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The Impact of Social Media Engagement on Mental Health

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Abstract
This study explores the relationship between social media use patterns and mental health, focusing specifically on depression, anxiety, and sleep disturbances. With the rapid integration of social media into daily life, concerns have arisen about its potential negative effects on psychological well-being. Using a data set of 481 participants, the study employs statistical models, including correlation heatmaps, linear regression, and ordered logit models, to investigate how behaviors such as validation search and the frequency of browsing social media relate to mental health indicators. The analysis reveals that increased social media engagement is significantly associated with higher depression levels, particularly among non-binary individuals, who report the highest levels of distress. Regression models show that both browsing frequency and validation-seeking behaviors contribute to increased depressive symptoms, with the likelihood of depression increasing alongside these behaviors. Furthermore, interaction models reveal age- and gender-specific differences in mental health outcomes, with middleaged people experiencing lower levels of depression compared to younger adults. The study also finds significant variability in how different social media platforms impact the mental health of users, with TikTok and Snapchat being associated with the highest levels of depression. This research underscores the importance of understanding the role of social media in mental health, particularly with regard to marginalized groups. The policy implications suggest that social media platforms should consider mental health in their design, encourage healthier usage patterns, and promote content that promotes well-being. Clinical recommendations highlight the need for mental health professionals to incorporate social media usage into assessments, particularly when treating individuals with depression or anxiety. Future research should focus on longitudinal studies to better understand the causal relationship between social media engagement and mental health outcomes.

Keywords: social media; mental health; anxiety; depression; well-being; FOMO (Fear of missing out); self esteem

1 Introduction

1.1 General introduction

Social media has become an integral part of daily life, influencing communication, self-expression, and well-being. While it provides numerous benefits, concerns have arisen about its potential negative effects on mental health. This study explores the relationship between social media engagement and mental health indicators, particularly depression, sleep issues, and anxiety. Using statistical models, we aim to determine whether increased social media usage is significantly associated with negative psychological outcomes.

1.2 Literature Review

The rapid expansion of social media has provided researchers with valuable insights into mental health trends, particularly concerning depression and anxiety. Early studies, such as De Choudhury et al. (2013), demonstrated that linguistic patterns in social media posts could predict depressive symptoms, highlighting the potential of digital platforms for early mental health detection. Subsequent research has reinforced these findings, with studies like Primack et al. (2017) revealing a correlation between high social media usage and increased feelings of loneliness, particularly among young adults. Similarly, Keles, McCrae, and Grealish (2020) conducted a systematic review showing that problematic social media use is consistently associated with higher levels of psychological distress, underscoring the dual impact of social media on mental well-being.

To analyze mental health indicators on social media, researchers have employed various methodologies, including natural language processing (NLP), sentiment analysis, and network analysis. Coppersmith, Dredze, and Harman (2015) utilized NLP techniques to examine word frequencies and sentiment in social media posts, demonstrating the scalability of these methods for monitoring mental health trends. Additionally, network analysis has been instrumental in assessing social support structures, as users with weaker online connections often report poorer mental health outcomes. Sentiment analysis and time-series modeling have also been used to track emotional fluctuations over time, providing valuable insights into how external events influence mental wellbeing.

Despite the promise of social media data in mental health research, ethical challenges remain a critical concern. Privacy is a primary issue, as researchers must balance the public availability of social media content with users' rights to confidentiality. Moreover, the informal nature of online communication can lead to misinterpretation, where sarcasm or humor may be mistakenly identified as distress signals. Ethical guidelines emphasize the need for robust anonymization techniques, interdisciplinary collaboration, and responsible data interpretation to prevent stigmatization and unintended harm (Keles et al., 2020).

Advancements in artificial intelligence (AI) have further expanded the potential of social mediabased mental health analysis, with AI-driven tools now being used for early detection and intervention. Predictive analytics can identify at-risk individuals, while chatbots offer real-time mental health support. However, concerns about informed consent and over-reliance on automated systems highlight the need for careful regulation. Moving forward, interdisciplinary research should focus on developing standardized frameworks and longitudinal studies to ensure both the ethical and methodological integrity of social media-based mental health analysis.

2 Methodology

2.1 Data collection

A survey was conducted among 481 participants, collecting data on their social media usage patterns and mental health indicators. Variables included frequency of browsing, validation-seeking behaviour, feeling depressed, being bothered by worries, and sleep issues. Dataset Link

2.2 Statistical Models Used

In this study, we used several statistical models to examine the relationship between social media usage patterns and mental health indicators. These models were chosen to better understand how various social media behaviors influence mental health, while also accounting for demographic factors such as gender, age, and other potential confounders.

2.2.1 Linear Regression Model

The linear regression model was employed to analyze the relationship between social media behaviors and the continuous outcome variable, Feeling Depressed. This technique estimates how one or more independent variables (predictors) affect a dependent variable. Here, the predictors were the frequency of social media browsing and validation-seeking behaviors, while the dependent variable was the level of depression participants reported. This model helped quantify how changes in these behaviors—like more frequent social media browsing and a higher tendency to seek validation—are related to changes in depressive symptoms. The regression analysis provided coefficients that indicated the strength and direction of these relationships, helping to assess the significance of the predictors and the overall fit of the model (e.g., the R-squared value). This approach allowed us to understand how individual social media behaviors contribute to mental health outcomes, setting the stage for more complex models.

2.2.2 Ordered Logit Model

To predict the likelihood of participants experiencing different levels of depression (categorized as ”Not Depressed,” ”Mildly Depressed,” ”Moderately Depressed,” and ”Severely Depressed”), we used the ordered logit model. Unlike linear regression, which assumes a continuous outcome, the ordered logit model is suited for situations where the dependent variable is made up of ordered categories. This was particularly useful for analyzing depression data, as depression is often assessed on a scale rather than as a single continuous measure. The ordered logit model estimates the probability that a participant falls into one of these depression categories based on their social media usage behaviors. The model also provides coefficients that help us understand the relationship between predictors (like browsing frequency or validation-seeking) and the likelihood of moving between depression categories. This approach is ideal when the outcome is not normally distributed and doesn't follow a fixed scale.

2.2.3 Interaction Models for Gender and Age Effects

To explore whether the relationship between social media use and mental health varies by factors like gender and age, we employed interaction models. These models allowed us to examine how the effects of one predictor (e.g., browsing frequency) change depending on the value of another variable (e.g., gender or age). For example, we tested whether the impact of browsing frequency on depression differs across genders (male, female, non-binary) or age groups (e.g., young adults vs. middle-aged adults). By adding interaction terms into the models, we were able to analyze if, for example, browsing frequency has a stronger effect on depression in females than in males, or if younger adults experience more significant depressive symptoms from social media use compared to older adults. This approach helps us capture the nuances in how demographic characteristics influence the relationship between social media behavior and mental health.

2.2.4 Network Graph Analysis

Finally, we used network graph analysis to visualize how different social media platforms and their co-usage patterns are related to depression levels. In this analysis, each node represents a social media platform, and the edges (connections) represent users who frequently engage with multiple platforms. This visualization technique allowed us to better understand how using different platforms together correlates with mental health outcomes. For instance, we were able to identify which platforms are most strongly associated with high depression levels and which platforms are linked to lower distress. The size of each node reflects the average depression score of users on that platform, and the color gradient indicates depression levels, ranging from low (blue) to high (red). The analysis also shows the strength of co-usage between platforms, highlighting patterns of engagement that may contribute to mental health outcomes. For example, it might reveal that users who frequently switch between platforms like Instagram, Facebook, and YouTube tend to report lower depression levels, while those who primarily engage with platforms like TikTok and Snapchat show higher depression scores.

3 Results and Discussion

3.1 Correlation Heatmap

The correlation heatmap highlights key relationships between social media usage and mental health indicators:

1. Feeling Depressed and Bothered by Worries (0.59) – A strong positive correlation suggests that individuals experiencing higher anxiety levels also report greater depressive symptoms.
2. Feeling Depressed and Sleep Issues (0.38) – A moderate correlation indicates that depressive symptoms are associated with sleep disturbances.
3. Validation Seeking and Feeling Depressed (0.27) – A weak to moderate correlation suggests that individuals seeking validation on social media may be at a slightly higher risk of depression.

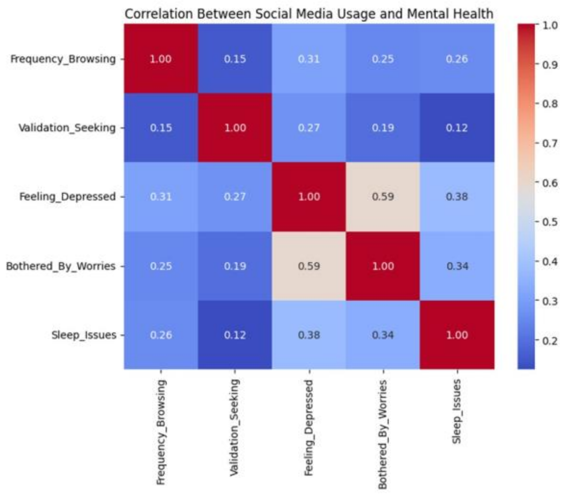


Figure 1: The correlation heatmap

4. Frequency of Browsing and Feeling Depressed (0.31) – A weak to moderate correlation implies that increased time spent on social media is linked to higher depression levels.
5. Bothered by Worries and Sleep Issues (0.34) – A moderate correlation suggests that anxiety and sleep problems often co-occur.
6. Validation Seeking and Sleep Issues (0.12) – A weak correlation indicates little to no relationship between validation-seeking and sleep disturbances.

The strongest correlations are observed between Feeling Depressed and Bothered by Worries (0.59) and Feeling Depressed and Sleep Issues (0.38), reinforcing the connection between mental distress and sleep-related concerns. While social media engagement shows weaker correlations with mental health outcomes, the trends suggest a potential link between increased usage and negative psychological effects.

3.2 Key Findings from the Regression Model 3.2.1 Model Fit

OLS Regression Results			
Dep. Variable:	Feeling_Depressed	**R-squared:**	0.146
Model:	OLS	**Adj. R-squared:**	0.142
Method:	Least Squares	**F-statistic:**	38.31
Date:	Tue, 01 Apr 2025	**Prob (F-statistic):**	4.39E-16
Time:	15:24:35	**Log-Likelihood:**	-727.64
No. Observations:	451	**AIC:**	1461
Df Residuals:	448	**BIC:**	1474
Df Model:	2	**Covariance Type:**	nonrobust
Omnibus:	**22.327**	**Durbin-Watson:**	**1.955**
Prob(Omnibus):	**0**	Jarque-Bera (JB):	**10.375**
Skew:	**-0.135**	Prob(JB):	**0.00559**
Kurtosis:	**2.308**	**Cond. No.**	**17.4**

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.4945	**0.213**	7.004	**0**	1.075	**1.914**
Frequency_Browsing	07:49:09	**0.053**	02:42:43	**0**	05:18:14	**0.43**
Validation_Seeking	0.2466	**0.047**	5.25	**0**	0.154	**0.339**

The regression model explains 14.6% of the variance in Feeling Depressed ($R^2 = 0.146$), and the adjusted value remains similar at 14.2%. The overall model is statistically significant ($F - statistic = 38.31$, $p - value < 0.001$), confirming that the predictors have a meaningful relationship with the dependent variable.

3.2.2 Coefficients Interpretation

Both Frequency Browsing and Validation Seeking are positively associated with Feeling Depressed. A one-unit increase in Frequency Browsing corresponds to a 0.3258-unit increase in depressive symptoms, while a one-unit increase in Validation Seeking leads to a 0.2466-unit increase in Feeling Depressed. These effects are statistically significant ($p - value < 0.001$) meaning they are unlikely to be due to chance.

3.2.3 Statistical Significance

The predictors have p-values below 0.001, reinforcing their strong statistical significance. Additionally, the 95% confidence intervals do not include zero, further confirming their impact on depressive symptoms.

3.2.4 Model Assumptions Check

Assumption tests indicate that the model is statistically robust. The Durbin-Watson value of 1.955 suggests no strong autocorrelation, and the Jarque-Bera test ($p = 0.00559$) shows a slight deviation from normality, though not extreme. The Condition Number of 17.4 indicates no severe multicollinearity.

This analysis confirms that social media behaviours, particularly browsing frequency and validationseeking, significantly contribute to depressive symptoms. Both factors show a positive correlation with Feeling Depressed, suggesting that increased social media engagement may exacerbate mental health struggles. However, as the model only explains 14.6% of the variance, other psychological and environmental factors likely play a substantial role in depression.

3.3 Gender Differences in Mental Health Indicators

Gender	Feeling_Depressed	Bothered_By_Worries	Sleep_Issues
Female	3.391837	**3.693878**	3.191837
Male	**3.079602**	**3.402985**	**3.228856**
Non binary	5	5	1
Non-binary	**4**	**5**	**4**
Nonbinary	4	**4**	1
There are others???	**1**	**1**	**1**
unsure	3	**2**	5

3.3.1 Gender Differences in Feeling Depressed

Non-binary individuals report the highest levels of depressive symptoms, with scores ranging from 4.0 to 5.0. Females report slightly higher levels of Feeling Depressed (3.39) compared to males (3.08). Other identities, such as "There are others???" and "unsure," report the lowest scores (1.00 and 3.00, respectively), though the sample size for these groups is unclear.

3.3.2 Bothered by Worries

Similar to depression levels, non-binary individuals also report the highest levels of being bothered by worries, with scores between 4.0 and 5.0. Females (3.69) experience slightly more worries than males (3.40). The ”There are others???” group reports the lowest worry levels (1.00), though sample size considerations remain.

3.3.3 Sleep Issues

Males and females report similar sleep issue levels (around 3.2). Non-binary individuals show mixed experiences, with some reporting severe sleep issues (4.0) and others reporting very low sleep problems (1.0), indicating significant variability. The ”unsure” group reports the highest sleep issues (5.0).

Key Takeaways

- Non-binary individuals consistently report higher levels of distress, particularly in Feeling Depressed and Bothered by Worries.
- Females tend to report slightly higher distress levels than males across all categories.
- The ”There are others???” group reports the lowest distress levels, though their sample size may be small.
- Non-binary respondents show wide variability in sleep issues, with some reporting extreme difficulty and others reporting none.

3.4 Ordered Logit Model Findings

Dep. Variable:	Feeling_Depressed	Log-Likelihood:	-677.41
Model:	OrderedModel	AIC:	1367
Method:	Maximum Likelihood	BIC:	1391
Df Residuals:	445	Df Model:	2

	coef	std err	z	P>|z|	[0.025	0.975]
Frequency_Browsing	0.485	0.083	5.869	0	0.323	0.647
Validation_Seeking	0.3887	0.074	5.243	0	0.243	0.534
45689	0.547	0.33	1.658	0.097	-0.099	1.193
45718	0.1695	0.107	1.577	0.115	-0.041	0.38
45750	0.1458	0.087	1.684	0.092	-0.024	0.316
45781	0.188	0.089	2.121	0.034	0.014	0.362

3.4.1 Model Fit and Optimization

The Ordered Logit Model predicts Feeling Depressed based on Frequency of Browsing and Validation Seeking behaviors. The model shows a good fit: • Log-Likelihood: -677.41. • AIC: 1367 — BIC: 1391 • Optimization terminated successfully, meaning the model converged properly. • Number of observations: 451. • Residual Degrees of Freedom: 445, reflecting model complexity.

3.4.2 Key Coefficients and Interpretation

- Frequency of Browsing ($\beta = 0.4850$, $p < 0.001$): Higher browsing frequency significantly increases the likelihood of depression.
- Validation Seeking ($\beta = 0.3887$, $p < 0.001$): Seeking validation (e.g., through likes or comments) is also associated with increased depression risk.

3.4.3 Thresholds and Classification

The model uses thresholds to classify different levels of Feeling Depressed:

- 4/5 threshold is significant ($p = 0.034$), suggesting a strong differentiation at higher depression levels.
- Other thresholds are not strongly significant, indicating more uncertainty in distinguishing between lower levels of depression.

3.4.4 Interpretation and Key Insights

- Both Frequency of Browsing and Validation Seeking significantly contribute to increased depression levels ($p < 0.001$).

- Validation Seeking has a slightly smaller effect than Browsing Frequency, but both are strong predictors.
- Higher thresholds indicate clearer distinctions between extreme levels of depression.
- Policy Implication: If excessive browsing and validation-seeking behaviors elevate depression risks, reducing social media exposure or changing engagement patterns could help mitigate negative mental health effects.

OLS Regression Results			
Dep. Variable:	Feeling_Depressed	**R-squared:**	0.118
Model:	**OLS**	**Adj. R-squared:**	**0.102**
Method:	**Least Squares**	**F-statistic:**	**7.38**
No. Observations:	**451**	**Prob (F-statistic):**	3.11E-09
Df Residuals:	442	**Log-Likelihood:**	-734.97
Df Model:	**8**	**AIC:**	**1488**
Covariance Type:	**nonrobust**	**BIC:**	1525
Omnibus:	**29.986**	**Durbin-Watson:**	**1.966**
Prob(Omnibus):	**0**	**Jarque-Bera (JB):**	**12.549**
Skew:	**-0.157**	**Prob(JB):**	**0.00188**
Kurtosis:	**2.245**	**Cond. No.**	**4.08E+17**

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.9606	0.286	6.86	0	1.399	2.522
Gender[T.Male]	-0.048	0.402	-0.12	0.905	-0.837	0.741
Gender[T.Non binary]	0.0857	0.074	1.165	0.245	-0.059	0.23
Gender[T.Non-binary]	0.2496	0.251	0.994	0.321	-0.244	0.743
Gender[T.Nonbinary]	0.0852	0.125	0.681	0.496	-0.161	0.331
Gender[T.There are others???]	-0.1496	0.074	-2.035	0.042	-0.294	-0.005
Gender[T.unsure]	-0.032	0.074	-0.435	0.664	-0.176	0.113
Frequency_Browsing	0.3958	0.076	5.214	0	0.247	0.545
Frequency_Browsing:Gender[T.Male]	-0.0592	0.108	-0.547	0.585	-0.272	0.154
Frequency_Browsing:Gender[T.Non binary]	0.3427	0.294	1.165	0.245	-0.235	0.921
Frequency_Browsing:Gender[T.Non-binary]	0.4991	0.502	0.994	0.321	-0.488	1.486
Frequency_Browsing:Gender[T.Nonbinary]	0.2556	0.375	0.681	0.496	-0.482	0.993
Frequency_Browsing:Gender[T.There are others???]	-0.5985	0.294	-2.035	0.042	-1.177	-0.021
Frequency_Browsing:Gender[T.unsure]	-0.1279	0.294	-0.435	0.664	-0.706	0.45

3.5 Interaction Effects of Gender and Age on Social Media Usage

3.5.1 Model 1: Gender and Browsing Frequency Interaction

This model examines whether the relationship between Browsing Frequency and Feeling Depressed varies across different gender identities.

Model Fit:

The model explains 11.8% of the variance in depression levels, with an adjusted R-squared of 10.2%, suggesting that adding predictors did not significantly improve the model. The F-statistic (7.380, p ¡ 0.001) indicates overall statistical significance. However, the model has a high condition number (4.08e+17), signaling potential multicollinearity issues.

Key Findings

- Browsing Frequency is a strong predictor of depression (= 0.3958, p ¡ 0.001), indicating that more frequent social media browsing is associated with increased depression levels. • Gender alone does not significantly predict depression (p = 0.905), meaning that males and other gender identities do not show substantial differences in their depression levels. • The interaction between Browsing Frequency and being male is not significant (= -0.0592, p = 0.585), suggesting that browsing affects males and others similarly.
- A significant negative interaction is found for individuals identifying as ”others” (= -0.5985, p = 0.042), indicating that for this group, higher browsing frequency is associated with lower depression levels.

Summary:

Browsing frequency is a significant factor in predicting depression. However, gender alone does not strongly influence depression levels, except for individuals in the ”others” category, where increased browsing is linked to reduced depression. Despite these findings, multicollinearity concerns suggest possible redundancy among predictors, requiring careful interpretation.

3.5.2 Model 2: Age Group and Browsing Frequency Interaction

OLS Regression Results			
Dep. Variable:	Feeling_Depressed	R-squared:	0.212
Model:	OLS	Adj. R-squared:	0.2
Method:	Least Squares	F-statistic:	17.03
No. Observations:	451	Prob (F-statistic):	5.8E-20
Df Residuals:	443	Log-Likelihood:	-709.51
Df Model:	7	AIC:	1435
Covariance Type:	nonrobust	BIC:	1468
Omnibus:	24.374	Durbin-Watson:	2.103
Prob(Omnibus):	0	Jarque-Bera (JB):	14.445
Skew:	-0.286	Prob(JB):	0.00073
Kurtosis:	2.336	Cond. No.	147

This model explores whether the relationship between Browsing Frequency and Feeling Depressed differs by age group.

Model Fit: This model explains 21.2% of the variance in depression levels, a significant improvement over Model 1. The adjusted R-squared of 20.0% confirms a reasonably strong model.

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.3423	0.705	3.324	0.001	0.957	3.727
Age_Group[T.Young_Adult]	0.3625	0.744	0.487	0.626	-1.1	1.825
Age_Group[T.Middle_Aged]	-1.7802	0.803	-2.217	0.027	-3.358	-0.202
Age_Group[T.Older]	0.5055	1.257	0.402	0.688	-1.966	2.977
Frequency_Browsing	0.2585	0.2	1.291	0.198	-0.135	0.652
Frequency_Browsing:Age_Group[T.Young_Adult]	-0.0392	0.21	-0.187	0.852	-0.451	0.373
Frequency_Browsing:Age_Group[T.Middle_Aged]	0.2722	0.233	1.17	0.243	-0.185	0.729
Frequency_Browsing:Age_Group[T.Older]	-0.4759	0.401	-1.187	0.236	-1.264	0.312

The F-statistic (17.03, p ¡ 0.001) indicates high statistical significance. Unlike Model 1, no serious multicollinearity issues were detected.

Key Findings

- Middle-aged individuals report significantly lower depression than young adults (= -1.7802, p = 0.027), suggesting that depression levels decline with age.
- Older individuals do not show a significant difference in depression compared to young adults (p = 0.688).
- Browsing Frequency is not a significant predictor in this model (p = 0.198), unlike in Model 1, where it played a key role.
- No significant interactions are found between browsing frequency and age groups, indicating that the effect of browsing does not vary meaningfully by age.

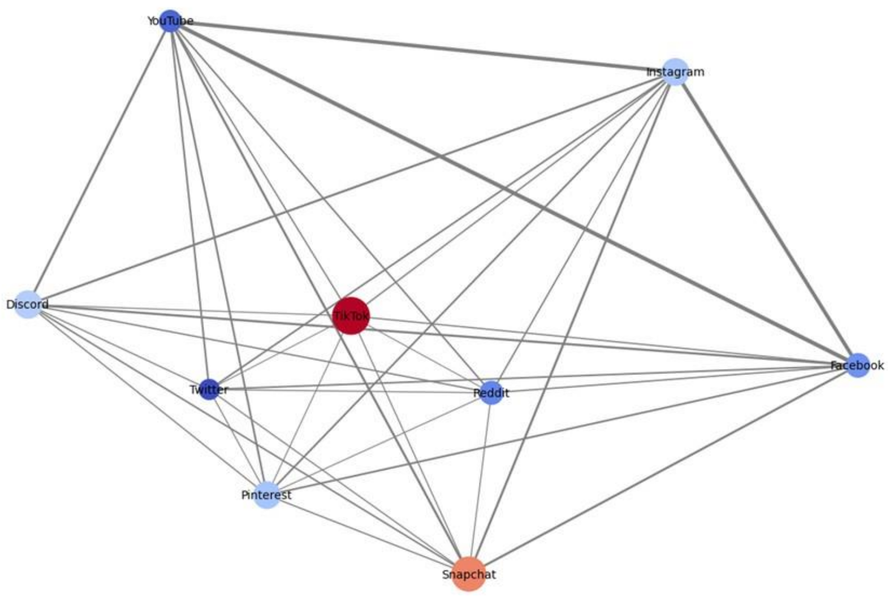
Summary:

Middle-aged individuals report significantly lower depression levels than young adults, but browsing frequency does not play a significant role in this model. Unlike Model 1, where browsing was strongly linked to depression, this model suggests that age is a more relevant predictor than browsing frequency.

Comparison of the models

Model 1 highlights Browsing Frequency as a strong predictor of depression, particularly among certain gender identities. However, gender itself does not significantly impact depression. In contrast, Model 2 suggests that age is a more important factor, with middle-aged individuals reporting lower depression, but browsing frequency showing no significant effect. Overall, Model 2 provides a better fit for explaining variations in depression levels, as indicated by its higher explanatory power and lack of multicollinearity issues. Meanwhile, Model 1's findings suggest that the relationship between social media use and depression may be influenced by gender identity, particularly among those who identify outside traditional male/female categories.

3.6 Network Graph of Social Media Platforms and Depression



This network visualization maps how different social media platforms are used together and how their users' depression levels compare. It highlights potential patterns in social media engagement and mental health.

Key Features of the Graph 1. Nodes (Circles) Represent Platforms

- Each node corresponds to a social media platform (e.g., TikTok, Instagram, YouTube).
- The size of the node represents the average depression score of its users—larger nodes indicate higher depression levels.
- TikTok and Snapchat have larger nodes, suggesting their users report higher depression levels.

2. Edges (Connections) Represent Co-Usage

- An edge (line) between two platforms means users frequently use both together.
- Thicker edges indicate stronger co-usage (e.g., Instagram and Facebook are heavily linked).

3. Color Gradient Represents Depression Levels

- Redder nodes indicate higher depression levels.
- Bluer nodes indicate lower depression levels.
- TikTok appears the most red, suggesting it has the highest depression score.
- Platforms like YouTube and Discord appear in cooler colors, indicating lower depression levels.

Summary of Findings

- TikTok and Snapchat users report higher depression scores.
- Facebook, YouTube, and Instagram are highly interconnected, suggesting frequent co-usage.
- Platforms with strong connections are often used together, indicating users may switch between them regularly.

4 Conclusion

4.1 Conclusion

This study reveals significant relationships between social media engagement and mental health, with key insights into depression, anxiety, and sleep disturbances. Our analysis highlights that:

1. **Social Media Usage and Depression**: Increased frequency of social media browsing and engagement in validation-seeking behaviours are strongly linked to higher levels of depressive symptoms. Individuals who engage more frequently with social media platforms are more likely to experience feelings of depression.
2. **Gender and Mental Health**: Non-binary individuals report the highest levels of mental distress, particularly depression and anxiety. While females show slightly higher distress than males, the most striking finding is the marked mental health challenges faced by non-binary individuals.
3. **Age-Related Variations**: Age plays a crucial role in mental health outcomes. Middle-aged individuals tend to experience lower levels of depression than younger adults, suggesting that depression may decrease with age, independent of social media usage patterns.
4. **Platform-Specific Effects**: Certain social media platforms, particularly TikTok and Snapchat, are associated with higher levels of depression among their users. This highlights the potential risks of engagement with these platforms, which could contribute to mental health concerns.

Overall, the study underscores the complex interplay between social media behaviours and mental health. While social media is a powerful tool for connection, excessive usage and behaviours driven by validation-seeking may exacerbate psychological distress, particularly for vulnerable groups such as non-binary individuals and younger adults.

4.2 Implications

1. **Policy Recommendations**: Social media platforms should prioritize mental health by encouraging healthier engagement patterns. Features that promote positive content, reduce harmful comparisons, and discourage excessive usage could help mitigate the psychological risks associated with these platforms. Additionally, policies that address the specific needs of marginalized groups, particularly non-binary individuals, could reduce mental health disparities linked to social media use.
2. **Clinical Applications**: Mental health professionals should consider social media usage when diagnosing and treating individuals, particularly those showing signs of depression or anxiety. Clinicians could incorporate assessments of social media habits into their therapeutic approaches to better understand the role of digital engagement in mental health. Cognitivebehavioural strategies that help individuals manage their social media engagement might be useful in treatment plans.
3. **Future Research**: Future studies should explore causality between social media use and mental health outcomes using experimental designs. Longitudinal research could provide deeper insights into the long-term psychological effects of different social media platforms. Furthermore, investigating the impact of specific features (like validation-seeking behaviours or content consumption patterns) could refine our understanding of the mechanisms behind social media's effect on mental health.
4. **Public Health Campaigns**: Public health initiatives should focus on raising awareness about the potential mental health risks of excessive social media use. Educational campaigns aimed at young adults and vulnerable groups, such as non-binary individuals, could help promote healthier digital habits. These campaigns could also encourage individuals to seek help if they experience mental health struggles related to social media engagement.

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