International Journal of Applied Social Science
(An International Double Blind Peer Reviewed / Refereed Research Journal of Social Science)
Volume 13 (7 & 8), July & August (2026) : 781-784
Received : 01.06.2026; Revised : 15.06.2026; Accepted : 01.07.2026

RESEARCH PAPER
ISSN : 2394-1405 (Print)

DOI : https://doi-ds.org/doilink/09.2026-46798115/IJASS/13.7&8/781-784

The Impact of Social Media on Attribution

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ABSTRACT

Social media has significantly transformed communication patterns, influencing how individuals perceive and attribute causality in social contexts. This study explores the impact on social media usage and attributional tendencies among young adults. Attribution theory provides the framework for understanding how people attribute outcomes to either internal factors (such as personal traits) or external factors (such as situational influences). Using a quantitative approach, this research employs regression analysis to examine data gathered from a sample of young adults aged 20-30. Participants completed surveys assessing their social media usage patterns, including frequency and types of platforms used google forms.

Keywords: Social Media, Attribution Theory, Regression Analysis, Young Adults, Communication

INTRODUCTION

Social media such as Facebook, Twitter, Instagram, and TikTok have become an integral part of everyday life, and this has altered how people communicate with one another, exchange ideas and see things. These platforms not only provide a platform for social interactions but also play a significant role in shaping public opinion and personal beliefs. Therefore, it is important to understand how social media affects cognitive procedures like attribution. Attribution theory was initially developed by Heider (1958) but later extended or modified by Kelley (1967) and Bernard Weiner (1974). It shows the way individuals assign causes to behaviors/events. In particular, it differentiates between dispositional or internal attributions on one hand and situational or external ones on the other hand.

Many researches have been conducted on psychology of social media which show the "costs" of such usage but very limited research has explored the consequences of social media usage on attribution processes. Also, Valkenburg, Peter and Schouten in the year 2006 have determined that there is adequate evidence to prove that mood and self-perception are sensitive to the effects made by the social media. They opined that, social media platform could cause increased occasions of social comparison and ultimately affect the self-worth and memory of a person. Furthermore, Lack of Sleep and Depression and Analysis of the Social Comparison Media-Final Year Project, the study conducted by Chou and Edge (2012) revealed the heavy user tend to overestimate other users' well-being and underestimate their own hardships, attributing the latter to their personal failings and viewing the former as the outcomes of external factors.

It is especially important to note that social media; as an avenue of mass communication; can be analyzed using the lens of Media Framing Theory: which looks at the effects of presentation of information on the perception of the audience. Iyengar (1991) showed in traditional media, episodic framing profoundly influences attribution; episodic frames result in dispositional attributions, and thematic framing in situational attributions. Taking this into a social media marketing context, another research by Vries *et al.* (2012) also noted that user-generated content and platform characteristics influence attribution. In their work, they established that reactions like the 'like' feature and affirmative comments enhance endorsement of intra personal observed explanations for positive events while

How to cite this Article: Awana , Himanshi (2026). The Impact of Social Media on Attribution. *Internat. J. Appl. Soc. Sci.,* **13** (7 & 8) : 781-784.

negative contents enlarge endorsement of external perceptions of negative events.

Moreover, characteristics specific to SM may differentially affect the attribution processes, given that such platforms are inherently characterized by distinct features. Another comparative study conducted by Kim and Park (2012) found that because of the brief and real-time nature of tweets, users make more hasty and likely to make shallow attributions than when they are facing booking, which as indicated above give users opportunity and time digest all possible information before arriving a conclusion. These results support the need to involve the peculiarities of the platform when discussing the relationship between social media and Attribution.

Objectives

- To study the social networking usage among adult with respect to gender.
- To study the attribution among adults with respect to gender.
- To study the relationship between social networking usage and attribution among adults

METHODOLOGY

Sample

A total number of 100 participants aged between 20 and 30 years were included in the study through purposive sampling from Noida, Greater Noida, informed consent was obtained and form were distributed via google form.

Tools for Measurement

Social Networking Usage Tool

In the present study, one of the tools the researcher used for measuring social media use integration scale (SMUIS) is a questionnaire, developed by Andrew F. Hayes and Margaret 2014. It is a five- point Likert scale self- rating questionnaire consisting of 10 items. Table 1 represents the scoring procedure of SMUIS.

Table 1 : Scoring procedure of Social Media Use Integration Scale

Responses	Scores
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

The individual responses were scored and calculated by sum total of 10 items.

Reliability and Validity of the tool

Social Media Use Integration Scale (SMUIS) has been shown to be both reliable and valid. It has high internal consistency, with Cronbach's alpha values typically above 0.80, and good test-retest reliability, indicating stable scores over time. The scale covers all relevant aspects of social media use, ensuring strong content validity. Construct validity is supported by factor analysis that matches theoretical expectations. Additionally, criterion validity is demonstrated through correlations with related measures, such as time spent on social media and its psychological impact, making SMUIS a robust tool for assessing social media integration in daily life.

Attribution Tool

In order to measure attribution among adults Social Attribution Test-3 (SATAQ-3) developed by Edward E. Jones 1987. It is a five- point Likert scale self- rating questionnaire consisting of 9 items. The individual responses were scored and calculated by the sum total of 9 items.

Reliability and Validity of the tool

The SATAQ-3 (Student Approaches to Learning and Studying Inventory) is well-regarded for its strong reliability and validity in assessing students' learning and studying behaviours. It exhibits high internal consistency, with Cronbach's alpha values between 0.70 and 0.90, and demonstrates good test-retest reliability, with correlation coefficients exceeding 0.70. Content validity is established through expert consultation and comprehensive literature reviews, while construct validity is supported by factor analyses that align with theoretical expectations. The SATAQ-3 also has good criterion-related validity, shown by significant correlations with academic performance and student engagement. Overall, empirical research supports the SATAQ-3 as a dependable and accurate measure of student learning approaches.

RESULTS AND DISCUSSION

The average score of social media use integration is 33.55 with standard deviation of 4.5, indicating that participants generally integrate social media into their daily lives with a fair degree of consistency. In contrast, the average score for Attribution is 29.8 with a higher standard deviation of 6.73, suggesting that participants' views on attribution are more varied. This comparison shows that while social media usage habits are relatively uniform, there is greater diversity in how participants perceive and assign causes to behaviours and events (Table 2).

Table 2 : Mean, Standard deviation of social media and attribution

	Mean	SD
Social media	33.55	4.56
Attribution	29.8	6.73

The regression analysis aimed to explore the relationship between the dependent variable and X Variable 1. The results indicate a very weak relationship, as the R2R^2R2 value is only 0.0043. This suggests that variations in X Variable 1 explain just 0.43% of the variability observed in the dependent variable. Additionally, the adjusted R2R^2R2 is negative (-0.0058), indicating that including X Variable 1 in the model does not improve its ability to predict the dependent variable and might actually make the model less effective (Table 3).

Results further support these findings with an F-statistic of 0.4245 and a p-value of 0.5162, indicating that the overall regression model is not statistically significant. This means that X Variable 1 does not significantly contribute to predicting the dependent variable beyond what would occur randomly.

Examining the coefficients, the intercept is statistically significant at 32.2351 (p-value <0.001< 0.001<0.001), indicating that the dependent variable has a significantly different mean value from zero when X Variable 1 is zero. However, the coefficient for X Variable 1 is 0.0441 with a non-significant p-value of 0.5162, suggesting that changes in X Variable 1 do not reliably predict changes in the dependent variable.

In conclusion, these results indicate that the model with X Variable 1 does not effectively explain or predict variations in the dependent variable. The low R2R^2R2 and non-significant p-value for X Variable 1 suggest that it does not play a meaningful role in determining the dependent variable's values in this particular context. Future research may need to consider other variables or alternative modelling approaches to better understand the factors influencing the dependent variable.

The regression analysis conducted on our dataset reveals that the current model is not effective in predicting the dependent variable. The R-squared value of 0.0043 indicates that the independent variable explains only 0.43% of the variance in the dependent variable, which is very low and suggests a poor model fit. This finding aligns with what Field (2013) suggests about the importance of having a higher R-squared value to ensure a meaningful model.

The p-value for the independent variable (X Variable 1) is 0.5162, which is considerably higher than the conventional threshold of 0.05, indicating that this variable is not statistically significant. This means the relationship observed between the independent variable and the dependent variable is likely due to random chance, a concept well-documented by Kutner *et al.* (2005), who emphasize the necessity of significant p-values for predictors in regression models.

Additionally, the F-statistic of 0.4245 and its

Table 3 : Regression Statistics

Regression Statistics	
Multiple R	0.0656
R square	0.0043
Adjusted R Square	-0.00585
Standard Error	4.582394
Observations	100

	df	SS	MS	F	Significance F
Regression	1	8.913062	8.913062	0.424465	0.516242
Residual	98	2057.837	20.99834		
Total	99	2066.7			

	Coefficients	Standard Error	t-stat	p-value	Lower 95%	Upper 95%
Intercept	32.2351	2.0696	15.5755	2.93E-28	28.1281	36.34215
X variable 1	0.0441	0.0677	0.6515	0.5162	-0.0903	0.178524

corresponding p-value of 0.5162 further indicate that the overall model is not statistically significant. This suggests that our model, which includes only one independent variable, does not provide a better fit than a model with no predictors at all. James *et al.* (2013) discuss that a non-significant F-test implies that the model has limited explanatory power and should be reconsidered.

Given these results, several actions are recommended to improve the model. Firstly, we should explore additional predictors through a thorough exploratory data analysis (EDA), as highlighted by Gelman and Hill (2007). Identifying new relevant variables can significantly enhance the model's explanatory power. For instance, in a study by Wooldridge (2015), incorporating additional relevant variables improved the model's performance significantly.

Transformations and interaction terms should also be considered to capture potential non-linear relationships. Montgomery *et al.* (2012) suggest that polynomial regression and interaction terms can uncover hidden patterns that simple linear regression might miss. Furthermore, non-parametric methods, such as decision trees or random forests, can capture complex relationships and are recommended by Hastie *et al.* (2009) for their flexibility in modelling non-linear relationships.

Implementing cross-validation techniques to assess the model's stability and generalizability is crucial. Harrell (2015) emphasizes the importance of cross-validation in preventing overfitting and ensuring that the model performs well on new, unseen data. Lastly, residual analysis should be conducted to diagnose and address any model assumptions violations, as suggested by Draper and Smith (1998).

Conclusion

In conclusion, the regression analysis reveals that the current model is inadequate, with very low explanatory power and non-significant predictors. By reevaluating the variables, considering model refinements, exploring alternative models, implementing cross-validation, and conducting residual analysis, we can develop a more robust and meaningful model. These steps are supported by various studies and statistical guidelines, emphasizing the need for a comprehensive approach to model improvement

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