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Study of Investor Behavior on Stock Investment Decision Making with Self-Monitoring as a Moderating Variable in Generation Y and Generation Z

Eni Duwita Sigalingging
Department of Accounting, Universitas Sumatera Utara,
Faculty of Economics and Business, Medan, Indonesia
Email: eniduita@gmail.com

Azhar Maksum
Department of Accounting, Universitas Sumatera Utara,
Faculty of Economics and Business, Medan, Indonesia
****Corresponding author* Email:** syaiful56azhar@gmail.com

Rina Bukit
Department of Accounting, Universitas Sumatera Utara,
Faculty of Economics and Business, Medan, Indonesia
Email: rina.bukit@usu.ac.id

Muammar Khaddaf
Department of Sharia Accounting and Finance Science,
Faculty of Economics and Business, Universitas Malikussaleh Aceh, Indonesia
Email: khaddafi@unimal.ac.id

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Abstract

Purpose: This study examines the influence of psychological biases (trait anger, trait anxiety, overconfidence, and herding) on stock investment decisions among Generation Y and Z investors in North Sumatra. It uniquely investigates the role of self-monitoring as a moderating variable to determine if high self-regulation can mitigate irrational investment behaviors.

Design/Methodology/Approach: This research employs a quantitative approach, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze data from 384 retail investors. Additionally, an independent sample t-test is conducted to identify generational differences in decision-making patterns.

Findings: The results indicate that trait anger and anxiety negatively affect investment decisions, while herding and self-monitoring have a positive influence. Crucially, self-monitoring significantly moderates the relationship between trait anger and herding behavior on investment decisions. Generation Z is found to be more risk-tolerant and technology-driven, whereas Generation Y is more cautious and analytical.

Practical Implications: The findings suggest that financial literacy programs for young investors should go beyond technical analysis to include psychological conditioning. Regulators and investment managers can utilize these insights to design "cooling-off" mechanisms in trading apps or educational modules that enhance self-monitoring skills, thereby reducing impulsive trading.

Originality/Value: Unlike previous studies that solely focus on the direct effects of behavioral biases, this study bridges a theoretical gap by introducing self-monitoring as a psychological buffer. It provides a novel behavioral model for emerging markets, demonstrating how self-regulation can dampen the adverse effects of herding and emotional instability.

Keywords: Investment Decision; Generation Y; Generation Z; Self-Monitoring; Trait Anger

JEL Classifications: K16, H11, H83, D73

1. Introduction

While traditional finance literature predominantly focuses on rational decision-making models, this study addresses a critical gap by examining the influence of emotional biases—specifically anger and anxiety—on investment decisions. In reality, capital markets are driven by investor behavior, often leading to price deviations from fair value due to irrational choices. Consequently, understanding investor sentiment, which is shaped by both cognitive and emotional factors, is essential for explaining market anomalies. This research explicitly explores the dynamics among the growing population of Generation Y and Z investors in North Sumatra, investigating how internal psychological cues significantly influence their investment attitudes and risk assessments. The desire of investors to make trades based on the company's accounting data or fundamentals is known as investor sentiment. Investor sentiment causes money to move into securities that do not offer the highest returns at a given degree of risk. The cognitive, affective, and collaborative aspects of the investment decision-making process demand high capability power from capital market participants. These include the ability of individual investors to process financial and non-financial information, apply investment knowledge to aspects of fundamental and technical analysis, adjust their investment preferences and perceptions of risk and return, and the investment learning process (Akhter & Ahmed, 2013).

However, the surge in young investors (Generation Y and Z) presents a significant challenge. Many of these new investors are inexperienced and highly susceptible to psychological biases, such as herding and emotional instability (anger and anxiety). Without proper self-regulation, this vulnerability can lead to irrational investment decisions, substantial financial losses, and market volatility. Therefore, this study is critically important for two reasons. First, theoretically, it fills a gap in the literature by introducing Self-Monitoring as a potential moderating mechanism—an area largely underexplored in behavioral finance. Second, practically, understanding these behavioral drivers is urgent for regulators to design educational interventions that go beyond technical skills to include psychological conditioning for younger generations."

The rise in the number of stock investors in North Sumatra, particularly among Generation Y and Z, highlights the need to understand how these generations make investment decisions. As shown in Table 1, the number of stock investors has steadily increased, with Generation Z now constituting the largest group. North Sumatra Province is ranked sixth among provinces with the most significant number of capital market investors in Indonesia. Based on KSEI data as of July 31, 2024, the number of investors was 595,333. Of the total investors in North Sumatra province, 273,318 are investors who invest in stocks. Individual stock investors investing in North Sumatra Province continue to increase from year to year, as shown in Table 1 below:

Table 1. Number of North Sumatra stock investors 2017-2024 Period

No.	Year	Number of SIDs	Increase (%)
1	2017	27.137	
2	2018	37.832	39%

3	2019	50.023	32%
4	2020	85.267	70%
5	2021	165.968	95%
6	2022	208.200	25%
7	2023	245.955	18%
8	July 2024	273.318	11%

Source: OJK 2017-2024

Table 1 shows that, based on the Single Investor Identification (SID), the number of stock investors in North Sumatra continues to increase from year to year. In 2017, the number of stock investors in North Sumatra was 27,137 SID and continued to rise until July 2024, reaching 273,318 SID. The number of investors rose significantly in 2020, with a growth rate of 70%, and in 2021, with a growth rate of 95%. Based on data from the Indonesia Stock Exchange North Sumatra, the stock capital market is ranked first, dominated by Generation Z with a single investor identity (Single Investor Identification), followed in second place by Generation Y stock investors. Generation Y was born between 1981 and 1996, and its members are now around 28-43 years old. Generation Z was born between 1997 and 2012 and is now under 30 years old. The following breakdown of investors by age is presented in Table 2.

Table 2. Demographics of stock investors by age

No.	Age (Years)	Number of Investors	Description
1	>30 Years	157.130	Generation Z
2	31-40 Years	65.101	Generation Y
3	41-100 Years	50.152	Generation X and Baby Boomers.
Total		222.231	

Source: BEI July 2024

In Table 2, it can be seen that Generation Z stock investors are 157,130 SID. At the same time, Generation Y is 65,101 SID. With the increase in the number of stock investors, stock investment decision-making in North Sumatra has become more diverse, and behavioral biases may be present in making stock investment decisions. In making decisions, investors consider several factors, including the positive aspects of the business as reflected in its financial statements, performance, portfolio, track record, risk, and media appraisals of its financial and economic circumstances, as well as the business prospects of the issuer and other relevant factors. Several factors, including investor behavioral decisions, will reveal economic sustainability (Dios-Palomares et al., 2015)

These considerations can influence an investor's actions when making investment decisions (Pradhana, 2018). The primary purpose of investing is to generate a profit and build assets for the future. Investors investing in stocks will benefit from capital gains and dividends in the future. Stock investment is considered the most popular investment because it provides relatively high returns, but carries considerable risk compared to other investment instruments; therefore, stock investment is often referred to as high-risk-high-return (Haymans Manurung et al., 2020). When making investment decisions, investors must be able to analyze which stocks are more profitable to buy, and they must also be able to identify the factors that can affect stock price movements. Several financial theories and models assume that investors always act logically when making investments. Based on their rationality, investors are presumed to be able and ready to accept and evaluate all relevant information. However, with the increase in stock investment, investor behavior in decision-making can be influenced by factors such as Angry Nature, Anxious Nature, Overconfidence, Herding, and self-monitoring.

Relevant parties should focus on two key areas to boost young people's engagement in North Sumatra and enhance their ability to make informed investment decisions. Enhancing financial literacy and understanding in relation to technical and fundamental analysis is the first step. The second is to enhance psychological conduct, which can aid in avoiding foolish or illogical investment choices. Understanding the existence and types of behavioral biases among individual investors in a nation is crucial for improving their investment behavior (Rahman & Gan, 2020). From low degrees of annoyance or mild irritation to high levels of fury and rage, anger is an emotional state in which the combination of feelings varies in intensity (Spielberger & Sydeman, 1994).

Psychology research on anger reveals a positive correlation with optimistic risk assessment (Lerner & Tiedens, 2006). Anger will interpret negative actions. Psychology research on anger reveals a positive correlation with optimistic risk assessment (Lemer & Keltner, 2001). Anxiety is the reaction when one anticipates a threat. The unpredictability of future demand and the declining appeal of investment products induce anxiety (Caplin & Leahy, 2001). Consequently, the more knowledge investors have, the more fear they feel. An investor with anxiety is likely to stick to their portfolio approach and resist change. The term "overconfidence" refers to a skewed perspective in which one's belief in one's own abilities exceeds reality. Overconfident individuals tend to underestimate their margin of error (Shiller, 1999). The tendency of individuals to follow instructions or behaviors is known as the herding factor. Scholars and practitioners will continue to study the presence of herding in financial markets. Stock prices may diverge from their fundamental worth due to the herding effect (Tan et al., 2008). This may have an effect on the characteristics of return and risk models as well as the perspectives of asset pricing theories. Practitioners express concern over the exploitation of stock price fluctuations for profit through the herding effect (Bennet et al., 2012). In the modern digital era, the Internet has streamlined trading activities, making information access significantly faster and more cost-effective. Information delivery and trading: Online trading enables investors to respond to new information more quickly. Thus, tech-savvy members of generations Y and Z can obtain news online more quickly (Caparrelli et al., 2004). It has been claimed that the herding effect is a contributing factor to speculative bubbles. Psychological elements such as inherent anger, anxiety, and overconfidence frequently sway investors during their investment decisions, leading to irrational actions. This study examines the impact of these biases on the investment choices made by North Sumatra's Generation Y and Z investors."

Self-monitoring is a person's ability to adjust their personal behavior to fit the social environment (Biais et al., 2005). Personality traits and psychological biases, such as social influence, significantly influence investment decisions (Kourtidis et al., 2011). This variable is considered capable of moderating decision-making because investors can modify and control their behavior in different situations. Self-monitoring refers to an individual's ability to adjust their behavior in response to social cues, and in the context of investment decisions, it can moderate the effects of emotional and cognitive biases. Innovation is a key factor in making informed decisions in the economy (Dios-Palomares et al., 2015; Zuniga-Gonzalez et al., 2024).

Given this background, a focused investigation into investment decision-making is essential. Research indicates that investor behavior is inextricably linked to emotions; specifically, transient feelings of anxiety can distort risk assessments and final choices. Consequently, evaluating these emotional drivers is a critical step in understanding the overall decision-making process. The motivation for this study stems from two critical urgencies: theoretical and practical. Theoretically, while existing literature has extensively documented the existence of behavioral biases like herding and overconfidence (Shiller, 1999; Tan et al., 2008), there is a scarcity of research exploring how these biases can be controlled or mitigated by individual personality traits. Most studies treat behavioral biases as fixed irrationalities. This study fills that gap by proposing Self-Monitoring as a corrective mechanism, offering a more dynamic view of investor behavior where individuals can adapt their actions based on social and internal cues.

Practically, the urgency is driven by the demographic shift in the Indonesian capital market. As highlighted in Table 1 and Table 2, the dominance of Generation Z and Y investors brings a new risk profile to the market—one that is highly technologically savvy but potentially vulnerable to emotional volatility and "Fear of Missing Out" (FOMO). Understanding the specific psychological drivers of these young investors is no longer optional but essential for market stability. This study provides regulators and exchange authorities with the empirical basis to formulate targeted interventions that are not just informational (financial literacy) but also behavioral (emotional regulation).

This study distinguishes itself from prior work in three ways. First, it integrates Self-Monitoring as a moderator, a variable rarely applied in financial contexts, to test whether high self-regulators are less prone to market noise. Second, it offers a comparative analysis of Generation Y and Z in an emerging market context (North Sumatra), providing granular insights often missed in generalized studies. Third, it extends the behavioral finance literature by linking personality traits (anger/anxiety) directly to strategic investment outcomes, moving beyond simple risk tolerance assessments.

Therefore, the research problem assumes that investors make decisions based on rational analysis of available information. However, the increasing influence of emotional and cognitive biases suggests otherwise. Along with the development of investment, investor behavior in decision-making can be influenced by factors such as the nature of anger, anxiety, Overconfidence, Herding Effects, and Self-Monitoring. This can lead to bias in investment decisions. The rapid growth of stock investors among Generation Y and Z underscores the need to investigate how these generational cohorts, with their distinct behavioral traits, may exhibit different biases in investment decision-making. Decision-making can be biased due to information obtained by investors. This information can come from internal and external companies in which to invest.

According to Stillman and Stillman (2017), one of the ways Generation Z differs from Generation Y is that they are more adept at using technology, have a more receptive mindset, and are less concerned about conventions. Based on a study conducted by Rahman and Gan (2020), the primary reasons why members of Generation Y are so hesitant to engage in the stock market are ignorance and fear of failure. Therefore, this study will conduct a separate test to compare the outcomes of stock investment decision-making in Generation Y and Generation Z.

Our research aims to examine and analyze the influence of investor behavior factors on stock investment decision-making with self-monitoring as a moderating variable in the case study of stock investors in North Sumatra. Our research also analyzes the differences in the results of stock investment decision-making in Generation Y and Generation Z and answers the following questions:

1. Does anger affect individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
2. Does Trait Anxiety affect individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
3. Does overconfidence affect individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
4. Does herding influence individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
5. Does Self-monitoring affect individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
6. Does self-monitoring moderate Anger Trait in individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
7. Does self-monitoring moderate anxiety in individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
8. Is self-monitoring able to moderate *overconfidence* in individual stock investment decision-making among Generation Y and Generation Z in North Sumatra
9. Is self-monitoring able to moderate the Herding Factor in individual stock investment decision-making among Generation Y and Generation Z in North Sumatra?
10. Is Generation Y's stock investment decision-making different from Generation Z's stock investment decision-making in North Sumatra?

To develop suitable regulations that encourage Generations Y and Z to engage in the North Sumatra stock market, our research helps us understand the behavioral biases of stock investors in the region. We anticipate that this study will enhance investors' comprehension of the decision-making process in North Sumatra stock investing.

By investigating emotional and psychological biases through the lens of behavioral finance, this study contributes to the field of Decision Sciences by providing empirical evidence on how affective and cognitive factors shape financial decision-making under uncertainty. This research offers an original contribution by integrating self-monitoring as a moderating variable within the behavioral finance model, highlighting its role in moderating emotional biases among young investors in the Indonesian capital market context.

2. Literature Review

2.1 Judgment and Decision-Making (JDM) in Behavioral Finance

Judgment and decision-making (JDM) theory draws from multiple disciplines, ranging from empirical psychology to neuroscience, to understand how individuals make social and economic decisions (Ngamake et al., 2024). In the financial context, JDM explains how emotional and cognitive factors influence investors' risk perception, information processing, and portfolio selection. Negative emotions such as anger and anxiety, as well as psychological biases like overconfidence and herding, can distort rational judgment and lead to suboptimal investment outcomes (Abuaddous et al., 2018).

Previous studies (Shim et al., 2023) have demonstrated that both personal characteristics and environmental factors, including exposure to company information and perceptions of future market trends, influence investors' decisions. Effective emotional regulation—through mindfulness, diversification, or professional advice—has been suggested as a mechanism to mitigate these behavioral distortions.

2.2 Emotional and Psychological Biases in Investment Decision-Making

2.2.1 Anger and Financial Decisions

Anger is a negative emotional state associated with perceptions of injustice or frustration (Spielberger & Sydeman, 1994). Anger can narrow cognitive focus and trigger impulsive decisions (Kaya & Tosun, 2018). Empirical studies (Forgas, 2000; Lemer & Keltner, 2001; Slovic et al., 2004) demonstrate that anger increases optimism and risk-taking, potentially leading to irrational investment behavior.

2.2.2 Anxiety and Investment Avoidance

Anxiety is characterized by excessive worry and risk aversion, which may hinder rational financial judgment. High anxiety levels reduce confidence and lead investors to rely excessively on others' opinions (Gambetti & Giusberti, 2012). Research by Caplin and Leahy (2001) and Rahman and Gan (2020) shows that anxious investors tend to maintain existing portfolios rather than exploring new opportunities.

2.2.3 Overconfidence and Excessive Trading

Overconfidence refers to an inflated belief in one's judgment accuracy (Hoffrage, 2022). This bias can cause investors to underestimate risk, ignore diversification, and overtrade (De Bondt & Thaler, 1995; Odean, 1998). Overconfident individuals often misjudge their margin of error (Shiller, 1999) and assume information precision that may not exist (Adel & Mariem, 2013).

2.2.4 Herding Behavior and Social Influence

Herding occurs when investors imitate the actions of others without conducting independent analysis (Tan et al., 2008). It may lead to speculative bubbles and deviations in prices from their intrinsic values (Bennet et al., 2012; Caparrelli et al., 2004). In the digital era, online trading and social media amplify herding effects and FOMO-driven decision-making (Mahmood et al., 2020).

2.3 Personality Traits and Moderating Factors

Self-monitoring refers to an individual's ability to adjust their behavior and communication in response to situational demands (Christopher et al., 2004). Individuals high in self-monitoring demonstrate greater adaptability, self-regulation, and interpersonal awareness, which can buffer the effects of emotional biases on decision-making (Biais et al., 2005; Kourtidis et al., 2011).

Generational factors also shape financial behavior. Generation Y (born 1981–1996) tends to be cautious and stability-oriented, whereas Generation Z (born 1997–2012) is more technologically adept and risk-tolerant (Rahman & Gan, 2020; Stillman & Stillman, 2017). These generational differences may influence emotional processing and risk preferences in investment contexts.

3. Theoretical Framework and Hypothesis Development

3.1 Theoretical Framework

This study integrates key perspectives from Prospect Theory (Kahneman & Tversky, 1979), Behavioral Portfolio Theory (Shefrin & Statman, 2000), and the Behavioral Finance framework to examine how emotional and psychological biases influence stock investment decisions. Prospect Theory highlights loss aversion and emotional responses to uncertainty. At the same time, Behavioral Portfolio Theory emphasizes mental accounting and the neglect of diversification among overconfident investors.

Self-monitoring is proposed as a moderating variable that regulates the influence of emotional states on decision-making. A conceptual model is developed to reflect these relationships, with a focus on Generation Y and Z investors in North Sumatra.

3.2. Hypothesis Development

H1: Anger has a significant influence on individual stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H2: Anxiety negatively affects individual stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H3: Overconfidence positively influences individual stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H4: Herding behavior positively affects individual stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H5: Self-monitoring directly influences individual stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H6: Self-monitoring moderates the relationship between anger and stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H7: Self-monitoring moderates the relationship between anxiety and stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H8: Self-monitoring moderates the relationship between overconfidence and stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H9: Self-monitoring moderates the relationship between herding and stock investment decision-making among Generation Y and Generation Z investors in North Sumatra.

H10: Investment decision-making differs significantly between Generation Y and Generation Z investors.

4. Methodology

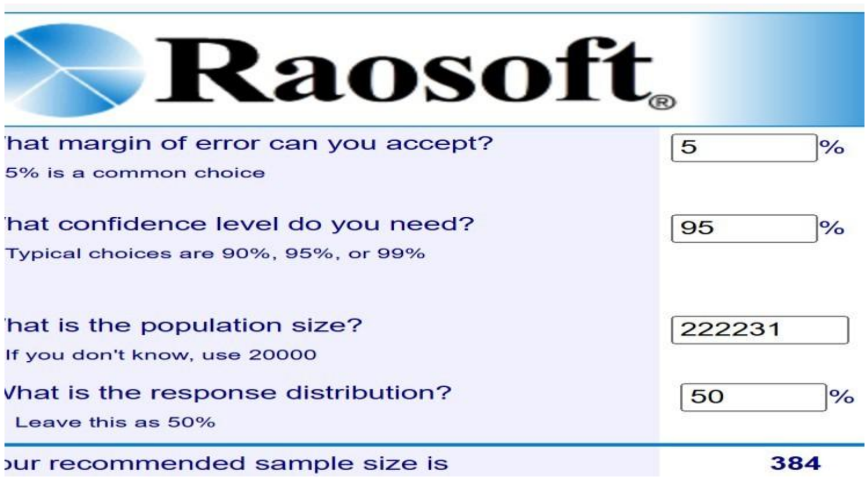
4.1 Data Collection

Using stratified random sampling, a random sample is selected from each subgroup after the population is divided into subgroups based on specific characteristics, such as age, gender, and educational attainment. There is a proportionality between the sample size and the population size of each stratum. Non-proportional: Because each stratum's sample size is not proportional, it might not represent the majority of the smaller strata. Benefits: Compared to random sampling, it is more representative, especially in cases when strata differ significantly.

The population of this research consists of Generation Y and Generation Z retail investors, sourced from the Securities Banks in North Sumatra. Based on North Sumatra IDX data as of July 2024, the number of stock investors in North Sumatra is 273,318 SID. From this population, the sampling technique employed was purposive sampling, selected to ensure that respondents met specific criteria relevant to the research objectives: (1) belonging to the Generation Y or Z age group, and (2) having active experience in stock investment decisions. The final sample consisted of 230 respondents (divided into 115 Generation Y and 115 Generation Z). This sample size is considered adequate as it meets the "10-times rule" requirement for PLS-SEM analysis. According to Hair et al. (2019), the minimum sample size should be ten times the largest number of structural paths directed at a particular latent construct. Since the maximum number of structural paths in this study is well within this limit, the sample size of 230 is sufficient to ensure statistical power and valid results. Generation Z, those under the age of 30, ranks at the top, with 157,130 SID. Generation Y is in second place, with a total of 65,101. Therefore, the population of this study is as follows:

Because the population used is quite large, researchers aim to facilitate research by conducting random sampling, which is expected to represent the entire intended population. The sample size calculation was performed using the sample size calculator feature available on the website www.raosoft.com. In the calculation, the population size is entered in the population size column, with a 95% confidence level, a 50% response distribution, and a 5% margin of error. The calculation is as shown in Figure 1.

Figure 1. Sample size calculation results



Based on Figure 1, this study's participants were 384. Preferably, the sample size should be 100 or greater. Generally, the minimum sample size is at least five times the number of items being analyzed (Hair et al., 2019). The number of questions in this study was 29, so the minimum sample size was 29 × 5 = 145 respondents, ensuring that the sample size in this study meets the general rules.

The data collection technique used in this study involves distributing online questionnaires created in Google Forms to investors in North Sumatra. These questionnaires were sent via social media applications, specifically WhatsApp. Accessibility: Respondents can complete the questionnaire at their convenience, provided they have an internet connection.

The questionnaire distributed was measured on a Likert scale to make it easier for respondents to understand the scoring, ranging from highest to lowest (Hair et al., 2019). There are 5 rating scales as follows:

1. Strongly disagree (1)
2. Disagree (2)
3. Neutral (3)
4. Agree (4)
5. Strongly Agree (5)

4.2 Justification for Ordinal Data Treatment:

Although Likert scales produce ordinal data, previous studies have demonstrated that multi-item Likert scales can be treated as interval data in social and behavioral sciences. This approach allows the use of parametric statistical techniques such as SEM and t-tests (Carifio & Perla, 2008; Norman, 2010). Because the scale items represent approximately equal intervals in respondents' perceptions, multi-item Likert data are treated as interval-level data for analysis purposes.

Operational Definition of Variables:

Latent Variable	Operational Definition	Measurement Source
Trait Anger	A stable tendency to experience anger across a range of situations.	Spielberger (1999)
Trait Anxiety	A person's tendency to perceive situations as threatening and to respond with anxiety.	Spielberger (1999)
Overconfidence	The tendency to overestimate one's knowledge and judgment in investment decisions.	Odean (1998)
Herding Effect	The tendency of investors to follow the actions of others rather than their own information.	Banerjee (1992)
Self-Monitoring	The degree to which individuals regulate their behavior in social contexts.	Snyder (1974)
Investment Decision	The process through which investors evaluate and choose investment alternatives.	Adapted from Shanmugam and Zaman (2019)

Demographic Profile of Respondents:

Demographic Variable	Categories	Percentage (%)
Gender	Male / Female	58 / 42
Age	18–25, 26–35	64 / 36
Education	Bachelor, Master	82 / 18
Income Level	< Rp5 million, Rp5–10 million, > Rp10 million	40 / 45 / 15
Investment Experience	<1 year, 1–3 years, >3 years	35 / 44 / 21

4.3 Data Analysis Technique

This study uses SmartPLS software to analyze quantitative data. We use the Structural Equation Model (SEM) for data analysis to test hypotheses. We will analyze the data collected for this investigation using a statistical program named SmartPLS (Ghozali & Latan, 2014). Partial least squares (PLS) analysis is a multivariate statistical method that examines several independent and dependent variables (Ghozali & Fuad, 2014). The assessment of the PLS model involves evaluating both the inner and outer models **(**Equations 1 and 2**).** The inner model is a structural model (Equation 3) that predicts the causal relationship between latent variables.

In contrast, the outer model is a measurement model that predicts the relationship between the estimated indicators or parameters and their latent variables. Validity and dependability are critical for outer model analysis. An outer model analysis tool, Cronbach's Alpha and composite reliability, is used to check the structure's average variance extracted (AVE), heterotrait-monotrait ratio (HTMT), and general dependability. Additionally, it examines the discriminant validity and convergence of the indicators. One part of PLS-SEM that evaluates the causal links between variables is model analysis. It entails analyzing the correlations between variables and determining the predictive significance of the model. To find important variations in the model, we employ differential testing. This investigation evaluated SmartPLS's bootstrapping, sampling, multi-group analysis (MGA), and moderating features.

This research also utilizes SPSS analysis tools to conduct a differential test on the stock investment decision-making of Generation Y and Generation Z. The Chi-Square Test, a statistical method, examines the relationship between two categorical variables. We analyze the data using SPSS and the p-value to determine whether a significant relationship exists. We use the differential test with a moderator variable to investigate the impact of an independent variable on a dependent variable. The process involves creating interaction variables, conducting ANOVA, and implementing multi-group analysis in PLS-SEM. The differential test analysis encompasses hypothesis formulation, test selection, data preparation, assumption testing, test implementation, result interpretation, and reporting.

Measurement Model (Outer Model)

The measurement model specifies the relationship between observed indicators and their corresponding latent variables. The general form of the measurement model is as follows:

$$x = \Lambda x \, \xi + \delta, \tag{1}$$

$$y = \Lambda y \, \eta + \varepsilon, \tag{2}$$

where:

x, y = vectors of observed indicators,
ξ = exogenous latent variables,
η = endogenous latent variables,
$\Lambda x, \Lambda y$ = loading matrices,
δ, ε = measurement errors.

Structural Model (Inner Model)

The structural model specifies the relationships between latent variables, expressed as:

$$\eta = \beta\eta + \Gamma\xi + \zeta, \tag{3}$$

where:

β = path coefficient matrix among endogenous variables,
Γ = path coefficient matrix linking exogenous to endogenous variables,
ζ = residual terms (errors).

Both models were estimated using SmartPLS 4.0 with a bootstrapping procedure (5000 resamples) to evaluate the significance of path coefficients.

PLS-SEM analysis involves two main stages:

1. Evaluation of the Outer Model: to assess indicator reliability, composite reliability, convergent validity (AVE > 0.5), and discriminant validity (HTMT < 0.9).

2. Evaluation of the Inner Model: to assess R^2, path coefficients, and effect size (f^2).

SPSS was used to perform differential tests (independent samples t-test) to examine whether significant differences exist in investment decisions between Generation Y and Generation Z investors.

5. Analysis of Results

5.1 Outer Model Analysis

We perform outer model analysis to ensure the measurement is appropriate, valid, and trustworthy. The measurement model, also known as the outer model, tests the instrument's reliability and variable validity. We conduct a validity test to determine whether the research instrument accurately measures what it is intended to measure. The reliability test evaluates a notion and measures the consistency with which respondents answer questions in a research tool or questionnaire.

The purpose of the outer model is to evaluate the model's validity and dependability. We assess outer models using reflective indicators, evaluating composite reliability, Cronbach's Alpha for the indicator block, and the convergent and discriminant validity of latent construct-forming indicators. Convergent validity is the test conducted on the outer model. The factor loading value on the latent variable, along with its indicators, represents the convergent validity value; the predicted value is greater than 0.7. The value of the cross-loading factor, or Average Variance Extracted (AVE), is known as discriminant validity. Composite reliability and the predicted AVE value are both greater than 0.5. The composite reliability of high-reliability data is greater than 0.7.

Cronbach's Alpha specifically strengthens the reliability test. For every variable, the predicted value is greater than 0.6.

Figure 2. Outer Model Evaluation

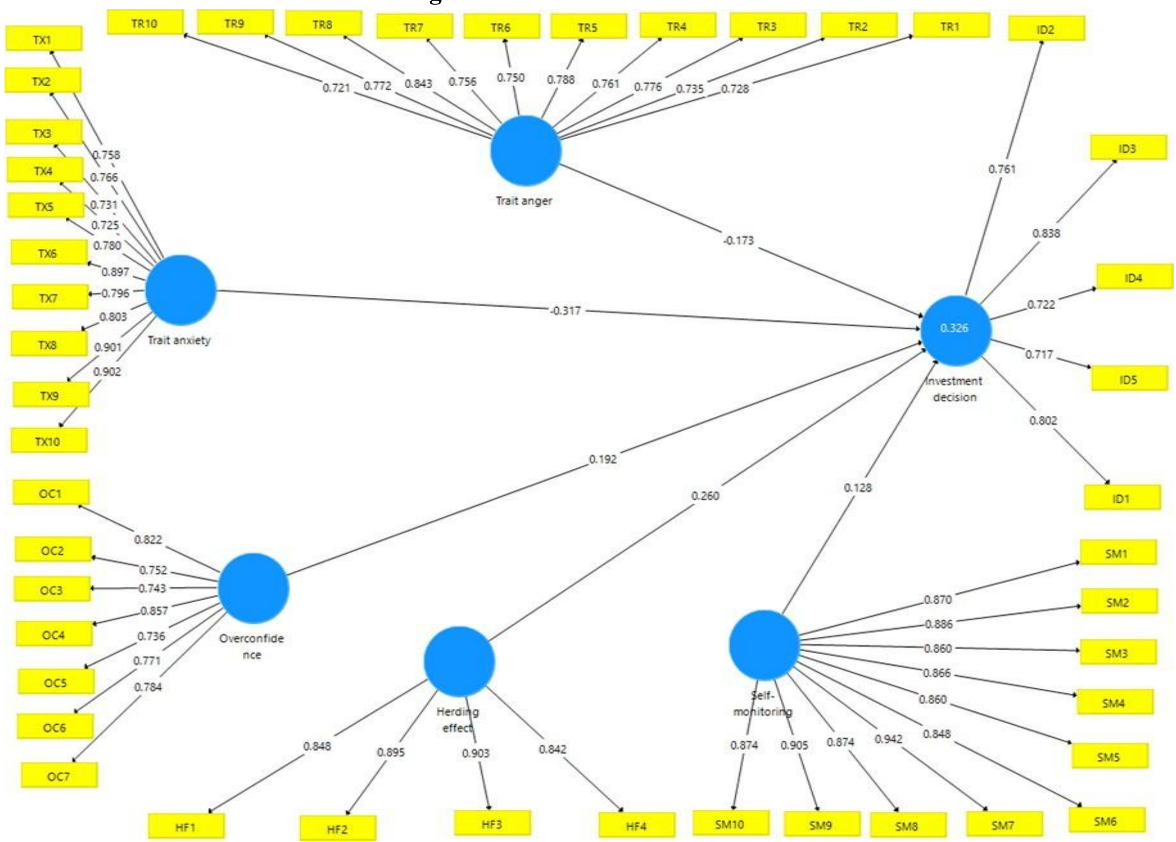


Table 3. Evaluating the Measurement Model using Outer Loadings, Alpha, Composite Reliability, and AVE.

Variables	**Indicators**	**Outer Loadings**	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted**
	TR.1	0.728			
	TR.2	0.735			
	TR.3	0.776			
	TR.4	0.761			
Trait anger	TR.5	0.788	0.921	0.935	0.583
	TR.6	0.750			
	TR.7	0.756			
	TR.8	0.843			
	TR.9	0.772			
	TR.10	0.721			
	TX.1	0.758			
	TX.2	0.766			
	TX.3	0.731			
	TX.4	0.725			
Trait anxiety	TX.5	0.780	0.941	0.949	0.654
	TX.6	0.897			
	TX.7	0.796			
	TX.8	0.803			
	TX.9	0.901			

	TX.10	0.902			
Overconfidence	OC.1	0.822	0.899	0.916	0.611
	OC.2	0.752			
	OC.3	0.743			
	OC.4	0.857			
	OC.5	0.736			
	OC.6	0.771			
	OC.7	0.784			
Herding effect	HF.1	0.848	0.897	0.927	0.761
	HF.2	0.895			
	HF.3	0.903			
	HF.4	0.842			
Investment Decision	ID.1	0.761	0.829	0.879	0.592
	ID.2	0.838			
	ID.3	0.722			
	ID.4	0.717			
	ID.5	0.802			
Self monitoring	SM.1	0.870	0.967	0.971	0.772
	SM.2	0.886			
	SM.3	0.860			
	SM.4	0.866			
	SM.5	0.860			
	SM.6	0.848			
	SM.7	0.942			
	SM.8	0.874			
	SM.9	0.905			
	SM.10	0.874			

Note: This table summarizes the results of the Outer Model (Measurement Model) evaluation (Equations 1 and 2). Outer Loadings confirm individual indicator reliability (required threshold > 0.7). Cronbach's Alpha and Composite Reliability assess internal consistency (required threshold > 0.7). Average Variance Extracted (AVE) measures convergent validity (required threshold > 0.5).

Based on Table 3, all indicators used in the variables of this study, such as trait anger, trait anxiety, overconfidence, herding effect, investment decision, and self-monitoring, have outer loading values greater than 0.7. Therefore, it can be concluded that all indicators in all variables used in this study are valid. The average value for each variable is greater than 0.5, as indicated by the convergent validity test results in Table 3. Therefore, we can affirm the genuineness and reliability of the following factors: trait anger, trait anxiety, overconfidence, the herding effect, self-monitoring, and investment decisions. Table 3 above indicates that the study's Cronbach's Alpha and Composite Reliability values exceed the predetermined threshold of 0.70. This indicates that the tool's consistency as a measurement device is high.

Table 4. Discriminant Validity Heterotrait-Monotrait Ratio (HTMT)

	Herding Effect	Investment Decision	Overconfidence	Self Monitoring	Trait Anger	Trait Anxiety
Herding Effect						
Investment Decision	0.377					
Overconfidence	0.532	0.302				
Self Monitoring	0.299	0.283	0.323			
Trait Anger	0.097	0.330	0.201	0.093		
Trait Anxiety	0.325	0.349	0.342	0.148	0.496	

Note: The table shows the Heterotrait-Monotrait Ratio (HTMT) used to assess discriminant validity of the indicators defined in Equations 1 and 2. Good discriminant validity is achieved when the HTMT values between all pairs of constructs are below the critical threshold of 0.90.

Based on Table 4, the results of the discriminant validity test using the Heterotrait-Monotrait Ratio (HTMT) show that all values between constructs are below the 0.90 limit. This indicates that each variable, namely Trait anger, Trait anxiety, overconfidence, the herding effect, Self-Monitoring, and stock investment decision-making, has good discriminant validity.

Before assessing the structural relationships, the overall model fit was evaluated. Unlike covariance-based SEM (CB-SEM), which relies on Chi-square-based indices (e.g., GFI, CFI, Chi-square/d.f), PLS-SEM is non-parametric and uses the Standardized Root Mean Square Residual (SRMR) as the primary measure of model fit (Hair et al., 2019). The SRMR is defined as the difference between the observed correlation and the model-implied correlation matrix. A value less than 0.08 is considered a good fit (Hu & Bentler, 1999). The analysis results show an SRMR value of 0.072, which is below the recommended threshold, indicating that the proposed model has a satisfactory fit for the empirical data.

5.2 Inner Model Analysis

We examine the path coefficient value and the dependent variable's R-squared value, also known as the coefficient of determination, to test the inner model. The suggested research model's prediction model performs better when the R-squared value is higher. The path coefficient value, on the other hand, indicates the degree to which the independent variable influences the dependent variable. The inner model analysis also employs moderating factors and partial hypotheses for hypothesis testing.

Figure 3. Inner Model Evaluation

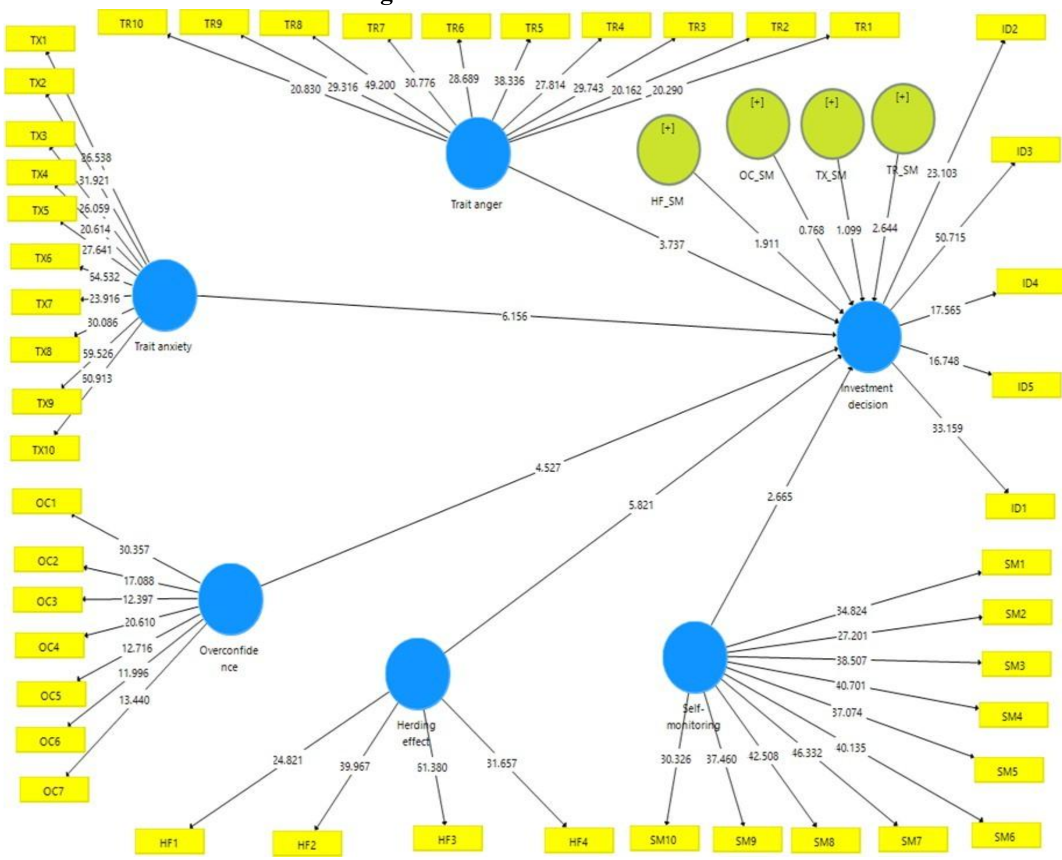


Table 5. Model Evaluation with R-squared

	R Square	R Square Adjusted
Investment Decision	0.326	0.317

Note: R Square (Coefficient of Determination) indicates the proportion of the variance in the dependent variable (Investment Decision) that is predictable from the independent and moderating variables (based on Structural Model Equation 3). R Square Adjusted is the R-squared value adjusted for the number of predictors in the model.

Based on Table 5, the R-squared value obtained in this study is 0.326. This value indicates that stock investment decision-making, which can be influenced by Trait anger, Trait anxiety, overconfidence, the Herding effect, and Self-monitoring, accounts for 32.6%. In contrast, the remaining 67.4% is attributed to other variables not considered in this study.

Table 6. Bootstrap Path Coefficient value

	Coefficients	T Statistics	P Values*	Decision
Trait Anger -> Investment decision	-0.206***	3.712	0.000	Supported
Trait Anxiety -> Investment decision	-0.289***	6.527	0.000	Supported
Overconfidence -> Investment decision	0.242	4.763	0.000	Supported
Herding effect -> Investment decision	0.279***	6.015	0.000	Supported
Self-Monitoring -> Investment decision	0.142***	2.665	0.008	Supported

Trait Anger × Self-Monitoring -> Investment decision	0.099***	2.757	0.006	Supported
Trait Anxiety × Self-Monitoring -> Investment decision	-0.038	1.159	0.247	Not Supported
Overconfidence × Self-Monitoring -> Investment decision	0.039	0.846	0.398	Not Supported
Herding Effect × Self-Monitoring -> Investment decision	-0.078**	1.998	0.041	Supported

Note: The table presents the path coefficients from the PLS-SEM Inner Model (Structural Model) analysis (Equation 3). Path coefficients indicate the strength and direction of the relationships between latent variables. The significance levels are defined as follows: ***p < 0.001, **p < 0.01, *p < 0.05 (based on a two-tailed t-test with 5000 bootstrap resamples).

Based on Table 6, Trait Anger has a negative and significant effect on individual stock investment decision-making, with a coefficient value of -0.206, a t-value of 3.712, and a P-value of 0.000, which means that hypothesis H1 is supported. This suggests that as the investor's anger decreases, the quality of their stock investment decision-making improves, because anger is negatively correlated with effective decision-making. Investors who can suppress their anger can reduce the risk in decision-making, because anger is positively correlated with risk.

Hypothesis H2 in this study proves that the nature of anxiety has a negative and significant effect on individual stock investment making, with a coefficient value of - 0.289, a t-value of 6.527, and a P-value of 0.000, meaning that hypothesis H2 is supported. The more an investor's anxiety level decreases, the more the investor's confidence level increases in making stock investment decisions, because the nature of anxiety affects the level of confidence of an investor, and the nature of anxiety motivates individuals to avoid investment.

Hypothesis H3 in this study is supported because the results of data analysis show a coefficient value of 0.242, a t-value of 4.763, and a P-value of 0.000, meaning that overconfidence has a positive and significant effect on stock investment decision-making. This means that the higher the level of investor confidence, the more investor decision-making increases. However, this study confirms hypothesis H4, which posits that the Herding factor is positively related to individual stock investment decision-making, with a coefficient value of 0.279, a t-value of 6.015, and a P-value of 0.000, indicating that hypothesis H4 is supported. The higher the herding factor, the more comfortable investors are in making decisions. Hypothesis H5 proves that self-monitoring is positively related to individual stock investment decision-making, with a coefficient value of 0.142, a t-value of 2.665, and a P-value of 0.008, meaning that hypothesis H5 is supported. This indicates that high self-monitoring is more careful in avoiding decisions that can lead to conflict. They tend to consider the impact of decisions, thereby reducing the risks. Hypothesis H6 of this study proves that self-monitoring can moderate Anger Traits on Individual stock investment decision making, with a P-value of 0.006, which means hypothesis H6 is supported. "Interestingly, this study found that self-monitoring did not significantly moderate the effects of anxiety (H7) and overconfidence (H8) on investment decisions. A plausible explanation for the lack of moderation on anxiety is that anxiety operates as a visceral, high-arousal emotional state that consumes cognitive resources. According to Attentional Control Theory (Eysenck et al., 2007), high anxiety creates 'tunnel vision,' focusing attention solely on the perceived threat (financial loss), which may override the individual's capacity for social self-regulation. Consequently, even high self-monitors may find their regulatory mechanisms paralyzed when overwhelmed by the internal physiological stress of anxiety.

Similarly, the insignificant moderation for overconfidence suggests that this bias acts as a cognitive shield against external cues. Overconfidence is characterized by an inflated belief in the precision of one's own private information (Odean, 1998). While self-monitoring involves adjusting behavior based on social feedback, overconfident investors tend to dismiss external opinions that contradict their beliefs. Therefore, the conviction driven by overconfidence appears to be robust enough to bypass the adaptive filtering mechanisms of self-monitoring, leading investors to act on their biased judgments regardless of their social sensitivity."

5.3 Normality Test (Shapiro-Wilk)

The Normality Test was conducted to assess the distribution of the dependent variable (Investment Decision) for both generational cohorts prior to the differential test. The results, as presented in Table 7, show conflicting findings between the two common normality tests employed.

Table 7. Normality Test Results

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
GenerationY	.072	115	.000	.869	115	.061
GenerationZ	.087	115	.031	.979	115	.070

a. Lilliefors Significance Correction

Note: The Shapiro-Wilk and Kolmogorov-Smirnov tests assess the null hypothesis of normal distribution for the dependent variable (Investment Decision) across the two generational groups. Sig. (p-value) > 0.05 suggests the data is normally distributed. df = degrees of freedom.

The Kolmogorov-Smirnov (K-S) test yields significance values of 0.000 (Generation Y) and 0.031 (Generation Z)2. Since both values are less than the critical level of $p < 0.05$, the K-S test formally rejects the null hypothesis of normality for both groups. Conversely, the Shapiro-Wilk (S-W) test yields significance values of 0.061 (Generation Y) and 0.070 (Generation Z). As both values are greater than $p > 0.05$, the S-W test does not reject the null hypothesis of normality**.**

This conflict in results must be addressed. We justify proceeding with the parametric tests (PLS-SEM and the *t*-test) based on two arguments, as suggested by the literature:

1. Supremacy of Shapiro-Wilk for Sample Size: The Shapiro-Wilk test is generally considered more powerful than the Kolmogorov-Smirnov test, particularly for moderate sample sizes ($n < 2000$). Given that the individual generational samples for the differential test (n_Y=115 and n_Z=115) are within the range where the S-W test exhibits greater statistical power, the S-W results (0.061 and 0.070) are prioritized, suggesting sufficient normality to proceed with parametric testing.

2. Robustness of Analysis Method: Furthermore, the primary structural analysis method used is PLS-SEM, which is distribution-free and highly robust to violations of the normality assumption. For the subsequent independent samples *t*-test (differential test), violations of normality are generally acceptable when the sample size is relatively large (Central Limit Theorem) and when the scale data, derived from multi-item Likert scales, are treated as interval data, which helps mitigate the non-normality effect.

Therefore, based on the non-rejection of normality by the more sensitive Shapiro-Wilk test and the inherent robustness of PLS-SEM to moderate violations, we conclude that the data distribution is suitable for the subsequent analyses.

5.4 Differential Test

The two variants are the same if the F count with equal variance assumed (assuming both variances are equal) has a significance > 0.05. On the other hand, it is said that the two variances are different if the F-count with equal variance assumed (assuming both variances are equal) has a significant value (p-value) <0.05. Table 8 displays the findings of the t-test used in this investigation.

Table 8. Differential Test Results

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Investment Decision Making	Equal variances assumed	32.823	0.000	9.005	230	0.000	3.12069	0.34657	2.43784	3.80354
	Equal variances not assumed			9.005	174.759	0.000	3.12069	0.34657	2.43669	3.80469

Note: This independent samples t-test compares the mean Investment Decision scores between Generation Y and Generation Z. Levene's Test (F, Sig.) tests the equality of variances (Sig. < 0.05 indicates unequal variances). Sig. (2-tailed) is the p-value for the difference in means. A Sig. < 0.05 indicates a statistically significant difference in investment decision-making between the two groups.

Table 8 shows that the Sig. (2-tailed) of 0.000, which indicates that Generation Y's stock investment decision-making and Generation Z's investment decision-making differ, thereby supporting hypothesis H10.

6. Discussions

The findings of this study indicate that Trait Anger has a negative and significant effect on individual stock investment decision-making. This suggests that in a state of anger, people often make decisions impulsively without considering the long-term consequences. This is due to a strong emotional drive that makes them need to act immediately. Therefore, managing angry emotions well will help in making more objective, rational, and strategic decisions. This research is supported by Lerner and Tiedens (2006), who suggest that anger is positively correlated with risk estimation and optimistic beliefs that arise from anger. They also said that the nature of anger will interpret adverse events. This study also proves that the nature of anxiety has a negative and significant effect on individual stock investment decisions. This suggests that the lower an investor's anxiety level, the higher their level of confidence in making stock investment decisions, as the nature of anxiety affects an investor's confidence level. This research is supported by research conducted by Gambetti and Giusberti (2012), which says the nature of high anxiety motivates individuals to avoid investing. Therefore, investors try to accept that in every decision, there will always be a level of uncertainty. Avoiding perfection can reduce pressure in the decision-making process.

The study's findings also demonstrate a favorable correlation between the herding factor and the individual decision to invest in stocks. This means that by following the actions of others who are experienced or considered experts, one can avoid mistakes and get better results by imitating behavior or decisions that have proven effective. When time is at a premium, herding can help speed up decision-making. In emergencies or those that require a quick response, following the actions of others can help you act quickly without in-depth analysis. This research is supported by Caparrelli et al. (2004), who claim that one of the causes of speculative bubbles is the herding effect. This study also demonstrates a beneficial relationship between self-monitoring and the decision to invest in stocks. High self-monitoring people are frequently more cautious and astute in avoiding choices that can lead to conflict. They tend to consider the impact of decisions on others, which can reduce the risk of social tension. This finding aligns with research conducted by Blakely et al. (2003), which suggests that individuals with high self-monitoring are generally more sensitive and adjust their behavior to specific situations, thereby enhancing their communication abilities and interpersonal skills compared to those with low self-monitoring.

This study also shows that self-monitoring variables can moderate the nature of anger and herding factors in decision-making. This demonstrates that self-monitoring can be a powerful tool for making effective and adaptive decisions without compromising personal integrity or long-term goals. The results of this study also indicate that Generation Z's approach to making stock investment decisions differs from that of Generation Y. In making decisions, Generation Z tends to rely on social media, applications, and digital sources that are fast and direct.

They often make informed decisions quickly and can adapt to more dynamic trends. Generation Y prioritizes experience and often makes decisions based on long-term impact, whether in terms of career, finances, or relationships. They tend to prioritize work-life balance and choose decisions that provide them with stability and growth opportunities in the long run. Generation Z relies heavily on technology and tends to be more risk-taking. At the same time, Generation Y focuses on stability and balance between short-term and long-term decisions. This research is supported by Stillman and Stillman's (2017) study, which suggests that Generation Y differs from Generation Z, as Generation Z is more advanced, more open-minded, and less concerned with traditional norms. Generation Y tends to make more stable and thoughtful decisions. In contrast, Generation Z is faster, more intuitive, and more adaptive in the face of change. Generation Z relies heavily on technology and tends to be more risk-taking. At the same time, Generation Y prioritizes stability and balances short-term and long-term decisions.

The implications of this study's results are to provide information about the behavioral biases of stock investors in North Sumatra, offering direction for developing appropriate policies that can motivate Generation Y and Generation Z to participate in the stock market in North Sumatra. Furthermore, this research is also expected to enhance investors' understanding of the stock investment decision-making process in North Sumatra.

7. Conclusion

7.1. Conclusion

The rapid democratization of capital markets has precipitated a massive influx of Generation Y and Z investors. While this phenomenon signals improved financial inclusion, it simultaneously unveils a critical problem: some novice investors are often characterized by limited experience and high susceptibility to psychological biases. The existing situation underscores that without adequate self-regulation, young investors are prone to irrational behaviors—specifically, herding and emotional instability (anger and anxiety)—which could exacerbate market volatility and individual financial distress. Consequently, the primary motive of this study is to move beyond the traditional focus on financial literacy and investigate the psychological mechanisms that can mitigate the biases. This inquiry is theoretically salient as it addresses a significant gap in behavioral finance: understanding how internal personality traits, specifically, Self-Monitoring, serve as regulatory filters in investment decision-making.

The empirical findings of this study offer deep insights into investor psychology. The results demonstrate that emotional traits (Trait Anger and Anxiety) have a detrimental negative effect on investment decision quality, impairing cognitive processing and leading to impulsive errors. Conversely, Herding behavior exerts a strong positive influence, indicating that young investors heavily rely on collective market sentiment rather than fundamental analysis, thereby exposing themselves to speculative risks. Most significantly, this study establishes that Self-Monitoring acts as a crucial moderator. High self-monitors possess the cognitive flexibility to discern social cues without blindly following them, effectively buffering the negative impact of emotional biases and reducing the tendency to herd.

Theoretically, this research makes a distinct and original contribution to the literature. Unlike prior studies that treat behavioral biases as inevitable, this study provides a novel model demonstrating that psychological self-regulation (Self-Monitoring) can attenuate irrational tendencies. This finding enriches both Prospect Theory and Social Learning Theory by introducing a personality-based moderator that explains why some investors remain rational amidst market turbulence while others do not.

7.2. Practical and Managerial Implications

For practitioners and regulators, the findings from our paper could be used to develop some urgently-needed strategies. On the other hand, based on our findings, investment managers and fintech developers should not merely focus on technical accessibility but also on behavioral architecture. However, trading platforms should integrate features that detect impulsive trading patterns (e.g., rapid-fire buying during high volatility) and trigger "cooling-off" interventions or "reflective prompts" to activate the user's self-monitoring mechanism. Furthermore, based on our findings, regulators should redesign financial education curricula to include psychological conditioning, training young investors to recognize their emotional triggers (anger/anxiety) and resist the urge to herd, thereby fostering a more resilient investor generation.

7.3. Limitations and Future Research Directions

Despite the rigorous analysis, this study acknowledges several limitations that provide avenues for future study. For example, our study employs a cross-sectional design that can only capture investor psychology at a single point in time. Consequently, it cannot establish causality or observe how self-monitoring evolves during shifting market cycles (e.g., the psychological shift from a bull market to a bear market) or other time periods. Thus, one area of the extension of our paper is to study the issue in different time frames.

Another limitation of our study is that our sample is concentrated only in North Sumatra, but not in other areas. In addition, representatives of emerging markets, cultural nuances in other regions, or major financial hubs (e.g., Jakarta, Singapore) might yield different behavioral baselines. Therefore, future research should circumvent the limitations by adopting longitudinal or experimental designs to track the stability of self-monitoring and its long-term impact on portfolio performance. Expanding the geographical scope to a national or comparative international level to enhance generalizability. Exploring additional moderators, such as Locus of Control, Financial Self-Efficacy, or the Dark Triad personality traits, to build a more comprehensive model of investor irrationality mitigation.

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References

Abuaddous, M., Bataineh, H., & Alabood, E. M. (2018). Burnout and auditor's judgment decision making: An experimental investigation into control risk assessment. *Academy of Accounting and Financial Studies Journal, 22*(1), 1–12.

Adel, B., & Mariem, T. (2013). The impact of overconfidence on investors' decisions. *Business and Economic Research*, *3*(2), 53. https://doi.org/10.5296/ber.v3i2.4200

Akhter, R., & Ahmed, S. (2013). Behavioral aspects of individual investors for investment in Bangladesh stock market 58. In International Journal of Ethics in Social Sciences (Vol. 1, Issue 1).

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107*(3), 797–817. https://doi.org/10.2307/2118364

Bennet, E., Selvam, M., Vivek, N., & Shalin, E. E. (2012). The impact of investors' sentiment on the equity market: Evidence from Indian stock market. *AFRICAN JOURNAL OF BUSINESS MANAGEMENT*, *6*(32). https://doi.org/10.5897/ajbm11.588

Biais, B., Hilton, D., Mazurier, K., & Pouget, E. (2005). Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market. Review of Economic Studies, 72, 287–312.

Blakely, G. L., Andrews, M. C., & Fuller, J. (2003). Are chameleons good citizens? A longitudinal study of the relationship between self-monitoring and organizational citizenship behavior. Journal of Business and Psychology, 18(2), 131–144. [suspicious link removed]

Caparrelli, F., D'Arcangelis, A. M., & Cassuto, A. (2004). Herding in the Italian stock market: a case of behavioral finance. *The Journal of Behavioral Finance*, *5*(4), 222-230. https://doi.org/10.1207/s15427579jpfm0504_5

Caplin, A., & Leahy, J. (2001). Psychological expected utility theory and anticipatory feelings. The Quarterly Journal of Economics, 116(1), 55–79. https://doi.org/10.1162/003355301556347

Carifio, J., & Perla, R. J. (2008). Resolving the 50-year debate around using and abusing Likert scales. *Medical Education, 42*(12), 1150–1152. https://doi.org/10.1111/j.1365-2923.2008.03172.x

Christopher, A. N., Dobbins, E. M., Marek, P., & Jones, J. R. (2004). Three decades of social psychology: A longitudinal analysis of Baron and Byrne's textbook. Teaching of Psychology, 31(1), 31–36. https://doi.org/10.1207/s15328023top3101_8

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. Handbooks in operations research and management science, 9, 385-410..

Dios-Palomares, R., Alcaide, D., Diz, J., Jurado, M., Prieto, A., Morantes, M., & Zuniga, C. A. (2015). Analysis of the efficiency of farming systems in Latin America and the Caribbean considering environmental issues. http://www.redalyc.org/articulo.oa?id=95934122007

Eysenck, M. W., Derakshan, S., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional Control Theory. Emotion, 7(2), 336–353. https://doi.org/10.1037/1528-3542.7.2.336

Forgas, J. P. (2000). Feeling and thinking: The role of affect in social cognition. Cambridge University Press.

Gambetti, E., & Giusberti, F. (2012). The effect of anger and anxiety traits on investment decisions. Journal of Economic Psychology, 33(6), 1059–1069. https://doi.org/10.1016/j.joep.2012.07.001

Ghozali, I., & Fuad, F. (2014). Structural equation modeling :Teori, konsep, dan aplikasi dengan program Lisrel 9.10.

Ghozali, I., & Latan, H. (2014). Partial least squares konsep, metode dan aplikasi menggunakan program WARPPLS 4.0.

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*, *53*(4), 566–584. https://doi.org/10.1108/EJM-10-2018-0665

Hoffrage, U. (2022). Overconfidence. In *Cognitive Illusions* (pp. 287–306). Routledge. https://doi.org/10.4324/9781003154730-21

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

Kaya, N., & Tosun, H. (2018). The relationship between nurses' sociotropy–autonomy personality characteristics and trait anger: Anger expression styles. SAGE Open, 8(2). https://doi.org/10.1177/2158244018772874

Kourtidis, D., Šević, Ž., & Chatzoglou, P. (2011). Investors' trading activity: A behavioural perspective and empirical results. *Journal of Socio-Economics*, *40*(5), 548–557. https://doi.org/10.1016/j.socec.2011.04.008

Lemer, J. S., & Keltner, D. (2001). Fear, anger, and risk. Journal of Personality and Social Psychology, 81(1), 146–159. https://doi.org/10.1037//O022-3514.81.1.146

Lerner, J. S., & Tiedens, L. Z. (2006). Portrait of the angry decision maker: How appraisal tendencies shape anger's influence on cognition. In *Journal of Behavioral Decision Making* (Vol. 19, Issue 2, pp. 115–137). John Wiley and Sons Ltd. https://doi.org/10.1002/bdm.515

Mahmood, T., Ayyub, R. M., Imran, M., Naeem, S., & Abbas, W. (2020). The behavioral analysis and financial performance of individual investors at pakistan stock exchange. International Journal of Economics and Financial Issues, 10(5), 158–164. https://doi.org/10.32479/ijefi.10112

Manurung, A. H., Riri, V., & Kartika, T. R. (2020). The effect of overconfidence and behavioural motivation on stock investment decisions. International Journal of Creative Research Thoughts, 8(2), 1924–1930.

Ngamake, S. T., Raveepatarakul, J., & Sawang, S. (2024). An evolving landscape of the psychology of judgment and decision-making: A bibliometric analysis. Administrative Sciences, 14(8). https://doi.org/10.3390/admsci14080162

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*(5), 625–632. https://doi.org/10.1007/s10459-010-9222-y

Odean, T. (1998). Are investors reluctant to realize their losses? The Journal of Finance, 53(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Pradhana, R. W. (2018). Pengaruh financial literacy, cognitive bias, dan emotional bias terhadap keputusan investasi (studi pada investor galeri investasi universitas negeri surabaya). Jurnal Ilmu Manajemen, Jurusan Manajemen Fakultas Ekonomi Universitas Negeri Surabaya, 6(3).

https://core.ac.uk/outputs/230763794/?utm_source=pdf&utm_medium=banner&utm_campaign=pdf-decoration-v1

Rahman, M., & Gan, S. S. (2020). Generation Y investment decision: an analysis using behavioural factors. *Managerial Finance*, *46*(8), 1023–1041. https://doi.org/10.1108/MF-10-2018-0534

Shanmugam, R., & Zaman, R. (2019). An empirical analysis of individual investors' behavior in the Indian stock market. *International Journal of Business and Management Invention, 8*(3), 1–8.

Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. The Journal of Financial and Quantitative Analysis, 35(2), 127–151. https://doi.org/10.2307/2676187

Shiller, R. J. (1999). Human behavior and the efficiency of the financial system. *Handbook of macroeconomics*, *1*, 1305-1340.

Shim, H., Koo, J. E., & Shim, T. S. (2023). The effect of implementation of the Stewardship Code on nonprofessional investors' judgment and decision-making. Applied Economics, 55(16), 1769–1789. https://doi.org/10.1080/00036846.2022.2099526

Slovic, P., Finucane, M. L., Peters, E., & Macgregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. In Risk Analysis (Vol. 24, Issue 2).

Snyder, M. (1974). Self-monitoring of expressive behavior. Journal of Personality and Social Psychology, 30(4), 526–537. https://doi.org/10.1037/h0037039

Spielberger, C. D. (1999). *State-Trait Anger Expression Inventory-2 (STAXI-2): Professional manual*. Psychological Assessment Resources.

Spielberger, C. D., & Sydeman, S. J. (1994). State-Trait anxiety inventory and state-trait anger expression inventory. In The use of psychological testing for treatment planning and outcome assessment. (pp. 292–321). Lawrence Erlbaum Associates, Inc.

Stillman, D., & Stillman, J. (2017). *Gen Z@ work: How the next generation is transforming the workplace*. HarperCollins.

Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal*, *16*(1–2), 61–77. https://doi.org/10.1016/j.pacfin.2007.04.004

Zuniga-Gonzalez, C. A., Quiroga-Canaviri, J. L., Brambila-Paz, J. J., Ceballos-Pérez, S. G., & Rojas-Rojas, M. M. (2024). Formulation of an innovative model for the bioeconomy. *PloS One*, *19*(11), e0309358. https://doi.org/10.1371/journal.pone.0309358

Appendix

Study of Investor Behavior on Stock Investment Decision Making with Self Monitoring as a Moderating Variable in Generation Y and Generation Z

I. RESPONDENT IDENTITY.

1. Your Name : ____
2. Age : ____
3. Gender : a) Male
   b) Female
4. Education : a) Junior High School/Equivalent
   b) High School/Equivalent.
   c) D1-D3.
   d) Bachelor's Degree
   e) Master's Degree
   f) Doctorate
5. Investment period : ____________________________

II. Instructions for Completing the Questionnaire

Before answering the questionnaire questions, respondents are requested to first fill in their identity details in accordance with the provided form

1. Read the questions carefully and circle the answer that you think is correct
2. Please do not try to analyze the questions intensively, and answer according to your own experience/opinion without coercion from any party (honestly), because there are no wrong or right answers.
3. Please do not discuss the questions/answers with others. Note:

STS = Strongly disagree
TS = Disagree.
N = Neutral.
S = Agree.
SS = Strongly Agree.

1. Investment Decision (ID)

The questions/statements below relate to your perception of stock investment decision making.

No	Question	STS	TS	N	S	SS
1	In most cases, my investment decisions support my investment goals	1	2	3	4	5
2	My reaction to loss is normal	1	2	3	4	5
3	I usually get the expected results from my investment decisions	1	2	3	4	5
4	I have a tolerance for risk when it comes to my investment decisions	1	2	3	4	5
5	My investment holding period is spread over a long period of time	1	2	3	4	5

2. Trait Anger (TR)

The questions/statements below relate to your perception of Trait Anger in stock investment decision-making.

No	Question	STS	TS	N	S	SS
1	I get angry quickly	1	2	3	4	5
2	I feel upset if I am not given recognition for a job well done	1	2	3	4	5
3	I am a short-tempered person	1	2	3	4	5
4	I get angry when I am told that I am wrong in front of other people	1	2	3	4	5
5	I lost control	1	2	3	4	5
6	When I get angry, I say things that bad	1	2	3	4	5
7	When I am frustrated, I feel like hitting someone	1	2	3	4	5
8	I feel angry when I do a job well and receive a bad evaluation	1	2	3	4	5
9	I get angry when I have to wait because of someone else's mistake	1	2	3	4	5
10	I am an impulsive person	1	2	3	4	5

3. Trait anxiety (TX)

The questions/statements below relate to your perception of Trait Anxiety in stock investment decision- making.

No	Question	STS	TS	N	S	SS
1	I get tired quickly	1	2	3	4	5
2	Some unimportant thoughts crossed my mind and bother me	1	2	3	4	5
3	I feel overwhelmed and unable to cope	1	2	3	4	5
4	I hope to be as happy as other people	1	2	3	4	5
5	I would worry about something that is actually not important	1	2	3	4	5
6	I take disappointment so hard that I can't get rid of it. my thoughts	1	2	3	4	5
7	I experience tension or confusion when thinking about my recent concerns and interests.	1	2	3	4	5
8	I lost a lot because I couldn't make decisions quickly	1	2	3	4	5
9	I feel happy	1	2	3	4	5
10	I am "calm, cool, and collected" too confident	1	2	3	4	5

4. Overconfidence (OC)

The questions/statements below relate to your perception of overconfidence in stock investment decision- making.

No	Question	STS	TS	N	S	SS
1	You believe that your expertise and knowledge of the stock market can help you outperform the market	1	2	3	4	5
2	You feel you have sufficient ability to manipulate investments for your own benefit	1	2	3	4	5
3	You always feel lucky when investing in the best offers.	1	2	3	4	5
4	You feel experienced enough to predict winning investments	1	2	3	4	5
5	You take as little time as possible to analyze and rely on available market statistics	1	2	3	4	5
6	You conduct more trades between accounting periods	1	2	3	5	5
7	You feel that you have control over the flow of investment returns	1	2	3	5	5

5. Herding effect (HF)

The questions/statements below relate to your perception of the Herding Factor in stock investment decision- making.

No	Question	STS	TS	N	S	SS
1	Other investors' decisions regarding stock volume affect your investment decisions	1	2	3	4	5
2	Other investors' decisions to buy and selling stocks affect your investment decisions	1	2	3	4	5
3	Other investors' decisions in choosing stock types affect your investment decisions	1	2	3	4	5
4	You usually react quickly to changes in other investors' decisions and follow their reactions to the stock market	1	2	3	4	5

6. Self Monitoring (SM)

The questions/statements below relate to your perception of Self Monitoring in making stock investment decisions.

No	Question	STS	TS	N	S	SS
1	I feel a little awkward in public and don't perform as well as I should	1	2	3	4	5
2	I can give impromptu speeches even on topics about which I have almost no information	1	2	3	4	5
3	I can only debate ideas that I already believe in	1	2	3	4	5
4	At parties and social gatherings, I don't try to do or say things that other people like.	1	2	3	4	5
5	I have difficulty changing my behavior to suit different people and situations	1	2	3	4	5
6	I find it difficult to imitate other people's behavior	1	2	3	4	5
7	I will not change my opinion (or the way I do things) to please someone or win their favor	1	2	3	4	5
8	I feel like I'm performing to impress or entertain others	1	2	3	4	5
9	I can look anyone in the eye and lie with a straight face	1	2	3	4	5
10	I can deceive others by being friendly when I really dislike them	1	2	3	4	5