INFERRING THE ROLE OF SOCIAL MEDIA ON GEN Z'S INVESTMENTS DECISIONS

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ABSTRACT

Purpose: The aim behind conducting this research is to investigate the impact of social media (SM) its impact on enhancing their Financial Literacy (FL) and how it influences Gen Z Community Behaviour (GzCB). This will help us to know that how all these independent variables will affect the dependent investment decisions (ID) of the GenZ investors.

Design/ Methodology/ Approach: A self-prepared and self-administered structured questionnaire was used to collect precise information and provide a rigorous approach to the research. The link between the constructs was investigated using a descriptive study approach. Using Google Forms, an online questionnaire was distributed to gather data. G*Power software was used to generate the sample size, and Smart PLS software was used to apply a structural equation model for additional data analysis.

Findings: The findings of this study revealed a substantial link between social media and investment decisions, with all three independent variables correlating favourably with the dependent variable (investment decision). To put it another way, the findings of this study show that social media has an impact on Gen Z investment decisions.

Practical Implications: There is a need to promote financial literacy among Indian citizens, particularly the Gen Z generation, because they are the ones who have recently begun or will soon begin earning an income. If Gen Z starts investing some part of their income in the capital markets, Early investment will be good for them as well as for the country in the long term.

Originality Value: This study intends to add to the body of knowledge for future financial research on an important topic: the impact of social media on Gen Z community behaviour (GzCB).

Keywords: Information from social media, Online Community Behaviour, Investment Decision, Behavioural Finance.

INTRODUCTION

While finance has been studied for a long time, behavioural finance, which analyses how psychological variables might affect market results, is still a relatively new field, with plenty of room for more research. Social media has been recognized as a significant instrument for forecasting future occurrences, spawning various research on the subject. Despite this, little research has been done on how social media material affects real-life situations. The goal of the study is to see how social media influences Gen Z investment decisions. The rapid growth and integration of social media into everyday life has been acknowledged, and social media analytics has emerged as a key research subject. When it comes to choosing between things, buyers are depending less on expert counsel and more on the advice of their peers, which has been made easier by the rise of social media. However, one area that still needs to be investigated is how social media material influences other real-life time-dependent occurrences. Most individuals nowadays communicate with one another using WhatsApp, Facebook, Twitter, and other social media platforms. Companies can utilize social media platforms to improve internal and external communications while collaborating and communicating with customers, partners, and other stakeholders, including investors.

A stock market, also known as an equity market, is a collective market to publicly and/or privately purchasing and selling of various instruments. Volatility is a feature of the stock market that makes analyzing market behaviour difficult. (Thakkar & Chaudhari, 2021, p. 1). Fundamental analysis entails the examination of quantitative data such as stock price and volume, as well as qualitative information about such firms such as profiles and strategies. By utilizing stock attributes and the associated correlations, technical analysis can aid in the forecast of future market behaviour. (Thakkar & Chaudhari, 2021, p. 1). While a wide range of information is used, social network analysis is a relatively modern version that has proven useful for stock predictions. (Bustos & Pomares-Quimbaya, 2020, p. 1). Over the years, investment in the stock market has been considered as very unpredictable, especially given the restricted availability of data and analytics to the general public. However, the gap has narrowed over time, and it is now easy for newbies to comprehend it to some level. Furthermore, while various research has been conducted to anticipate stock price movements in the future, the stock market is not only based on previous data. The internet's and social networks' great expansion allows for the sharing of user ideas about business shares, and there are even social networks specifically built for shareholders that allow users to exchange and discuss their beliefs about the future of each stock. (Derakhshan & Beigy, 2019, p. 569). Traditionally, in open societies, public opinion was studied using face-to-face, telephone, or internet surveys. The emergence and rising popularity of social media sites like Facebook and Twitter have made gathering and analyzing public opinion simpler than ever before. They allow for the exchange of ideas on a variety of topics, including social, economic, and political concerns.

Previous studies suggested that the patterns contained in social media may help provide information that allows for a better understanding and prediction of social events. Previous methods of obtaining information about public opinions, such as questionnaire surveys, have proven to be effective but expensive and time-consuming, whereas social media platforms, which are extremely popular and contain massive amounts of data, can provide valuable sources for sentiment if an effective method of data analysis is available. The internet, which has evolved into the dominant means for acquiring information, is generally thought to have eclipsed the mass media. It is critical in obtaining, analyzing, and disseminating data from the public to individual investors. Various changes in social and business life have happened because of rapid technological advancement, as seen by increased internet use and availability, one of which is the introduction of social media. (Akmese et al., 2016).

Every week, an increasing number of individuals use social media to get news, with some citing it as their major source of news. Financial market-related material now accounts for a sizable portion of social media traffic. On the other hand, psychologists have revealed that humans are not as logical as many economists believe. As a result, a new branch of finance known as "behavioural finance" has arisen, which investigates how various psychological factors influence people or groups operating as investors, analysts, and portfolio managers. It seeks to explain how emotions and subjective norms impact individual investor behaviour, as well as to explain why and how investors might operate outside the bounds of rationality in ways that contradict what they are intended to do. (Bakar & Yi, 2016, p. 320). Big data research relies heavily on sentiment analysis. It's also known as "opinion mining," and it refers to a set of computational techniques for detecting, extracting, and distilling human emotions, thoughts, or opinions from textual data in internet content directed at specific entities. p. 20 (Bukovina, 2016). The complex behaviour of a society is captured in big data from social media. The behavioural finance framework serves as the primary incentive for the use of social media data in the field of capital markets because this behaviour and its relationship to capital markets dominates the subject of behavioural science study. p. 20 (Bukovina, 2016).

LITERATURE REVIEW

Companies are increasingly touting social media technologies as a way to alter businesses and improve organisational performance. Social media metrics (Web blogs and customer evaluations) are major leading determinants of company stock value. Surprisingly, standard online behavioural metrics (Google searches and Web traffic) are revealed to have a substantial but much less predictive relationship with firm stock value than social media data. It also reveals that social media has a better predictive value, resulting in a shorter "wear-in" period than traditional web media. (Nilsson, J. Luo, X., Zhang, J., & Duan, W. 2021). Further, Women and better educated investors were more likely to devote a greater portion of their income to market investments. Nilsson, J. (2008). Consumers are increasingly looking to their peers for product recommendations, a trend facilitated by the emergence of social media and the accompanying generation and consumption of user-generated content. (Chen, H., De, P., Hu, Y. J., & Hwang, B. H. (2013). Also, crowd funding ventures benefit from the use of social media. Lu, C. T., Xie, S., Kong, X., & Yu, P. S. (2014, February). Social media now precisely represents public emotion and opinion regarding current events. Researching public mood, in particular, has piqued the interest of scholars interested in researching public mood. Stock market forecasting based on public opinion reported on Twitter has been an exciting area of study. It is known that there is a high correlation between the rise and fall in stock prices and public sentiment in tweets. Pagolu, V. S., Reddy, K. N., Panda, G., & Majhi, B. (2016, October). Sociable households in areas with high participation rates are more inclined to invest in the stock market. Social contact is critical in conveying valuable information to potential investors. However, the informative value of social contact may be influenced by other information routes, which have been largely overlooked in prior research. Liang, P., and Guo, S. (2015). Investors' attitudes (AT) are influenced by a variety of circumstances, including ambiguity, risk, and an abundance of alternatives. Financial Literacy (FL) is critical in such situations. When an investor has financial literacy, he or she is in a better position to evaluate his or her investment risk based on the signals he or she receives and the ability to process information in a better manner (Raut, R. K. 2020).

CONCEPTUAL FRAMEWORK

The primary goal of this study is to investigate social media and determine whether it affects investment decisions. The goal of the research is to establish a link between online social media and investing decision-making, as well as to add to the field of behavioural finance. To see if social media has an impact on investment decisions, the authors used the investment decision as a dependent variable (Y) and three explanatory variables. The three explanatory variables are: social media (SM), financial literacy (FL), and Gen Z community behaviour (GzCB) to assess the dependent variable investment decisions (ID) of GenZ investors.

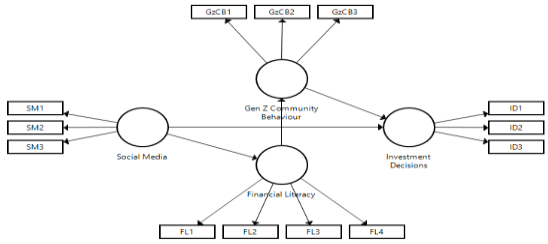

Figure 1: Conceptual Framework

HYPOTHESIS

H1: There is no significant impact of Social Media on Financial Literacy of Gen Z.
H2: There is no significant impact of Financial Literacy on Gen Z Community Behaviour.
H3: There is no significant impact of Gen Z Community Behaviour on Gen Z Investment Decisions.
H4: There is no significant impact of Social Media on Gen Z Investment Decisions.

RESEARCH METHODOLOGY

The data was gathered using a standardised questionnaire. The suitability of the sample size was determined using G* Power software. The software generates the sample size for the study based on the number of predictors (i.e., independent variables), the desired effect size, and the probability error. With three predictors, the software estimated the sample size to be 262. (figures 2 and 3). Despite the fact that a sample size of 262 was deemed adequate, the study used data from 404 respondents. The relationship between the constructs was studied using a descriptive study approach. Smart PLS SEM was used to analyze the data collected.

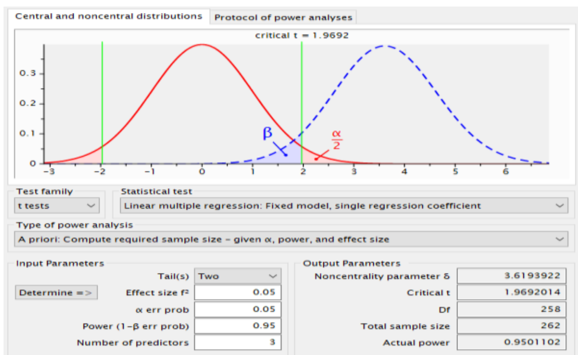

Figure 2: Determination of Sample Size

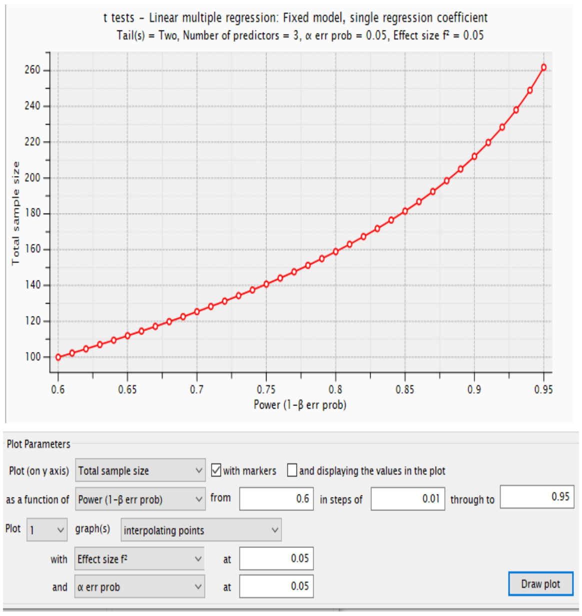

Figure 3: Determination of Sample Size

Source: Authors' Own Calculation using G*Power

FINDING AND ANALYSIS

Demographic Profile

Table 1: Summary of Demographic Profile (Using Counts, Percentage and Cumulative %)

Levels	Counts	% Of Total	Cumulative %
Frequencies of Gender			
Female	153	37.87%	37.87 %
Male	251	62.713%	100 %
Frequencies of highest Qualifications			
Bachelor's Degree	165	40.84 %	40.84 %
Master's Degree	213	52.73%	93.57%
BE/ CA / CS or any such professional degree	26	6.43 %	100.0 %

Source: Authors Own Calculations using Jamovi.

The information was gathered from 404 respondents, all of them were under the age of

CONFIRMATORY COMPOSITE ANALYSIS

Measurement Model

The constructs' reliability was assessed using confirmatory composite analysis. Cronbach's Alpha, Composite Reliability, and Rho A with a value of 0.7 were employed in this investigation. All three components (table 2) had Cronbach's Alpha (Nunnally, 1978), Composite Reliability (Hair et al., 2010), and Rho A (Henseler, 2015) values greater than 0.7, or greater than 0.6 (Morgan, Leech, Gloeckner, and Barret, 2004), indicating that the questionnaire was reliable based on this model. Cronbach's alpha is an internal consistency metric that expresses how closely a group of items are related. Unlike Cronbach's alpha, composite reliability is an internal consistency reliability measure that does not presume equal indicator loadings. The average variance extracted (AVE) is a convergent validity metric that describes how well a latent concept explains the variance of its indicators. The average variance extracted (AVE) celling limit is 0.50, which means that anything above 0.50 is acceptable. The questionnaire also fits the criteria for AVE, as shown in Table 2. As a result, the data can be concluded to meet all of the requirements for reliability. In Smart PLS software, the factor

Constructs	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Social Media	0.918 0.899 0.874	0.878	0.879	0.925	0.805
Financial Literacy	0.789 0.882 0.878 0.743	0.843	0.858	0.895	0.681
Gen Z Community Behaviour	0.855 0.904 0.837	0.832	0.840	0.899	0.749

Table 2: Construct Reliability and Validity

Constructs	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Social Media	0.918 0.899 0.874	0.878	0.879	0.925	0.805
Financial Literacy	0.789 0.882 0.878 0.743	0.843	0.858	0.895	0.681
Gen Z Community Behaviour	0.855 0.904 0.837	0.832	0.840	0.899	0.749
Investment Decisions	0.883 0.843 0.909	0.853	0.867	0.910	0.772

Source: Authors Own Calculations using Smart PLS.

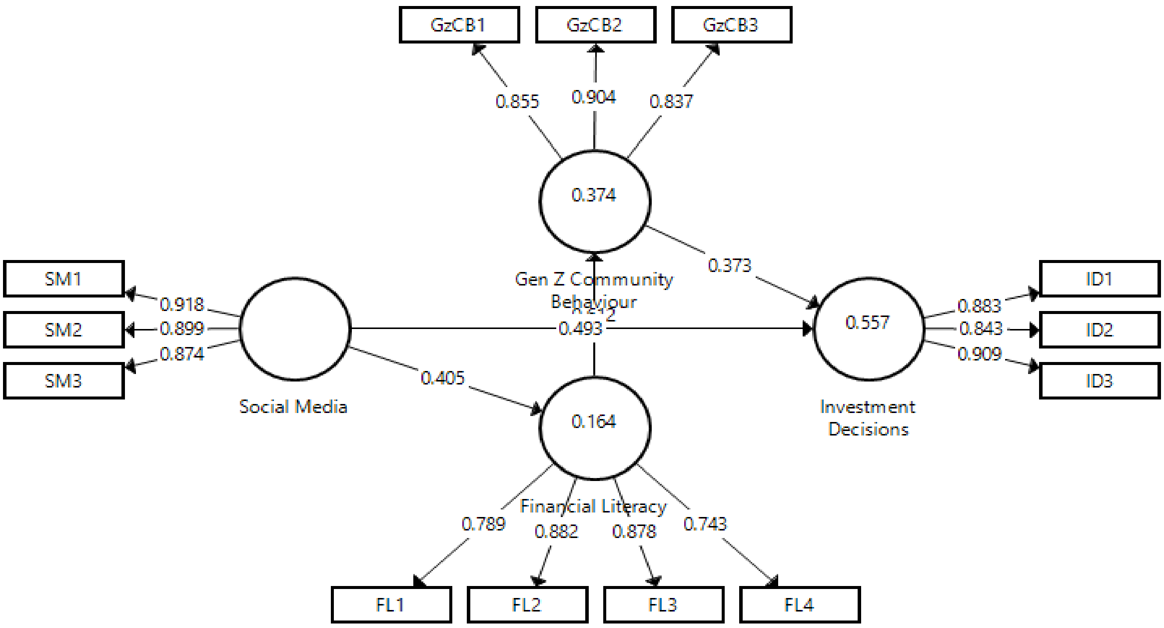

Figure 4: Measurement Model

Source: Authors' Own Calculation using Smart PLS

DISCRIMINANT VALIDITY

Discriminant validity was used to investigate the variables further and determine whether they were truly distinct. Discriminant variables are used to identify whether measures that appear to be unrelated are indeed unconnected.

The Fornell-Larcker Criterion (1981), which compares the square root of each construct's average variance retrieved with its correlations with all other constructs in the model, is a degree-to-shared variance approach.

Table 3: Fornell-Larcker Criterion

Constructs	Social Media	Financial Literacy	Gen Z Community Behaviour	Investmnt Decisions
Social Media	**0.897**			
Financial Literacy	0.405	**0.825**		
Gen Z Community Behaviour	0.475	0.612	**0.866**	
Investmnt Decisions	0.670	0.535	0.607	**0.879**

Source: Authors Own Calculations using Smart PLS.

The Fornell-Larcker criteria reveal that the study has discriminating validity because the square root of the average variance is bigger than the cross-correlation constructs, as shown in Table 3.

Table 4: Heterotrait-Monotrait Ratio (HTMT)

Constructs	Social Media	Financial Literacy	Gen Z Community Behaviour
Financial Literacy	0.461		
Gen Z Community Behaviour	0.552	0.721	
Investment Decisions	0.769	0.628	0.714

Source: Authors Own Calculations using Smart PLS.

The HTMT is the average of all correlations of indicators across constructs, comparing the average correlations of indicators measuring the same construct to the average correlations of indicators measuring other constructs. The intended HTMT threshold is set at a maximum of 0.85 (Kline, 2011, Henseler et al., 2015) and (Teo et al., 2008) (Gold et al., 2001) 0.90 criterion. Table 4 shows that the value is less than 0.85, indicating that the construct has discriminant validity using HTMT as well.

Table 5: R Square

Constructs	R Square	R Square Adjusted
Financial Literacy	0.164	0.162
Gen Z Community Behaviour	0.374	0.373
Investment Decisions	0.557	0.555

Source: Authors Own Calculations using Smart PLS.

R-square calculates the relationship between the movements of a dependent and independent variable. Table 5 contains information on the R square. Social media clearly influences 55.5 percent of investment decisions.

Table 6: Model Fit

	Saturated Model	Estimated Model
SRMR	0.073	0.099
d_ULS	0.479	0.893
d_G	0.259	0.27
Chi-Square	637.41	625.517
NFI	0.809	0.813

Source: Authors Own Calculations using Smart PLS.

A more thorough examination of model fit was also carried out. Calculations for model fit are shown in Table 6. SRMR is an acronym for "Standardized (Standardized Root Mean Square Residual) A good match is defined as a value of less than 0.10. (1999, Hu and Bentler). The SRMR is 0.073 in Table 6, indicating that it is a model fit. Hair et al. (2010) define model fit as being less than 0.90. (Hair et al., 2010). NFI is 0.809 in Table 6, indicating that the model is fit.

STRUCTURAL EQUATION MODEL

A bootstrapping technique with 5000 bootstraps was performed to test the hypothesis and examine the model's predictive power. Figure 5 and Table 7 illustrate the findings of the analysis. The hypothesis's outcomes are indicated by the T test and P-value. Statistical significance is defined as a p-value of less than 0.05. It provides significant evidence against the null hypothesis, as the null hypothesis has less than a 5% chance of being right. As a result of the P value and T test, hypotheses H1, H2, H3 and H4 are rejected, implying that social media had a substantial impact on Gen Z investment decisions directly as well as indirectly.

Table 7 – Results of the Structural Model Hypotheses Testing

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1: There is no significant impact of Social Media on Financial Literacy of Gen Z.	0.405	0.407	0.044	9.129	0.000
H2: There is no significant impact of Financial Literacy on Gen Z Community Behaviour.	0.612	0.613	0.029	20.949	0.000
H3: There is no significant impact of Gen Z Community Behaviour on Gen Z Investment Decisions.	0.373	0.373	0.035	10.545	0.000
H4: There is no significant impact of Social Media on Gen Z Investment Decisions.	0.493	0.494	0.033	15.02	0.000

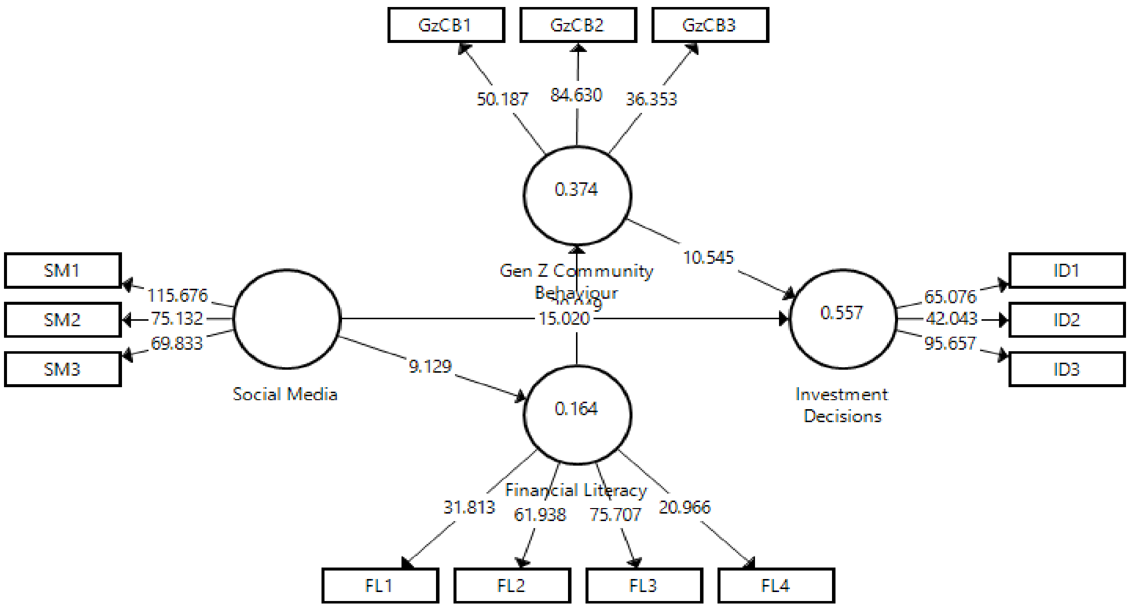

Figure 5: Structural Equation model (Hypotheses Testing)

Table 8: Direct and Indirect Impact

Dependent Variables ↓		Independent Variables ↓		
		Social Media	**Financial Literacy**	**Gen Z Community Behaviour**
Financial Literacy	**DE**	0.405		
	IE	**-**		
	TE	0.405		
Gen Z Community Behaviour	**DE**	**-**	0.612	
	IE	0.248	-	
	TE	**0.248**	**0.612**	
Investment Decisions	**DE**	0.494	-	0.373
	IE	0.092	0.228	-
	TE	**0.586**	**0.228**	**0.373**

Source: Authors Own Calculations using Smart PLS.
Note: DE: Direct Effects, IE: Indirect Effects, and
TE: Total Effects

The direct and indirect effects of all the independent variables, such as Social Media, Financial Literacy, and Gen Z Community Behaviour, were considered while determining the effects of various constructs on the dependent variable (Gen Z Investment Decisions). According to the study's findings, social media has the greatest direct influence on Gen Z investment decisions (β=0.494), followed by Gen Z community behaviour (β = 0.373). Social media was also helpful in increasing Gen Z's financial literacy (β=0.405). Financial Literacy also had a significant impact on Gen Z's community behaviour (β = 0.612). Financial literacy (β = 0.228) had the greatest indirect effect on Gen Z investment decisions, followed by social media (β = 0.092). Thus, it may be stated that social media and Gen Z community behaviour are the two most important elements that influence the investment decisions of Gen Z.

CONCLUSION

The findings of this study highlight that the availability of information about various investments on the internet influences investing decisions. The research focused on information gathered from people using social media sites such as YouTube, Facebook, and Twitter. This study discovered a link between social media information and investment decisions, with the likelihood of making a purchase increasing as the amount of information on a particular investment increase on social media. The authors conclude from the data analysis that there is empirical evidence that suggests that there is a connection between the information in social media and investment decisions.

The study adds to prior studies that indicate that internet information has a major impact on investing decisions, particularly for individual investors. Because information from social media is easily obtained, constantly updated, and available in real-time. As a result, investors frequently utilize this chance to make a better investment choice. The behaviour of online communities appears to have an influence on investment decisions as well. In other words, it has been demonstrated that online community behaviour has an influence on investment decisions. This study backs up another study conducted by Forbes (2013), which concluded that social media affects customer purchasing behaviour. The findings of this study back up previous research that demonstrated that good social media posts inspire investors to acquire stock in a company.

LIMITATIONS AND FURTHER STUDY

Gen Z from Bhopal, India, was the target group. It's possible that Gen Z's perspectives differ from those in other parts of the country or around the world. Other specialized categories, such as university students, Gen Y, Gen X, and so on, can be studied further. Only responders with an internet presence were examined in this study. Individuals who are not engaged on these platforms could be the subject of future research. A broader range of investments, rather than only the stock market, might be covered. Other factors or more independent variables could also be included.

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