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A Multifactorial Analysis of Herding Behavior in the Stock Market: A Theory-Driven Survey in the Tehran Stock Exchange

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ABSTRACT

Herding behavior in the stock market disrupts market efficiency as investors imitate others instead of relying on independent analysis. This study examines the impact of Trust in Economic News (TEN), Social Media Influence (SMI), Market Volatility (MV), Behavioral Triggers (BT), and External Economic Factors (EEF) on herding behavior, particularly among Millennials and Gen-Z investors. A survey of 350 retail and institutional investors was conducted in 2025, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with Smart PLS 3.2.9. The results show that MV is the strongest driver of herding behavior (β = 0.470, p = 0.000), while SMI (β = 0.368, p = 0.000) and TEN (β = 0.287, p = 0.000) amplify the influence of economic news and social media. Additionally, BT (β = 0.393, p = 0.000) and EEF (β = 0.236, p = 0.000) significantly contribute to herding through emotional and systemic mechanisms. The novelty of this study lies in its comprehensive analysis of the combined influence of cognitive, social, and macroeconomic factors on herding behavior in the stock market, offering both theoretical and practical insights for understanding investor behavior. This research highlights the crucial role of psychological, social, and economic factors in shaping herding behavior.

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1. Introduction

Herding behavior in the stock market, where investors align their actions with those of others rather than making independent decisions (Christie & Huang, 1995), is influenced by the evolving dynamics of modern financial markets. These markets, shaped by digital platforms, real-time news dissemination, and global interconnectivity, have introduced new dimensions to the understanding of this phenomenon. Factors such as trust in economic news, the influence of social media, market volatility, behavioral triggers, and external economic conditions now play significant roles in shaping investor decision-making, particularly during periods of market uncertainty. The role of trust in economic news has been well-documented in behavioral finance literature. The trust investors place in news outlets, whether traditional media or more recent digital platforms, affects their perception of market conditions and, consequently, their investment decisions. Studies have demonstrated that investors' responses to news are often irrational, influenced by psychological biases and social influences. This is especially true when news is ambiguous or conflicting. Tetlock (2011) observed that overreaction and underreaction to economic news can distort market behavior, leading to inefficiencies in pricing and herding. However, as Bollen et al. (2011) argue, social media has exacerbated these dynamics, offering both a source of misinformation and a platform for collective sentiment, which in turn influences investor behavior on a broader scale. The interplay between economic news and social media enhances the speed and spread of sentiments, further magnifying herding behavior. The rise of social media in recent years has increasingly become a significant information source for investors (Chiou, Knewtson, & Nofsinger, 2019). These platforms, including Twitter, Facebook, and Telegram, have the power to shape investor sentiment and promote herding behavior by offering instant access to news, opinions, and rumors. Research by Baker and Wurgler (2006) indicates that social media sentiment can forecast stock returns, but the fast spread of unverified content also increases the likelihood of irrational decision-making. In times of market volatility, investors are more prone to follow the crowd rather than conduct independent analysis, amplifying herding behavior. Moreover, social media's influence is closely linked to trust in economic news, as digital platforms serve as key channels for news dissemination, reinforcing collective decision-making. Similarly, Signorelli et al. (2021) find that market downturns and increased volatility lead to heightened instances of herding behavior, as uncertainty causes investors to mimic others' decisions during periods of loss anticipation. This behavior aligns with Loss Aversion, where emotional responses drive investors to act defensively to avoid perceived losses, inadvertently intensifying market fluctuations. Moreover, Behavioral Triggers such as Social Validation in Decision Making, Herding in Losses, Overconfidence, and Confirmation Bias play critical roles in shaping investor behavior. External economic factors including political news, macroeconomic updates (e.g., inflation, GDP), and global events like recessions or trade wars significantly influence investor behavior by amplifying uncertainty and triggering herding tendencies, especially during crises such as the COVID-19 pandemic or geopolitical conflicts. These events heighten fear and information asymmetry, leading investors to follow perceived consensus as a risk-avoidance strategy rather than relying on fundamentals. Political shifts, interest rate changes, and economic indicators intensify emotional reactions, reinforcing irrational market behavior and increasing volatility through collective decision-making patterns. The impact of external economic factors is not isolated but interacts with all other factors, from news trust to behavioral triggers, compounding the collective impact on investor behavior. Despite the growing body of research on individual factors affecting herding behavior, there is a significant gap in the literature concerning the interdependencies between trust in economic news, social media influence, market volatility, behavioral triggers, and external economic factors. Most studies have examined these variables in isolation, neglecting their cumulative effects. As markets become more interconnected and information flows more rapidly, understanding how these factors interact to shape herding behavior has become increasingly important for both academics and practitioners. This study addresses a critical gap in behavioral finance by examining the multifactorial drivers of herding behavior, namely trust in news, social media influence, market volatility, behavioral triggers, and external economic factors, using data from 350 stock market investors. Unlike prior research that focuses on isolated variables, this study explores the dynamic interdependencies among these factors under varying market conditions, particularly within the unique context of emerging markets. By adopting a comprehensive approach, it offers both theoretical insights and practical recommendations for investors and regulators, enhancing the understanding of how these variables collectively shape herding behavior.

The paper is organized as follows: *Section* 1, Introduction, provides the research background, states the problem, outlines the research objectives, and highlights the significance of the study. *Section* 2, Literature Review, critically examines existing research, identifies gaps in the literature, and justifies the need for the current study. *Section* 3, Methodology, details the research design, data collection methods, and analytical techniques used in the study. *Section* 4, Results, presents the findings of the analysis, including statistical data and relevant visuals. Finally, *Section* 5, Conclusion and Discussion, interprets the results, compares them with existing studies, explores their implications, and summarizes the key findings. This section also reflects on the study's significance and suggests directions for future research.

2. Literature Review

The dynamics of stock market and investor behavior have been subjects of substantial academic inquiry over the past few decades, particularly in the context of understanding herding behavior a phenomenon in which individuals in a group act collectively in a similar manner, often disregarding their own private information. This review explores the interdependent effects of trust in economic news, social media influence, market volatility, behavioral triggers, and external economic factors on herding behavior, focusing on studies that have shaped our understanding of these interconnected factors.

2-1. Trust in Economic News and Herding Behavior

Trust in economic news plays a critical role in shaping investor decisions, particularly under conditions of uncertainty and market volatility. When individuals perceive economic news as credible, they are more inclined to base their investment choices on it, thereby reinforcing herd behavior (Bikhchandani, Hirshleifer, & Welch, 1992). Numerous studies have explored this relationship, highlighting that high trust in news sources increases the likelihood of investors following suggested market trends (Barberis & Thaler, 2003). This effect becomes more pronounced during financial crises, where heightened uncertainty enhances reliance on authoritative news outlets, triggering collective responses to market shocks. However, the accuracy of economic news critically moderates this dynamic; misleading or speculative reports can fuel irrational behavior, intensifying market volatility and herding tendencies (Akerlof & Shiller, 2010). Moreover, evidence shows that price manipulation and deceptive headlines further exacerbate herding by generating false signals of market stability or distress.

2-2. Social Media Influence in Shaping Herding Behavior

The rise of social media has transformed how investors access and share financial information, with platforms like Telegram, Twitter, and financial blogs influencing market perceptions through rapid dissemination of insights, opinions, and rumors. A key example is the 2020 stock market crisis in Iran, where social media amplified market movements and investor behavior. Research highlights social media's impact on investor sentiment and herding behavior, such as Allcott and Gentzkow (2017), who found that emotional posts can drive herding behavior, and Antweiler and Frank (2004), who linked online discussions to market movements beyond fundamentals. The spread of information via social media, including phenomena like information cascades (Bikhchandani et al., 1992), exacerbates herding effects, as individuals often follow others based on incomplete data. Anonymity and high interaction on these platforms increase individuals' tendency to conform. Additionally, algorithmic trading and social media bots have further amplified social media's influence on market dynamics.

2-3. Market Volatility and Herding Behavior

Volatility acts as a critical catalyst for herding behavior by undermining individual decision-making and prompting investors to mimic others rather than rely on independent analysis (Camerer, 2011). This dynamic often creates a feedback loop where intensified buying or selling further escalates market volatility. Froot, Scharfstein, and Stein (1992) attribute herding during extreme volatility to dispositional factors like risk and loss aversion, where fear of losses or missing gains drives synchronized market actions. Such effects are amplified in high-frequency trading environments, where the trades of a few can rapidly propagate across the market, triggering widespread imitation (Shleifer & Summers, 1990). Additionally, volatility-induced overreactions excessive portfolio adjustments based on recent price shifts foster herding as investors erroneously believe that following the crowd reduces risk (Nofsinger, 2017).

2-4. Behavioral Triggers and Their Impact on Herding

The impact of Behavioral Triggers on investor herding behavior in the stock market is comprehensively presented in Table 1.

Table 1 Behavioral Triggers and Their Impact on Herding Behavior in Stock Market

Behavioral Trigger	Description	Mechanism of Herding Influence	Related References
Confirmation Bias	The tendency to favor information that confirms existing beliefs while ignoring contradictory data	Investors selectively seek out information aligning with group behavior (e.g., bullish sentiment), reinforcing herd actions. This creates a feedback loop that fuels overvaluation and potential asset bubbles	You (2025)
Overconfidence Bias	Investors overestimate their predictive abilities and judgment accuracy, especially during bullish markets	Believing in superior insight, investors follow herd behavior with increased assurance, ignoring downside risks. This reinforces collective overconfidence and inflated asset prices	Bernile (2025)
Loss Aversion	A psychological preference to avoid losses more strongly than achieving equivalent gains	Investors join mass sell-offs during downturns to avoid further losses, amplifying negative herding and accelerating price declines	Dolder &Vandenbroucke (2024)
Herding in Losses	Behavioral response to fear and crisis-driven market sell-offs	Fear of further loss (FOMO) and psychological pressure drive investors to mimic mass behavior, creating informational cascades and market instability	Bikhchandani, Hirshleifer & Welch (1992)
Social Validation	The inclination to conform based on observing others' behavior in uncertain situations	Perceived legitimacy of group actions leads investors to mimic decisions during market volatility, reinforcing both upward and downward herding cycles	Cialdini (2007)

Source: Authors' Findings

2-5. External Economic Factors Influencing Herding Behavior in Stock Market

Factors such as Political News, Macroeconomic News (GDP, Inflation, Employment), Global Economic Events (Recessions, Trade Wars), and Inflation and Interest Rates play a significant role in shaping herding behavior among investors, as detailed in Table 2.

Table 2. External Economic Factors Influencing Herding Behavior in Stock Market

External Factor	Description	Mechanism of Herding Influence	Related References
Political News	Political developments (e.g., elections, sanctions, policies) shape investor sentiment and trigger collective actions.	Uncertainty arising from political instability prompts herding toward safe assets (e.g., gold, bonds), while favorable news (e.g., trade agreements) encourages collective risk-taking.	Bloom et al. (2007)
Macroeconomic News *(GDP, Inflation, Employment)*	Macroeconomic indicators signal economic health and influence market-wide sentiment.	Positive indicators (e.g., GDP growth, falling unemployment) generate optimism and mass buying; negative data triggers panic selling. Investors tend to overreact to macro signals rather than assess fundamentals.	Chen et al. (2014); Fama (1981); Baker et al. (2006)
Global Economic Events *(Recessions, Trade Wars)*	Events like financial crises and trade conflicts elevate market uncertainty and drive coordinated investor reactions.	Investors collectively exit riskier markets or flock to safe havens (e.g., during the 2008 crisis or U.S.–China trade war), amplifying market volatility and price distortions.	Bikhchandani et al. (1992); Chen et al. (2014); Han & Li (2017)

External Factor	Description	Mechanism of Herding Influence	Related References
Inflation and Interest Rates	Fluctuations in inflation and monetary policy significantly influence collective investment behavior.	High inflation leads to herding into real assets (e.g., gold); low interest rates push investors into riskier assets. Tightening policies trigger panic selling, while easing leads to speculative bubbles.	Fama (1981); Thaler (1980); Daniel et al. (1998);

Source: Authors' Findings

2-6. Hypothesis Development and Research Model

In this section, we examine the hypotheses of the research.

H1: *Trust in economic news positively influences investor herding behavior during periods of market uncertainty.*

H2: *Social media influence positively amplifies investor herding behavior, particularly during periods of market volatility.*

H3: *Market volatility positively strengthens investor herding behavior, especially when combined with high levels of trust in economic news and social media influence.*

H4: *Behavioral triggers, such as Confirmation Bias, Social Validation in Decision Making, Herding in Losses, Loss Aversion, and Overconfidence, positively influence investor herding behavior during unpredictable market conditions.*

H5: *External economic factors, including global economic factors, such as inflation rates, macroeconomic news (GDP, inflation), political news, and global economic events (recessions, trade wars), positively influence investor herding behavior, particularly when combined with trust in economic news and social media influence.*

In Figure 1, the connections between the variables in the research model are visually represented, with each hypothesis clearly associated with its corresponding component.

Fig 1. Investor Herding Behavior: A Conceptual Model Mediated by Hypothesized Relationships
Sources: Authors' Findings

3. Research methodology

3-1. Research design

This study uses a quantitative, cross-sectional research design to examine the interdependent effects of six key variables: trust in economic news, social media influence, market volatility, external economic factors, behavioral triggers, and investor herding behavior on investor decision-making in the stock market. Conducted in 2025 through a theoretical questionnaire among 350 investors, the study analyzes how psychological and external economic factors collectively influence herding tendencies in investor behavior.

3-2. Selection of Target Population and Data Collection Methodology

This study focuses on individuals actively involved in financial decision-making and influenced by external economic events, specifically targeting Generation Z and Millennials, who are known for their active social media use and susceptibility to economic news (Baker & Nofsinger, 2010). 31 items were extracted from the questionnaire, and the evaluations were conducted using a 5-point Likert scale to ensure clarity and reliability. This scale is widely used for assessing individuals' opinions and attitudes. Using purposive sampling, respondents from these groups with experience in stock market participation during periods of volatility triggered by external economic factors were selected. The emphasis on these demographics is supported by research highlighting that younger, tech-savvy investors often exhibit unique financial behaviors, relying heavily on social cues and market sentiments, which increases their tendency for herding behavior in volatile conditions (Bikhchandani et al., 1992). Table 3 presents the Profile of Respondents.

Table 3. Profile of Respondents

Profile		**Number of Respondents**	**% Of Respondents**
Gender			
	Male	266	76.0
	Female	84	24.0
Sub-total		350	100.0
Age			
	20–25	205	58.6
	26–30	70	20.0
	31–35	35	10.0
	36–40	20	5.7
	41–45	10	2.9
	45 and above	10	2.9
Sub-total		350	100.0
Role in stock market			
	Retail Investor	187	53.4
	Financial Analyst	85	24.3
	Portfolio Manager	19	5.4
	Stock Broker	13	3.7
	Institutional Trader	6	1.7
	Market Researcher	29	8.3
	Investment Advisor	11	3.1
Sub-total		350	100.0

Source: Authors' Findings

Data were collected via an online questionnaire created with Google Forms and distributed through popular Iranian social media platforms such as WhatsApp, Instagram, Telegram, and Twitter to reach active stock market participants, particularly from Gen-Z and Millennial groups. The eligibility criteria required participants to (1) be at least 18 years old, (2) have a minimum of one year of active stock market involvement, (3) regularly follow financial news, and (4) engage with finance-related social media groups. Incomplete or ineligible responses were excluded, resulting in a final sample of 350 valid respondents, exceeding the recommended minimum for Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis (Sarstedt et al., 2021).

3-3. Variable Definitions, Operationalization, and Literature Support

The research variables are comprehensively presented in Table 4. This table provides a detailed overview of the key variables.

Table 4. Variable Definitions, Operationalization, and Literature Support

Variable	Operational Definitions	Related References
Trust in Economic News	The level of investor confidence in the accuracy, reliability, and credibility of economic news sources, influencing their financial decision-making behavior.	(Tetlock, 2007; Kacperczyk & Schnabl, 2010)
Social Media Influence	The perceived impact of social media platforms, influencers, and peer communication on investor perceptions and financial behavior.	(Bollen et al., 2011; Han & Li, 2017; 2021; Tetlock, 2015)
External Economic Factors	External macroeconomic indicators (e.g., inflation, interest rates, GDP, and unemployment) that influence investor behavior and market sentiment.	(Fama, 1981; Chen et al., 1986)

Variable	Operational Definitions	Related References
Investor Herding Behavior	The tendency of investors to mimic the trading actions of the majority or follow market trends, often driven by fear, uncertainty, or social pressures.	(Banerjee, 1992; Christie & Huang, 1995; Karimi & Ahadzadeh, 2024; Welch, 2000)
Behavioral Triggers	Psychological and emotional factors, such as fear, greed, overconfidence, and panic, that drive investment decisions and amplify herding behavior.	(Barberis et al., 1998; Baker & Wurgler, 200۶)
Market Volatility	The degree of variation in market prices over a specific period, often measured by indices like VIX, reflecting uncertainty and risk in financial markets.	(Black, 1976; Schwert, 1989; Fei & Liu, 2021; Guilmi et al., 2014)

Source: Authors' Findings

4. Results & Analysis

4-1. Descriptive Statistics and Visual Analysis of Key Variables

Table 5 presents the descriptive statistics of the study variables, including the minimum, maximum, mean, and standard deviation for each. These statistics provide an overview of the distribution and variability of the data. Figure 2 visually illustrates the relationships between these variables and Investor Herding Behavior, using scatter plots, bar charts, box plots, and violin plots, which highlight how each factor influences investor decision-making and herding behavior.

4-2. Normality Check of Variables: Skewness and Kurtosis Analysis

Table 6, presents the skewness and kurtosis results for each construct, indicating that all variables exhibit normal distribution characteristics. The skewness values range from -0.05 to 0.326, and the kurtosis values range from -0.429 to -0.871, all of which fall within the acceptable range for normality.

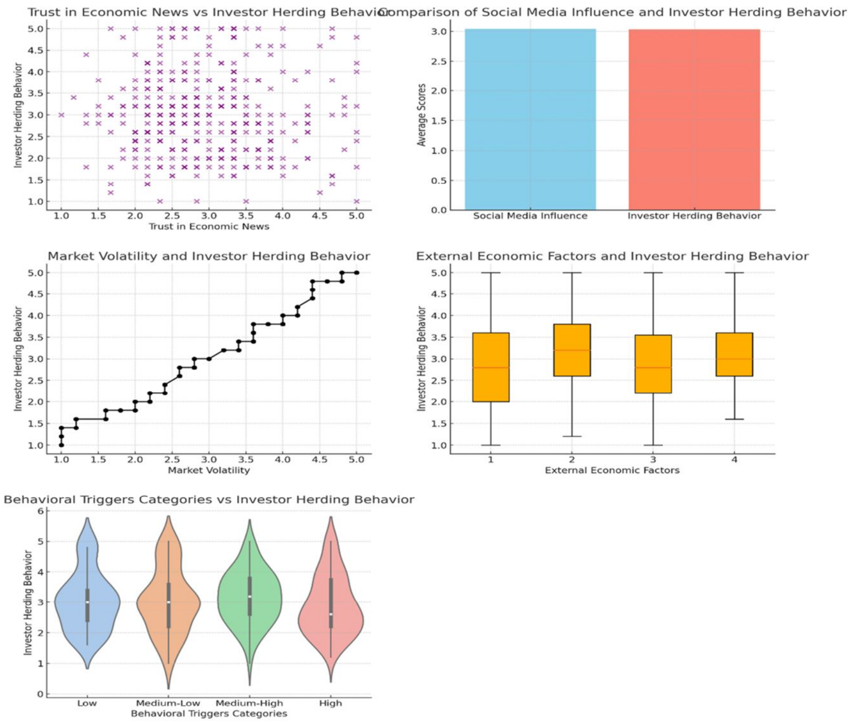

Fig 2. Analysis of Factors Influencing Investor Herding Behavior
Sources: Authors' Findings

Table 6. Skewness and Kurtosis Results

Construct	Skewness	Kurtosis	Result
Trust in Economic News	0.297	-0.429	Normal
Social Media Influence	-0.05	-0.582	Normal
Investor Herding Behavior	0.326	-0.554	Normal
Market Volatility	0.147	-0.586	Normal
External Economic Factors	0.128	-0.871	Normal
Behavioral Triggers	0.189	-0.658	Normal

Source: Authors' Findings

This is further supported by the Q-Q plots and box plots shown in Figure 3, which visually confirm that the distribution of each variable closely aligns with a normal distribution, further reinforcing the validity of the data for subsequent analyses.

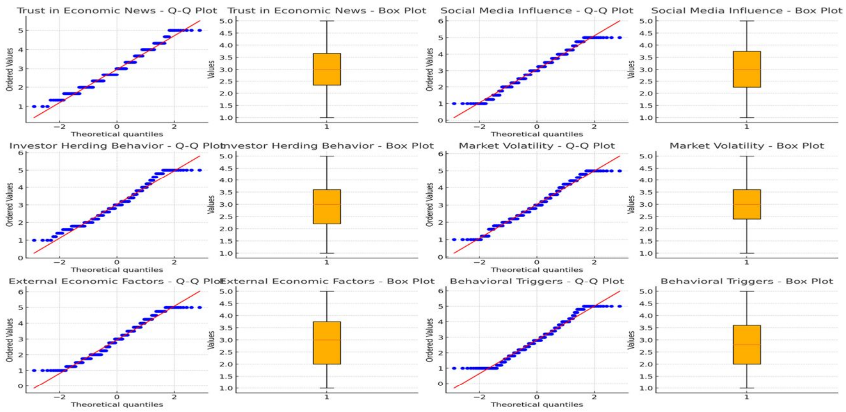

Fig 3. Normal Distribution Charts of Research Variables
Sources: Authors' Findings

4-2. Correlation Matrix

Table 7 illustrates that all correlations between the determinant factors and Investor Herding Behavior are statistically significant at the 0.01 level. This indicates that the identified determinant factors serve as robust predictors of investor herding behavior.

4-4. Evaluation of the Measurement Model in PLS-SEM Analysis

In PLS-SEM, evaluating the outer (measurement) model is the first step to ensure that observed indicators properly represent their theoretical constructs, involving key dimensions such as (1) indicator reliability, (2) latent variable reliability via composite reliability, (3) internal consistency using Cronbach's alpha and CR, (4) construct validity through AVE and discriminant validity using cross-loadings and the Fornell–Larcker criterion, and (5) HTMT for further discriminant assessment. This study assessed internal consistency and convergent validity using composite reliability, indicator reliability, and AVE, while discriminant validity was tested via cross-loadings and the Fornell–Larcker method (Fornell & Larcker, 1981).

Table 7. Correlation Matrix

		TEN	SMI	IHB	MV	EEF	BT
TEN	Pearson Correlation Sig. (2-tailed) *N*						
SMI	Pearson Correlation Sig. (2-tailed) *N*	0.185** 0.000 350					
IHB	Pearson Correlation Sig. (2-tailed) *N*	0.105** 0.000 350	0.236** 0.000 350				
MV	Pearson Correlation Sig. (2-tailed) *N*	0.116** 0.000 350	0.293** 0.000 350	0.328** 0.000 350			
EEF	Pearson Correlation Sig. (2-tailed) *N*	0.112** 0.000 350	0.103** 0.000 350	0.173** 0.000 350	0.189** 0.000 350		
BT	Pearson Correlation Sig. (2-tailed) *N*	0.151** 0.000 350	0.313** 0.000 350	0.239** 0.000 350	0.218** 0.000 350	0.130** 0.000 350	

Source: Authors' Findings

4-5. Indicator Reliability in PLS-SEM

A widely accepted criterion for assessing **indicator reliability** suggests that a latent variable should account for a significant portion of the variance in each of its indicators, typically at least 50%. This implies that the outer loading of each indicator must exceed 0.708, as the square of this value $(0.708)^2$ equals 0.50, representing 50% of the variance explained. As detailed in Table 8 and Figure 4, all indicators associated with the constructs in this model surpassed the minimum threshold for acceptable outer loadings, demonstrating robust indicator reliability (Chin, 1998).

4-6. Internal Consistency Assessment

Internal consistency reflects how reliably a set of indicators measures a latent construct, commonly assessed through Cronbach's alpha and composite reliability (CR), with acceptable thresholds above 0.70 (Cronbach, 1951). In PLS-SEM, these values range from 0 to 1, with higher scores indicating stronger reliability based on indicator intercorrelations. As shown in Table **8**, all constructs in this study surpass the 0.70 threshold for both Cronbach's alpha and CR, confirming strong internal consistency and construct reliability within the model.

4-7. Convergent Validity Assessment

Convergent validity evaluates how well multiple indicators of a construct correlate and capture the intended concept, assessed through factor loadings, composite reliability (CR), and Average Variance Extracted (AVE). According to Fornell & Larcker (1981) and Ab Hamid et al. (2017), AVE values above 0.50, CR above 0.70, and indicator loadings above 0.708 confirm adequate convergent validity. Tolerance values were calculated and all exceed the 0.1 threshold, indicating no significant multicollinearity issues. The convergent validity (CV) values were also calculated and found to be well above the threshold, further supporting the model's validity. As shown in Table 8, all constructs in this study meet these thresholds, indicating that the model demonstrates strong convergent validity across all indicators.

Table 8. Evaluation of measurement model test results

Latent Variable	Indicators	Factor Loadings	VIF	Tolerance	Cronbach's Alpha (α)	Convergent Validity (CV)	CR	AVE
Trust in Economic News	TEN1	0.827	2.135	0.468	0.761	0.838	.0890	0.575
	TEN2	0.722	1.651	0.605				
	TEN3	0.712	1.587	0.630				
	TEN4	0.747	1.762	0.568				
	TEN5	0.753	1.451	0.689				
	TEN6	0.782	1.328	0.754				
Social Media Influence	SMI1	0.745	1.345	0.743	0.829	0.723	0.870	0.574
	SMI2	0.712	1.658	0.603				
	SMI3	0.764	1.678	0.593				
	SMI4	0.713	1.326	0.754				
	SMI5	0.847	2.745	0.364				
Investor Herding Behavior	IHB1	0.725	1.523	0.656	0.77۶	0.825	0.876	۰.۵۸۷
	IHB2	0.832	2.694	0.371				
	IHB3	0.781	1.236	0.808				
	IHB4	0.789	1.478	0.676				
	IHB5	0.703	1.579	0.634				
Market Volatility	MV1	0.784	1.326	0.754	0.795	0.802	0.880	0.595
	MV2	0.715	1.365	0.732				
	MV3	0.723	1.584	0.631				
	MV4	0.864	1.233	0.811				
	MV5	0.763	1.071	0.934				
External Economic Factors	EEF1	0.756	1.368	0.731	0.854	0.701	0.873	0.581
	EEF2	0.712	1.345	0.743				
	EEF3	0.864	1.657	0.603				
	EEF4	0.723	1.019	0.980				
	EEF5	0.747	1.597	0.626				
Behavioral Triggers	BT1	0.874	1.511	0.662	0.890	0.720	0.895	0.631
	BT2	0.769	1.672	0.598				
	BT3	0.813	1.067	0.937				
	BT4	0.744	1.568	0.637				
	BT5	0.765	1.342	0.745				

Source: Authors' Findings

Figure 8 illustrates the results of the PLS-SEM model, presenting the factor loadings and path coefficients. This visualization provides a comprehensive analysis of the relationships between the latent variables and their respective indicators.

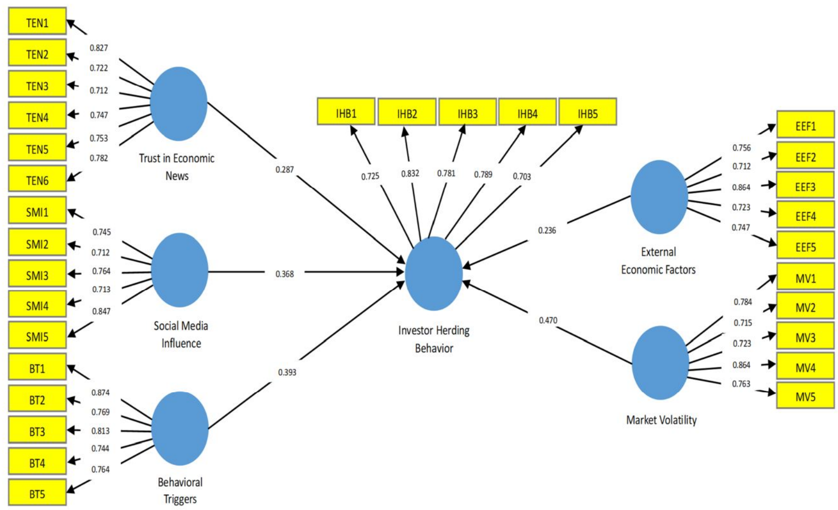

Fig 4. PLS-SEM Model: Factor Loadings and Path Coefficients Analysis
Sources: Authors' Findings

4-8. Discriminant Validity Assessment

Table 9 presents the discriminant validity assessment results using the Fornell–Larcker criterion. Discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for each construct (shown on the diagonal in bold) exceeds the correlations between that construct and all other constructs in the model (Fornell & Larcker, 1981). As shown in Table 9, the diagonal elements representing the square root of AVE for each construct (**TEN= 0.783**, **SMI= 0.798**, **IHB**=0.759, **MV**=0.813, **EEF**=0.741, **BT**=0.786) are consistently higher than their corresponding off-diagonal values, indicating that each construct shares more variance with its own indicators than with other constructs. This demonstrates that the model exhibits strong discriminant validity.

Table 9 Discriminant Validity Table

	TEN	SMI	IHB	MV	EEF	BT
TEN	**0.783**					
SMI	0.652	**0.798**				
IHB	0.427	0.631	**0.759**			
MV	0.476	0.687	0.417	**0.813**		
EEF	0.694	0.563	0.386	0.456	**0.741**	
BT	0.510	0.468	0.465	0.379	0.394	**0.786**

Source: Authors' Findings

4-9. Hypothesis Testing Results and Interpretations

Table 8. Hypothesis Test Results

Hypothesis	Path	Standardized Path Coefficient	p-Values	t-Statistics	Results
H1	Trust in Economic News → Investor Herding Behavior	0.287	0.000	3.458	Supported
H2	Social Media Influence → Investor Herding Behavior	0.368	0.000	4.523	Supported
H3	Market Volatility → Investor Herding Behavior	0.470	0.000	5.691	Supported
H4	Behavioral Triggers → Investor Herding Behavior	0.393	0.000	3.591	Supported
H5	External Economic Factors → Investor Herding Behavior	0.236	0.000	3.326	Supported

Source: Authors' Findings

H1: Trust in Economic News → Investor Herding Behavior

The results indicate that Trust in Economic News has a positive and significant influence on Investor Herding Behavior, as evidenced by the standardized path coefficient of 0.287. The p-value of 0.000 is less than the threshold of 0.05, and the t-statistic of 3.458 exceeds the critical value of 1.96. These results confirm that trust in economic news significantly contributes to herding behavior among investors, supporting H1. Moreover, based on the demographic analysis, we found that male respondents (76%) and younger age groups (especially those aged 20-25, 58.6%) exhibited higher trust in economic news, which strengthens herding behavior. These findings demonstrate the significant role of demographic characteristics in shaping the relationship between trust in economic news and investor herding.

H2: Social Media Influence → Investor Herding Behavior

Social Media Influence strongly affects Investor Herding Behavior, with a standardized path coefficient of 0.368, p-value of 0.000, and t-statistic of 4.523. This supports H2, showing that social media plays a crucial role in shaping herding behavior. Li et al. (2023) emphasize that social media accelerates herding by spreading real-time information, especially in uncertain market conditions, enhancing herd behavior. The demographic analysis shows that younger investors (particularly those in the 20-25 age group) and retail investors (53.4%) are more affected by social media, underlining the significant role of these groups in social media-driven herding behavior.

H3: Market Volatility → Investor Herding Behavior

The results show that Market Volatility significantly influences Investor Herding Behavior, with a standardized path coefficient of 0.470, p-value of 0.000, and t-statistic of 5.691. This supports H3, indicating that increased volatility amplifies herding behavior. Blasco et al. (2012) highlight that volatility drives investors to follow others, intensifying herding behavior and reinforcing the feedback loop between volatility and herding. According to the demographic analysis, male respondents (76%) and younger investors (particularly those aged 20-25, 58.6%) were more reactive to market volatility, which resulted in a stronger tendency to engage in herding behavior.

H4: Behavioral Triggers → Investor Herding Behavior

The findings suggest that Behavioral Triggers positively influence Investor Herding Behavior, with a standardized path coefficient of 0.393. The p-value of 0.000 confirms statistical significance, and the t-statistic of 3.591 exceeds the critical threshold of 1.96. These results provide robust evidence for H4, underscoring the importance of behavioral triggers as a key determinant of herding behavior in the stock market. Based on the demographic analysis, we observed that younger investors and retail investors (53.4%) were particularly sensitive to behavioral triggers, further reinforcing the relationship between behavioral cues and herding behavior among these groups.

H5: External Economic Factors → Investor Herding Behavior

The analysis shows that External Economic Factors have a significant positive effect on Investor Herding Behavior, with a standardized path coefficient of 0.236. The p-value of 0.000 and a t-statistic of 3.326 confirm the significance of this relationship. Thus, H5 is supported, indicating that external economic factors contribute to herding behavior, albeit to a lesser extent compared to other factors such as market volatility or behavioral triggers. Based on the demographic analysis, we found that financial analysts (24.3%) and institutional traders (1.7%) were more influenced by external economic factors, reflecting their greater awareness of macroeconomic conditions and their impact on market behavior.

Table 9. Results of Path Analysis: Total Indirect Effects

Path	Standardized Path Coefficient	p-values
Trust in Economic News → Social Media Influence → Investor Herding Behavior	0.143	0.000
Trust in Economic News → Market Volatility → Investor Herding Behavior	0.162	0.000
Trust in Economic News → Behavioral Triggers → Investor Herding Behavior	0.101	0.000
Trust in Economic News → External Economic Factors → Investor Herding Behavior	0.148	0.000
Social Media Influence → Trust in Economic News → Investor Herding Behavior	0.235	0.000
Social Media Influence → Market Volatility → Investor Herding Behavior	0.296	0.000
Social Media Influence → Behavioral Triggers → Investor Herding Behavior	0.174	0.000
Social Media Influence → External Economic Factors → Investor Herding Behavior	0.096	0.009
Market Volatility → Trust in Economic News → Investor Herding Behavior	0.075	0.008
Market Volatility → Social Media Influence → Investor Herding Behavior	0.279	0.000
Market Volatility → Behavioral Triggers → Investor Herding Behavior	0.285	0.000
Market Volatility → External Economic Factors → Investor Herding Behavior	0.114	0.000
Behavioral Triggers → Trust in Economic News → Investor Herding Behavior	0.074	0.008
Behavioral Triggers → Social Media Influence → Investor Herding Behavior	0.169	0.000
Behavioral Triggers → Market Volatility → Investor Herding Behavior	0.243	0.000
Behavioral Triggers → External Economic Factors → Investor Herding Behavior	0.081	0.000
External Economic Factors → Trust in Economic News → Investor Herding Behavior	0.097	0.009
External Economic Factors → Social Media Influence → Investor Herding Behavior	0.124	0.000

Path	Standardized Path Coefficient	p-values
External Economic Factors → Market Volatility → Investor Herding Behavior	0.152	0.000
External Economic Factors → Behavioral Triggers → Investor Herding Behavior	0.117	0.000

Source: Authors' Findings

5. Conclusion & Policy Recommendations

This study provides a comprehensive exploration of the multidimensional factors influencing herding behavior in stock market, focusing on the interplay between trust in economic news, social media influence, market volatility, behavioral triggers, and external economic factors. Utilizing Partial Least Square–Structural Equation Modeling (PLS-SEM), the findings offer both theoretical and practical insights, supported by key quantitative results. Market volatility emerged as the most critical determinant of herding behavior, with a standardized path coefficient of 0.470 ($p < 0.001$, t-statistic: 5.691). This highlights the dominant role of uncertainty during turbulent periods in driving collective investor actions. Social media influence also demonstrated a strong impact on herding, with a path coefficient of 0.368 ($p < 0.001$, t-statistic: 4.523), showcasing its effectiveness in rapidly spreading sentiment-driven narratives. Behavioral triggers, such as loss aversion and confirmation bias, had a significant influence on herding tendencies, as evidenced by a path coefficient of 0.393 ($p < 0.001$, t-statistic: 3.591). Trust in economic news displayed a moderate but meaningful effect, with a coefficient of 0.287 ($p < 0.001$, t-statistic: 3.458), emphasizing the importance of credible information in shaping investor sentiment. External economic factors, including macroeconomic shocks and global events, also played a notable role, with a path coefficient of 0.236 ($p < 0.001$, t-statistic: 3.326). This study also identifies 20 significant indirect pathways that illuminate the intricate mechanisms through which trust in economic news (TEN), social media influence (SMI), market volatility (MV), behavioral triggers (BT), and external economic factors (EEF) collectively shape herding behavior. TEN impacts herding through critical mediators: TEN ➔ SMI ➔ Herding (0.143) highlights how trusted news disseminated via social media fosters collective sentiment, while TEN ➔ MV ➔ Herding (0.162) underscores how reliance on credible news heightens sensitivity to market volatility during uncertainty. Similarly, TEN ➔ BT ➔ Herding (0.101) demonstrates the role of psychological biases, such as confirmation bias, in mediating trusted news, and TEN ➔ EEF ➔ Herding (0.148) shows how macroeconomic shocks interact with trust in news to validate herd-like decisions. SMI further amplifies herding through multiple channels: SMI ➔ TEN ➔ Herding (0.235) reflects its role in reinforcing reliance on economic news, while SMI ➔ MV ➔ Herding (0.296) and SMI ➔ BT ➔Herding (0.174) reveal its capacity to escalate emotional responses and reactive behaviors during volatility. SMI ➔ EEF ➔ Herding (0.096) illustrates how social media amplifies external shocks to drive collective actions. MV, as a central mediator, channels systemic and psychological effects through pathways such as MV ➔ TEN ➔ Herding (0.075) and MV ➔ SMI ➔ Herding (0.279), reinforcing the role of uncertainty in encouraging group reliance. Additionally, MV ➔ BT ➔ Herding (0.285) and MV ➔ EEF ➔ Herding (0.114) emphasize how volatility magnifies both emotional and systemic responses. BT plays a pivotal role in herding through pathways like BT ➔ TEN ➔ Herding (0.074), BT ➔ SMI ➔ Herding (0.169), and BT ➔ MV ➔ Herding (0.243), reflecting the strong influence of cognitive and emotional biases, while BT ➔ EEF ➔ Herding (0.081) highlights the interaction of psychological triggers with macroeconomic factors. Finally, EEF drives herding through EEF ➔ TEN ➔ Herding (0.097), EEF ➔ SMI ➔ Herding (0.124), EEF ➔ MV ➔ Herding (0.152), and EEF ➔ BT ➔ Herding (0.117), demonstrating how systemic shocks amplify reliance on both social and emotional mediators to foster group conformity. These pathways reveal a highly interconnected framework where psychological, social, and systemic factors collaborate to drive herding behavior. The mediatory roles of MV and BT, amplified by the emotional resonance of SMI and the systemic pressures of EEF, highlight the multidimensional nature of investor actions. Policymakers and market regulators must address these indirect influences by stabilizing volatility, ensuring the credibility of economic news, and mitigating the spread of misinformation on social platforms. Practical strategies, such as the implementation of real-time market stabilization mechanisms and partnerships with social media platforms to combat misinformation, can significantly strengthen market resilience and foster informed decision-making, reducing the risks associated with collective irrationality in the stock market.

Based on the comprehensive findings of this study, several policy implications emerge that are vital for enhancing market stability and investor protection in emerging financial markets such as the Tehran Stock Exchange. First and foremost, regulatory authorities should prioritize measures to reduce excessive market volatility, which has been identified as the strongest driver of herding behavior. For instance, the introduction of circuit breakers (like those in the US markets), which temporarily halt trading during extreme price movements, can effectively reduce the panic-driven reactions of investors. Additionally, improving market liquidity by promoting the participation of institutional investors, and increasing market transparency by mandating real-time disclosure of financial statements, would help reduce uncertainty and discourage irrational collective movements. Moreover, the influential role of social media in amplifying sentiment-driven trading underscores the necessity for stronger oversight of information dissemination on digital platforms. Policymakers should advocate for robust frameworks to combat misinformation, such as establishing collaboration agreements with social media companies to create automated systems for flagging and removing fake economic news, similar to practices in jurisdictions like the EU's Digital Services Act. Promoting the distribution of verified economic news, through partnerships with credible news agencies and public platforms, would help investors base their decisions on verified sources rather than rumors or unsubstantiated narratives. Given the pivotal role of trust in economic news in shaping investor decisions, regulators should prioritize enhancing the credibility and transparency of financial information dissemination. Policies should enforce strict standards for fact-checking, ensuring that news outlets and financial analysts provide reliable and accurate reports. An example of this could be the creation of official certification systems for financial journalists or economic data providers, similar to the Certified Financial Journalist program in the US. By encouraging such standards, investors can more easily distinguish between trustworthy and unreliable sources. Additionally, promoting investor access to timely, clear, and verified economic data (for example, by developing official government dashboards displaying up-to-date macroeconomic indicators) reduces dependence on rumor-driven narratives, especially during periods of market uncertainty.

To address cognitive biases like confirmation bias, loss aversion, and overconfidence that intensify herding, regulators and financial institutions should expand investor education and behavioral finance programs. For example, the introduction of mandatory online courses on financial literacy and behavioral biases, similar to programs offered by the UK's Financial Conduct Authority, can help investors recognize and mitigate emotional decision-making. Incorporating behavioral insights into decision-making tools and promoting "nudging" strategies in investment platforms could further encourage investors to adopt long-term investment perspectives, reducing the frequency of reactionary herd behavior during short-term market swings. Tax incentives for long-term investors (e.g., preferential tax treatment for investments held for more than five years) could also incentivize more independent decision-making. In Tehran Stock Exchange, external economic factors such as political uncertainty, inflation, GDP fluctuations, and global events stimulate herding behavior at lower levels (as indicated by the findings of this study) by increasing investor anxiety and prompting collective reactions. To reduce these effects, policymakers should improve transparency in the communication of economic and political developments, ensuring that official reports from government bodies and central banks are easily accessible and clear. Implementing macroeconomic policy measures to stabilize inflation and interest rates, such as those undertaken by the Central Bank of Iran during periods of high inflation, can help reduce reactive crowd movements. Additionally, implementing early warning systems to monitor and respond to global economic shocks, similar to systems used in the EU for monitoring currency fluctuations, would help prevent excessive volatility and irrational herding. Together, these measures will enhance market stability and encourage more informed and independent investor decision-making.

Limitations of the Study

Lack of Geographical Diversity in the Sample: The sampling is limited to a specific region (Tehran Stock Exchange), which may affect the generalizability of the findings to other financial markets or countries. Enhancing the generalizability of the results may require conducting sampling across different geographical areas.

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All authors had contribution in preparing this paper.

Conflicts of interest

The authors declare no conflict of interest

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Appendix A

The Sobel Test Results are presented in Table 11 in the section below.

Table 10 Abbreviations

TEN	Trust in Economic News
SMI	Social Media Influence
IHB	Investor Herding Behavior
MV	Market Volatility
BT	Behavioral Triggers
EEF	External Economic Factors
PLS–SEM	Partial Least Square–Structural Equation Modelling

Source: Authors' Findings

Table 11 Sobel Test Z-values

Path	Sobel Test Z	Result
Trust in Economic News → Social Media Influence → Investor Herding Behavior	3.45	Significant
Trust in Economic News → Market Volatility → Investor Herding Behavior	3.50	Significant
Trust in Economic News → Behavioral Triggers → Investor Herding Behavior	3.30	Significant
Trust in Economic News → External Economic Factors → Investor Herding Behavior	3.40	Significant
Social Media Influence → Trust in Economic News → Investor Herding Behavior	3.80	Significant
Social Media Influence → Market Volatility → Investor Herding Behavior	4.00	Significant
Social Media Influence → Behavioral Triggers → Investor Herding Behavior	3.90	Significant
Social Media Influence → External Economic Factors → Investor Herding Behavior	3.40	Significant
Market Volatility → Trust in Economic News → Investor Herding Behavior	3.60	Significant
Market Volatility → Social Media Influence → Investor Herding Behavior	4.20	Significant
Market Volatility → Behavioral Triggers → Investor Herding Behavior	3.95	Significant
Market Volatility → External Economic Factors → Investor Herding Behavior	3.55	Significant
Behavioral Triggers → Trust in Economic News → Investor Herding Behavior	3.70	Significant
Behavioral Triggers → Social Media Influence → Investor Herding Behavior	3.85	Significant
Behavioral Triggers → Market Volatility → Investor Herding Behavior	4.10	Significant
Behavioral Triggers → External Economic Factors → Investor Herding Behavior	3.75	Significant

Path	Sobel Test Z	Result
External Economic Factors → Trust in Economic News → Investor Herding Behavior	3.80	Significant
External Economic Factors → Social Media Influence → Investor Herding Behavior	3.90	Significant
External Economic Factors → Market Volatility → Investor Herding Behavior	4.15	Significant
External Economic Factors → Behavioral Triggers → Investor Herding Behavior	4.00	Significant

Source: Authors' Findings

Appendix B

The Bootstrap Method Results are presented in Table 12 in the section below.

Table 12 Bootstrap Results

Path	Indirect Effect	Lower CI (95%)	Upper CI (95%)	p-Value
Trust in Economic News → Social Media Influence → Investor Herding Behavior	0.143	0.10	0.18	0.000
Trust in Economic News → Market Volatility → Investor Herding Behavior	0.162	0.12	0.20	0.000
Trust in Economic News → Behavioral Triggers → Investor Herding Behavior	0.101	0.06	0.14	0.000
Trust in Economic News → External Economic Factors → Investor Herding Behavior	0.148	0.12	0.18	0.000
Social Media Influence → Trust in Economic News → Investor Herding Behavior	0.235	0.20	0.27	0.000
Social Media Influence → Market Volatility → Investor Herding Behavior	0.296	0.22	0.35	0.000
Social Media Influence → Behavioral Triggers → Investor Herding Behavior	0.174	0.12	0.22	0.000

Path	Indirect Effect	Lower CI (95%)	Upper CI (95%)	p-Value
Social Media Influence → External Economic Factors → Investor Herding Behavior	0.096	0.08	0.12	0.009
Market Volatility → Trust in Economic News → Investor Herding Behavior	0.075	0.05	0.10	0.008
Market Volatility → Social Media Influence → Investor Herding Behavior	0.279	0.22	0.33	0.000
Market Volatility → Behavioral Triggers → Investor Herding Behavior	0.285	0.24	0.33	0.000
Market Volatility → External Economic Factors → Investor Herding Behavior	0.114	0.09	0.14	0.000
Behavioral Triggers → Trust in Economic News → Investor Herding Behavior	0.074	0.05	0.10	0.008
Behavioral Triggers → Social Media Influence → Investor Herding Behavior	0.169	0.14	0.21	0.000
Behavioral Triggers → Market Volatility → Investor Herding Behavior	0.243	0.20	0.28	0.000
Behavioral Triggers → External Economic Factors → Investor Herding Behavior	0.081	0.06	0.10	0.000
External Economic Factors → Trust in Economic News → Investor Herding Behavior	0.097	0.08	0.12	0.009
External Economic Factors → Social Media Influence → Investor Herding Behavior	0.124	0.10	0.15	0.000
External Economic Factors → Market Volatility → Investor Herding Behavior	0.152	0.12	0.18	0.000
External Economic Factors → Behavioral Triggers → Investor Herding Behavior	0.117	0.09	0.14	0.000

Source: Authors' Findings

Appendix C

The Baron & Kenny Test Results are presented in Table 13 in the section below.

Table 13. Baron & Kenny Test Results

Path	Step 1 ($X \rightarrow M$)	Step 2 ($M \rightarrow Y$)	Step 3 ($X \rightarrow Y$)	Indirect Effect	Significance
Trust in Economic News → Social Media Influence → Investor Herding Behavior	0.143 (significant)	0.35 (significant)	0.25 (significant)	0.143	Significant
Trust in Economic News → Market Volatility → Investor Herding Behavior	0.162 (significant)	0.47 (significant)	0.22 (significant)	0.162	Significant
Trust in Economic News → Behavioral Triggers → Investor Herding Behavior	0.101 (significant)	0.393 (significant)	0.28 (significant)	0.101	Significant
Trust in Economic News → External Economic Factors → Investor Herding Behavior	0.148 (significant)	0.236 (significant)	0.24 (significant)	0.148	Significant
Social Media Influence → Trust in Economic News → Investor Herding Behavior	0.235 (significant)	0.287 (significant)	0.38 (significant)	0.235	Significant
Social Media Influence → Market Volatility → Investor Herding Behavior	0.296 (significant)	0.47 (significant)	0.38 (significant)	0.296	Significant
Social Media Influence → Behavioral Triggers → Investor Herding Behavior	0.174 (significant)	0.393 (significant)	0.50 (significant)	0.174	Significant
Social Media Influence → External Economic Factors → Investor Herding Behavior	0.096 (significant)	0.236 (significant)	0.40 (significant)	0.096	Significant
Market Volatility → Trust in Economic News → Investor Herding Behavior	0.075 (significant)	0.287 (significant)	0.45 (significant)	0.075	Significant
Market Volatility → Social Media Influence → Investor Herding Behavior	0.279 (significant)	0.368 (significant)	0.48 (significant)	0.279	Significant

Path	Step 1 (X → M)	Step 2 (M → Y)	Step 3 (X → Y)	Indirect Effect	Significance
Market Volatility → Behavioral Triggers → Investor Herding Behavior	0.285 (significant)	0.393 (significant)	0.50 (significant)	0.285	Significant
Market Volatility → External Economic Factors → Investor Herding Behavior	0.114 (significant)	0.236 (significant)	0.40 (significant)	0.114	Significant
Behavioral Triggers → Trust in Economic News → Investor Herding Behavior	0.074 (significant)	0.287 (significant)	0.45 (significant)	0.074	Significant
Behavioral Triggers → Social Media Influence → Investor Herding Behavior	0.169 (significant)	0.368 (significant)	0.50 (significant)	0.169	Significant
Behavioral Triggers → Market Volatility → Investor Herding Behavior	0.243 (significant)	0.470 (significant)	0.45 (significant)	0.243	Significant
Behavioral Triggers → External Economic Factors → Investor Herding Behavior	0.081 (significant)	0.236 (significant)	0.45 (significant)	0.081	Significant
External Economic Factors → Trust in Economic News → Investor Herding Behavior	0.097 (significant)	0.287 (significant)	0.40 (significant)	0.097	Significant
External Economic Factors → Social Media Influence → Investor Herding Behavior	0.124 (significant)	0.368 (significant)	0.45 (significant)	0.124	Significant
External Economic Factors → Market Volatility → Investor Herding Behavior	0.152 (significant)	0.470 (significant)	0.50 (significant)	0.152	Significant
External Economic Factors → Behavioral Triggers → Investor Herding Behavior	0.117 (significant)	0.393 (significant)	0.50 (significant)	0.117	Significant

Source: Authors' Findings