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IMPACT OF SOCIAL MEDIA INFLUENCERS ON RETAIL INVESTORS' STOCK MARKET DECISIONS: A BEHAVIOURAL FINANCE PERSPECTIVE

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Abstract *The study investigates the influence of social media influencers (SMIs) on retail investors' stock market decisions from a behavioural finance perspective. Utilising a quantitative, cross-sectional survey methodology, data were collected from 300 retail investors in India who actively follow financial influencers on platforms such as Instagram, LinkedIn, and X (formerly Twitter). The study examines the extent of reliance on influencers, the role of influencer credibility (IC), and the emotional triggers (ET) such as fear of missing out (FOMO) that shape investment behaviours. Structural equation modelling (SEM) via Amos and descriptive statistics were employed to analyse the data. Findings reveal that SMIs significantly impact retail investors' decisions, with ET acting as mediating variables, while IC has a nuanced, sometimes inverse effect. The results highlight the behavioural biases that influence retail investors and underscore the growing importance of digital platforms in shaping financial literacy and investment strategies. The study contributes to the literature by linking behavioural finance with digital engagement, offering insights for improving investor awareness, curbing misinformation, and encouraging responsible financial communication on social media.*

Keywords: *Social Media Influencers, Retail Investors, Behavioural Finance, Stock Market Decisions, Emotional Triggers, Structural Equation Modelling*

INTRODUCTION

The decision-making process is only one area where the utilisation of social media platforms has grown pervasive. One area where the proliferation of social media has had an effect is investment choices in the banking sector. Investors may obtain knowledge, learn from their peers, and make educated investment decisions, thanks to the ease of access to information and the capacity to interact with a wider network. Research on the effects of social media on financial decision making has attracted attention from academics since it sheds light on the ways in which users' actions on investment platforms are shaped by social media (Hwang, 2023).

Utilising social media channels for the sake of investing is nothing new. To facilitate the exchange of ideas, opinions, and experiences among investors, online investment groups have been around for a while. With the advent of social media, however, these groups have grown and changed, with investors now having more opportunities than ever to network with one another, as well as with investment professionals, financial advisers, and experts in the field. Investors are increasingly turning to social media sites such as Facebook, LinkedIn, and X (formerly Twitter) for news and information about various industries, businesses, and the stock market (Massaro et al., 2017).

In recent years, social media has become a major source of information, influencing what people buy and how they make financial choices. Stock market investors are looking to social media influencers (SMIs) for help instead of traditional financial experts. Influencers have many followers and can persuade people, making them strong sources for sharing

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financial knowledge. Their ability to influence people has increased interest in how this affects retail buyers' choices in the stock market. SMIs have a strong effect on younger people such as millennials and Gen Z (Mistri et al., 2020). They rely on influencers more than traditional financial experts. This change in how people receive financial help brings both opportunities and challenges when it comes to how investors act and how the market works.

Behavioural finance looks at how psychological and emotional factors affect how people make investment choices. It helps explain how SMIs can impact regular investors' actions in the stock market. Traditional finance theory believes that investors make smart choices based on the information and facts available in the market. Behavioural finance understands that people's feelings, biases, and social influences can lead them to make choices that are not always logical. SMIs tap into these biases, such as herding behaviour, overconfidence, and the availability heuristic, to affect the investment decisions of their followers. For instance, when an influencer recommends a certain stock, it can make their followers feel like it is a good choice (Sánchez-Fernández & Jiménez-Castillo, 2021). As a result, many followers may buy the stock without checking it out for themselves. This behaviour is often motivated by the need to fit in with a group or not to miss out on possible benefits. This keeps SMIs involved in people's financial choices.

Social media leaders often take advantage of herding behaviour, which is when people tend to follow what others do, especially when they are unsure. Retail investors might feel pressured to buy a stock just because an influencer or a popular group is pushing it, even if they do not completely understand the investment or its risks (Lal et al., 2020). This group behaviour can cause market problems, making stock prices influenced more by social trends than by real business values. Also, being overly confident affects how people make business choices based on social media. Influencers often act like experts, which makes their fans trust their suggestions. This can cause everyday investors to think they know more than they do or trust the information too much, which can affect their investment decisions without considering the risks involved (Chatzigeorgiou, 2017).

The emotional contagion theory explains how social media leaders affect the choices of retail investors. Emotional contagion is when one person's feelings, like joy or fear, spread to someone else. SMIs are good at connecting emotionally with their followers, either by creating excitement about a stock or making people feel afraid of losing out on a chance to invest profitably. Emotional involvement can increase the biases that affect investment choices. This can cause regular investors to make quick or emotionally based decisions that do not match their long-term financial goals. For example, when an influencer shares an exciting post about a 'hot stock', it can create a surge of interest among their followers, leading them to spend without really thinking about the company's actual financial health (Debreceny et al., 2017).

While people are starting to realise how social media affects investment choices, there is not enough detailed study that combines behavioural finance theories with how social media influences everyday investors in the stock market. Some studies have shown that social media affects financial decisions, but not many have looked at how certain psychological ideas – such as following the crowd, being overly confident, and catching others' emotions – work with social media to impact how investors act. This gap in the literature shows the importance of further research to understand the psychological processes at play when retail investors make stock market decisions based on influencer recommendations. By exploring these behavioural dynamics, researchers can gain a better insight into the forces driving stock market movements in the digital age (Saivasan & Lokhande, 2022).

Objectives of the Study

- To examine the extent to which retail investors rely on SMIs for stock market decisions.
- To analyse the influence of SMIs' credibility (e.g., expertise, trustworthiness) on retail investors' investment decisions.
- To study the role of emotions triggered by SMIs in shaping retail investors' stock market behaviour.
- To provide recommendations for retail investors on mitigating potential risks associated with relying on SMIs for stock market decisions.

LITERATURE REVIEW

Vrontis et al. (2021) looked into the rise of influencer marketing (IM) and the role that SMIs play in shaping customer decisions. There was a need for a thorough systematic evaluation because study in this area was still scattered, despite the fact that it was of great academic and practical interest. Findings included important themes, mediators, moderators, and contextual variables influencing consumer behaviour; the study builds it was integrative multidimensional framework by reviewing 68 papers from 29 journals listed by the Chartered Association of Business Schools. Similarly, Dim (2020) investigated the world of social media investment analysts (SMAs) and how they impact the financial markets, uncovering the fact that individuals depend on these amateurs for investing advice. The study discovered that SMAs with a high level of skill, which makes up 13% of the total, can provide far larger abnormal returns than SMAs with a lower level of skill, when machine learning was used to infer their stock opinions. In addition, SMAs were prone to behavioural biases including herding and extrapolating from previous results; nevertheless, these biases did not always result in bad investment decisions. Taken together, these studies showed how social media was becoming an integral part of consumer and investor decision making. Digital influencers, whether in marketing or finance, play an important role in influencing current economic behaviours.

Chung et al. (2020) examined the monetary effects of companies' social media communication methods; posting good comments to customer remarks had no effect on market performance, but responding quickly to negative messages has a favourable effect. Through an analysis of financial indices and X data, Valle-Cruz et al. (2022) investigated the impact of financial sentiment on stock market behaviour, finding a correlation between sentiment on X and market movements that was time-lagged, especially during the pandemic.

Gupta and Goyal (2024) looked at how millennials' herding behaviour and the impact of social connections vary by gender, and how they are comparable in terms of influencer selection, but different when it comes to familial influence, with girls being more influenced by their parents and siblings. Contrary to popular belief, their regression model reveals that both sexes seek advice from specialists, but they mostly follow the herd when it comes to financial decisions, influenced by recommendations from friends and family. Meanwhile, Al-Okaily et al. (2023) investigated the elements that propelled the incorporation of AIS hosted in the cloud amid the COVID-19 pandemic, building upon the Unified Theory of Acceptance and Use of Technology (UTAUT).

Lee and Theokary (2021) investigated the monetary achievement of SMIs by applying an elaboration likelihood model of persuasion based on language expectancy theory and emotional contagion theory. In contrast to previous study on persuasion, their study using structural equation modelling (SEM), surveys, speech-to-text analysis, and archive data reveals that viewers of superstar influencers place a higher value on emotional contagion and linguistic style than on content and production expertise. Meanwhile, Nofer and Hinz (2015) examined the impact of online sentiment on the German stock market by sifting through almost 100 million tweets published between 2011 and 2013. Although their initial analysis did not directly link X mood to stock market volatility, a strong association was revealed when they account for mood contagion through follower impact. Their study results in a trading approach that, in just six months, increases a portfolio's value by 36%.

Lim et al. (2017) studied the efficacy of advertising campaigns featuring SMIs, with a focus on reaching a younger demographic and increasing brands' visibility on these platforms. In the study, the author looked into how customer attitude mediated the relationship between influencer traits including source legitimacy, attractiveness, product match-up, and meaning transmission. The study highlighted the significance of consumer perception in influencer marketing by using partial least squares (PLS)-SEM on a dataset consisting of 200 respondents. It found support for all hypotheses except source credibility. In a similar vein Kumar et al. (2024) investigated how fear of missing out (FOMO) and investment intention mediate the connection between behavioural biases and investment choices made by retail investors in India. They found that herding, overconfidence, and loss aversion biases greatly affect investing intention and FOMO in two cross-sectional quantitative investigations. The first study included 405 self-employed individuals, while the second included 393 paid investors. Both groups were affected by herding and loss aversion when it comes to investment decisions, but self-employed investors were not impacted by overconfidence bias. Financial analysts and investors can benefit from the study's theoretical framework, which incorporates FOMO and investment intention into investment decision making. The study makes a contribution to behavioural finance. Whether it was flaws in financial decision making or influencer marketing tactics, both studies show how psychological and social factors impact investor and consumer behaviour.

Saxton and Guo (2020) asserted that the overwhelming majority of organisations' engagement with social media sites such as Instagram, Facebook, and X stems from the conviction that doing so can produce both material and immaterial benefits. To better comprehend the acquisition, expenditure, and possible contribution of 'social media capital' to organisational results, they present the idea of this resource as a novel kind and offer a framework for doing so. This was of utmost importance when it comes to calculating ROI and creating flexible accounting systems that utilised real-time data analytics. Along the same lines**,** Ren et al. (2024) delved into the ways social media acts as a magnet for conventional media, particularly as it pertains to the financial market. They showed that stock-related social media posts, particularly those with a more passionate or positive tone, can greatly impact the number of people who watch news stories about that stock in the future. Their study highlighted the importance of social media as an amplification tool, demonstrating that it was more than simply a conduit for information; it also stimulated interest in more conventional forms of media, bringing new energy to the interplay between different types of media ecosystems. Both studies showed that social media was becoming an increasingly important strategic tool and attention driver in the digital era, impacting both organisational behaviour and media consumption.

Lee and Raschke (2023) determined the effects of sustainable practices on Environmental, Social, and Governance (ESG) performance and financial results, with a specific emphasis on the increasing pressure on enterprises to implement these practices as a result of stakeholder activism. The authors used legitimacy theory to investigate the extent to which ethical ESG activities contribute to ESG performance and the potential impact of ESG performance on financial outcomes. Their study indicated that green washing was more common among companies with low ESG performance, even though it has little bearing on financial results in and of itself. During the COVID-19 epidemic, Mishra et al. (2023) examined how investors acted in relation to mutual funds in light of the growing digital landscape and the impact of social media. They find that attitude, awareness, and investment involvement were important factors in investment intention using a combination of SEM and Artificial Neural Network (ANN) techniques; meanwhile, they find that social media influence and herd behaviour have no substantial effect on investment choices. Financial analysts and planners can learn from their study on the importance of self-efficacy, perceived utility, and subjective norms in influencing investors' attitudes and intentions towards investing. In today's technologically advanced and socially conscious world, both studies highlight the changing dynamics of corporate practices and investing behaviour.

RESEARCH METHODOLOGY

A researcher's methodology outlines the approach and execution of a study or investigation aimed at addressing a certain issue or question. A clearly articulated research methodology underpins the entire study process. It outlines the process of collecting pertinent information, evaluating hypotheses, and deriving conclusions. It also tackles sample concerns, data collection procedures, data analysis techniques, and ethical considerations pertinent to the study process.

Hypothesis Formulation

Based on the research questions and objectives, the following hypotheses (assumptions) are made:

H1: Retail investors significantly rely on SMIs' recommendations for making stock market decisions.

H2: The credibility of SMIs positively impacts retail investors' stock market decision making.

H3: Emotional triggers (ET), such as FOMO and excitement, mediated by SMIs, significantly influence retail investors' stock market behaviour.

Research Design

To examine how SMIs affect the decision-making process of retail investors, this study used a quantitative, cross-sectional survey methodology. The project will use a structured questionnaire to gather primary data from retail investors who are active on social media and follow financial influencers on platforms such as Instagram, LinkedIn, and X. In this study, SMIs and the credibility of those influencers will serve as the independent variables, while the stock market decision-making behaviour of retail investors will be the dependent variable. ET, such as FOMO and excitement, will be examined as mediating variables. Contributing to the larger subject of behavioural finance, this study seeks to offer empirical insights into the ways in which SMIs' behavioural biases impact the financial decisions of retail investors.

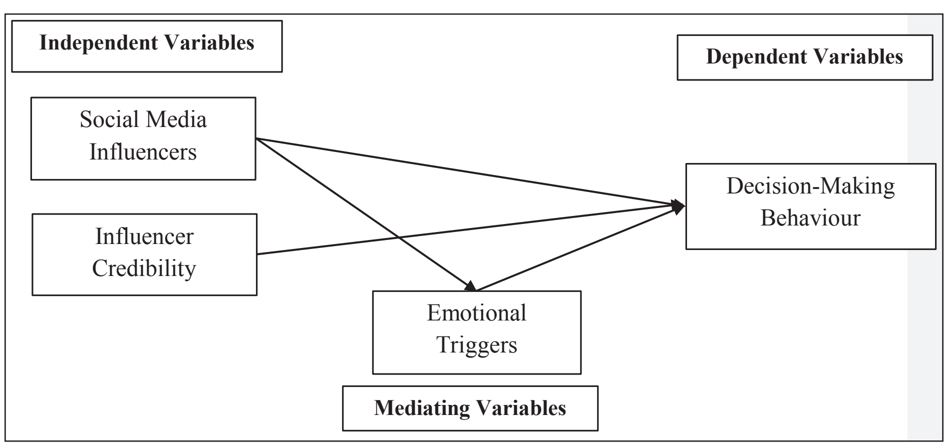

Fig. 1: Research Model

Data Collection and Sample Size of the Study

The study's data comes from a structured survey that asked participants to fill out a questionnaire on their experiences trading and investing in stocks. The main sources of information are online communities where retail investors often go for financial advice, such as investing groups, social media communities, and forums. The questionnaire is designed to measure three things: how much people rely on SMIs for investment decisions (H1), how much people believe these influencers and how it affects decision making (H2), and how much of an impact ET such as FOMO and excitement have on retail investors' behaviour (H3). The questions are close-ended and measured on a Likert scale, so for example, 1 = strongly disagree and 5 = strongly agree. We will also collect demographic information such as age, investment experience, how often people use social media to get financial insights, and how much risk-taking they are willing to do in order to account for differences in investor profiles. The method of sampling is based on a purposive sample strategy, and it aims to reach retail investors who are regular users of social media for financial content, such as Instagram, LinkedIn, and X.

To ensure a comprehensive evaluation, the study's sample size was selected from 300 retail investors from India. This sample captures a wide range of perspectives and experiences because it includes people from different demographic origins and sectors. Purposive sampling was used to select participants from a wide range of ages, occupations, and regions. The response rate was 84.5%, meaning that 338 out of 400 surveys were returned. However, 38 of those responses were null and void because they were either incomplete or incorrect.

Data Analysis Method

From a behavioural finance standpoint, this study uses a mix of Amos and Excel to conduct SEM and descriptive statistics to analyse how SMIs affect retail investors' stock market decisions. To have a better understanding of the dataset's distribution and normalcy, Excel is initially utilised for data preprocessing tasks such as data cleaning, missing value treatment, and basic descriptive statistics. For the purpose of conducting hypothesis testing, SEM and confirmatory factor analysis (CFA) are implemented in IBM SPSS Amos 25.0. By evaluating reliability (Cronbach's alpha, Composite Reliability), construct validity, and convergent and discriminant validity (AVE, factor loadings), CFA ensures that the measurement model is legitimate. Using SEM, we will evaluate the model by looking at the mediated and direct links between the variables. The purpose of this path analysis in Amos is to test three hypotheses: first, that SMIs have an effect on retail investors' decisions (H1), second, that influencer credibility (IC) plays a role (H2), and third, that ET serve as a mediating variable (H3), with the help of bootstrapping modelling. As a means of checking whether the model is adequate, we will look at model fit indices such as Chi-square/df ratio, RMSEA, SRMR, and CFI. A strong statistical framework is created by combining these methodologies to comprehend the behavioural effect of SMIs on the stock market decisions made by individual investors.

DATA ANALYSIS AND RESULTS

Demographic Profile

Table 1: Demographic Profile of Retail Investors

Sr. No.	Demographic Factors	Category	N	%
1	Age	20–30 years	72	24.00%
		31–40 years	80	26.70%
		41–50 years	74	24.70%
		Above 50 years	74	24.70%
2	Gender	Female	152	50.70%
		Male	148	49.30%
3	Educational Qualification	Undergraduate	114	38.00%
		Postgraduate	88	29.30%
		Professional Degree	58	19.30%
		Others	40	13.30%

Sr. No.	Demographic Factors	Category	N	%
4	Occupation	Business Owner/Self-employed	66	22.00%
		Salaried Employee (Public/Private)	86	28.70%
		Part-time Employee	65	21.70%
		Retired	41	13.70%
		Others	42	14.00%
5	Monthly Income	INR25,000–INR50,000	83	27.70%
		INR50,001–INR1,00,000	69	23.00%
		INR1,00,001 –INR2,00,000	63	21.00%
		Above INR2,00,000	85	28.30%
6	Investment Experience in Stock Market	Less than 1 year	68	22.70%
		1–3 years	72	24.00%
		4–7 years	82	27.30%
		More than 7 years	78	26.00%
7	Average Monthly Investment in Stock Market	Below INR10,000	79	26.30%
		INR10,001–INR50,000	73	24.30%
		INR50,001–INR1,00,000	65	21.70%
		Above INR1,00,000	83	27.70%
8	How often do you consume stock market-related content from social media influencers?	Daily	60	20.00%
		Weekly	99	33.00%
		Occasionally	92	30.70%
		Never	49	16.30%

Source: Authors' own calculation.

There is diversity among retail investors based on their demographic profile. According to age, the largest group is between the ages 31 and 40 (26.7%), followed by those between the ages 41 and 50 (24.7%), and finally, those above 50 (24.7%). The gender breakdown among investors is quite even, with 50.7% being female and 49.3% being male. Regarding educational qualification, the majority have bachelor's degrees (38%), followed by 29.3% with master's degrees, and 19.3% with doctoral degrees. When broken down by occupation, the biggest category is salaried employees at 28.7%, followed by self-employed people at 22.2%, and finally, part-timers at 21.7%. There is a very even distribution of monthly incomes; 28.3% make more than INR2,00,000, while 27.7% earn between INR25,000 and INR50,000. While 26.3% have been in the investment industry for more than seven years, 27.3% have been in the industry for four to seven years. About 27.7% of the investors put more than INR1,00,000 into their accounts every month, while 26.3% put less than INR10,000. Among social media users, 33% consume stock market-related content weekly, 30.7% rarely, and 20% daily, all of which have an impact on investment behaviour.

Assessment of Measurement Model

Both the measurement and structural models are analysed using the Amos 23.0 program. To estimate the parameters of the structural model and investigate the measurement model's psychometric features, statistical software is employed. This study examines all four of the main validity and reliability tests in detail: discriminant validity, convergent validity, indicator reliability, and internal consistency reliability. Following this, you will see the results of all the studies that were carried out to check the reliability and validity of the measurement model.

When evaluating the reliability of measuring instruments, one common method is Cronbach's alpha (CA). Building supplies of superior grade, the items included in the construct were all of similar range and importance, according to CA (Cronbach, 1971). To determine reliability, one may use CA by looking at the correlations between the variables. Composite reliability (CR) (Chin, 2009) is used to find the internal consistency in SEM. While both CR and CA evaluate internal consistency, the latter considers the fact that indicator loadings could fluctuate. Results for CR and CA are displayed in Table 2. CR ratings ranged from 0.800 to 0.912, while CA values were between 0.803 and 0.910. Both statistical measures of construct dependability are more than 0.70, which means that construct dependability has been shown.

When the average variance extracted (AVE) of a construction is 0.5 or higher, it is said to have reached its AVE, according to Fornell and Larcker (1981). The Convergent Validity of a measurement model can be ascertained by looking at its AVE value. The constructs are said to have good convergent validity when their AVE is 0.5 or higher. From the Convergent Validity study, the AVE statistics can be seen in Table 2. The measurement model exhibits good convergent validity, as seen in Table 2, where the AVE ranges from 0.751 to 0.820.

When a concept's square root of AVE is greater than its correlation with all other concepts, discriminant validity is proven, according to Fornell and Larcker (1981). You can see that a construct's square root of AVE is bigger than its correlation with other constructs in Table 3, which provides the results of discriminant validity 'Fornell and Larcker's criteria (FL)' for indicators. Therefore, it provides evidence in favour of the discriminant validity scenario.

Cross-loadings are useful for getting access when an object from one construct loads tightly onto its parent construct instead of any other construct. Factor loadings for all items are higher on the underlying construct to which they belong rather than the other construct, as seen in Table 4, which presents the findings of cross-loadings of indicators and items. Consequently, discriminant validity has been attained according to the study of the cross-loadings.

Table 2: Factors Loading with Communality and Redundancy, Convergent Validity, Reliability, and Internal Composite Reliability

Construct	Items	Factor Loadings	Communality	Redundancy (p-Value)	Average Variance Extracted (AVE)	Cronbach's α	Composite Reliability (Dillon-Goldstein's Rho)
SMI					0.820	0.910	0.912
	SMI1	0.827	0.740	0.000			
	SMI2	0.819	0.713	0.000			
	SMI3	0.856	0.777	0.000			
	SMI4	0.773	0.690	0.000			
	SMI5	0.826	0.734	0.000			
IC					0.812	0.905	0.907
	IC1	0.886	0.798	0.000			
	IC2	0.803	0.716	0.000			
	IC3	0.788	0.674	0.000			
	IC4	0.795	0.701	0.000			
	IC5	0.787	0.680	0.000			
DMB					0.808	0.901	0.905
	DMB1	0.787	0.672	0.000			
	DMB2	0.796	0.707	0.000			
	DMB3	0.775	0.688	0.000			
	DMB4	0.909	0.831	0.000			
	DMB5	0.773	0.637	0.000			
ET					0.751	0.803	0.800
	ET3	0.614	0.636	0.000			
	ET4	0.757	0.749	0.000			
	ET5	0.883	0.688	0.000			

Source: Authors' own calculation.

Table 3: Discriminant Validity (Fornell-Larcker Criterion: Correlation Matrix of Constructs and Square Root of AVE)

	SMI	IC	DMB	ET
SMI	0.906			
IC	0.709	0.901		
DMB	0.418	0.268	0.899	
ET	0.338	0.21	0.425	0.867

Source: Authors' own calculation.

Table 4: Cross-Loadings of Measurement Model

	DMB	IC	SMI	ET
DMB				
DMB4	**.905**	.142	.059	.083
DMB5	**.821**	.108	.076	.095
DMB3	.809	-.019	.204	.018
DMB2	**.806**	-.004	.229	.033
DMB1	**.792**	.115	SMI.181	.060
IC				
IC1	.118	**.811**	.340	.096
IC4	.008	**.802**	.250	.076
IC2	.034	**.797**	.268	.132
IC3	.125	**.789**	.230	.117
IC5	.109	**.772**	.279	.104
SMI				
SMI1	.175	.290	**.806**	.016
SMI3	.261	.266	**.786**	.138
SMI5	.183	.291	**.778**	.124
SMI2	.189	.304	**.773**	.086
SMI4	.076	.373	**.721**	.174
ET				
ET4	.014	-.026	.218	**.845**
ET5	.007	.267	.110	**.820**
ET3	.409	.216	-.011	**.620**

Source: Authors' own calculation.

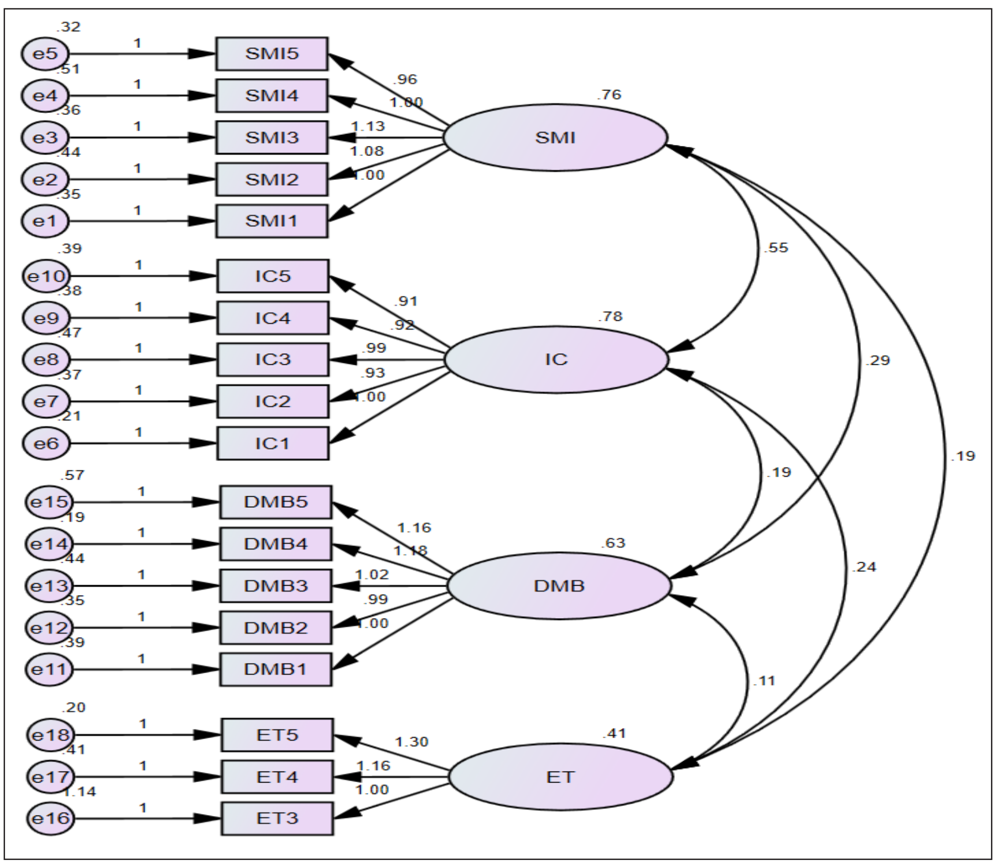

Fig. 2: Measurement Model

Assessment of Structural Model

Research on the prediction capability and component-to-component links is at the heart of structural model assessment (Hair et al., 2016). All of the building's parts and their known relationships are included in the structural model. The structural model shows how the latent variables interact with each other. Structural equation modelling's hypothesis testing phase looks into the proposed link. Hypothesis testing (path coefficient magnitude and significance), model fit, and collinearity statistics are used to evaluate the structural model. Two methods for assessing the validity of a structural model are detailed below: first, by looking at the route coefficients; and second, by doing hypothesis testing.

The structural model shows a satisfactory match to the data, according to the goodness-of-fit indices in Table 5. A goodness-of-fit index (GFI) of 0.910 is considered adequate, as it surpasses the recommended level of 0.90 (Hair et al., 2010). Similarly, the model appears to be adequate, since the adjusted GFI (AGFI) is 0.855, which is higher than the minimal acceptable value of 0.80 (Hu & Bentler, 1999). The model's robustness is further reinforced by the fact that both the normed fit index (NFI) and the comparative fit index (CFI) are greater than 0.90, which is the recommended criterion (Bentler & Paul, 1996). The standardised root mean square residual (SRMR) is 0.066, which is close to the suggested cut-off of < 0.07 (Hu & Bentler, 1999), and the root mean square error of approximation (RMSEA) is 0.073, which is within the acceptable range of < 0.08. In addition, the model fit is satisfactory. The findings show that the structural model is good enough to continue on to the next stage of analysis because it satisfies the good-fit criterion.

The structural model and hypothesis testing pertaining to retail investors' dependence on SMIs in stock market decision making (DMB) are thoroughly examined in Table 6. A normalised estimate of 0.395, a t-value of 4.134, and a p-value of .000 indicate a large and statistically significant positive effect, lending credence to Hypothesis H1, which states that retail investors heavily depend on recommendations from SMIs. A negative standardised estimate of -0.076, a t-value of -1.931, and a p-value of .012 further support Hypothesis H2, which examines the role of IC in stock market decision making. These results imply that, although credibility does impact decision making, the relationship is weak and inverse, possibly because people are skeptical of influencer recommendations. A standardised estimate of 0.125, a t-value of 1.507, and a p-value of .031 support Hypothesis H3, which tests the mediating role of ET such as FOMO and excitement in the influence of SMIs on stock market behaviour. This confirms that ET significantly shapes investor behaviour through influencer-driven content. All things considered, these results show that SMIs have a complicated but important role in influencing the financial decisions of retail investors, with credibility having a subtle effect and emotions playing a critical mediating function.

Table 5: Goodness of Model Fit

Fit Indices	Structural Model Value	Recommended Value	References
GFI	.910	> .90	Hair et al. (2010)
AGFI	.855	> .80	Hu and Bentler (1999)
NFI	.906	> .90	Bentler and Paul (1996)
CFI	.940	> .90	Bentler and Paul (1996)
RMSEA	.073	< .08	Hu and Bentler (1999)
SRMR	.066	< .07	Hu and Bentler (1999)

Table 6: Hypothesis Testing and Structural Model Evaluation

Sr. No.	Hypothesis Testing	Standardised Estimates	t-Value	p-Value	Results
H1	SMII□DMB	0.395	4.134	.000	Supported
H2	IC□DMB	-0.076	-1.931	.012	Supported
H3	SMI□ET □ DMB	0.125	1.507	.031	Supported

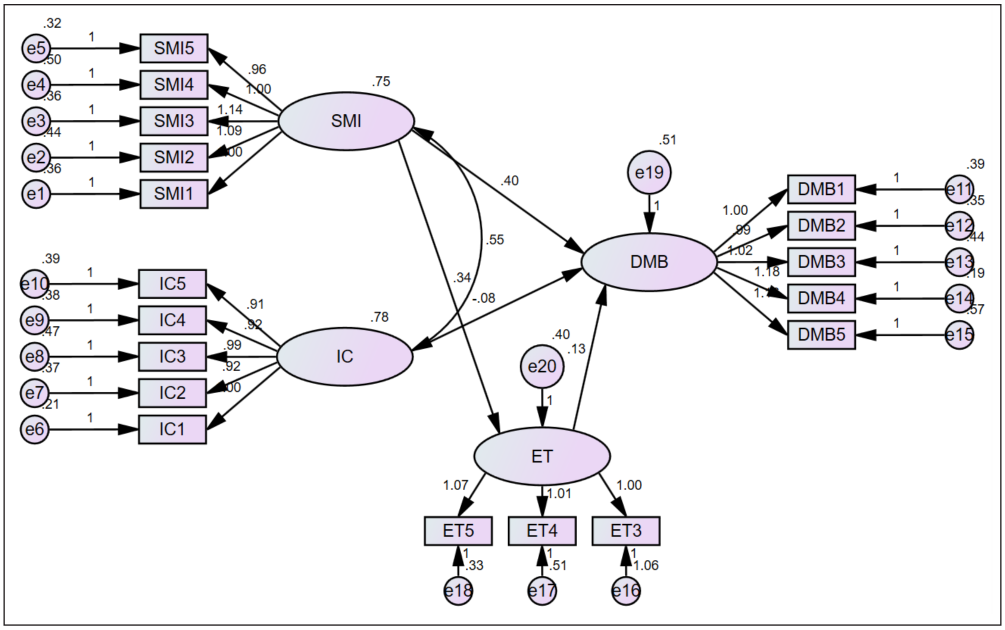

Fig. 3: Structural Model

CONCLUSION

Findings from the study corroborate the importance of SMIs in influencing the stock market choices of individual investors. Although there is a complex relationship between IC and other factors, ET such as FOMO play a substantial mediating role. The results show that retail investors should carefully consider how social media affects their financial decisions and that it is crucial to comprehend behavioural finance concepts in relation to digital information consumption. Investors' information consumption, processing, and action upon that information are all impacted by the ubiquitous and multidimensional influence of social media. The line between influencer-driven content and professional financial advice is blurring as digital platforms grow more integrated into daily life, which presents new opportunities and difficulties for investors. Impulsive or ill-informed financial choices may result from the emotional engagement encouraged by influencers, which is frequently magnified by the immediacy and connectivity of social media. Having said this, the same connectedness also makes financial information more accessible, which opens the stock market to a wider range of people. Due to the two-sided nature of this effect, it is important to teach investors to control their emotions and not let them get in the way of making the most of social media. A key task for policymakers and financial educators is to steer this changing landscape in a way that maximises the benefits of digital financial guidance while limiting its risks. Emotional intelligence and critical thinking are just as important as conventional financial literacy in today's complex digital financial ecosystem, as this study shows.

LIMITATIONS

Despite its contributions, the study has several limitations. The sample is restricted to retail investors in India, which may limit the generalisability of the findings to other regions. The reliance on self-reported data could introduce biases such as social desirability bias. In addition, the cross-sectional design captures a snapshot in time, limiting the ability to infer causality.

Future research could address these limitations by incorporating longitudinal designs, expanding the sample to include international investors, and employing experimental methods to establish causal relationships.

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