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Do social media sentiments affect investment decisions? A moderated mediation analysis of the relationship between social media sentiments, trust, and investment decisions

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Abstract: The study explores the effect of social media sentiments on the social media attitude of investors. The objective is to determine whether an investor's trust in social media sentiments influences social media attitudes while making investment decisions. A standardised questionnaire was made to obtain data from Indian retail investors. The data was evaluated and analysed using smart PLS to investigate the association concerning constructs like Twitter, Facebook and YouTube. Here, investor's trust mediates between social media sentiments and social media attitude, while investment choice is a moderator between social media sentiments and trust. The significant result of this study shows how trust factors affect a person's eagerness to take financial risks and participate in risky securities. Trust also affects investment diversification and individual investor perception. The study offers valuable awareness for individual investors, financial experts, opinion formers, educationists, and other shareholders.

Keywords: social media sentiments; SMSs; social media attitude; SMA; stock market; investor behaviour; investment choice; trust.

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1 Introduction

According to conventional financial theories, investors' choice of investments is based on their analysis of historical data, and they are assumed to be entirely rational when choosing their investments. It is founded on the facts and statistics of market values and is unaffected by subjective emotions. As a result, investors would not take any chances based on their feelings. Instead, they will do so if specific market data supports their rational thinking (Kamoune and Ibenrissoul, 2022). Researchers are always interested in discovering ways to forecast what will happen. With the rapid growth in the economically oriented society, there is always a need in the stock market to explore and identify the vast amount of valuable information that helps to identify a better stock (Garg and Tiwari, 2021).

Our world is currently being turned upside down by social media. Information is more readily available than ever because of the introduction of technologies in social media. Investors are regularly encouraged to 'like' or 'follow' posts on several social media platforms. Tremendous growth has been seen among people who use various social media platforms. The average time spent on these platforms has increased considerably, encouraging educationalists, stock market experts, or investment advisors to give better investment strategies. The Pew Research Centre published a report in 2021 and found that 49% of individuals admit to using social media frequently. In 2020, more than 3.6 billion individuals were using social media. By 2025, it is predicted to be close to 4.41 billion users.

Social media has also drawn researchers' interest, and their implications and service are being examined from different perspectives. Social media gives people an enormous platform to produce, share, and bookmark material. Online forums, Twitter, Facebook, blogs, and microblogs are beneficial resources for anticipating, detecting, and forecasting major societal events (Earle et al., 2012). The fast growth in the field of social media changes people's daily life and promotes fundamental changes in the distribution of information. The online world of websites of discussion, taking decisions such as investor's review, investor's expectation, and blogs are being engaged by the investors to capture the latest information about the company's future prediction.

Social media is a part of daily life in the modern world, so it is essential to consider how it impacts our society. For example, every investor makes a decision based on their expected return on investment. While it took radio 38 years to get 50 million listeners and 13 years for television to gain 50 million viewers, Facebook just took one and a half years to accomplish that milestone (Natalia, 2016).

The rise of new technologies and applications has created various innovative social and interactive environments for mining information, data, and knowledge of the stock market (Atzmueller, 2012). Every stock market participant uses social networking websites such as YouTube, Facebook, and Twitter to learn about the various aspects influencing stock market investment, such as the company's financial performance, current events, long and short-term returns, etc. (Sun and Ng, 2014). However, findings have disregarded the prospect of trust working as a mediating factor between social media sentiments (SMSs) and attitudes because investors require financial knowledge and faith in the financial system. The association between trust and SMSs can justify why people desire to invest in stocks belonging to familiar firms. Trust is an indispensable element in social media to explicate its climate. Investors have varying levels of trust, which mediates the impact of SMSs on social media attitudes (SMAs) (Ventre et al., 2021).

1.1 Significance of the study

The study aimed to highlight the prominence and significance of social networking media like Twitter, Facebook, and YouTube, as social media platforms have become an integral part of daily life and are highly used by retail investors to make informed investment decisions. Social media platforms allow users to share and exchange financial information and opinions, which in turn leads to a potential impact on the investment decision of retail investors. Focusing on the Indian stock market context, the study examines whether investor trust towards social media significantly affects investor investment decisions. Trust plays a significant role between SMSs and SMA. The results indicate that SMA and social trust influence investment patterns and influence the individual's willingness to take financial risks and invest in risky instruments.

1.2 Need of the study

The use of social media is increasing day by day, which results in a large and diverse amount of data. Discovering knowledge through social media helps in decision-making and investigation. Social media performs a robust role in individual investor's decision-making and offers a practical method for evaluating market sentiments. The investors themselves do not affect the stocks' performance. They tend to rely on media recommendations for research before making investment decisions. Numerous studies have examined the impact of SMSs on stock prices or trading volume. However, fewer studies have examined considering the trust factor of retail investors on social media during the investment decision-making process. However, other studies have found mixed results or no significant relationship between SMSs and SMA. Therefore, researchers need to pay a critical eye approach to examine the linkage between investor trust and the dependencies of their investment decisions on SMSs.

Previous studies also have overlooked the probability of 'investment choice' which acts as a moderating variable between SMSs and trust. However, based on a literature review, we can conclude that there is a potential importance of mediating and moderating variables of trust and investment choice. We need to analyse them methodically.

The study investigates trust as a mediator between SMSs and SMA while investment choice as a moderator between SMSs and trust. The study's objective is to inspect the attributes of SMSs, especially Twitter, YouTube, and Facebook, that influence investor's attitudes toward social media and investment choices.

This study's key objectives are as follows:

1 To identify the usage of social networking platforms by investors for investment decision-making in the Indian stock market.

2 To analyse the attribute of various SMSs and their impact on investor attitude.

3 To analyse the impact of investor's trust and investment choices on social media while making investment decisions.

The study first determines the numerous factors that influence investor sentiments. To analyse the data, firstly validity and reliability of the variables of the scale of the items are required to be measured. Then, it is estimated to discover the association among the values of the variables, and further partial least square (PLS) method is used to find the relationship in the model. To put our contributions into perspective, the study begins by outlining the prior work, then discusses the conceptual framework and research hypothesis before reviewing the data sources, empirical model, and model estimation. It also provides a summary of quantitative empirical research. It closes and offers directions for additional research after reporting and discussing the result.

2 Literature review and hypothesis development

2.1 SMSs and SMA

People often use social media sites to exchange information concerning stock market developments and discuss their opinions (Glowacki et al., 2017). It allows people to successfully connect, collaborate, and grow online (Helmond, 2015). Many investors use social media daily to watch the news, with some mentioning it as their primary information resource. More than 70% of people have used multiple social media networks, and the proportion of users who say it is difficult to live without these platforms keeps rising (Brooke Auxier and Anderson, 2021).

Content related to the stock market is now devoted to a significant social media share (Jiao et al., 2020). The rise in acceptance of social media platforms like Facebook and Twitter has made collecting and evaluating public belief easier than ever (Li et al., 2017). The result of speedy technological advancements, as seen by the increased use of the internet and its accessibility, information could be spread globally through social media and its connectedness, making it simple for people to interact and share information with one another (Akmese et al., 2016).

The investment decision is crucial to choose the best option out of alternatives to achieve better returns. Social media has a substantial role in supplying information to investors, and has become a vital tool for investment decision-making (Ismail et al., 2018).

2.2 SMSs and trust

Social media sites like Facebook, YouTube, and Twitter are used by more than half of the global population because of the widespread belief that these sites are effective for spreading the word about new products and services. In addition, most investors rely on social media recommendations for research before making investment decisions (Kadous et al., 2019). They also believe that this data improves the ability to predict the performance of securities in the future. Social media allows companies to develop goodwill to promote substantial awareness and positive participant reactions. This practice is distinguished by communication, comments, mention, responses about the information, and the appearance of the sentiments. Hence, a rise in companies with public attention and media coverage directly influences investors (Hendrawaty et al., 2020).

Trust plays a vital role in choosing and relying on the information provided by many social media platforms. The information may also lead to false impressions, which further misleads investors in their decision-making. The stock market is vital to a healthy economy because it facilitates the trading of surplus fund units (investors) and deficit fund units (stock issuers), both of which are essential to the functioning of the market (Fauzi and Wahyudi, 2016). This shows that the information published on popular social media sites may influence stock performance. In addition, this study reveals a trust difference among online communities as well.

2.3 Trust and SMA

Using social media to deliver blog or website information about the stock market is a great approach to enlighten investors. According to Reddy Bollampelly (2016), social media promptly provides investors with other financial news and knowledge, permitting them to rationalise their investment decision-making process.

The benefit of social media is that it provides a public platform for two-way communication between a firm and its shareholders. Many investors actively adopt suggestions from these social media sites to guide their investment choices (Brown, 2015).

The paper by Nguyen et al. (2015) stated that some findings claimed that SMSs had inadequate or no predictive power, while others claimed that social media has strong predictive power. Various forthcoming ways of propagating knowledge and communicating with the crowd have risen due to the expansion of digital technologies and improved internet applications.

2.4 Trust as a mediator

Investors will trust a company with substantial market value, goodwill, and performance. Individuals make decisions based on trust values or trust networks (Sutcliffe et al., 2015). Trust relates to people's opinions and beliefs concerning honesty and behaviour stability (Zafar et al., 2020). These characteristics signify trust as an indication (Hajli, 2014). Trust is also considered as one of the essential elements of investor behaviour. The research indicates that high net-worth investors have engaged in social media in large numbers and are paying attention to what their colleagues say. Another study shows that a lack of trust can have damaging outcomes as the investors may also want to explore other investment opportunities investors should study the trust factor associated with SMSs (Durkin et al., 2013).

2.5 Investment choice as a moderator

Research in the field of behavioural finance focuses primarily on the psychological and emotional factors that play a vital role in investment decisions. However, investment choices are also affected by other factors, such as social contacts or peer influences. Investments in the stock market are risky as their value fluctuates constantly. Predicting how stock prices will move in the future is an essential topic for businesses and organisations, but developing a reliable model for doing so has proven challenging. Most institutional investors (almost 80%) use social media daily and out of them, 30% say that social media content directly influences an investment recommendation. Presently, 34% of retail investors have made at least one change to their investment strategies because of social media (Aggarwal, 2021).

The study found that investors make an enormous return in the stock market when they buy the stocks of a good reputation firm that has risen on social media (Brammer et al., 2006). This effect allows businesses to invest in their image to establish a positive reputation. Social media is vital in individual investors' decision-making process and offers a practical method for evaluating market sentiments (Sul et al., 2017). The study that looks at the effect of social media on investing outcomes, exposes three key trends: investors are very active on social media, fellow opinion influences investors' stock market decisions, and social media causes people to doubt the integrity of knowledge from official sources.

Schniederjans et al. (2013) examine the relationship between social media and a company's image and establishes a moderately favourable relationship between social media usage and investors' investment choices. Based on a detailed analysis of the literature, it is found that many studies have established the relationship between SMSs and investment decisions based on historical data. Further, it is also found that SMSs predict stock price volatility. The above studies are also supporting these findings. However, in the context of Indian retail investors with varied investment volume, this study is intended to find out the impact of other factors like trust and investment choice, which is missing in the literature on stock news on social media platforms (Facebook, Twitter, YouTube, etc.) and recommendations for investment decisions.

The following hypothesis is developed based on the above literature:

H1 SMSs significantly influence SMA.

H2 SMSs significantly influence trust.

H3 Trust affects the SMA.

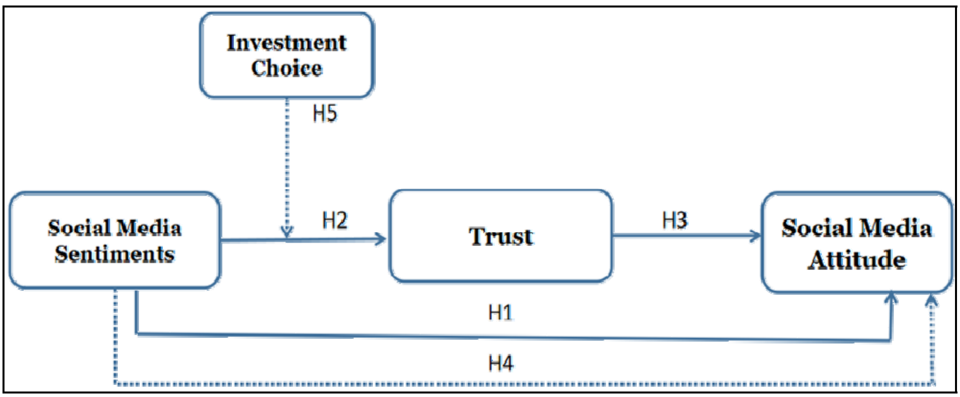
H4 Trust significantly mediates the relationship between SMSs and SMA.

H5 Investment choice positively moderates the relationship between SMSs and trust.

3 Conceptual framework

Based on behavioural finance theories such as prospect theory, mental accounting bias, information processing bias, etc. it is essential to understand the behaviour of human beings. Figure 1 is the conceptual framework of the present report. The objective is to determine whether an investor's trust in SMSs influences SMAs while making investment decisions. SMA is the dependent variable (DV), whereas SMSs of Twitter, Facebook, and YouTube are independent variables (IV). Trust is the mediator variable, and Investment choice is the moderator variable.

Figure 1 Conceptual framework (see online version for colours)



Source: Author's proposed model

4 Theoretical background

According to the efficient market hypothesis (EMH) theory by Fama (1965), stock pricing is based on market data and is always exchanged at a fair price. This means that investors could not purchase inexpensive supplies or sell overvalued stocks. In other words, the EMH asserted that the latest information has already been integrated into stock values, and the present and previous data cannot facilitate investors to predict future prices. The theoretical backdrop has discussed the evolution of modern Behavioural finance ideas from classical finance theories. Black and Scholes (1973) revolutionised the financial approach and established the groundwork for the explosive rise of the derivatives market. These finance theories are based on the concept of a rational man.

As a result, the study aims to present and explain the most relevant arguments in behavioural finance and its ability to understand markets. Under specific circumstances, traditional finance theory, defined by the expected utility theory and the EMH, could not explain the behaviour of investor choices and investment characteristics. This has inspired additional financial modules to discover the features influencing an investor's decision-making in several situations.

The prospect theory, proposed by Black and Scholes (1973), disputed the expected utility theory, which claims that investors must select among risky holdings by equating utility values based on the chance of occurrence. That utility is contingent on existing means. On the other hand, prospect theory suggests that people buy from the middle of two preferences that have both risk and premium in terms of anticipated utility returns. Individuals choose between probabilistic alternatives in their investment approach. As a result, behavioural finance has evolved as a new finance branch that studies how people or groups' distinct psychological aspects operate as investors, analysts, or portfolio managers.

Behavioural finance focuses on the psychology of individuals and aims to comprehend how emotions and cognitive errors manipulate the behaviour of individual investors (De Bondt and Thaler, 1985).

The relationship between behavioural finance components and asset return is presented in two opposing financial theories: classical and behavioural finance theories. According to classical finance theory, prices are not influenced by behavioural finance aspects because arbitragers' transactions neutralise demand, limiting the potential impact of emotional investors. On the contrary, behavioural finance theory holds that behavioural finance aspects impact asset values. Traditional asset price methods are challenging to use and have trouble describing value in this new ecosystem (Naughton, 2002).

5 Research methodology

5.1 Variables and measurement

The population under this study are the retail investors of the Indian stock market who actively invest in stocks. The attitude of the investors towards social media is considered a DV. The purchase and sale of stocks represent the investors' investment decisions in the stock market. Therefore, the investment choices of the investors are measured by the investors' response to the purchase and sale of stocks. To calculate the attitudes mentioned above, a structured questionnaire was constructed. A five-point Likert scale was employed to measure items of each construct. The scale ranged from 1 to 5, which conveys the feeling of strongly disagree to strongly agree for each of the questions.

5.2 Sample size

An exploratory study was conducted to analyse the objectives and the proposed hypotheses. As per the August 2022 report of SEBI, the equity market all over India has 4,828 registered stockbrokers. Each population unit contributing to the study is part of the sample frame. The study incorporates 175 broking firms as its sample. For the survey, two respondents from the 175 brokerage firms were selected. The questionnaire was sent to 350 individuals, out of which 279 accurate responses were received. 71 responses were not considered, as some did not reply, and the remaining responses were incorrect in the study of behavioural finance.

5.3 Sources of data collection

There are 23 questions about investing habits, social media participation, sentiments, points of view, and investment choices. There are three distinct categories in the survey. The first is based on a person's demographic profile; the second is on data collected from social media such as news outlets, websites, blogs, platforms, etc. and the third is on the elements that affect people's attitudes on social media. Research studies were conducted to analyse the influence of SMSs on SMAs in the Indian stock market, and these findings were used to validate the questionnaire.

To ensure that a single dimension could represent all variables, exploratory factor analysis (varimax rotation and principal component analysis extraction methods) was used. In total, 126 participants were chosen to participate in the pilot study.

Data were acquired in two stages, representative and random sampling. A stratified sample of 25 Indian stock market security businesses was selected in the first stage. The security businesses' brokers were contacted in the following step to obtain support and approval for the data collection procedures. Just one Indian state was used to get the data. Purposive sampling was used in the second phase. It provides better responses and conserves resources and time. The sample was obtained through stock market brokers using a standardised questionnaire given to individual investors. Academic authorities have reviewed and evaluated this research process. The experts considered advice and viewpoints without changing the inquiries' essence.

5.4 Data analysis

The anticipated research relationship has been tested using the structural equation modelling technique. It is a statistical technique for evaluating the cause-and-effect relationship between a set of constructs characterised by multiple measurable variables/items in a single model. SEM was chosen because it directly determines observable and latent correlations among the variables and establishes their relationship (Hair, 2011; Sarstedt et al., 2019). There are two approaches.

The co-variance based technique (CB-SEM) and variance-based partial least square (PLS-SEM) (Hair et al., 2012). PLS-SEM is created to care for reflective and formative constructs, unlike CB-SEM works only with reflective constructs. Similarly, it runs well with non-normally distributed data. It is customised to carry small sample sizes instead of covariance-based structural equation modelling, which usually utilises large sample sizes to assess model parameters (Sarstedt et al., 2019).

SEM is a group of statistical techniques for calculating the causal relationship and association between each variable over the range of visible indicators and more than two suppressed variables. Its primary goal is to increase the variance of the DVs supported by the IVs (Haenlein and Kaplan, 2004; Hirshleifer, 2015).

This investigation confirmed the suggested research model using the variance-based or PLS approach. The link between the variables is examined using the model. This model has two components:

1 Measurement model that assists in assessing the reliability and validity of the construct.

2 Structural model that helps in assessing the relationship between variables.

5.5 Sample characteristics

Table 1 Respondent profile

Variables	*Categories*	*Frequency*	*%*
Gender	Male	167	60
	Female	112	40
Age	18–25	99	35.43
	25–35	128	46.00
	35–45	39	14.00
	45–55	11	3.71
	Above 55	2	0.86
Education	High school and above	10	3.43
	Undergraduate	100	36.00
	Postgraduate	155	55.43
	Other	14	5.14
Employment status	Unemployed	40	14.57
	Employed	175	62.57
	Self-employed	64	22.86
Marital status	Married	202	72.54
	Unmarried	77	27.46

Source: Data has been collected on the author's end

6 Assessment of a measurement model

6.1 Reliability indicator

The primary stage of internal reliability is examining the indicator loadings: loading above 0.708 is recommended. Construction validity measures the extent to which the results obtained using measures align with the theories on which the model is established. The loading factor of the items can be used to check the measurement model's validity (Hair et al., 2012). Table 2 shows that the construct on which all the items are loaded significantly confirms the content's validity. For all things, the loading factor is more than 0.7, i.e., considered significant and shows the product and the construction fit well because the number squared suggests the construct score comprises at least 50% of the variable's variance (Hair et al., 2012).

The average variance extracted (AVE) ranges from 0.54 to 0.89. The recommended value is more than 0.5. Table 3 shows the AVE values for Facebook, Twitter, YouTube, SMSs, SMA, and trust are 0.560, 0.622, 0.515, 0.650, 0.716, and 0.770, respectively.

Composite reliability and Cronbach's alpha were used to evaluate the construct's reliability (CR). The model's internal consistency reliability is tested using composite reliability. It sets the higher dependability estimation and has a similar cut-off value of 0.70 and above. For this, the more excellent value represents a greater level of reliability. The items are weighted and established on the construct indicator.

Table 2 Indicator loadings

Abbreviations		*1*	*2*	*3*	*4*	*5*
Facebook (FB)	FB1	0.819				
	FB1	0.691				
	FB2	0.743				
	FB2	0.743				
	FB3	0.783				
	FB3	0.743				
	FB4	0.641				
	FB4	0.743				
	FB5	0.604				
	FB5	0.707				
Social media attitude (SMA)	SMA1		0.849			
	SMA2		0.815			
	SMA3		0.850			
	SMA4		0.871			
Trust (T)	T1				0.765	
	T2				0.991	
	T3				0.903	
	T4				0.894	
	T5				0.818	
Twitter (TW)	TW1			0.715		
	TW1			0.625		
	TW2			0.833		
	TW2			0.762		
	TW3			0.777		
	TW3			0.713		
	TW4			0.781		
	TW4			0.746		
	TW5			0.805		
	TW5			0.731		
	TW6			0.817		
	TW6			0.741		
YouTube (YT)	YT1					0.871
	YT1					0.559
	YT2					0.720
	YT2					0.659
	YT3					0.688
	YT3					0.759

Source: Author's own calculation

Table 3 Internal consistency and convergent validity

Indicator	*Cronbach's alpha*	*rho_A*	*Composite reliability*	*Average variance*
Extracted (AVE)				
Facebook	0.782	0.779	0.759	0.560
SMA	0.910	0.910	0.910	0.716
SMS	0.889	0.905	0.889	0.650
Trust	0.943	0.949	0.943	0.770
Twitter	0.907	0.909	0.908	0.622
YouTube	0.839	0.857	0.838	0.515

Source: Author's own calculation

Cronbach's alpha (a) is a measure of internal consistency that should be greater than (0.70). It measures the reliability of the construct. It gives less value as compared to composite reliability. The Cronbach alpha and composite reliability values are more than the recommended value of 0.7 (Runco and Albert, 1985; Sarstedt et al., 2019). All reliability matters are near 0.9, implying high uniformity among all items of the constructs. Both reliability measures are acceptable and in line with the suggested values.

It also checks the internal consistency reliability of the model. Reliability would be more sensitive to the number of items. For this, small numbers usually result in more reliability, and many scale items tend to have high reliability, but Cronbach's alpha is an older mean to calculate reliability. Therefore, an alternative as 'rho A' was proposed by (Dijkstra and Henseler, 2015), which is considered a precise measure of CR. The value of rho_A should be between the alpha value and reliability value.

6.2 Discriminant validity

In structural equation modelling, the next stage is examining the discriminant reliability that measures the differentiation in the constructs. Each of the constructs in the study has its identity and is different from the other constructs (Dijkstra and Henseler, 2015; Sarstedt et al., 2019). The related product's exterior loading should be higher than other structures (cross loading). The discriminant validity is confirmed by Table 4, which provides the cross-loading matrix. Cross loadings and (Fornell and Larcker, 1981) criteria are utilised to test it. The value is the square root of AVE for a particular construct should be higher than all the correlations with all other constructs. Each item's outer loading with its construction should be higher than the exterior loading with other constructs (cross loading). Table 4, which shows the cross-loading matrix, confirms discriminant validity.

6.3 Heterotrait-monotrait ratio

It is a modern method to establish discriminant validity. It is also based on correlations. The value should be less than 0.8. In some cases, there is (0.90). The discriminant validity is established because it is less than 0.85. The two criteria were deemed insufficient for determining discriminatory validity. As a result, the heterotrait-monotrait (HTMT) correlation ratio was constructed by Henseler et al. (2015). This criterion also evaluates complete correlation and enhances discriminatory validity measurements.

According to HTMT, a correlation value of less than one between two variables indicates that the variables are separate. For example, the HTMT ratio of network capacity development to organisational function in Table 5 is 0.5363, which suggests that these two factors are distinct.

Table 4 Fornell and Larcker

	FB	*SMA*	*SMS*	*Trust*	*TW*	*YT*
FB	0.748					
SMA	0.419	0.846				
SMS	0.925	0.539	0.806			
Trust	0.377	0.507	0.385	0.877		
TW	0.626	0.542	0.985	0.352	0.788	
YT	0.535	0.271	0.755	0.189	0.411	0.717

Source: Author's own calculation

Table 5 HTMT ratio

Indicator	*FB*	*SMA*	*SMS*	*Trust*	*TW*	*YT*
FB						
SMA	0.396					
SMS	0.937	0.521				
Trust	0.364	0.505	0.376			
TW	0.576	0.543	0.921	0.350		
YT	0.505	0.271	0.844	0.179	0.403	

Source: Author's own calculation

7 Assessment of a structural model

The structural model was calculated using the Smart-PLS software's 5,000 bootstrap approach. The model fitness was assessed using standardised root mean square (SRMR) values. According to Henseler et al. (2015), the SRMR should be less than 0.08, while Cho et al. (2020) found that for a sample size of less than 100, the SRMR should be less than 0.08. This study shows a suitable level of model fitness with an SRMR value of (0.06). Table 6 encapsulates the outcome of the structural model using PLS-SEM analysis. The structural model is shown in Figure 2. The R-square values for the model are 0.67 and 0.33, which means that the model explains 67% and 33% variance in the DVs (SMA and trust), respectively. The three antecedents of SMA explain a 67% variance in SMA. Further, SMA is an exogenous variable that defines a 33% variance in trust.

7.1 Predictive relevance of the model (Q^2)

The quality of the PLS path model is evaluated using Q^2 statistics and is computed under blind conditions (Tenenhaus and Esposito Vinzi, 2005). Q^2 was assessed using a cross-validated communality scale. The cross-verified redundancy threshold value is zero. Therefore, the construct's predictive accuracy is reasonable if cross-verified redundancy values are more significant than zero. The findings of the blindfolding test reveal that the path model has good predictive validity.

Table 6 R^2, Q^2 and F^2

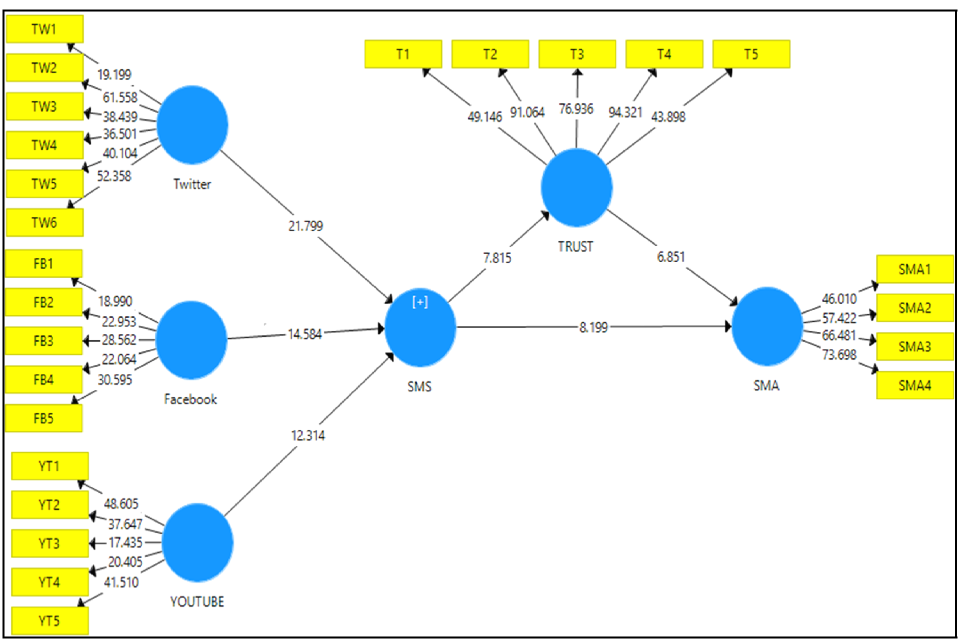
Construct	R^2	*Adj.* R^2	Q^2	F^2	*SRMR*
SMA	0.67	0.393	0.446	0.038	0.06
TRUST	0.33	0.146	0.099		

Source: Author's own calculation

7.2 *Measuring the effect size (f^2)*

The f^2 value determines the impact of each exogenous latent construct on the endogenous latent construct. The coefficient of determination (R^2) changes when an independent construct is removed from the path model, indicating whether the removed latent exogenous construct significantly impacts the value of the latent endogenous construct. Additionally, F^2 is shown as small (0.02), medium (0.15), and significant (0.35) (Gignac and Szodorai, 2016; Tenenhaus and Esposito Vinzi, 2005), and if the f^2 value is less than 0.02, there is no effect. Moreover, the findings show a significant impact (0.038).

Figure 2 Framework of factors affecting SMSs (see online version for colours)



Source: The model is structured through smart PLS

7.3 Path coefficients interpretation

This section describes the path coefficients using PLS-SEM. The path coefficients are expressed using standardised regression coefficients. The values of the path coefficient range from (+1) to (–1). The closer values to (+1) indicate a strong positive relationship, whereas the (–1) value indicates a negative relationship. Zero signifies no relationship between endogenous and exogenous variables. The results show that SMSs positively and significantly influenced trust, as shown in Table 7 (β = 0.11, t = 2.832, p = <0.005). Furthermore, trust entirely influenced the SMA (β = 0.36, t = 7.170, p = <0.000).

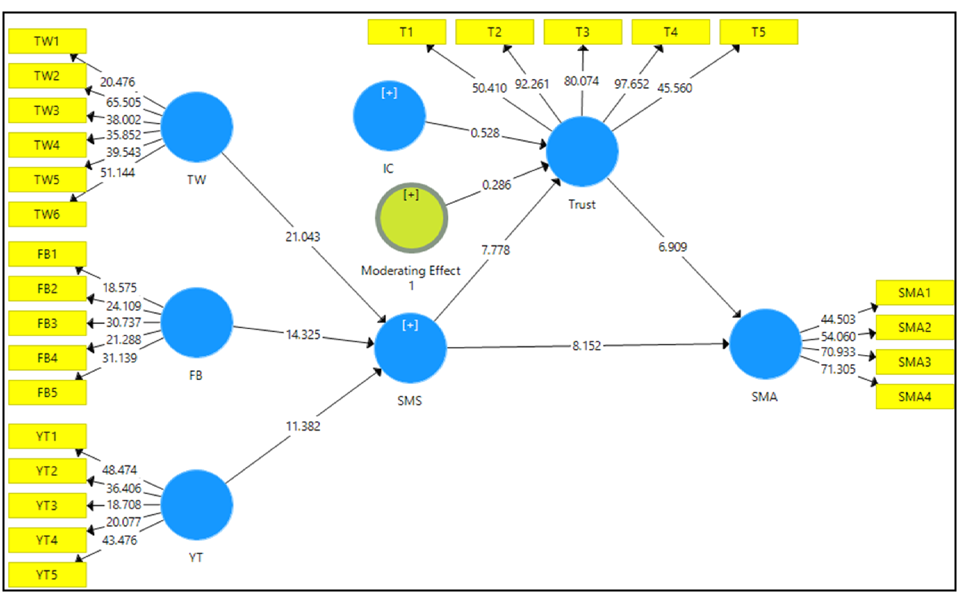
Similarly, SMSs positively and significantly influence SMA (β = 0.27, t = 17.427, p = <0.000). Moreover, a recent study discovered the significance of indirect consequences through the bootstrapping method.

Table 7 Summary of hypothesis

Hypothesis	*Structural relationships*	*β*	*Standard error*	*t-value*	*P values*	*Decision*
Direct						
Hypothesis 1	SMS	0.11	0.039	2.832	0.005	Supported
Hypothesis 2	TRUST	0.36	0.021	7.170	0.000	Supported
Hypothesis 3	SMS	0.27	0.029	17.427	0.000	Supported
Indirect or mediating/moderating						
Hypothesis 4	SMS	0.11	0.036	3.191	0.002	Supported
Hypothesis 5	SMS	0.020	0.071	0.286	0.775	Not supported

Source: Author's own calculation

Figure 3 SEM model moderation (see online version for colours)



Source: The model is structured through smart PLS

7.4 Trust as a mediating factor

According to Baron and Kenny (1986), the relation comprises the third construct that explains the relationship between the IVs and DVs. A variable may be considered a mediator to the degree to which it impacts a given IV to a given DV. The effect of variable SMSs as an independent construct on the SMA as a dependent construct is mediated by variable trust. Trust significantly variates SMA (β = 0.11, t = 3.191, p = <0.002), and trust in SMA was positive and significant.

7.5 Investment choice as a moderation factor

The study also talks about the strength and weaknesses of a relationship by considering Investment choice as a moderator to predict the investment choice decision moderation mechanism between SMSs and trust. Table 5 and Figure 3 show that investment choice has negatively and insignificantly moderated the relationship between SMSs and trust (β = 0.020, t = 0.286, p = <0.775). H5 is not supported.

8 Results and discussion

Nowadays, the financial requirements of investors are highly complex and far exceed the guidance given on investments. The result shows that investor's SMSs significantly influence individuals' attitudes. The present study suggests that investors should consider trust factors in the financial system while making investment decisions. The result shows that investors are making decisions based on SMSs. Investors estimate the execution of a company before deciding to purchase its stock and avoid buying risky ones. This estimation analyses the company's performance on social media and financial news channels. The model and hypotheses proposed in the study have been supported by empirical evidence.

Each variable is vital in measuring SMA and plays a significant role in measuring the attitude towards social media while making an investment decision. The study shows that trust plays a significant role in investment decision-making, and SMSs positively and significantly affect trust, so further H1 is accepted (β = 0.11, p = <0.005). Trust is widely acknowledged as an essential element in forming and developing interpersonal relationships. The ability to acquire the trust of their audience and consumers is critical to the success of many businesses and practically all news organisations. Therefore, estimating trust between people can be a good starting point for evaluating trust-based relationships.

According to research, people with more optimistic attitudes toward technology are more inclined to adopt it (Pavlou and Fygenson, 2006). Additionally, research indicates that user opinions regarding social media influence their pleasure and frequency of use. Thus, a more positive approach to social media would make users happier with their experience and encourage them to take on more active roles, such as commenting and mentioning, instead of simply liking and following (Shin et al., 2008). The findings further revealed that trust and SMSs significantly affected SMAs, supporting H2 (β = 0.36, p = <0.000).

The research on factor trust indicates that many high-net-worth investors use social media and pay attention to their colleagues' comments. However, another study demonstrates that a lack of trust might have negative consequences because investors may want to examine other investment alternatives (Khadim et al., 2018). Therefore, an investor should investigate the trust factor related to SMSs, and trust affects the SMA H3 ($\beta = 0.36$, $p = <0.000$).

According to Khong et al. (2013), the investor's empowerment or the presence of psychological and structural circumstances through users' views of greater ability to share information and access and complete transactions on social media platforms builds trust. Hence H4 is supported ($\beta = 0.11$, $p = <0.002$).

The result explained that Investment choice negatively and insignificantly moderates the relationship between SMSs and trust. Hence H5 is not supported ($\beta = 0.020$, $p = <0.775$).

9 Conclusions

The investment decision is crucial to choose the best option out of alternatives to achieve better returns. From a practical perspective, investors could potentially use SMSs in their trading strategies. The anticipating power of SMS for stock returns may influence market participants' trading decisions. Governments consistently make more effort to encourage people to accumulate capital. This study fills the gap in the body of knowledge regarding how social media influences investors' decision-making process. Investors are interested in precise stock market forecasts. The changes in the stock market are essential for examining the external factors that affect stock performance, and this information may also impact investor's behaviour. Constant technological advancements have transformed investor social media usage. Social media is simple to use and has a large user base. It is vital that marketers, content providers, and advertisers consider it an essential aspect of communication since it has influenced and revolutionised the role of the internet in people's lives. The study establishes the role of trust in changing investors' attitudes toward social media-related information to make better investment decisions.

10 Implications

This study confirms the presence and influence of social interaction on the relationship between SMSs and attitudes. In a way, the study develops the trust and confidence of individual investors and stock market analysts to consider the aspect of SMSs. As a result, individual investors are ready to make new investments to increase their chances of earning a profit, but they should tread carefully while choosing a new investment strategy.

Most investors consider trust a personal finance road map that enables them to look honestly at their financial state, as identifying financial objectives and risk tolerance is the first stage in achieving investment success. In addition, the amount of cash available for investment should be the first consideration for investors, as this is another aspect associated with their investment behaviour. According to the research, people are more willing to take chances with smaller quantities of money than with more significant sums. The tendency towards 'loss aversion' justifies this conclusion as Kahneman and Tversky (2013) stated that people prefer avoiding loss versus making a profit.

Based on the results, it can be calculated that the 'loss aversion' factor automatically vanishes when the trust factor is there. According to Agnihotri et al. (2012), practical guidance for a social media approach to be successful is setting clear objectives that drive information sharing, collecting information about competitors, and observing performance. Given the outcomes of this study, it is evident that this guidance must be followed to maximise investors' satisfaction with investment decisions using social media.

This study's findings suggest that investors' trust is directly proportional to their risk-taking capacity. SMSs can indirectly impact acceptance; thus, it is positively related to investor satisfaction and investment decision-making in the Indian stock market. Businesses should worry about managing their social media accounts on Facebook, Twitter, LinkedIn, and YouTube because social media has tremendously shown to be extremely important in the changes occurring in stock prices.

They should implement the essential procedures, awareness campaigns, and marketing strategies every company follows nowadays. In addition, collecting insights from numerous social networks make it easier to develop models that can disclose valuable information about the behaviours of multiple stakeholders to anticipate future trends.

11 Future direction of the study

For future studies, a more systematic technique for determining social media news will obtain better results for stock market prediction. Another possible direction for future research is to use other social media data, such as Stock Twits and Instagram, to compare their effects on the stock market prediction. Furthermore, future research may examine the applicability of the results in various contexts. In addition, future research could examine whether the same factors are significant in various contexts by sampling different types of investors, thereby enhancing our understanding of the social media use phenomenon. Additionally, it would be interesting to study the various levels of attitude and the factors that influence SMA. In addition, future research could examine the mediating effect of socio-demographic factors on SMAs, which could yield fascinating insights.

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