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Exploring overconfidence bias and demographic moderation in aggressive investor behavior; Evidence from Indonesia stock exchange (IDX)

Exploración del sesgo de sobreconfianza y la moderación demográfica en el comportamiento agresivo de los inversores; evidencia de la Bolsa de Valores de Indonesia (IDX)

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Abstract

This study aims to investigate two primary objectives: first, to examine the role of overconfident variables in mediating the impact of fundamental information and bandarmology on aggressive investor behavior; and second, to assess the influence of demographic factors in moderating the effect of overconfident variables on aggressive investor behavior. The research employed a questionnaire as the primary data collection tool, utilizing Google Forms for distribution through multistage purposive random sampling techniques to reach 981 investors across diverse regions in Indonesia. Data analysis was conducted using structural equation modeling via the smartPLS software, revealing that overconfident variables can mediate the influence of fundamental, technical, and bandarmology information on aggressive investor behavior. Moreover, demographic factors like domicile, education, and marital status were found to moderate the relationship between overconfident variables and aggressive investor behavior on the Indonesia Stock Exchange. These findings contribute significantly to the advancement of financial

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behavior theory, particularly prospect theory and overconfidence. The novelty of this study lies in its exploration of the intricate relationship between demographic factors and their potential moderating impact on overconfidence in aggressive investor behavior, marking a new avenue in understanding the behavior of aggressive investors within the Indonesian market.

JEL Code: G11, G14, D81
Keywords: investor behavior; overconfidence; demographic factors; financial markets; structural equation modelling

Resumen

Esta investigación tiene como objetivo examinar dos aspectos clave: primero, la influencia de los factores demográficos en moderar el impacto de la sobreconfianza en el comportamiento agresivo del inversor y, segundo, el papel de las variables de sobreconfianza en mediar los efectos de la información fundamental y la bandarmología en dicho comportamiento. El estudio empleó un cuestionario para la recopilación de datos, distribuido a través de Google Forms mediante técnicas de muestreo aleatorio intencional de múltiples etapas, con 981 inversores en diversas regiones de Indonesia como muestra. Se utilizó el modelado de ecuaciones estructurales a través del software smartPLS para el análisis de datos. Los resultados demuestran que el impacto de la información fundamental, técnica y bandarmológica en el comportamiento agresivo del inversor puede ser mediado por la sobreconfianza. Además, se encontró que variables demográficas, especialmente el domicilio, la educación y el estado civil, moderaron la relación entre la sobreconfianza y el comportamiento agresivo del inversor en la Bolsa de Valores de Indonesia. Este estudio contribuye a la teoría del comportamiento financiero, en particular a la teoría prospectiva y la sobreconfianza, al explorar la conexión novedosa entre los factores demográficos y su potencial efecto moderador en la sobreconfianza en el comportamiento agresivo del inversor. Cabe destacar que no se ha investigado previamente la relación entre los factores demográficos y el comportamiento de los inversores agresivos.

Código JEL: G11, G14, D81
Palabras clave: comportamiento del inversor; sobreconfianza; factores demográficos; mercados financieros; modelado de ecuaciones estructurales

Introduction

Stock investors exhibit a blend of rational and irrational behaviors, both of which significantly influence decision-making processes on the stock exchange. While standard economic theory posits that rational considerations and shared interests form the foundation of investor decision-making, empirical evidence suggests that not all investors adhere strictly to rationality, nor do economic actors consistently align their actions with others (Shiller, 2003).

The advent of technology has profoundly impacted global capital markets, with electronic systems dominating stock transactions and high-frequency trading (HFT) systems accelerating transaction speeds (Akansu, 2017; Santosa, 2020). Market microstructure theory elucidates that stock trading transactions, encompassing buying and selling, unfold within a limit order book (LOB) containing critical transactional information such as strike price, ask price, bid price, ask size, and bid size, all stemming from investor behavior. Price volatility, trading volume, and frequency are heavily influenced by investor order aggressiveness, necessitating careful consideration when choosing between limit orders and market orders (Lee et al., 2020; Rzayev & Ibikunle, 2021).

Despite previous research delving into investor behavior from the limit order book perspective, few studies have interlinked this discussion with financial behavioral biases like overconfidence (Tariqul & Khan, 2015) and other biases explaining decision-making tendencies (Kumar & Goyal, 2015). One prevalent bias in capital markets is overconfidence, wherein investors tend to place excessive trust in positive news, overlook risks, and engage in heightened financial activity, potentially inflating asset prices beyond their intrinsic worth and leading to market bubbles.

Behavioral finance posits that overconfident bias is one of the most common biases observed among investors in financial markets. This bias manifests as a tendency to discount negative news, excessively trust positive news, ignore risk factors, engage in heightened trading activity, and inflate asset prices, resulting in market bubbles. The correlation between overconfidence and increased trading volume is well-documented in behavioral finance literature.

The findings of academic research consistently indicate that overconfidence exerts a positive influence on purchasing decisions, yet subsequently yields a negative impact on investor portfolio performance (Annick, 2020). Numerous studies across various countries, particularly in developed nations, have extensively investigated the ramifications of overconfidence on decision-making processes. This, in turn, significantly influences the quality of investment performance and often leads to decision-making characterized by higher risks (Agha & Pramathevan, 2023). A study conducted in the United States market, focusing specifically on investment managers, discovered that overconfidence tends to lead them to overestimate the information available to them (Adebambo & Yan, 2018). Moreover, research conducted in Hungary revealed a notable correlation between overconfidence and financial well-being (Vörös et al., 2021). Additionally, studies examining the relationship between overconfidence and artificial intelligence within the financial sector have highlighted that investors exhibiting overconfidence tendencies are inclined to utilize AI-based robo-advisors (Piehlmaier, 2022). The dual nature of the effects stemming from overconfidence variables presents opportunities for further investigation. The ongoing development of the capital market coupled with the rapid integration of technology offers ample prospects for behavioral finance theories to expand their scope, particularly in the domain of market microstructure analysis (Subrahmanyam, 2008).

Furthermore, investors rely heavily on information to guide their decision-making processes. Oberlechner (2001) notes that investors often use fundamental and technical information to forecast stock prices, with some favoring technical information. A study involving 692 respondents across Germany, Switzerland, America, Italy, and Thailand emphasizes the significance of technical information and its correlation with psychological factors like herding and overconfidence (Menkhoff, 2010).

Contrary findings from research in Indonesia suggest that technical information may not always impact decision-making, with some investors still prioritizing fundamental information. This disparity underscores the need for further investigation into investors' decision-making methods, particularly their preference for technical or fundamental information (Nuzula, 2019).

The expansion of stock market information sources poses challenges for investors in predicting stock price movements, volatility, and trading volume fluctuations. This complexity prompts inquiries into the dynamics of stock price changes, with market movers playing a crucial role in influencing these fluctuations. Bandarmology analysis, a relatively underexplored topic in academic literature but gaining popularity among stock investors, focuses on understanding market price movers and requires detailed transaction data facilitated by technological advancements (Filbert, 2016; Karo-karo, 2017; Listyorini, 2020).

Behavioral finance theory underscores the importance of demographic factors in shaping investor behavior (Barber & Odean, 2001). These factors, such as gender, financial literacy, risk tolerance, decision-making skills, and information-seeking behavior, play a pivotal role in determining investors' actions (Adrianto & Hamidi, 2020; Baker et al., 2019; Eckel & Grossman, 2008; Musnadi et al., 2023). Drawing from both theoretical insights and empirical observations, this study delves into the intricacies of aggressive investor decision behavior within the context of financial behavior, specifically examining the influence of overconfident bias and demographic factors. The study seeks to fill a gap in existing literature by exploring the moderating role of demographic factors on overconfident bias in aggressive investor decision-making—a topic that, to the best of the author's knowledge, remains largely unexplored.

The premise of this research lies in the recognition that investor behavior varies based on demographic factors, necessitating a more focused investigation into how these factors moderate the relationship between overconfident bias and aggressive investor behavior. Additionally, there is a need to delineate distinct investor behaviors based on demographic factors to mitigate the adverse effects of overconfidence on investors.

This study has two primary objectives. Firstly, to discern the moderating role of demographic factors in shaping the impact of overconfident bias on aggressive investor behavior. Secondly, to ascertain the mediating effect of overconfident variables on the relationship between fundamental information, bandarmology, and aggressive investor behavior.

This paper contributes to the field of behavioral finance in three key aspects. Firstly, it enhances the understanding of behavioral finance theory, specifically regarding the influence of demographic factors on aggressive investor behavior. Secondly, it investigates how demographic factors moderate the impact of overconfident bias on aggressive investor behavior. The findings reveal that overconfident bias can mediate the influence of fundamental, technical, and bandarmology information on aggressive investor behavior. Moreover, demographic variables such as domicile, education, and marital status are shown to moderate the relationship between overconfident bias and aggressive investor behavior on the Indonesia Stock Exchange, thereby enriching the study of financial behavior theory, particularly prospect theory and overconfident bias.

This study is structured into five sections. The first section provides a background overview of the study, followed by a comprehensive literature review in the second section. The third section delineates the methodology employed in the research. Subsequently, the fourth section presents the research findings and conducts discussions. Lastly, the fifth section presents conclusions, discusses implications, and outlines the study's limitations.

Literature review

This study aims to delve deeper into the impact of diverse information sources on aggressive investor behavior, mediated by overconfidence. It also investigates how demographic factors either enhance or diminish the influence of overconfidence on aggressive investor behavior on the Indonesia Stock Exchange. The subsequent section will provide detailed explanations of the research variables and the literature reviews.

Market micro structure

Market microstructure theory discusses how the stock trading process is carried out in a capital market. The scope of the discussion relates to the trading process, market structure, market regulation, fairness and how to design markets that affect asset exchange, price information and asset price formation (Harris, 2004; Stoll, 2002). In a stock trading system there is the term order, an order is an instruction to trade both sales and purchases on the Limit Order Book (LOB).

The classification of investors in the capital market can be categorized into active and passive investors, aggressive investors will carry out transaction orders using market orders, while patient investors in making transactions will use limit orders (Harris, 2004; Stoll, 2002).

The development of technology and capital markets gave rise to a concept of how the stock exchange operates described in the study of market microstructure. Decision making can be categorized into two categories, namely market orders and limit orders, market orders are orders to sell / buy at the best price (best bid / best offer) while limit orders are orders to sell / buy with a queuing system at a level below the best bid / offer so that the transaction is executed.

Aggressive investors can be seen from the way these investors conduct their transactions, namely through the use of market orders when executing their transactions, on the other hand, non-aggressive investors use limit orders when executing their transactions (Chiu et al., 2017; Hung et al., 2015; Lee et al., 2020).

Overconfident

Researchers have proven that the market overreacts to the information received, the study was conducted using stock market return data. Overreaction to information indicates the existence of limited rational behavior (Werner et al., 1985). One of the biases that dominate investor behavior is overconfidence. Overconfident makes them overestimate the accuracy of the information they obtain, underestimate the risk and overestimate their capacity when controlling various events (Kim & Nofsinger, 2008).

Parveen (2020) conducted research in the Pakistani capital market proving that the effects of overconfident and representative bias affect decision making significantly. Research in Amman-Jordan shows the same conditions as in the Pakistani capital market, overconfident behavior significantly affects investor decision making (Areiqat et al., 2019), other research conducted in the Egyptian area, proving the existence of overconfident behavior on investor decision making (Metawa et al., 2019). Furthermore, in India, the results prove the existence of overconfident behavior and a moderate impact on investor decision making (Y. Gupta & Ahmed, 2017).

Fundamental and technical information

Fundamental information is an approach that uses financial information to assess the fair price of shares with an instrinsic value or fair value approach. Fundamental analysis will provide information on whether the stock price is in a condition where the stock price is lower than its instrinsic value (underpricing) or a condition where the stock price is higher than its intrinsic value (overpricing) (Elbialy, 2019). According to Elbialy (2019), fundamental information has 2 (two) approaches, namely top down analysis, then bottom up analysis is the opposite of the first approach to see the fair value of the stock. This approach analyzes economic conditions, industry conditions, organizational conditions, then bottom up analysis is the opposite of the first approach, namely an analysis that starts from analyzing the shares of a particular company then analyzing the company's industrial environment and then analyzing economic conditions to see the fair value of the shares.

Technical information is information that allows predicting future prices of financial assets by studying past price data, which is generally dominated by stock prices and trading volume (Menkhoff, 2010; Yamamoto, 2012). Academics have long been skeptical of the usefulness of technical information despite its widespread acceptance and use among practitioners. Some of the academics who rejected technical analysis due to differences in principles and no underlying theory were Cowles, (1933) and Fama & Blume, (1966). On the other hand, Menkhoff (2010) says that some investors use technical information and it is very important as a source of information.

Bandarmology information

Alternative information that has developed among retail investors is information that seeks to monitor and follow the movements of market price movers (market makers). This information is generally often referred to as bandarmology information (Filbert, 2016; Karo-karo, 2017). The development of bandarmology information has been quite rapid in the past five years. This is also supported by the use of electronic commerce which can provide very detailed and complete transaction data. This bandarmology information is able to detect the transactions of large traders who control market prices. While bandarmology analysis is rarely discussed in scientific articles today, it is widely used by individual investors.

Information bandarmology has a belief that the price movement of a stock cannot move freely, but is controlled by a price driving force called a dealer (market maker). These market makers control stock prices whether they are bullish, bearish or flat (Markiewicz et al., 2020). The basic principle of bandarmology analysis is to follow the bookie by studying its transaction behavior and become one of the sources of information for investors when making purchasing decisions (Filbert, 2016).

From the various explanations of operational definitions and the relationship between variables, the following research hypothesis can be formed:

Hypothesis 1 (H1): Fundamental information, technical information, and bandarmology information, affect the decision making of aggressive investors on the Indonesia Stock Exchange.

Hypothesis 2 (H2): Fundamental information, technical information, and bandarmology information affect overconfident on the Indonesia Stock Exchange.

Hypothesis 3 (H3): Overconfident affects aggressive investor decision making on the Indonesia Stock Exchange.

Hypothesis 4 (H4): Fundamental information, technical information, bandarmology information indirectly affect aggressive investor decision making through overconfident on the Indonesia Stock Exchange.

Demographic factors

Many studies in recent years have been conducted to examine investor behavior related to demographic factors such as occupational factors, education, marital status, lifestyle (Chin, 2012; Katper et al., 2019). Research by Barber & Odean, (2001) states that the female gender is less confident than the male gender in decision making and men tend to take higher risks than women.

According to nurture theory, differences between men and women are essentially the result of socio-cultural construction that can result in different tasks and roles. The difference is that women are often left behind and neglected roles or contributions in society, family, state, nation. According to the theory of nature, the differences between men and women are natures that cannot change and are universal.

Based on the description of the role of demographic factors on aggressive investor behavior, the hypothesis that the author proposes is as follows:

Hypothesis 5 (H5): Demographic factors are able to moderate the influence of Overconfident on aggressive investor decision making through the Indonesia Stock Exchange.

Methodology and dataset

This study employs a questionnaire as the primary data collection tool, referencing previous research that explored aggressive investors, overconfident individuals, and the information sources they utilize (Rizal et al., 2024). Following the distribution and completion of the questionnaire by the respondents, the researchers proceeded to tabulate the data obtained from each statement. The questionnaire used in this study consists of 31 statements concerning investor behavior and 11 statements related to investor characteristics. A total of 981 respondents were successfully gathered from investors spread across five major islands in Indonesia. The distribution of the questionnaire was facilitated using Google Forms, employing a multistage purposive random sampling technique.

The research was conducted in Indonesia, specifically targeting investors engaged in transactions on the Indonesia Stock Exchange (IDX) nationwide. The population for this study encompassed stock investors involved in transactions on the Indonesia Stock Exchange (IDX), amounting to 4,515,103 investors. The sample size for this study comprised 981 investors, meeting the minimum sample criteria stipulated by the Structural Equation Modeling (SEM) analysis, which requires a sample size at least five times the number of research indicators. Hence, the minimum sample size for this study was calculated as 5 multiplied by 40, resulting in 200 respondents (Hair et al., 2017).

The data analysis used in this study used structural equation modeling. SEM has the ability to analyze the path (path analytic) (Ghozali & Hengky, 2015). The path analysis that will be used in this study is partial least squares (PLS). The Partial Least Squares (PLS) analysis is employed in this study to ascertain latent variable relationships and predict structural indicators of constructs. The PLS evaluation model utilizes predictive measurements characterized by non-parametric properties. The PLS model encompasses several stages, including testing the outer and inner models prior to assessing the research hypotheses (Sarstedt et al., 2022).

All hypotheses in this study are tested using Partial Least Squares (PLS) via the t-test. The t-test is utilized to determine the significance of the constant and independent variables within the equation individually, as well as their impact on the dependent variable's value. The measurement of the percentage effect of all independent variables on the dependent variable's value is denoted by the coefficient of determination R-square (Sarstedt et al., 2022).

To analyze moderation effects, we employed the simple plot analysis approach following Aiken's (1991) methodology. Simple plot analysis in moderation effects involves using straightforward graphs to illustrate how the relationship between the independent variable and the dependent variable changes depending on the value of the moderating variable. By dividing the data sample into groups based on the moderating variable's values, this analysis allows us to observe whether the influence of the independent variable on the dependent variable differs among different groups of moderating variable values. The graphs generated from this analysis help identify whether the moderating variable strengthens or weakens the relationship between the independent and dependent variables, providing a more comprehensive understanding of the interaction between variables in the context of moderation (Aiken & West, 1991; Lorah, 2022). The simple slope analysis graphs can be generated with the assistance of SmartPLS or Microsoft Excel. These tools facilitate the calculation of graphs that depict how the relationship between the independent and dependent variables changes based on different values of the moderating variable. By utilizing SmartPLS or Microsoft Excel, researchers can conduct comprehensive analyses of moderation effects, allowing for a deeper understanding of how variables interact in different contexts.

The research construct model is depicted in the structural model as follows:

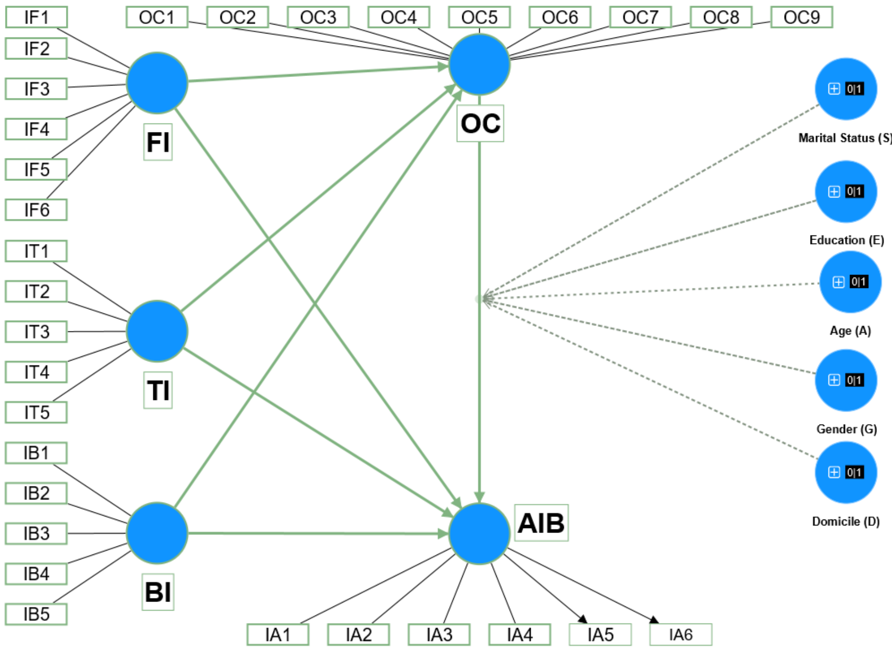

Figure 1. Structural Model.
Source: Author's Illustration (2023)

Where:

AIB = Aggressive Investor Behavior; a = constant; b = Variable coefficient; FI = Fundamental Information; TI = Technical Information; BI = Bandarmology Information; OC = Overconfident; G = Gender; D = Domicile; A = Age; E = Education; S = Marital Status.

From the research model above, the operational variables of the study can be detailed as follows: Fundamental Information (FI) refers to information related to evaluating company performance obtained through the analysis of company financial information, industry sector, and economic conditions. The indicators used include Macroeconomic Information, Industry Analysis Information, and Company Financial Information (Elbialy, 2019; Penman, 2013; Rizal et al., 2024). Technical information (TI) comprises analysis of stock price movements obtained by investors using technical analysis tools to predict stock prices. The indicators used to measure technical information include the use of basic technical analysis information (Support/resistance, Trendline), the use of advanced technical analysis information in the form of formations (head & shoulder, double bottom, etc.), and the use of technical indicator analysis information (RSI, MA, MACD, etc.) (Markiewicz et al., 2020; Nti et al., 2019; Rizal et al., 2024). Bandarmology information (BI) refers to information obtained from transactions conducted by market makers (local and foreign investors), and these movements can be observed from transaction records in stock broker summaries on the Indonesia Stock Exchange. The indicators we use include Broker transaction information, Accumulation and distribution information of domestic market makers (bandar), and Accumulation and distribution information of foreign market makers (bandar) (Foreign flow) (Czupryna, 2020; Filbert, 2016; Rizal et al., 2024).

The Overconfident (OC) variable is one of the financial behavior biases where there is a tendency for investors to overestimate their capacity in handling and controlling various events, believing they have better self-abilities than others, and having high confidence in the accuracy of the information they receive. The indicators we use are Overestimation, Overplacement, and Overprecision (Barber & Odean, 2000; Gill et al., 2018; Kapoor et al., 2017; Rizal et al., 2024). Lastly, as the dependent variable in this study, Aggressive Investor Behavior (AIB) refers to investors who submit market orders on the limit order book (LOB) because they seek more certain and quick order execution. The indicators we use in this study include the use of market order transactions in buying/selling under various market conditions.

Analysis of research results and discussion

Statistics description

Table 1 presents the results of correlation test between variables and the summary of descriptive statistics of the questionnaire data. The summary statistics of the research data show that the overall average of the Fundamental Information (FI) variable is 3.430 with a standard deviation of 0.873, which indicates that respondents have a positive attitude towards fundamental information. Fundamental information is information related to company performance that can affect stock price movements such as the company's financial condition (ROA/ROE), future company prospects, company life cycle and external factors such as interest rates, GDP. This condition shows that fundamental information is one of the sources of information for investors in making investment decisions.

Technical Information Variable (TI) is information related to stock price movement statistics such as in the form of graphs, candle sticks, support/resistance lines or certain statistical formulas (RSI, MACD) used by investors in understanding the movement or historical stock prices. Overall, the value of this variable has an average of 3.474 with a standard deviation of 0.824, which means that investors make technical information as important information in making decisions.

Bandarmology Information (BI) relates to information on market maker transactions (“bandar” or investor with a large amount of funds). Overall, this variable has an average of 3.398 with a standard deviation of 0.858, which means that bandarmology information is important for investors in making stock investment decisions.

The overconfident variable (OC) has an average of 3.391 with a standard deviation of 0.880, which means that the level of investor confidence in investing is relatively high. This high level of confidence comes from experience, knowledge and skills possessed such as trading plans so that they have confidence that they can predict stock price movements to make a profit.

Aggressive Investor Behavior (AIB) has an average of 3.357 with a standard deviation of 0.757 which identifies that investors have aggressive behavior in investing in stocks. Even though stock investment is full of risks, they view that risks can be minimized by the existence of abilities possessed in investing such as looking at fundamental analysis, technical analysis, bandarmology analysis and stock price movements (bullish/bearish).

Measurement model

The stages of the structural measurement analysis process and estimating SEM equations, we followed the stages carried out by Sahibzada et al., (2020) and Lai, (2019) including testing multicollinearity test, discriminant validity test, Cronbach alpha test, composite reliability (CR) test and loading factor test. The test results are reported in table 1, table 2 and table 3.

Table 1
Descriptive Statistics & Correlation

	Valid	Mean	Std. Dev	Min	Max	Correlation / Multicollinearity				
						FI	TI	BI	OC	AIB
FI	981	3,430	0,873	1	5	1,00				
TI	981	3,474	0,824	1	5	0,61	1,00			
BI	981	3,398	0,858	1	5	0,52	0,68	1,00		
OC	981	3,391	0,880	1	5	0,50	0,64	0,71	1,00	
AIB	981	3,337	0,757	1	5	0,46	0,65	0,72	0,70	1,00

Source: data processed (2023).
Notes: *Diagonal Value is the root of VE, Min is Minimum, Max is Maximum, FI is Fundamental Information, TI is Technical Information, BI is Bandarmology Information, OC is Overconfident and AIB is Aggressive Investor Behavior.

The results of the correlation between the research variables indicate the presence of multicollinearity, if the correlation value between variables shows a number exceeding 0.90 there is a suspicion of multicollinearity (Thrane, 2023). The results of checking the multicollinearity of this research data show that the correlation value between variables is less than 0.90 so it can be concluded that there is no multicollinearity between the research variables.

Next, the measurement model test can be seen in table 2 below:

Table 2
Measurement Model

Construct	Item	AIB	BI	FI	TI	OC	Alpha	CR	AVE	VIF
Aggressive Investors (AIB)	IA1	0,733					0,854	0,859	0,577	1,651
	IA2	0,770								1,818
	IA3	0,779								1,931
	IA4	0,770								2,249
	IA5	0,767								1,858
	IA6	0,738								1,763
Bandarmology Information (BI)	IB1		0,739				0,828	0,840	0,595	1,598
	IB2		0,874							2,402
	IB3		0,754							1,723
	IB4		0,765							1,662
	IB5		0,713							1,489
Fundamental Information (FI)	IF1			0,739			0,833	0,834	0,545	1,573
	IF2			0,747						1,577
	IF3			0,735						1,633
	IF4			0,716						1,614
	IF5			0,712						1,675
	IF6			0,778						1,942
Technical Information (TI)	IT1				0,735		0,812	0,820	0,571	1,568
	IT2				0,721					1,572
	IT3				0,779					1,690
	IT4				0,728					1,531
	IT5				0,811					1,768
Overconfident (OC)	OC1					0,795	0,923	0,929	0,622	2,419
	OC2					0,814				2,491
	OC3					0,872				3,297
	OC4					0,786				2,280
	OC5					0,800				2,392
	OC6					0,788				2,262
	OC7					0,712				1,780

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OC8	0,730	2,182
OC9	0,789	2,508

Source: data processed (2023).
Notes: *Diagonal value is the root of VE, Alpha is Cronbach Alpha, CR is Composite reliability, Min is Minimum, Max is Maximum, FI is Fundamental Information, TI is Technical Information, BI is Bandarmology Information, OC is Overconfident and AIB is Aggressive Investor Behavior.

Based on table 2, there are six items measuring the Fundamental Information (FI) variable, and the findings indicate that collectively, they exhibit a loading factor exceeding 0.70, signifying validity. The six items are valid on the measurement of Fundamental Information (FI). Loading factor measured between 0.712 - 0.778 where the highest item reflects the measurement of Fundamental Information (FI) is FI6 (LF=0.778). The item is related to the use of the company's fundamental information in obtaining profits. However, other measurement items are also considered important by respondents such as financial information on profitability ratios, industry life cycle analysis information, financial information on liquidity ratios and economic growth (GDP). The six items that measure the Fundamental Information (FI) variable have a Cronbach alpha level of 0.833> 0.7, a reliability level (CR) of 0.834> 0.70 and an AVE Convergent validity level of 0.545> 0.50. So, the model is considered feasible/fit.

There are 5 (five) items measuring the Technical Information (TI) variable which overall have a loading factor above 0.70 (valid). The five items validly reflect the measurement of Technical Information (TI) with a range of measured Loading factor values between 0.721 - 0.811 where the highest item reflecting the measurement of Technical Information (TI) is TI5 (LF = 0.811), which is related to technical information that helps investors in making decisions to buy/sell shares. Despite the high (valid) loading factor value on item 5, investors also have the view that the other four items are important such as support line analysis information, stock pattern analysis information, MACD information and Moving Average (MA) information on stock price movements. The five items that measure the Technical Information (TI) variable have a Cronbach alpha level of 0.812> 0.7, a reliability level (CR) of 0.820> 0.70 and an AVE Convergent validity level of 0.571> 0.50. So, the model is considered feasible/fit.

There are 5 (five) items measuring the Bandarmology Information (BI) variable which all have a loading factor above 0.70 (valid). The five valid items reflect the measurement of Bandarmology Information (BI) with a range of measured Loading factor values between 0.713 - 0.874 where the highest item reflects the measurement of Bandarmology Information (BI) is BI2 (LF = 0.874) this item is related to information on the accumulation and distribution by the bookie on a stock into consideration for investors in buying / selling shares. Other items in the variable of information bandarmology are also considered important, namely information on the accumulation and distribution of foreign fund flows, information on certain brokerage transactions and the price of a stock controlled by the dealer. The five items that measure the Bandarmology Information (BI) variable have a Cronbach alpha level of 0.828>

0.7, a reliability level (CR) of 0.840> 0.70 and an AVE Convergent validity level of 0.595> 0.50. So, that the model is considered feasible/fit.

The overconfident (OC) variable has 9 (five) measurement items where overall it has a loading factor above 0.70 (valid) with a range of measured Loading factor values between 0.712 - 0.872 where the highest item reflects the measurement of overconfident (OC) is OC3 (LF = 0.872) the existence of investor confidence in choosing stocks because of the truth of the information they have. Furthermore, respondents assessed that their overconfidence is very high in investing in stocks, especially the provision of knowledge, experience and belief that stock investment will provide high profits and gains / returns despite the risks. Overall, the nine items that measure the overconfident variable (OC) have a Cronbach alpha level of 0.923> 0.7, a reliability level (CR) of 0.929> 0.70 and an AVE Convergent validity level of 0.622> 0.50. So that the model is considered feasible/fit.

Aggressive Investor Behavior (AIB) variable has 6 (six) measurement items where overall it has a loading factor above 0.70 (valid) with a range of measured Loading factor values between 0.733 - 0.779 where the highest item reflects the measurement of Aggressive Investor Behavior (AIB) is IA3 (LF = 0.779), namely the use of market orders is the best choice when getting information that the dealer is accumulating/distributing. Other items are also considered important such as decision making seen in the characteristics of bullish/bearish stock trends, fundamental, technical information and social media influencers. The six items that measure the Aggressive Investor Behavior (PIA) variable have a Cronbach alpha level of 0.854> 0.7, a reliability level (CR) of 0.859> 0.70 and an AVE Convergent validity level of 0.577 > 0.50. So that the model is considered feasible/fit.

Another evaluation in the measurement model that needs to be considered is discriminant validity. Evaluation of discriminant validity in SEM can be used by comparing the root AVE variable with the correlation between variables (Sekaran & Bougie, 2011). The following are the results of data processing for evaluating discriminant validity which can be seen in table 3.

Table 3
Discriminant Validity (Fornell-Larcker criterion)

	AIB	BI	FI	TI	OC
AIB	0,760				
BI	0,723	0,771			
FI	0,463	0,516	0,738		
TI	0,647	0,678	0,613	0,755	
OC	0,700	0,707	0,500	0,637	0,788

Source: data processed (2023).
Notes: *Diagonal Value is the root of VE, Min is Minimum, Max is Maximum, FI is Fundamental Information, TI is Technical Information, BI is Bandarmology Information, OC is Overconfident.

The diagonal value is the root VE of each variable where the root VE value of each variable must be greater than the correlation value between variables (Sekaran & Bougie, 2011). The root value of the IA variable VE is 0.760 greater than the correlation value with the IB variable (0.723) and greater than the correlation with the FI, TI and OC variables, so discriminant validity for the Aggressive Investor Behavior (AIB) variable is met. The root value of the BI variable VE is 0.771 which is greater than the correlation value with the FI variable (0.516), TI variable (0.678), OC variable (0.707), so the discriminant validity for the Bandarmology Information variable (BI) is fulfilled. The root value of the FI variable VE is 0.738 which is greater than the correlation value with the TI variable (0.613), the OC variable (0.500), so the discriminant validity for the Technical Information (TI) variable is fulfilled. The root value of the TI variable VE is 0.755 greater than the correlation value with the OC variable (0.637), so the discriminant validity for the Technical Information variable (TI) is fulfilled. These results indicate that the variables used in this study are theoretically statistically tested.

Before the hypothesis testing process is carried out, we will first test for collinearity. In testing collinearity, we use VIF where the VIF value> 5 indicates the effect of collinearity. Ideally the VIF value should be close to 3 or below (Hair et al., 2019). In table 2. shows that all items show VIF values below 3 so it can be said that the items are free from collinearity.

Structural model

Structural Equation Modeling (SEM) analysis is used to test the theory model where this analysis consists of measurement model analysis and structural model evaluation. In Hair et al., (2010), SEM model testing is carried out in a two-stage approach, namely evaluating the model to obtain goodness of fit model and then proceeding to the second step of structural model testing.

In the next step, the SEM equation of this study is proposed using the goodness of fit index (Lei & Lomax, 2005). Based on the incremental goodness of fit measure criteria shown by R^2, F^2 and Q^2 and the collinearity test can be seen in table 4:

Table 4
Goodness Of Fit (GoF)

Construct	R^2	Q^2	F^2 - IA	F^2 - OC	Standardized RMR
AIB	0,624	0,557			0,067
OC	0,550	0,546	0,008		
BI			0,138	0,281	
FI			0,001	0,013	
TI			0,045	0,059	
Gender (G)			0,002		
Domicile (D)			0,012		
Age (A)			0,000		
Education (E)			0,019		
Marital Status (S)			0,001		
G x OC			0,001		
D x OC			0,007		
A x OC			0,000		
Ex OC			0,006		
S x OC			0,003		

Source: data processed, (2023).
Notes: *Diagonal Value is the root of VE, Min is Minimum, Max is Maximum, FI is Fundamental Information, TI is Technical Information, BI is Bandarmology Information, OC is Overconfident.

Based on table 4, it shows the R^2 value for AIB of 0.624 and for OC of 0.550, the level of ability of the aggressive investor behavior variable can be explained by the explanatory variables (R^2) in this model shows that it is at the medium level (R^2> 50) (Hair et al., 2019). Next is the Q^2 test which explains the model's ability to predict accuracy. Q^2 for IA and OC are 0.557 and 0.546 respectively, indicating that the model is very accurate in predicting (high accuracy > 0.50) (Hair et al., 2019). Furthermore, F^2 shows how much the effect of deleting a construct is if the construct is removed or in other words how much the role of exogenous constructs when removed will affect endogenous seen from the amount of F2. Table 4 shows that F2 for IA shows that only IT and IB constructs have F2 values at the middle level (F2 = 0.02-0.15). The F^2 value for Overconfident indicates that only the IT and IB constructs have a medium value while others have no effect (Hair et al., 2019).

After ensuring that all indicators are valid and reliable and the proposed estimation model meets the criteria, the research proceeds to the next stage by testing the proposed hypotheses. The findings of hypothesis testing are reported in the next section.

Path analysis and hypothesis testing

Evaluation of the structural model is done by testing the significance of the path coefficient of the estimated model. If the t value of the path coefficient statistic is more than 1.96 then there is a significant influence between the variables.

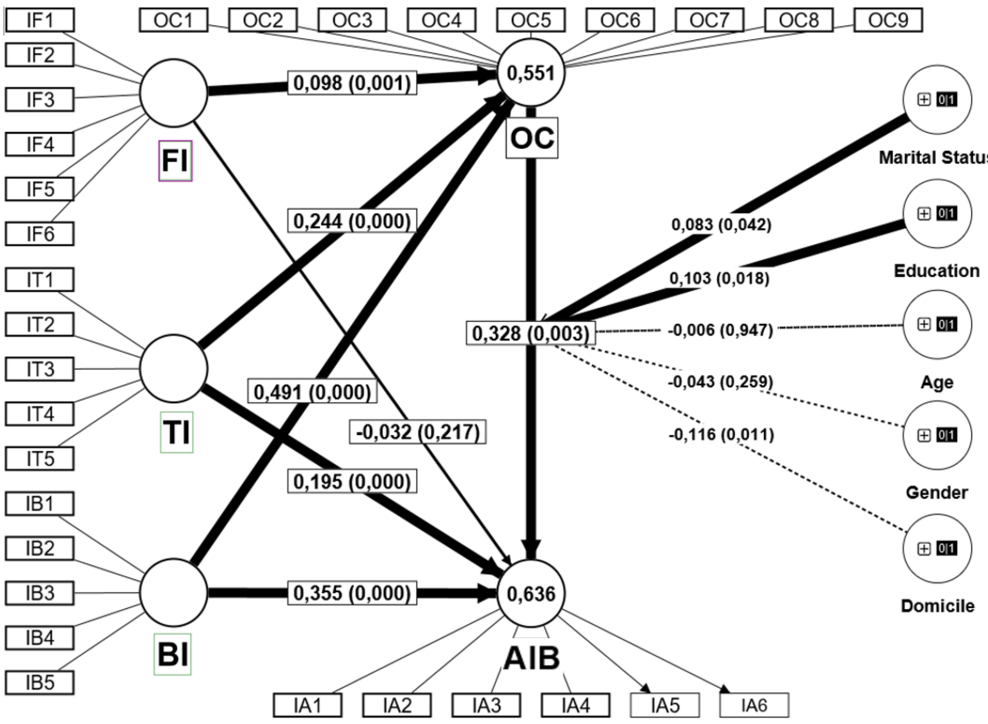

Figure 2. Structural Model.
Source: data processed, (2023).

The findings of testing the direct effect of fundamental information, technical information, bandarmology information and overconfident on aggressive investor behavior on the Indonesian stock exchange are reported in table 5.

Table 5
Hypothesis Test of Direct, Mediation and Moderation Effects

Hypothesis	Standardized Path Coefficient	SD	T Value	Description
Direct Effect				
H1a: FI → AIB	-0,032	0,026	1,236	Not Significant
H1b: TI → AIB	0,195	0,029	6,642	Significant
H1c: BI → AIB	0,355	0,035	10,267	Significant
H2a: FI → OC	0,098	0,029	3,394	Significant
H2b: TI → OC	0,244	0,037	6,597	Significant
H2c: BI → OC	0,491	0,032	15,268	Significant
H3: OC → AIB	0,328	0,109	2,993	Significant
G → AIB	-0,055	0,039	1,394	Not Significant
D → AIB	-0,153	0,045	3,384	Significant
A → AIB	-0,036	0,085	0,423	Not Significant
E → AIB	0,138	0,041	3,382	Significant
S → AIB	0,052	0,046	1,132	Not Significant
Indirect Effect (Mediation)				
H4a: FI → OC → AIB	0,032	0,014	2,239	Not Significant
H4b: TI → OC → AIB	0,080	0,030	2,649	Significant
H4c: BI → OC → AIB	0,161	0,054	2,968	Significant
Moderating Effect				
H5a: (G X OC) → AIB	-0,043	0,038	1,128	Not Significant
H5b: (D X OC) → AIB	-0,116	0,046	2,530	Significant
H5c: (A X OC) → AIB	-0,006	0,084	0,067	Not Significant
H5d: (E X OC) → AIB	0,103	0,043	2,374	Significant
H5a: (S X OC) → AIB	0,083	0,041	2,033	Significant

Source: data processed, (2023).
Notes: SD is standard deviation, FI is Fundamental Information, TI is Technical Information, BI is Bandarmology Information, OC is Overconfident, G is gender, D is Domicile, A is Age, E is Education, S is Marital Status.

As shown in table 5, this study establishes a noteworthy positive impact of bandarmology information on aggressive investor behavior (0.355) and technical information on aggressive investor behavior (0.355). Additionally, there is a positive and significant effect of fundamental information on overconfidence (0.098), technical information on overconfidence (0.244), bandarmology information on overconfidence (0.098), and overconfidence on aggressive investor behavior (0.328). These outcomes provide support for hypotheses H1b, H1c, H2a, H2b, H2c, and H3. Conversely, hypothesis H1a is rejected.

In Table 5, evidence is presented regarding the mediating role of overconfidence in the impact of fundamental information, technical information, and bandarmology information on aggressive investor behavior. The study identifies a noteworthy mediating effect of overconfidence in the relationship between fundamental information and aggressive investor behavior, thereby confirming hypothesis H4a. These outcomes suggest that overconfidence serves as a significant mediating variable, demonstrating a partial mediation effect (Hair et al., 2017).

Furthermore, this study revealed a significant mediating effect of overconfidence on the relationship between technical information and aggressive investor behavior. This finding supports hypothesis H4b, as indicated by the standardized path coefficient of the mediation (0.080) and t statistics (2.649) exceeding the critical value of 1.96. Overconfidence exhibits a substantial positive impact on aggressive investor behavior, and technical information also significantly influences such behavior. These results suggest that overconfidence serves as a significant mediating variable, demonstrating a partial mediation effect (Hair et al., 2017).

This study has discovered a noteworthy mediating effect of overconfidence in the relationship between bandarmoly information and aggressive investor behavior. This discovery confirms hypothesis H4c, as evidenced by the standardized path coefficient of mediation (0.161) and t statistics (2.968) > 1.96. Moreover, bandarmology information demonstrates a significant impact on aggressive investor behavior. These results support the idea that overconfidence serves as a significant mediating variable, showcasing a partial mediation effect (Hair et al., 2017).

Table 5 presents the results of the moderating effect analysis concerning demographic factors (gender, domicile, age, education, and marital status) on the relationship between overconfidence and aggressive investor behavior. This study revealed that domicile, education, and marital status significantly moderate the impact of overconfident investors on aggressive decision-making behavior in the Indonesia Stock Exchange, with moderation path coefficients of (-0.116) and t statistics (2.530) > 1.96, (0.103) and t statistics (2.374) > 1.96, (0.83) and t statistics (2.033) > 1.96, respectively. This outcome confirms hypotheses H5b, H5d, and H5e, indicating that demographic factors such as domicile, education, and marital status can moderate the influence of overconfident investors on aggressive decision-making behavior. However, the demographic factors of gender and age do not exhibit moderation effects on the relationship between overconfidence and aggressive investor behavior, leading to the rejection of hypotheses H5a and H5c.

There are four types of moderation variables: quasi moderation (pseudo moderation), pure moderation, moderation homogenizer, and antecedent/predictor. Table 5 reveals that the investor domicile variable significantly influences aggressive investor behavior (t statistics 3.384>1.96), and the moderation variable (D X OC) also significantly impacts aggressive investor behavior (2.530>1.96). This indicates that the type of moderation variable social media influencers belongs to is quasi moderation. Quasi moderation refers to a domicile variable that serves as both a moderating variable and an exogenous variable simultaneously (Sharma et al., 1981).

Furthermore, based on Table 5, it is evident that the investor's education variable significantly influences aggressive investor behavior (t statistics 3.382> 1.96), and the moderation variable (P X OC) also has a significant effect on aggressive investor behavior (2.374> 1.96). Therefore, it can be concluded that the moderation type of education falls under quasi-moderation.

Similarly, based on Table 5, the investor's marital status dummy variable does not have an effect on aggressive investor behavior (t statistic 1.132> 1.96), while the moderation variable (S X OC) significantly impacts aggressive investor behavior (2.033> 1.96). This leads to the conclusion that the type of moderation of the marital status dummy variable is pure moderation.

Discussion

This paper has two main objectives. First, to determine the role of demographic factors in moderating the effect of overconfident on aggressive investor behavior. Second, to determine the role of overconfident variables in mediating the effect of fundamental, technical and bandarmology information on aggressive investor behavior.

The findings of this study, indicating that overconfidence does not act as a mediator in the influence of fundamental information on aggressive investor behavior, align with prior research that has demonstrated the ineffectiveness of financial information in investment decision-making. Specifically, a study conducted in Malaysia involving 66 institutional investors by Khan et al., (2017) supports the idea that financial information has no discernible impact on investment decision-making among institutional investors. However, these findings diverge from research conducted by Boussaidi, (2020) which delves into the utilization of private information, encompassing financial information, technical information, interviews with managers, as well as rumors and news. In contrast to the current study, Boussaidi's research implies that the use of private information heightens overconfidence in decision-making, as evidenced by an increase in trading transactions. This suggests a nuanced relationship between the sources of information, overconfidence, and decision-making behavior in the investment context.

Moreover, this study has uncovered a significant mediating effect of overconfidence in the relationship between technical information and aggressive investor behavior. These findings highlight overconfidence as a significant mediating variable, demonstrating a partial mediation effect (Hair et al., 2017). Importantly, these results are consistent with conclusions drawn from prior research by Vasiliou et al. (2008). Building upon this foundation, our study emphasizes the substantial influence of psychological factors on investor behavior, especially concerning the utilization of technical information, and it suggests potential avenues for performance enhancement. However, research conducted in Indonesia presents contrasting outcomes. The findings of Nuzula's study (2019) challenge the idea that emotions and technical analysis have a discernible impact on investment decision-making. These discrepancies underscore the intricate and context-specific nature of investor behavior and the influence of technical information on decision-making processes.

Additionally, this study has provided compelling evidence of a significant mediating effect of overconfidence on the relationship between bandarmology information and aggressive investor behavior. These results demonstrate that overconfidence significantly acts as a mediating variable, showing a partial mediating effect (Hair et al., 2017). The findings, which indicate a link between professionals' stock accumulation actions and an increase in overconfident investors, have noteworthy implications for heightened stock trading transaction activity. This study is in line with Abreu & Mendes, (2012), who posited that investors tend to engage in greater trading transaction activity as they acquire more information. Similarly, research by Bian et al., (2018), focusing on aggressive orders, reveals that investor behavioral biases significantly influence their aggressiveness in holding/selling stocks. This behavior is observable through the order aggressiveness exhibited by investors in stock trading transactions.

Furthermore, this study examines the role of demographic factors in moderating the effect of overconfident on aggressive investor behavior, for the demographic factor of domicile significantly strengthens overconfident on aggressive investor behavior. The results of this study are in line with research conducted by Abreu & Mendes, (2020) who examined overconfident in two different locations and found the results that there are differences in overconfidence among investors. Similar results were also found by Paisarn et al., (2021), that domicile plays a significant role in distinguishing investor behavior in overconfident cases, further this research also proves that demographic factors have an important role in overconfident.

The finding that demographic factors, especially education, have an influence on overconfidence has been studied by Abreu & Mendes, (2020) and Bhandari & Deaves, (2006). These researchers mentioned that education level is associated with higher overconfidence. Corroborating these findings, Katper et al., (2019) conducted a study supporting the idea that socio-demographic factors moderate the relationship between investor bias behavior and investment behavior. However, divergent results were obtained by Kansal & Singh, (2018), whose study demonstrated that age, gender, and general education have no discernible impact on the level of overconfidence.

The demographic factor of marital status proves that marital status is able to moderate the influence of overconfident on aggressive investor behavior. The results of this study substantiate earlier observations regarding the role of socio-demographics in amplifying overconfident investor behavior. In alignment with these findings, Abreu & Mendes (2020) conducted research in two major cities, Porto and Lisbon, interviewing over 1500 investors. Their study revealed a connection between marital status and the level of overconfidence among investors.

Furthermore, a detailed interpretation of the role of demographic dummy variables in enhancing the link between overconfidence and aggressive investor behavior is provided through interaction graph simple slope analysis, as indicated by the moderation testing results mentioned earlier. To generate the simple slope analysis graph, data on the coefficients of independent variables, moderating variables, and interaction variables (moderation) are required. The procedure for calculating simple slope analysis follows the method outlined by Aiken and West (1991). These coefficients can be found in Table 5, and calculations are performed using Microsoft Excel. In Figure 3, the moderating effect of the domicile dummy variable, with dummy 1 representing investors domiciled in Java (DJ), reveals that the impact of overconfidence on aggressive investor behavior is more pronounced for investors residing outside Java (DLJ) compared to those within Java (DJ). This distinction arises from the negative dummy value of the domicile variable. Consequently, the escalation of overconfident investors impacting aggressive investor behavior will exert a more substantial effect on those residing outside the island of Java than on investors within Java.

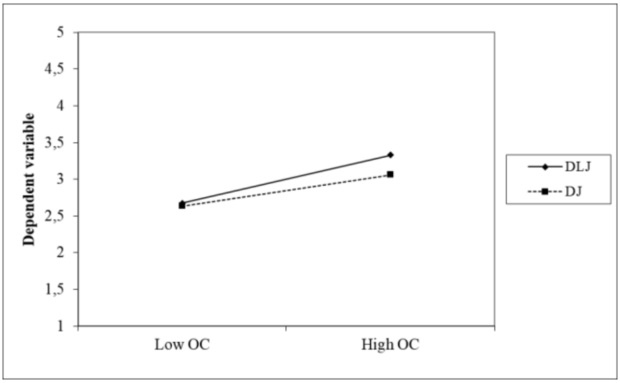

Figure 3. Interaction graph of Domicile variable effects.
Source: data processed, (2023)

The moderation role of education dummy variables, where dummy 1 represents investors with higher education (bachelor's, master's, and doctoral degrees) and dummy 0 represents investors with lower education (junior high school, senior high school, and equivalent), shows that the effect of overconfidence on aggressive investor behavior is more pronounced among investors with higher education (PT) compared to those with lower education (PR). This is attributed to the positive dummy value of the higher education variable. Consequently, an increase in overconfident investors impacting aggressive investor behavior will exert a stronger influence on highly educated investors (PT) than on investors with lower education (PR).

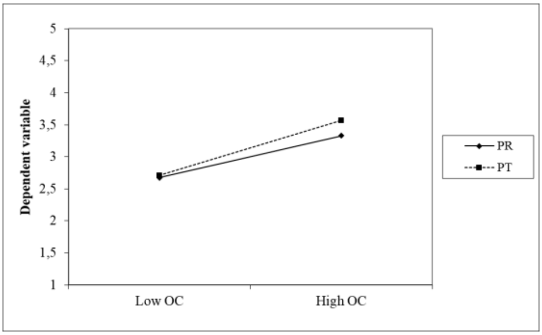

Figure 4. Interaction graph of the effect of education variables.
Source: data processed, (2023)

The moderation role of the marital status dummy variable where dummy 1 is a married investor and dummy 0 is an unmarried investor, the effect of overconfident on aggressive investor behavior is stronger for married investors (SM) than for unmarried investors (SBM), this is because the dummy value of the marital status variable is positive. Therefore, an increase in overconfident investors on aggressive investor behavior will have a stronger impact on investors who are married (SM) than investors who are not married yet (SBM).

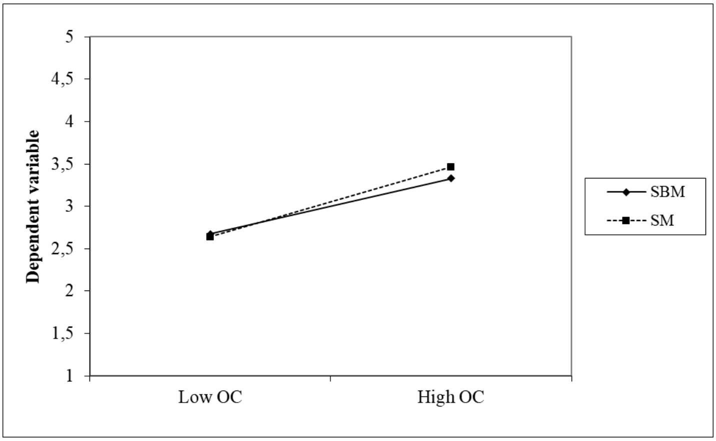

Figure 5. Interaction graph of the effect of Marital Status variable.
Source: data processed, (2023)

Conclusions, implications and future research

The study's findings on the mediation of fundamental information, technical information, and bandarmology information by overconfidence on aggressive investor behavior, coupled with the moderating influence of demographic factors in the relationship between overconfidence and aggressive investor behavior, offer compelling evidence that overconfidence acts as a mediator for the impact of fundamental, technical, and bandarmology information on aggressive investor behavior. Particularly noteworthy is the prominence of bandarmology information as the most influential factor in shaping overconfidence and subsequently influencing aggressive investor behavior. This is in line with Das Gupta, (2020) assertion that investors' overconfidence levels are significantly influenced by the information they possess. Additionally, the study emphasizes the significant role of demographic variables, namely domicile, education, and marital status, in moderating the relationship between overconfidence and aggressive investor behavior. For the domicile variable (D), the escalation of overconfident investors impacting aggressive investor behavior will exert a more substantial effect on those residing outside the island of Java than on investors within Java. Concerning the education variable (E), an increase in overconfident investors impacting aggressive investor behavior will have a stronger influence on highly educated investors (PT) than on investors with lower education (PR). As for the marital status variable, an increase in overconfident investors impacting aggressive investor behavior will have a stronger impact on investors who are married (SM) than investors who are not married yet (SBM). These findings contribute significantly to advancing financial behavior theory, especially within the prospect theory and overconfidence framework. Importantly, this study expands upon existing literature by delving into the decision-making processes of aggressive investors and those employing market orders in their stock transactions, an aspect often overlooked in prior research. Through this exploration, it enhances our comprehension of the intricate dynamics among information sources, overconfidence, demographic factors, and investor behavior in financial markets.

The findings of this study also bear significant implications for both investors and regulators. For investors, it is crucial to recognize the pivotal role of bandarmology information in shaping decision-making, particularly among aggressive investors. This form of information has the potential to heighten overconfidence in aggressive decision-making. Similarly, technical information can also contribute to reinforcing overconfidence in the decision-making processes of aggressive investors. However, it is important to note that an excessive increase in overconfidence can adversely impact the expected returns, as highlighted by Annick, (2020). Therefore, exercising good self-control becomes imperative to mitigate the level of overconfidence among investors. For regulators, addressing the issue of excessively high overconfidence is essential, as it can lead to diminished investment performance. Controlling overconfidence can be achieved through initiatives aimed at enhancing the financial literacy of investors. Socialization programs and educational campaigns can play a crucial role in reducing overconfidence among investors. Future research avenues may consider exploring socio-economic factors that moderate the impact of overconfidence on aggressive investor behavior in the specific context of Indonesia. Investigating these factors can provide deeper insights into the intricate dynamics influencing investor behavior and contribute to the development of more effective regulatory measures. Additionally, future studies in similar research areas could be conducted in developed countries to compare and contrast the findings with those in emerging markets like Indonesia. This comparative analysis can shed light on the universal aspects of investor behavior affected by overconfidence and the varying impact of regulatory measures across different economic contexts. Such comparative studies can contribute significantly to refining existing theories and enhancing the understanding of overconfidence in investment decision-making globally.

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