. The home page often serves as the initial page of the YouTube website or application. The home page of each user is unique, since it is tailored to give personalized content depending on the user's information. According to a post by Team YouTube on X platform, "our actions on YouTube, Google, and Chrome can impact several aspects such as YouTube search results, recommendations on the home page, in-app alerts, and suggested videos" (Team YouTube, 2023). There are over 500 hours of video content is uploaded every minute in YouTube (Marcoux et al., 2021). Among them only dozens of video content are displayed in the home page. This is compatible with the recommendation system design that resembles a funnel (Covington et al., 2016).

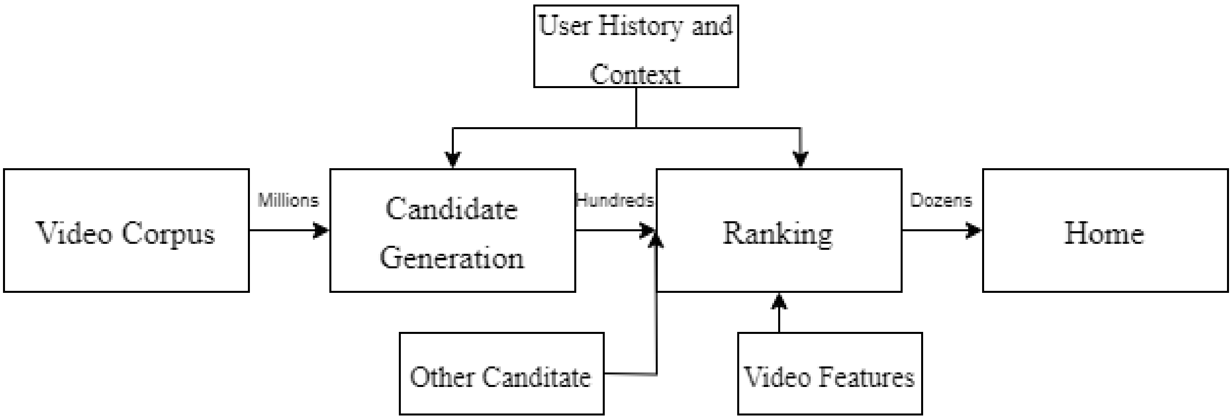

Fig 1.1

Based on this concept, the system is constructed using two neural networks. There is one for the purpose of generating candidates and another one for the purpose of ranking. Candidate Generation is a process that uses a user's YouTube activity history to produce a limited number of potential videos from a big collection. The purpose is to offer extensive customization with exceptional accuracy through collaborative filtering. Ranking refers to the process of evaluating and ordering items or individuals based on their relative position or importance. Following the process of candidate creation, the ranking component evaluates each video by assigning a score. This score is determined by a comprehensive collection of attributes that describe both the video and the viewer. The user is provided with the videos that have the highest scores, which are ordered based on their score. This process optimizes the recommendations to guarantee they are captivating and tailored to individual preferences funnel (Covington et al., 2016). These two processes collaborate to suggest videos from an extensive library while guaranteeing that the suggestions are customized to the user's preferences.

1.3 Binge-Scrolling:

Binge Scrolling is modern digital terminology that refers to the act of people consuming short-form content on platforms like TikTok and YouTube shorts, where the users rapidly scroll through a continuous stream of videos (Kendall, 2021). It is more like binge watching. Binge Watching is the practice of watching several episodes of a show in one sitting, whereas binge scrolling is the behaviour of aimlessly scrolling through social media for long periods of time (Alius, 2023). Both have comparable impacts on users, causing them to remain engaged with the information for an extended period. YouTube's recommendation system takes advantage of this nature by giving relevant and favourite content by customizing it according to the lurker's previous watching preferences. This will result the users by getting addiction to the scrolling habit. Excessive scrolling can evolve into a compulsive behaviour that negatively impacts relationships, productivity, concentration, and sleep patterns (Desk, 2024). The correlations between media use and mental health problems were statistically significant and favourable (Alimoradi et al., 2022).

1.4 Purpose of the Study:

Engaging in a binge-viewing session of a show triggers a consistent flow of dopamine in our brains. Dopamine provides the body with an innate, internal sense of pleasure that strengthens the desire to continue participating in a certain activity. The brain's signal serves as the means of communication to the body. (What Happens in Your Brain When You Binge-watch a TV Show, 2018). Bing-watching significantly causes five types of mental health concerns such as Stress, anxiety, depression, sleep problems and loneliness (Alimoradi et al., 2022). Streaming servicers create material with the intention of enticing the viewer to binge-watch. Many studies reveal that binge viewing is caused by seven variables provided by the content: engagement, positive emotion, desire-savoring, pleasure preservation, binge watching, dependency, and loss of control. (Flayelle et al., 2020, Binge-Watching as a Way of Coping: The Association Between Alexithymia, Binge-Watching, and Interpersonal Problems - University of Twente Student Theses, n.d., Billaux et al., 2023). This study examines the impact of these factors on binge-scrolling behavior on YouTube.

2. OBJECTIVE

2.1. To Analyse the relationship between Video recommendations and binge-scrolling.

3. HYPOTHESIS

H1 – There is no relationship between Recommendation and Engagement.
H2- There is no relationship between Recommendation and Binge watching.
H3 – There is no relationship between Recommendation and Dependency.
H4 - There is no relationship between Recommendation and Loss of Control.
H5 – There is no relationship between Binge-scrolling and Engagement.
H6 – There is no relationship between Binge-scrolling and Binge-watching.
H7- There is no relationship between Binge-scrolling and Dependency.
H8 – There is no relationship between Binge-scrolling and Loss of control.

4. METHODOLOGY

To examine the impact of YouTube Recommendation on the Lurker's scrolling behaviour, BWESQ (Binge-Watching Engagement and Symptoms Questionnaire) is used. BWESQ is the seven-factor model which consist of engagement, positive emotion, desire-savoring, pleasure preservation, binge watching, dependency, and loss of control. BWESQ is a fascinating instrument used for analysing the characteristics and symptoms of Binge-watching behavior. (Forte et al., 2021). Among them Positive emotion, desire-savoring and pleasure preservation is eliminated because these three factors cannot fit in the binge- scrolling, where it is purely based on watching behaviour. Additionally demographic variables and questionnaires to analyse Video recommendation and Binge-Scrolling are added along with BWESQ. The random sampling approach is employed to get samples from prominent locations around the metropolitan metropolis in India. Expected sample size is 385 with confidence level of 95% and margin of error with 5%. Sample received is 389 (N=389) which is collected through online data collection platform (Microsoft Forms). To analyse the relationship between the variables, SPSS is used to perform the Multiple Linear Regression between the variables.

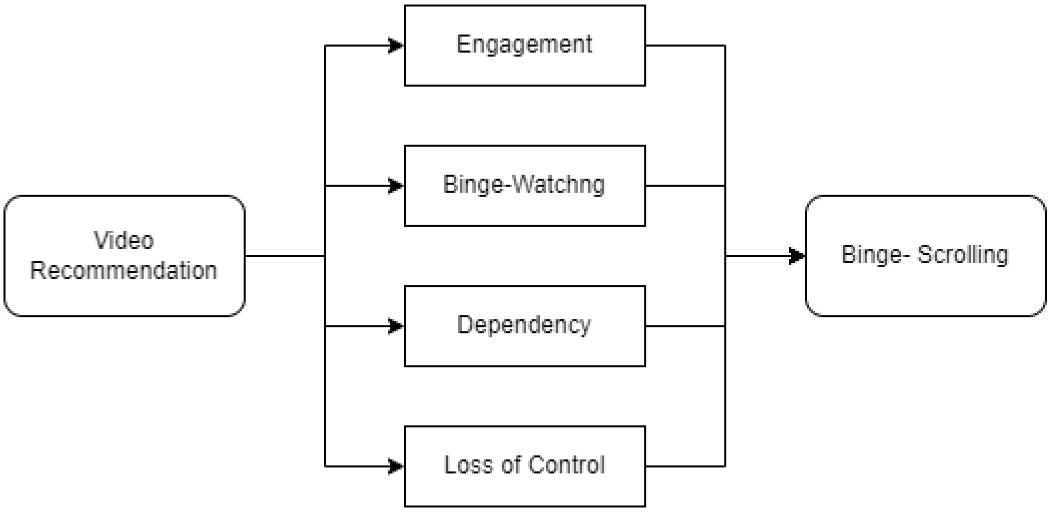

Fig 3.1 Conceptual Framework

This study aims to analyse the relationship between content provided by video recommendations and its factors such as Engagement, Binge-watching, Dependency and Loss of control. And the relationship between these four factors and Binge-scrolling behaviour.

5. ANALYSIS AND INTERPRETATION

Participants

In this study, data were collected from 389 individuals in a metropolitan area of India. Of these, 55.3% (215) are women, and 44.7% (174) are men. In terms of education, 51.9% (202) are graduates, 39% (152) have education higher than graduation, and 0.8% (30) are below graduation. Regarding locality, 73.3% (285) are from urban areas, 26.7% (104) are from semi-urban areas.

Reliability:

Scale	Items	Cronbach's Alpha
Recommendation	2	.707
Engagement	5	.867
Binge-Watching	6	.905
Dependency	5	.867
Loss of Control	7	.933
Binge-Scrolling	4	.854

Table 4.1

Hypothesis 1: There is no relationship between Recommendation and Engagement.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.622[a]	.387	.386	.67113	2.208

a. Predictors: (Constant), Recommendation

b. Dependent Variable: Engagement

Table 4.1.1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110.108	1	110.108	244.459	.000[b]
	Residual	174.310	387	.450		
	Total	284.418	388			

a. Dependent Variable: Engagement

b. Predictors: (Constant), Recommendation

Table 4.1.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.699	.172		4.074	.000		
	Recommendation	.744	.048	.622	15.635	.000	1.000	1.000

a. Dependent Variable: Engagement

Table 4.1.3

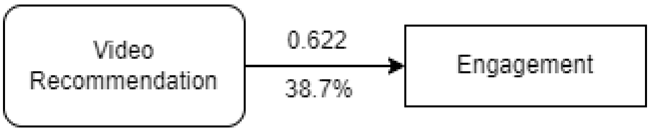

Figure 4.1.1

Table 4.1.1 shows a moderate positive relationship between Recommendation and Engagement. The model explains about 38.7% of the variance in Engagement, which indicates a reasonable but not complete explanatory power. Table 4.1.2 shows that the regression model is statistically significant, as indicated by the very low p-value (.000). The model explains a significant amount of the variance in Engagement, with an F-statistic of 244.459. The results suggest that the Recommendation is a significant of Engagement. In the table 4.1.2, The predictor variable Recommendation has a statistically significant positive effect on Engagement, as indicated by the p-value of 0.000 and the high t-statistic. In the table 4.1.3 ,the unstandardized coefficient of 0.744 suggests that with each unit increase in Recommendation, Engagement increases by 0.744 units. The standardized coefficient (Beta) of 0.622 shows a strong positive relationship between Recommendation and Engagement. Since there is a positive significant between recommendation and engagement, null hypothesis is rejected.

Hypothesis 2: There is no relationship between Recommendation and Binge-Watching.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.504[a]	.254	.252	.79735	1.832

a. Predictors: (Constant), Recommendation

b. Dependent Variable: BingeWatching

Table 4.2.1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110.108	1	110.108	244.459	.000[b]
	Residual	174.310	387	.450		
	Total	284.418	388			

a. Dependent Variable: Engagement

b. Predictors: (Constant), Recommendation

Table 4.2.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.665	.204		3.261	.001		
	Recommendation	.649	.057	.504	11.479	.000	1.000	1.000

a. Dependent Variable: BingeWatching

Table 4.2.3

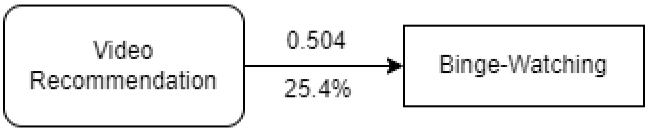

Figure 4.2.1

Table 4.2.1 shows a moderate positive correlation between Recommendation and Binge-Watching, with Recommendation explaining about 25.4% of the variance in Binge-Watching. Table 4.2.2 results suggest that the regression model is statistically significant, with a high F-value and a very low p-value. This means that the Recommendation variable significantly contributes to explaining the variation in Binge-Watching. In the table 4.2.3, For every unit increase in Recommendation, Binge-Watching is expected to increase by 0.649 units. The relationship is moderate, as indicated by the standardized coefficient (Beta = 0.504). Since the relationship is moderate, it is statistically proven then there is a relationship between Video recommendations and Binge-watching, which means that null hypothesis is rejected.

Hypothesis 3: There is no relationship between Recommendation and Dependency.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.231[a]	.053	.051	.76106	1.729

a. Predictors: (Constant), Recommendation

b. Dependent Variable: Dependency

Table 4.3.1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110.108	1	110.108	244.459	.000[b]
	Residual	174.310	387	.450		
	Total	284.418	388			

a. Dependent Variable: Engagement

b. Predictors: (Constant), Recommendation

Table 4.3.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.529	.195		7.856	.000		
	Recommendation	.252	.054	.231	4.671	.000	1.000	1.000

a. Dependent Variable: Dependency

Table 4.3.3

Figure 4.3.1

Table 4.3.1 shows a weak correlation between Recommendation and Dependency (R = 0.231). Only 5.3% of the variance in Dependency is explained by Recommendation ($R^2 = 0.053$). In the table 4.3.2 the F-statistic of 21.820 and the p-value of 0.000 suggest that the regression model is significant. This means that Recommendation does have a statistically significant effect on Dependency. In the table 4.3.3, the coefficient for Recommendation (0.252) is positive and statistically significant (p-value = 0.000). This means that higher values of Recommendation are associated with higher levels of Dependency. Even though the correlation between video recommendation and dependency is comparatively low, it is still statistically significant and has valid relationship between them. Which means null hypothesis is rejected.

Hypothesis 4: There is no relationship between Recommendation and Loss of Control.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.444[a]	.197	.195	.78739	1.680

a. Predictors: (Constant), Recommendation

b. Dependent Variable: LossofControl

Table 4.4.1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110.108	1	110.108	244.459	.000[b]
	Residual	174.310	387	.450		
	Total	284.418	388			

a. Dependent Variable: Engagement

b. Predictors: (Constant), Recommendation

Table 4.4.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.782	.201		3.881	.000		
	Recommendation	.544	.056	.444	9.741	.000	1.000	1.000

a. Dependent Variable: LossofControl

Table 4.4.3

Figure 4.4.1

In the table 4.4.1, R of 0.444 shows a moderate correlation between Recommendation and Loss of Control. R Square of 0.197 indicates that the model explains approximately 19.7% of the variance in Loss of Control. This is relatively low, suggesting that other factors not included in the model may also contribute to Loss of Control. In the table 4.4.2, F-Statistic of 94.878 with a p-value of .000 indicates that the model with Recommendation as a predictor significantly explains variation in Loss of Control. This means that Recommendation is a significant predictor of Loss of Control. In the table 4.4.3 Unstandardized Coefficient (B): Shows that a one-unit increase in Recommendation is associated with an increase of 0.544 units in Loss of Control Standardized Coefficient (Beta): Indicates a moderate positive effect of Recommendation on Loss of Control. t-Statistic and p-Value, both suggest that the effect of Recommendation on Loss of Control is statistically significant. The correlation between Recommendation and Loss of Control is statistically significant which is rejecting null hypothesis.

Hypothesis 5: There is no relationship between Binge-scrolling and Engagement.
Hypothesis 6: There is no relationship between Binge-scrolling and Binge-watching.
Hypothesis 7: There is no relationship between Binge-scrolling and Dependency.
Hypothesis 8: There is no relationship between Binge-scrolling and Loss of control.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.745[a]	.554	.550	.52228	2.034

a. Predictors: (Constant), LossofControl, Engagement, Dependency, BingeWatching

b. Dependent Variable: Bingescrolling

Table 4.5.1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	110.108	1	110.108	244.459	.000[b]
	Residual	174.310	387	.450		
	Total	284.418	388			

a. Dependent Variable: Engagement

b. Predictors: (Constant), Recommendation

Table 4.5.2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.193	.115		10.350	.000		
	Engagement	.235	.043	.258	5.400	.000	.507	1.971
	BingeWatching	.223	.054	.264	4.088	.000	.279	3.588
	Dependency	-.128	.043	-.129	-3.001	.003	.631	1.584
	LossofControl	.345	.052	.389	6.606	.000	.334	2.995

a. Dependent Variable: Bingescrolling

Table 4.5.3

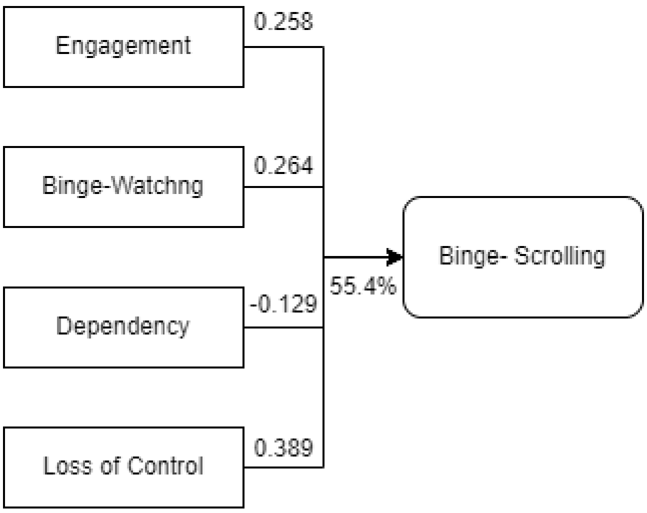

Figure 4.5.1

Table 4.5.1 explains a substantial portion (55.4%) of the variance in Binge-scrolling based on the independent variables (Loss of Control, Engagement, Dependency, and Binge-watching). Table 4.5.2 results indicate that the regression model significantly explains the variation in Binge-scrolling, with a highly significant F-value (119.470) and a p-value of .000. This confirms that the independent variables (Loss of Control, Engagement, Dependency, and Binge-watching) together have a statistically significant impact on Binge-scrolling. In table 4.5.3, All independent variables (Engagement, Binge-Watching, Dependency, and Loss of Control) are statistically significant predictors of Binge-scrolling. Loss of Control has the highest standardized coefficient, suggesting it has the strongest impact on Binge-scrolling. Since all the variables such as Engagement, Binge-Watching, Dependency and loss of control is statistically significant to Binge-Scrolling, Null hypothesis is rejected in H5, H6, H7 and H8.

6. DISCUSSION

6.1. Relationship between Recommendation and Engagement:

The research reveals a somewhat favorable correlation between suggestion and engagement, with the model accounting for 38.7% of the variability in engagement. This suggests that although recommendations are important for increasing engagement, additional elements that are not accounted for in the model also have an impact. The rejection of the null hypothesis validates that video suggestions serve as a substantial indicator of user engagement, consistent with prior research indicating that customized content enhances user involvement.

6.2. Relationship between Recommendation and Binge-Watching:

A Moderate level of positive connection was discovered between suggestion and binge-watching, with the model accounting for 25.4% of the variability. The standardized coefficient indicates a modest correlation, suggesting that suggestions influence binge-watching behavior, but there may be additional factors involved as well. The statistical significance of this correlation strengthens the notion that tailored material might result in extended periods of watching, strengthening worries over the addictive quality of such platforms.

6.3. Relationship between Recommendation and Dependency:

The relationship between recommendation and dependency is weaker compared to engagement and binge-watching, with only 5.3% of the variance in dependency explained by recommendations. Despite the weaker correlation, the relationship is still statistically significant, suggesting that recommendations do influence dependency, albeit to a lesser extent. This finding highlights the potential for recommendations to contribute to the development of dependency, even if they are not the sole factor.

6.4. Relationship between Recommendation and Loss of Control:

There is a moderate relationship between recommendations and loss of control, with 19.7% of the variance explained by the model. This suggests that while recommendations can contribute to a loss of control over viewing habits, other factors are also significant. The positive relationship between these variables underscores concerns about the impact of algorithm-driven recommendations on self-regulation and user autonomy.

6.5. Relationship between Binge variables and Binge-Scrolling:

The regression analysis demonstrates that engagement, binge-watching, dependency, and loss of control are all significant predictors of binge-scrolling, explaining 55.4% of the variance. Loss of control emerged as the strongest predictor, indicating that users who experience difficulties in regulating their viewing habits are more likely to engage in binge-scrolling. From the data, it is clear that these four factors have a influence in the lurker’s media usage to binge-scrolling which leads to increase in watch duration, watching content frequently etc.

7. CONCLUSION

Binge-watching and binge-scrolling are two prevalent behaviours that have experienced a rise in popularity in the era of digital technology. Both pastimes offer transient gratification from the user's exasperating daily routine. In the progression of the contemporary digital age, a large proportion of people prefer consuming short content (Chaves, 2024). This short form of content result in users engaging in the activity of scrolling through various videos. This behaviour is motivated by the pleasure principle and the element of unpredictability in discovering captivating content, which effectively keeps users engrossed (Alius, 2023). This practice is referred to as Binge-Scrolling. According to this study, binge-scrolling, like binge-watching, is likewise influenced by characteristics such as engagement, binge-watching, dependency, and loss of control. YouTube customizes its content to match the expectations and beliefs of its users by gathering data directly from them. The recommendation algorithm provides the user with relevant material. This recommended material encompasses all four elements that prompt users to allocate more time to the media. This generates a substantial audience for advertising, resulting in significant profits for the media corporation (How YouTube Makes Money - How YouTube Works, n.d.). However, the user continues to be dependent on the material, resulting in excessive and obsessive Binge-scrolling.

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