JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Motivating Factors of Individual Investors in a Bear Market

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ABSTRACT

The purpose of this study was to examine the motivating factors influencing individual investors in a bear market. Transactional data from 2,500 individual investors were collected from a major brokerage and technology company affiliated with the Tehran Stock Exchange over the period 2019–2021. Ultimately, data from 657 investors were extracted for analysis. The collected data were processed using Microsoft Excel and analyzed using EViews version 11. The results indicated that individual investors' personality traits significantly affect their trading behavior in the Iranian stock market. Past trading performance also influences the trading behavior of individual investors in the Iranian stock market. Furthermore, stocks with specific characteristics affect the trading behavior of individual investors in the Iranian stock market, and gambling behavior significantly influences the trading behavior of individual investors in the Iranian stock market.

Keywords: Individual investors, financial crisis, bear market, behavioral bias

Introduction

Financial markets play a central role in allocating capital, facilitating investment, and promoting economic growth, yet they are also characterized by complex behavioral dynamics that deviate substantially from traditional assumptions of rationality. Classical financial theory, particularly the Efficient Market Hypothesis, assumes that investors process all available information rationally and that asset prices fully reflect this information at all times. However, extensive empirical evidence demonstrates that investor behavior is often influenced by psychological biases, emotional responses, and cognitive limitations, which can lead to systematic deviations from rational expectations and contribute to anomalies such as excessive volatility, price bubbles, and market crashes (1, 2). Behavioral finance has emerged as a dominant framework to explain these deviations by integrating insights from psychology and economics, emphasizing that investor decisions are shaped not only by objective information but also by subjective perceptions, heuristics, and emotional reactions to market conditions (1, 3). These behavioral factors are particularly influential in bear markets, where declining prices, uncertainty, and negative sentiment amplify emotional responses and alter investor decision-making patterns.

Article history:
Received 11 September 2025
Revised 20 November 2025
Accepted 26 December 2025
Published online 01 January 2025

How to cite this article:
Asadi Zeidabadi, H., Vaez, S. A., Arman, S. A. & Abedi Sadaghiani, B. (2026). Motivating Factors of Individual Investors in a Bear Market. *Journal of Management and Business Solutions, 4*(1), 1-15. https://doi.org/10.61838/jmbs.4.1.223

Bear markets represent a critical phase in financial cycles characterized by prolonged price declines, heightened volatility, and widespread pessimism. These market conditions often trigger behavioral responses such as panic selling, loss aversion, and overreaction, which can exacerbate price declines and create feedback loops that reinforce market downturns. Empirical studies show that investor perception and sentiment significantly influence trading behavior during bearish trends, often leading to increased volatility and inefficient price adjustments (4, 5). Furthermore, the transmission of risk across financial markets is more pronounced during bear phases, highlighting the role of behavioral and informational mechanisms in amplifying market movements (5). Research on asset pricing also indicates that the determinants of stock returns differ substantially between bull and bear markets, suggesting that investor behavior is context-dependent and influenced by prevailing market conditions (6). This implies that understanding investor decision-making during bear markets is essential for explaining trading patterns, price formation, and market stability.

Individual investors, often referred to as retail investors, play a significant role in shaping market dynamics, particularly in emerging markets where their participation constitutes a substantial share of trading volume. Unlike institutional investors, individual investors are more likely to exhibit behavioral biases due to limited access to information, lower financial literacy, and greater susceptibility to emotional influences (7, 8). Studies have shown that individual investors often engage in excessive trading, exhibit overconfidence, and react disproportionately to market fluctuations, contributing to price inefficiencies and increased volatility (7, 9). Moreover, the relative influence of individual versus institutional investors varies across market conditions, with retail investors playing a more pronounced role during periods of market stress and uncertainty (9, 10). These findings underscore the importance of examining the behavioral determinants of individual investor trading behavior, particularly during bear markets.

One of the key determinants of trading behavior is investor personality traits, including demographic characteristics such as age, gender, and experience. Research indicates that demographic factors influence risk tolerance, investment horizon, and decision-making processes. For example, younger investors tend to exhibit higher risk tolerance and engage in more speculative trading, while older investors tend to adopt more conservative strategies (11). Similarly, experienced investors may develop behavioral patterns based on past market experiences, which influence their responses to future market conditions (3). Gender differences have also been observed, with male investors generally exhibiting higher levels of overconfidence and trading activity compared to female investors (12). These personality-related factors can significantly influence how investors respond to bear markets, affecting their willingness to buy, sell, or hold assets during periods of declining prices.

Past trading performance is another important factor influencing investor behavior, as investors often rely on past outcomes to guide future decisions. Behavioral theories suggest that investors exhibit extrapolative expectations, meaning they expect recent trends to continue, which can lead to excessive buying during bull markets and excessive selling during bear markets (13). Additionally, investors may develop overconfidence following successful trades, increasing their trading activity and risk-taking behavior (14). Conversely, losses experienced during bear markets may lead to loss aversion, causing investors to avoid risk or prematurely sell assets to prevent further losses (2). These behavioral responses highlight the importance of past trading performance as a determinant of trading behavior.

Stock-specific characteristics also play a crucial role in influencing investor decisions. Investors often exhibit preferences for stocks with certain attributes, such as high returns, high volatility, or low prices, which may reflect behavioral biases rather than rational evaluation. For example, abnormal returns and trading volume are often

associated with increased investor attention and speculative trading activity (15). Market capitalization also influences investor preferences, with some investors favoring smaller firms due to perceived growth opportunities or speculative potential (16). Furthermore, stock market contagion and interdependence can amplify investor reactions, particularly during periods of financial crisis or market downturns (17, 18). These findings suggest that stock characteristics interact with behavioral factors to influence trading decisions, particularly during bear markets.

Another important behavioral determinant of investor behavior is gambling preference, which reflects investors' tendency to seek high-risk, high-reward investments similar to gambling activities. Studies have shown that investors with stronger gambling preferences are more likely to invest in lottery-like stocks characterized by high volatility, skewness, and low prices (19). These investors are often motivated by the potential for large gains, even when the probability of success is low, leading to speculative trading behavior and increased market volatility (19). Gambling-related behavior has been linked to abnormal returns, excessive trading, and increased risk-taking, particularly among individual investors (20). These behavioral tendencies are especially pronounced during bear markets, where declining prices may encourage speculative behavior in an attempt to recover losses.

Market sentiment and psychological biases further contribute to deviations from rational trading behavior. Investor sentiment has been shown to influence price clustering, trading volume, and market volatility, reflecting the impact of collective emotional responses on financial markets (21). Behavioral biases such as overreaction, herding, and confirmation bias can lead to price inefficiencies and market anomalies (22). Overreaction to negative information during bear markets can result in excessive price declines, while herding behavior can amplify market trends as investors follow the actions of others rather than relying on independent analysis (20). Additionally, investor attention plays a critical role in shaping trading decisions, as investors tend to focus on salient or recent information, which can distort decision-making processes (15).

Advances in financial research and technology have further highlighted the importance of understanding behavioral dynamics in financial markets. Recent studies using artificial intelligence and advanced analytical techniques have demonstrated that investor behavior and market sentiment can be used to predict market trends and identify bull and bear market conditions (23). These findings underscore the importance of integrating behavioral insights into financial analysis to improve market predictions and investment strategies. Moreover, the informational environment and communication channels significantly influence investor behavior, particularly during bear markets when uncertainty is high and investors rely heavily on external information sources (24). These informational and behavioral dynamics contribute to the complexity of investor decision-making and highlight the need for empirical research examining the determinants of trading behavior.

Despite extensive research on investor behavior, there remains a need for empirical studies that specifically examine the factors influencing individual investor trading behavior during bear markets, particularly in emerging markets where behavioral effects may be more pronounced. Emerging markets often exhibit higher volatility, lower liquidity, and greater participation by individual investors, making them particularly susceptible to behavioral influences (5). Furthermore, differences in market structure, investor composition, and regulatory environment may influence behavioral patterns, highlighting the importance of context-specific research (9). Understanding the behavioral determinants of trading decisions during bear markets can provide valuable insights for investors, policymakers, and financial institutions seeking to improve market stability and investment outcomes.

Therefore, the aim of this study is to investigate the factors influencing the trading behavior of individual investors in a bear market, with particular emphasis on personality traits, past trading performance, stock-specific characteristics, and gambling behavior in the Iranian stock market.

Methods and Materials

In behavioral economics and finance, the role of natural (not necessarily rational) human behavioral responses is studied with greater emphasis as a variable influencing other economic and financial variables that were previously overlooked. According to Thaler, it will not be long before the term behavioral finance disappears and the resulting perspective remains as a dominant and pervasive approach (Barberis & Thaler, 2004). An independent variable is defined as a variable whose effect on other variables is examined by the researcher (Khaki, 2007). The independent variables include the following.

Personality traits of individual investors: Personality characteristics include gender, which is a dummy variable coded as 1 for male and 0 for female. Age refers to the investor's age in a given month. Experience is defined as the number of trading years, calculated as the difference between the account opening date and each trading month. Portfolio turnover represents the average purchase and sale turnover, following the methodology of Barber and Odean (2001). Account size is defined as the total value of the investor's portfolio plus the account balance in each month. Young is a dummy variable equal to 1 if the investor's age is less than 60 years and 0 otherwise.

Past trading performance: Past trading performance is defined as the investor's gross portfolio return at the beginning of month t−1.

Stocks with specific characteristics: Stock characteristics include:

(a) Abnormal return for each stock, measured as the stock return minus the market index return.

(b) Market value, defined as the natural logarithm of the stock's closing market value one day prior to the transaction.

(c) Stock turnover, calculated as the trading volume on day t divided by the total number of shares outstanding on that day.

Gambling: The method proposed by Kumar (2009b) is used to identify lottery-type stocks. In this approach, stocks in the lowest price percentile, highest idiosyncratic volatility percentile, and highest idiosyncratic skewness percentile are classified as lottery-type stocks.

The dependent variable, investor trading behavior, is measured using Net Individual Trading (NIT), which is calculated as the value of purchased shares minus the value of sold shares, divided by the total transaction value for each investor.

The trading data of individual investors were collected from a major brokerage or technology company affiliated with the Tehran Stock Exchange. The sample period spans from the beginning of 2019 to the end of September 2021. Between April 2019 and late August 2020, the stock market experienced a bullish period, during which the stock market index increased from approximately 180,000 points to approximately 2,100,000 points, representing a growth of about 953%. This was followed by a bearish period from September 2020 to early 2021, when the index declined to 1,100,000 points. Since then, the stock market gradually recovered from the bearish period, with the index increasing by approximately 43% from its lowest point to reach 1,580,000 points by the end of September 2021. Therefore, the dataset can be divided into three periods: (1) a bullish period from the beginning of 2019 to

late August 2020, when the index reached its historical peak; (2) a bearish period from September 2020 to early 2021; and (3) a recovery period from early 2021 to the end of September 2021. This dataset is ideal for research purposes because it enables the examination of investor trading behavior under different market conditions. This sample division into three periods is consistent with previous studies examining financial crises in the Chinese stock market. The composition of the dataset is broadly consistent with several prior and recent datasets used for individual investors (Barber & Odean, 2000, 2001; Chan, Wang, & Yang, 2019; Feng & Seasholes, 2005; Friedmann & Wang, 2020).

For each trading account, the dataset provides the following information: (1) investor characteristics, (2) stock holdings, and (3) trading records. All customer profiles include a unique identifier for each trading account, account opening date, date of birth, and gender. The cash balance includes the daily cash balance of each investor after each trading day. Stock holdings contain information on stock ownership and the number of shares held. Trading records include detailed transaction histories such as (a) transaction date, (b) traded stock, (c) number of shares purchased or sold, (d) transaction price, (e) total number of shares held after each transaction, and (f) transaction type (buy or sell). Information related to cash balances, stock holdings, and trading records is updated daily. To ensure alignment with the research objectives, trading accounts containing only mutual fund investments were excluded. Investors were required to be at least 18 years old at the time of account opening. Additionally, individual investors were required to be active during the sample period. To ensure data consistency, investors who closed their trading accounts during the sample period were excluded.

In addition to the primary dataset described above, stock market data were collected from the stock market database. These data include daily stock prices, index returns, trading volume, market capitalization, risk-free rate, and the Fama–French three factors.

Findings and Results

The first step in statistical analysis is to determine the summary characteristics of the data and compute descriptive indicators. The purpose of this analysis is to identify the internal relationships among variables and to illustrate the behavioral patterns of the subjects, thereby providing the basis for statistical analysis and revealing descriptive characteristics for further examination. Data analysis in this section was conducted by calculating measures of central tendency, including mean and median, and measures of dispersion, including standard deviation, maximum, and minimum values of the variables.

Table 1. Descriptive Statistics of Research Variables

Variable	Mean	Median	Maximum	Minimum	Std. Deviation	Skewness	Kurtosis	Observations
NIT	0.067682	0.021867	8.305826	-5.87888	0.788177	2.920796	60.78851	1314
TURNOVER	0.494364	0.495380	5.422658	0.000000	0.299202	3.797955	60.00538	1314
GENDER	0.795282	1.000000	1.000000	0.000000	0.403649	-1.46362	3.142175	1314
AGE	34.55860	34.00000	79.00000	21.00000	11.59976	1.340597	4.823978	1314
AGE2	0.955099	1.000000	1.000000	0.000000	0.207166	-4.39525	20.31820	1314
EXPERIENCE	9.417808	7.500000	42.00000	2.000000	5.946424	1.679002	7.232150	1314
PORTFOLIO_RETURN	0.939993	0.877816	19.05165	-12.8572	5.238713	0.087666	2.726256	1314
MARKET_VALUE	4.749402	4.807050	7.910837	0.477121	1.074458	-0.56826	4.312528	1314
TRADING_VOLUME	0.462640	0.417979	0.993379	-0.21184	0.253804	0.450389	2.171976	1314
ABNORMAL_RETURNS	1.721272	1.251624	70.71748	0.001569	3.474413	14.50505	255.3938	1314
LOTTERYPREFERENCEI	0.096071	0.084778	7.632442	-13.8296	1.328048	-6.8909	81.67747	1314

In this study, the Ordinary Least Squares (OLS) method was used to estimate the model parameters. The OLS method assumes that the dependent variable follows a normal distribution, and a non-normal distribution may violate the assumptions required for parameter estimation. Therefore, it is necessary to test the normality of the dependent variable. In the present study, normality was examined using the Jarque–Bera test statistic. If the significance level of this test is greater than 0.05, the null hypothesis of normality is accepted. The results of the Jarque–Bera test for the dependent variable are presented in Table 2.

Table 2. Jarque–Bera Test Statistic for the Dependent Variable

Normality Test	NIT
Jarque–Bera	184706.6
Significance	0.000000
Observations	1314

As shown in Table 2, since the significance level of the Jarque–Bera statistic for the dependent variable is less than 0.05, the null hypothesis of normality is rejected, indicating that the variable does not follow a normal distribution. However, given the large sample size (N > 30) and the high number of observations, the Central Limit Theorem is applied. According to the Central Limit Theorem, as the sample size increases, the variance among samples decreases and the sampling distribution of the mean approaches a normal distribution, and the normality of the distribution improves as the number of observations increases (Badri & Abdolbaghi, 2010).

Linear correlation among explanatory variables is referred to as multicollinearity (Souri, 2015). Multicollinearity occurs when an independent variable is a linear function of other independent variables. If multicollinearity is high in a regression equation, it indicates a strong correlation among independent variables, and despite a high coefficient of determination (R^2), the model may lack reliability (Momeni & Ghayoumi, 2012). Perfect multicollinearity violates the classical assumptions of regression models. One simple criterion for detecting multicollinearity is examining correlation coefficients among explanatory variables (Souri, 2015). To assess multicollinearity among independent and control variables, the Variance Inflation Factor (VIF) statistic was used. A VIF value less than 10 indicates that only a small portion of the variance of the independent variable is explained by other explanatory variables, while a value greater than 10 indicates that the variable is a linear combination of other variables, suggesting multicollinearity. The results of the VIF test are presented in Table 3.

Table 3. Variance Inflation Factor (VIF) of Explanatory Variables

Independent Variable	VIF
TURNOVER	1.321362
GENDER	1.009361
AGE	3.137108
AGE2	1.644510
EXPERIENCE	2.599917
PORTFOLIO_RETURN	1.012139
MARKET_VALUE	1.050454
TRADING_VOLUME	1.376282
ABNORMAL_RETURNS	1.046733
LOTTERYPREFERENCEI	1.093427

Based on the results presented in Table 3, all VIF values are below 10, indicating that there is no multicollinearity among the model variables. Therefore, the results obtained from the multiple regression analysis are considered reliable. This finding is further supported by the correlation matrix presented in Table 4.

Table 4. Absolute Values of Correlation Coefficients Among Explanatory Variables

No.	Variable	1	2	3	4	5	6	7	8	9	10
1	TURNOVER	1.000									
2	GENDER	0.009	1.000								
3	AGE	0.314	0.019	1.000							
4	AGE2	0.126	0.001	0.406	1.000						
5	EXPERIENCE	0.374	0.029	0.464	0.446	1.000					
6	PORTFOLIO_RETURN	0.017	0.029	0.010	0.013	0.010	1.000				
7	MARKET_VALUE	0.020	0.033	0.010	0.011	0.045	0.040	1.000			
8	TRADING_VOLUME	0.419	0.063	0.327	0.065	0.373	0.081	0.022	1.000		
9	ABNORMAL_RETURNS	0.029	0.027	0.126	0.014	0.142	0.037	0.020	0.041	1.000	
10	LOTTERYPREFERENCEI	0.051	0.063	0.066	0.003	0.048	0.010	0.200	0.122	0.126	1.000

As shown in Table 4, the highest absolute correlation coefficient among the independent variables is 0.464, and all other correlation values are relatively low. This indicates that there is no multicollinearity among the explanatory variables.

One of the important issues encountered in econometrics is heteroskedasticity. Heteroskedasticity refers to a condition in which the variance of the error terms in a regression model is not constant. In regression estimation using the Ordinary Least Squares (OLS) method, it is initially assumed that all error terms have equal variance (homoskedasticity). After estimating the model, various techniques and tests are applied to evaluate whether this assumption holds and whether heteroskedasticity exists in the model. However, in empirical econometric research, two key issues arise.

First, since the values of the error terms in the population are not directly observable, determining the presence of heteroskedasticity in the model becomes challenging. Second, in practice, it is highly unlikely that all error term variances are exactly equal, and typically, some degree of variation exists among them. Therefore, an important question arises as to whether there is a statistical measure capable of quantifying the degree of variance inequality, allowing researchers to determine whether heteroskedasticity is present beyond a certain threshold. To address this issue, economists use various statistical tests, including the ARCH test, the Breusch–Pagan test, the White test, and the Park test. In this study, the Breusch–Pagan test was employed.

Table 5. Results of the Breusch–Pagan Heteroskedasticity Test

Dependent Variable	F-Statistic	Significance
NIT	21.90997	0.2713

According to the results presented in Table 5, the significance level is greater than the error level of 0.05. Therefore, the null hypothesis of homoskedasticity is accepted, indicating that there is no heteroskedasticity problem in the model.

One of the classical assumptions in regression analysis is the absence of autocorrelation. To examine autocorrelation, the Breusch–Godfrey LM test was used. The results of this test are presented below.

Table 6. Results of the Breusch–Godfrey LM Autocorrelation Test

Dependent Variable	F-Statistic	Significance
NIT	20.88237	0.2148

In this test, the null hypothesis (H_0) states that there is no autocorrelation problem. Since the probability value of the F-statistic is greater than 5%, the null hypothesis is accepted. Therefore, the regression model does not suffer from autocorrelation.

To estimate the model related to the research hypotheses, the appropriate estimation method must first be determined. Therefore, the Chow test (F-Limer test) was used to determine whether the pooled data method or panel data method should be applied. This test examines whether the intercept is constant across all time periods under the assumption of fixed coefficients. In general, the following test is used to select between pooled and panel data models.

Table 7. Results of the F-Limer (Chow) Test

Dependent Variable	F-Limer Statistic	Degrees of Freedom	Significance	Result
NIT	1.577022	(656, 647)	0.0000	Panel Data (Panel Model)

Based on Table 7, the significance level is less than the error level of 0.05. Therefore, the null hypothesis, which indicates the preference for the pooled data method, is rejected. Consequently, the panel data method is preferred, and the intercept must be included in the regression equation.

After selecting the panel data approach, it is necessary to determine whether the fixed effects model or random effects model is more appropriate. This is done using the Hausman test. In other words, the test examines whether the intercept varies systematically across cross-sectional units (fixed effects) or whether the variation is random (random effects). These two approaches are widely known in panel data econometrics.

Fixed Effects:

A common approach in panel data modeling assumes that differences among cross-sectional units can be captured through differences in intercept terms. In this approach, each unit has its own specific intercept.

Random Effects:

This approach assumes that individual-specific effects are randomly distributed across cross-sectional units rather than fixed. The random effects model treats individual differences as part of the error structure rather than fixed constants.

The Hausman test was used to determine the appropriate model specification.

Table 8. Results of the Hausman Test

Dependent Variable	Hausman Statistic	Degrees of Freedom	Significance	Result
NIT	15.253241	10	0.1231	Random Effects

Since the significance level of the Hausman test is greater than the error level of 0.05, the null hypothesis is not rejected. Therefore, the random effects model is preferred for estimating the regression equation.

The results of the model estimation are reported in the table below.

Table 9. Estimation Results of the Research Model

Variable	Y = NIT (Coefficient)	t-Statistic	Significance (p-value)
TURNOVER	0.008289	0.157868	0.8746
GENDER	-0.048026	-1.416527	0.1569
AGE	-0.006101	-2.736846	0.0063
AGE2	-0.410411	-4.613860	0.0000
EXPERIENCE	0.035477	8.949935	0.0000
PORTFOLIO_RETURN	0.031838	12.73959	0.0000
MARKET_VALUE	0.017600	1.336746	0.1815
TRADING_VOLUME	-0.005263	-0.082529	0.9342
ABNORMAL_RETURNS	0.145758	35.30500	0.0000
LOTTERYPREFERENCEI	0.216441	20.58655	0.0000
C (Constant)	-0.012275	-0.085069	0.9322

R-squared= 0.601862; F-statistic= 196.9738; Prob(F)= 0.000; Durbin–Watson= 2.006238

The results obtained from estimating the regression model are presented in Table 9. The significance level associated with the F-statistic is less than 0.05, indicating that the set of included explanatory variables (including both control and independent variables) is jointly significant at the 95% confidence level and that the model exhibits an acceptable overall fit.

Hypothesis 1: The personality traits of individual investors influence the trading behavior of individual investors in a bear market.

1. It can be observed that the estimated coefficient of the first indicator of the independent variable "personality traits of individual investors" (GENDER) on the dependent variable "trading behavior of individual investors" (NIT) is −0.048026, and the corresponding test statistic is −1.416527. Since the absolute value of this statistic is smaller than the critical value at the 5% significance level (1.96), the estimated coefficient is not statistically significant. The p-value is 0.1569, which is greater than 0.05 and confirms the lack of statistical significance.
2. It can be observed that the estimated coefficient of the second indicator of the independent variable "personality traits of individual investors" (AGE) on the dependent variable (NIT) is −0.006101, and the corresponding test statistic is −2.736846. Since the absolute value of this statistic is greater than the critical value at the 5% significance level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0063, which is less than 0.05 and confirms statistical significance.
3. It can be observed that the estimated coefficient of the third indicator of the independent variable "personality traits of individual investors" (AGE2) on the dependent variable (NIT) is −0.410411, and the corresponding test statistic is −4.613860. Since the absolute value of this statistic is greater than the critical value at the 5% significance level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0000, which is less than 0.05 and confirms statistical significance.
4. It can be observed that the estimated coefficient of the fourth indicator of the independent variable "personality traits of individual investors" (EXPERIENCE) on the dependent variable (NIT) is 0.035477, and the corresponding test statistic is 8.949935. Since the absolute value of this statistic is greater than the critical value at the 5% significance level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0000, which is less than 0.05 and confirms statistical significance.
5. It can be observed that the estimated coefficient of the fifth indicator of the independent variable "personality traits of individual investors" (TURNOVER) on the dependent variable (NIT) is 0.008289, and the corresponding test statistic is 0.157868. Since the absolute value of this statistic is smaller than the critical value at the 5% significance level (1.96), the estimated coefficient is not statistically significant. The p-value is 0.8746, which is greater than 0.05 and confirms the lack of statistical significance.

Given that three indicators of the personality traits construct have statistically significant effects on the trading behavior of individual investors, it can be concluded that the personality traits of individual investors affect their trading behavior in the Iranian stock market; therefore, Hypothesis 1 is supported.

Hypothesis 2: Past trading performance influences the trading behavior of individual investors in a bear market.

1. It can be observed that the estimated coefficient of the independent variable "past trading performance" (PORTFOLIO_RETURN) on the dependent variable (NIT) is 0.031838, and the corresponding test statistic is 12.73959. Since the absolute value of this statistic is greater than the critical value at the 5% significance

level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0000, which is less than 0.05 and confirms statistical significance.

Given the confirmed significant effect of past trading performance on the trading behavior of individual investors, it can be concluded that past trading performance affects individual investors' trading behavior in the Iranian stock market; therefore, Hypothesis 2 is supported.

Hypothesis 3: Stocks with specific characteristics influence the trading behavior of individual investors in a bear market.

1. It can be observed that the estimated coefficient of the first indicator of "stocks with specific characteristics" (MARKET_VALUE) on the dependent variable (NIT) is 0.017600, and the corresponding test statistic is 1.336746. Since the absolute value of this statistic is smaller than the critical value at the 5% significance level (1.96), the estimated coefficient is not statistically significant. The p-value is 0.1815, which is greater than 0.05 and confirms the lack of statistical significance.
2. It can be observed that the estimated coefficient of the second indicator of "stocks with specific characteristics" (TRADING_VOLUME) on the dependent variable (NIT) is −0.005263, and the corresponding test statistic is −0.082529. Since the absolute value of this statistic is smaller than the critical value at the 5% significance level (1.96), the estimated coefficient is not statistically significant. The p-value is 0.9342, which is greater than 0.05 and confirms the lack of statistical significance.
3. It can be observed that the estimated coefficient of the third indicator of "stocks with specific characteristics" (ABNORMAL_RETURNS) on the dependent variable (NIT) is 0.145758, and the corresponding test statistic is 35.30500. Since the absolute value of this statistic is greater than the critical value at the 5% significance level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0000, which is less than 0.05 and confirms statistical significance.

Given that one indicator of the "stocks with specific characteristics" construct has a statistically significant effect on the trading behavior of individual investors, it can be concluded that stocks with specific characteristics affect individual investors' trading behavior in the Iranian stock market; therefore, Hypothesis 3 is supported.

Hypothesis 4: Gambling behavior influences the trading behavior of individual investors in a bear market.

It can be observed that the estimated coefficient of the independent variable "gambling behavior" (LOTTERYPREFERENCEI) on the dependent variable (NIT) is 0.216441, and the corresponding test statistic is 20.58655. Since the absolute value of this statistic is greater than the critical value at the 5% significance level (1.96), the estimated coefficient is statistically significant. The p-value is 0.0000, which is less than 0.05 and confirms statistical significance. Given the confirmed significant effect of gambling behavior on the trading behavior of individual investors, it can be concluded that gambling behavior affects individual investors' trading behavior in the Iranian stock market; therefore, Hypothesis 4 is supported.

Discussion and Conclusion

The findings of this study provide important empirical evidence on the behavioral determinants of individual investors' trading behavior in a bear market, highlighting the critical role of psychological, experiential, and stock-related factors in shaping decision-making processes. The regression results demonstrate that personality-related characteristics, particularly age, age squared, and investment experience, significantly influence trading behavior, while gender and portfolio turnover do not show statistically significant effects. These findings are consistent with

behavioral finance theory, which emphasizes that investor heterogeneity plays a central role in determining financial decision-making patterns. Specifically, the negative and significant effect of age suggests that older investors exhibit more conservative trading behavior during bear markets, likely due to higher risk aversion and greater sensitivity to potential losses. This result aligns with previous research indicating that individual investors' expectations, risk preferences, and trading decisions are strongly influenced by demographic factors such as age, which affect psychological responses to market uncertainty and financial risk (11). Similarly, the life-cycle learning framework suggests that investors accumulate knowledge and behavioral patterns over time, influencing their response to adverse market conditions (3). The negative coefficient of the squared age variable further indicates that the relationship between age and trading behavior is nonlinear, suggesting that behavioral conservatism increases disproportionately at higher ages, which is consistent with the notion that older investors are more loss-averse and less likely to engage in speculative trading during bear markets (2).

The positive and statistically significant effect of investment experience on trading behavior indicates that more experienced investors are more active or strategically engaged in trading during bear markets. This finding reflects the role of experiential learning and behavioral adaptation, whereby experienced investors develop cognitive frameworks that allow them to interpret market signals more effectively and respond strategically to market downturns. Prior research has shown that experienced investors are better able to process financial information and make more informed decisions, resulting in distinct trading patterns compared to less experienced investors (7). Furthermore, investment experience influences categorical thinking and stock selection behavior, as experienced investors rely on prior knowledge and mental models developed through repeated market exposure (14). This finding also aligns with research demonstrating that information processing ability and investment experience significantly moderate investment decisions, particularly during bear markets when uncertainty is high and information asymmetry is pronounced (24). These results suggest that investment experience enhances investor confidence and behavioral resilience, enabling experienced investors to navigate adverse market conditions more effectively.

In contrast, the insignificant effect of gender on trading behavior suggests that gender differences may not be a primary determinant of trading activity in bear market conditions within the studied context. While previous research has documented gender-based differences in trading frequency and risk-taking behavior, these differences may be context-dependent and influenced by market conditions, institutional environments, and investor characteristics (12). During bear markets, heightened uncertainty and risk may lead both male and female investors to adopt more cautious strategies, thereby reducing behavioral differences across genders. Similarly, the insignificant effect of portfolio turnover suggests that trading intensity measured through turnover alone may not capture the behavioral dimensions influencing trading behavior during bear markets, where emotional and psychological factors play a more dominant role than routine trading activity.

The results also demonstrate a significant positive relationship between past portfolio performance and trading behavior, indicating that investors who experienced higher returns in the past are more likely to engage in trading during bear markets. This finding supports behavioral theories of extrapolative expectations and overconfidence, which suggest that investors tend to rely on past success as a predictor of future performance, leading to increased trading activity even during adverse market conditions (13). Investors who previously achieved favorable returns may exhibit greater confidence in their investment abilities, resulting in continued engagement in trading despite market downturns. This behavior reflects cognitive biases such as self-attribution bias, where investors attribute

past success to their skill rather than external factors, reinforcing risk-taking behavior (2). Additionally, empirical evidence indicates that investors who experience positive performance are more likely to maintain higher levels of market participation and exhibit greater tolerance for risk (7). These findings confirm that past trading performance plays a critical role in shaping investor expectations and behavioral responses during bear markets.

With regard to stock-specific characteristics, the findings indicate that abnormal returns significantly influence investor trading behavior, while market value and trading volume do not exhibit statistically significant effects. The strong positive relationship between abnormal returns and trading behavior suggests that investors are highly responsive to perceived profit opportunities, even during bear markets. This behavior reflects investor attention and cognitive biases, as investors tend to focus on stocks exhibiting unusual performance patterns, interpreting abnormal returns as signals of potential profit opportunities (15). This finding is consistent with behavioral models suggesting that investors overreact to salient information, resulting in increased trading activity in response to abnormal returns (22). Furthermore, abnormal returns may attract speculative investors seeking to exploit short-term price movements, contributing to increased trading activity. This result also aligns with research showing that investor sentiment and firm-specific expectations significantly influence trading behavior and price formation (25). In contrast, the insignificant effects of market value and trading volume suggest that individual investors may prioritize behavioral signals such as abnormal returns over traditional financial indicators when making trading decisions during bear markets. This finding highlights the importance of behavioral factors over purely structural characteristics in shaping investor behavior.

The results also reveal a strong and statistically significant positive relationship between gambling preference and trading behavior, indicating that investors with stronger gambling tendencies are more likely to engage in trading during bear markets. This finding provides direct empirical support for behavioral finance theories that conceptualize certain types of investment behavior as analogous to gambling. Investors with gambling preferences are more likely to seek high-risk, high-reward opportunities, particularly in volatile and declining markets where traditional investment strategies may appear less attractive (19). This behavior reflects risk-seeking tendencies under loss conditions, consistent with prospect theory, which suggests that individuals become more willing to take risks when facing losses. Empirical evidence also indicates that investors exhibiting gambling-like behavior tend to invest in lottery-type stocks characterized by high volatility and skewness, contributing to increased market volatility and price inefficiencies (20). Furthermore, behavioral finance research demonstrates that emotional factors such as hope, regret, and loss aversion play a significant role in shaping gambling-related investment behavior (1). These findings confirm that gambling preferences are a key behavioral determinant of trading activity, particularly during bear markets.

The overall explanatory power of the model, as indicated by the statistically significant F-statistic and relatively high coefficient of determination, suggests that behavioral and experiential factors play a substantial role in explaining individual investor trading behavior during bear markets. These findings are consistent with broader empirical evidence demonstrating that behavioral factors significantly influence market dynamics, particularly during periods of financial stress and uncertainty (5). Market downturns are often characterized by increased behavioral biases, including overreaction, herding, and sentiment-driven trading, which amplify market volatility and contribute to deviations from fundamental values (21). Additionally, research on market contagion and financial crises has shown that investor behavior plays a critical role in transmitting shocks across financial markets, further emphasizing the importance of behavioral analysis in understanding market dynamics (17, 18). These findings

reinforce the argument that behavioral finance provides a powerful framework for understanding investor decision-making and market behavior.

The results of this study also contribute to the growing body of literature highlighting the role of individual investors in shaping market dynamics, particularly in emerging markets where retail participation is high. Individual investors often exhibit behavioral biases and limited information processing capabilities, resulting in distinct trading patterns compared to institutional investors (9). These behavioral differences can contribute to increased market volatility and price inefficiencies, particularly during bear markets when uncertainty and emotional responses are heightened. The findings of this study support previous research demonstrating that investor sentiment, behavioral biases, and psychological characteristics significantly influence trading behavior and market outcomes (10, 23). Overall, the results confirm that trading behavior during bear markets is strongly influenced by behavioral, experiential, and psychological factors rather than purely rational evaluation of financial information.

This study has several limitations that should be considered when interpreting the findings. First, the analysis focuses exclusively on individual investors in a single stock market, which may limit the generalizability of the findings to other markets with different institutional structures, regulatory environments, or investor compositions. Second, the study relies on observational trading data, which, while highly informative, does not directly capture psychological states such as emotions, cognitive biases, or subjective perceptions, which are central to behavioral finance theory. Third, the measurement of behavioral constructs such as gambling preference and personality traits is based on observable proxies rather than direct psychological assessments, which may introduce measurement error. Fourth, the study examines a specific bear market period, and investor behavior may vary across different bear markets depending on the underlying causes, severity, and duration of the market downturn.

Future research should expand the scope of analysis by incorporating cross-country comparisons to examine whether behavioral determinants of trading behavior differ across markets with varying levels of development, investor protection, and financial literacy. Researchers could also integrate psychological survey data with trading records to provide a more comprehensive understanding of the cognitive and emotional mechanisms underlying trading behavior. Additionally, future studies should examine the dynamic evolution of investor behavior across multiple market cycles, including bull, bear, and recovery phases, to identify temporal variations in behavioral responses. The application of advanced analytical techniques such as machine learning and artificial intelligence could also enhance the predictive modeling of investor behavior by capturing complex nonlinear relationships among behavioral and financial variables.

From a practical perspective, the findings of this study have important implications for investors, policymakers, and financial institutions. Investors should recognize the influence of psychological biases, past performance, and gambling tendencies on their trading decisions and adopt strategies that emphasize disciplined, long-term investment approaches rather than emotionally driven reactions to market fluctuations. Financial advisors and investment firms can develop educational programs to improve investor awareness of behavioral biases and promote more rational decision-making. Policymakers and regulators can also enhance market stability by implementing measures that improve transparency, reduce information asymmetry, and protect individual investors from behavioral traps and excessive speculation. Overall, improving investor awareness and promoting behavioral discipline can contribute to more efficient financial markets and better investment outcomes.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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