

MODELING INVESTOR BEHAVIOR AND INVESTMENT DECISIONS IN INDONESIA'S TECHNOLOGY SECTOR: A HYBRID FUZZY DEMATEL- MACHINE LEARNING FRAMEWORK

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ABSTRACT

This study aims to examine investor behavior and investment decision-making in Indonesia's technology sector by integrating Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) and Machine Learning within a hybrid analytical framework. A mixed-data approach employed secondary data from 22 technology companies listed on the Indonesia Stock Exchange during 2020-2024 and primary data from seven finance and investment experts. The analysis covered investor sentiment, market volatility, herding behavior, overconfidence, risk perception, stock return, financial leverage, and investment decisions. Fuzzy DEMATEL identified causal relationships, while Random Forest and XGBoost assessed predictive performance and feature importance. The results show that investor sentiment is the primary causal driver and strongest predictor of investment decisions, whereas market volatility acts as the central link between behavioral and financial factors. XGBoost achieved superior predictive accuracy ($R^2 = 0.94$). The integrated framework advances behavioral finance research by combining causal analysis with predictive modeling to better explain investment decision-making in emerging technology markets.

ABSTRAK

Penelitian ini bertujuan untuk menganalisis perilaku investor dan pengambilan keputusan investasi pada sektor teknologi di Indonesia melalui integrasi Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) dan Machine Learning dalam kerangka analisis hibrida. Pendekatan mixed-data menggunakan data sekunder dari 22 perusahaan teknologi yang terdaftar di Bursa Efek Indonesia selama periode 2020–2024 dan data primer dari tujuh pakar di bidang keuangan dan investasi. Analisis mencakup investor sentiment, market volatility, herding behavior, overconfidence, risk perception, stock return, financial leverage, dan investment decision. Fuzzy DEMATEL digunakan untuk mengidentifikasi hubungan kausal, sedangkan Random Forest dan XGBoost digunakan untuk mengevaluasi kinerja prediksi dan feature importance. Hasil penelitian menunjukkan bahwa investor sentiment merupakan faktor penyebab utama sekaligus prediktor terkuat dalam pengambilan keputusan investasi, sedangkan market volatility menjadi penghubung utama antara faktor perilaku dan keuangan. XGBoost menghasilkan kinerja prediksi terbaik ($R^2 = 0,94$). Kerangka terintegrasi ini berkontribusi pada pengembangan behavioral finance melalui penggabungan analisis kausal dan pemodelan prediktif untuk menjelaskan pengambilan keputusan investasi pada pasar teknologi negara berkembang.

INTRODUCTION

The rapid expansion of digital technology and capital markets has fundamentally transformed investment decision-making by increasing investor participation and improving access to financial information. Digital trading platforms enable investors to obtain market information and execute transactions in real time, thereby accelerating the diffusion of information across financial markets. However, greater information availability does not necessarily result in rational investment decisions because investors frequently rely on psychological judgments, emotions, and market expectations when interpreting financial signals. Consequently, investment behavior often deviates from the assumptions of traditional finance, making investor behavior one of the central issues in contemporary financial research (Baker & Wurgler, 2007; Barberis et al., 2021).

Behavioral Finance Theory argues that investors are boundedly rational and are influenced by psychological biases such as investor sentiment, overconfidence, herding behavior, and risk perception (Tversky & Kahneman, 1974; Thaler, 2016). These behavioral factors affect investors' expectations and consequently influence their willingness to buy, hold, or sell financial assets. Compared with traditional financial theories that emphasize firm fundamentals, behavioral finance recognizes that investment decisions are shaped by the interaction of psychological, market, and financial factors, particularly under conditions of uncertainty and high market volatility (Barberis et al., 2021; Kumar & Goyal, 2021; Abideen et al., (2023). The importance of behavioral factors is especially evident in technology companies, whose valuations are highly dependent on growth expectations, innovation, and future market prospects. As a result, technology firms generally experience higher stock price volatility than conventional industries because investors respond rapidly to changes in market sentiment and technological developments (Bouri et al., 2022; Vo et al., 2024).

Figure 1 illustrates the trends in market volatility, stock returns, and trading volume of technology firms listed on the Indonesia Stock Exchange during 2020–2024. Figure 1 shows substantial fluctuations in market volatility, stock returns, and trading volume throughout the observation period. The increase in market volatility during the post-pandemic adjustment period was accompanied by considerable changes in stock returns and trading activity, indicating that investment decisions were influenced not only by firms' financial performance but also by investors' behavioral responses to changing market conditions. These patterns suggest that behavioral and market dynamics play an important role in shaping investment decisions within Indonesia's technology sector (Bouri et al., 2022; Vo et al., 2024).

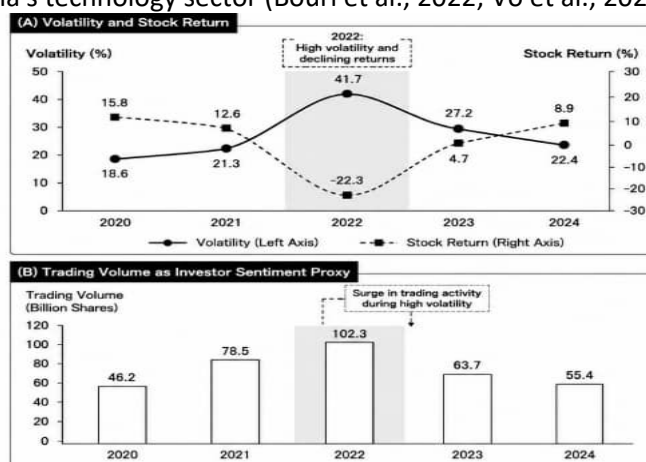


Figure 1. Trends in Market Volatility, Stock Returns, and Trading Volume in Indonesia's Technology Firms (2020–2024)

Source: Processed data (2026).

Among behavioral variables, investor sentiment has received considerable attention because it reflects investors' collective optimism or pessimism toward future market conditions. Unlike traditional financial indicators, investor sentiment captures subjective expectations that often influence market prices before fundamental information is fully incorporated into stock valuations (Tetlock, 2007; Baker & Wurgler, 2007). Empirical evidence consistently demonstrates that investor sentiment significantly affects stock returns, market volatility, and trading activity in both developed and emerging markets (Huang et al., 2022; Chen et al., 2023). Similar findings have also been reported in Indonesia, where investor sentiment significantly influences stock price movements and investment decisions, particularly during periods of market uncertainty (Pratama & Siregar, 2022; Hidayat et al., 2023). Nevertheless, previous studies generally examine behavioral variables independently using conventional econometric approaches, providing limited understanding of how behavioral, market, and financial variables interact as an integrated system.

Recent advances in Artificial Intelligence (AI), Particularly Machine Learning (ML), have introduced new approaches to financial modelling. Ensemble learning algorithms such as Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated superior predictive performance in modelling complex and nonlinear financial relationships compared with conventional statistical methods (Fischer & Krauss, 2018; Gu et al., 2020; Nti et al., 2023; Vo et al., 2024). Although Machine Learning provides high predictive accuracy, these models primarily focus on prediction and offer limited explanation regarding the causal relationships among behavioral, market, and financial variables.

Conversely, the Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) method has been widely employed to identify causal structures and interdependencies among variables under uncertain conditions (Wu & Lee, 2007; Tzeng & Huang, 2011). Fuzzy DEMATEL enables researchers to distinguish driving variables from dependent variables, making it particularly suitable for analysing complex behavioral systems. However, previous applications of Fuzzy DEMATEL have mainly focused on structural analysis and have rarely been integrated with predictive modelling techniques (Govindan et al., 2020; Kumar & Dixit, 2022).

Despite the growing literature, several important research gaps remain. First, previous studies generally employ either causal analysis or predictive modelling separately, limiting the ability to explain both causal relationships and predictive dynamics simultaneously (Gu et al., 2020; Nti et al., 2023). Second, behavioral variables such as investor sentiment, overconfidence, herding behavior, and risk perception are commonly analysed as isolated predictors rather than as interconnected components within a behavioral market financial system (Barberis et al., 2021). Third, empirical studies integrating Behavioral Finance Theory with Artificial Intelligence remain limited, particularly in Indonesia's technology sector, despite its high sensitivity to investor sentiment and market volatility (Bouri et al., 2022; Vo et al., 2024).

To clarify the position of this study within the existing literature, Table 1 summarizes the state of the art by comparing previous studies in terms of research focus, analytical methods, identified limitations, and the proposed contribution of this study. The comparison demonstrates that earlier studies have predominantly emphasized either explanatory analysis through conventional statistical methods or predictive analysis using Machine Learning, whereas studies integrating causal modelling and predictive analytics remain scarce.

Table 1. State of the Art of Previous Studies

Previous Studies	Primary Method	Main Contribution	Research Limitation	Contribution of the Present Study
Behavioral Finance Studies (Baker et al., 2021; Barberis et al., 2021)	Regression, SEM	Explain the influence of behavioral factors on investment decisions	Limited predictive capability and assumes linear relationships	Integrates behavioral variables into causal and predictive analyses
Machine Learning Studies (Gu et al., 2020; Nti et al., 2023; Vo et al., 2024)	Random Forest, XGBoost	Improve prediction accuracy of investment decisions	Limited explanation of causal relationships among variables	Combines predictive modelling with causal analysis
Fuzzy DEMATEL Studies (Govindan et al., 2020; Kumar & Dixit, 2022)	Fuzzy DEMATEL	Identify causal relationships among decision factors	No evaluation of predictive importance	Integrates causal modelling with Machine Learning prediction
Present Study	Fuzzy DEMATEL + Machine Learning	Simultaneously identifies causal relationships and predictive importance of behavioral, market, and financial variables	—	Provides an integrated analytical framework for investment decision-making in Indonesia's technology sector

Source: Processed data (2026)

To address these gaps, this study proposes a hybrid analytical framework integrating Fuzzy DEMATEL and Machine Learning. Fuzzy DEMATEL is employed to identify the causal relationships among behavioral, market, and financial variables, while Random Forest and XGBoost are used to evaluate their predictive importance. The integration of these complementary methods enables simultaneous identification of causal structures and predictive contributions, providing a more comprehensive understanding of investment decision-making.

The novelty of this study is primarily methodological by integrating causal modelling and predictive analytics within a unified analytical framework. From a theoretical perspective, the study extends Behavioral Finance Theory by conceptualizing investment decision-making as an integrated behavioral market financial system rather than a collection of independent determinants. From a practical perspective, the findings are expected to assist investors, portfolio managers, financial analysts, and policymakers in identifying both the principal driving factors and the strongest predictors of investment decisions in Indonesia's technology sector. Accordingly, this study aims to identify the causal relationships among investor sentiment, market volatility, herding behavior, overconfidence, risk perception, stock return, financial leverage, and investment decisions using Fuzzy DEMATEL, evaluate their predictive importance through Random Forest and XGBoost, and demonstrate how the integration of causal analysis and Machine Learning provides a more comprehensive explanation of investment decision-making in emerging technology markets.

LITERATURE REVIEW

Behavioral Finance and Investment Decision-Making

Behavioral Finance Theory emerged as a response to the limitations of traditional finance, which assumes that investors always behave rationally and make decisions solely based on available information. Tversky and Kahneman (1974) demonstrated that investment decisions are frequently affected by cognitive biases and heuristics, causing investors to deviate from rational judgment. This perspective was further

developed by Thaler (2016), who introduced concepts such as bounded rationality, mental accounting, and investor irrationality to explain behavioral anomalies observed in financial markets. Consequently, investment decisions are increasingly recognized as the outcome of interactions between psychological, market, and financial factors rather than purely objective financial information.

Among behavioral variables, investor sentiment represents investors' collective optimism or pessimism regarding future market conditions and has been widely recognized as a major determinant of market behavior. Baker and Wurgler (2006, 2007) showed that investor sentiment influences stock prices, trading activity, and market volatility beyond fundamental information. In this study, investor sentiment is proxied by Trading Volume Activity (TVA) because higher trading activity relative to outstanding shares reflects stronger investor participation and market expectations. Recent studies continue to support Trading Volume Activity as an effective proxy for investor sentiment in emerging markets (Huang et al., 2022; Vo et al., 2024).

Overconfidence refers to investors' tendency to overestimate their knowledge and forecasting ability, leading to excessive trading behavior (Barber & Odean, 2001). Overconfident investors generally underestimate investment risk and trade more aggressively than warranted by available information. Accordingly, this study measures overconfidence using Abnormal Trading Volume (ATV), which captures deviations of current trading volume from its historical average and reflects excessive trading activity associated with investor overconfidence (Barber & Odean, 2001; Kumar & Goyal, 2021).

Herding behavior occurs when investors imitate the decisions of other market participants rather than relying on their own information and analysis (Bikhchandani & Sharma, 2001). This phenomenon is commonly observed during periods of market uncertainty when investors seek confirmation from collective market behavior. Following Chang et al. (2000), this study measures herding behavior using the Cross-Sectional Absolute Deviation (CSAD), which captures the degree of return convergence among individual stocks. Recent empirical studies continue to validate CSAD as a reliable measure of herding behavior in financial markets (Putra et al., 2022; Vo et al., 2024).

Risk perception reflects investors' assessment of uncertainty and potential financial losses, which substantially influences investment preferences and portfolio allocation. Unlike market volatility, which measures overall price fluctuations, this study measures risk perception using downside volatility, represented by the semi-standard deviation of negative stock returns. This proxy better captures investors' sensitivity to adverse market movements and downside risk (Bouri et al., 2022).

Market and Financial Factors

In addition to behavioral factors, investment decisions are also affected by market and firm specific financial conditions. Stock return, derived from Asset Pricing Theory, represents the gain or loss generated from stock investment and reflects investors' realized investment performance (Fama & French, 2015). In this study, stock return is measured as the annual percentage change in stock prices. Although conventional finance considers return the primary determinant of investment decisions, behavioral finance suggests that returns often reflect the consequences of investor sentiment and market dynamics rather than purely firm fundamentals (Barberis et al., 2021).

Market volatility represents fluctuations in stock prices and overall market uncertainty. Higher volatility generally intensifies investor reactions and strengthens behavioral biases in financial markets (Vo et al., 2024). Accordingly, market volatility is measured using the standard deviation of daily stock returns, which is widely adopted in empirical finance research (Bouri et al., 2022).

Financial leverage reflects the extent to which firms rely on debt financing within their capital structure. According to Modigliani and Miller (1958), leverage influences firm risk and investors' perceptions of financial stability. Therefore, this study measures leverage using the Debt to Equity Ratio

(DER), where higher values indicate greater financial risk and potential vulnerability to market uncertainty (Hasan et al., 2021).

Finally, investment decision-making is represented by trading intensity, reflecting investors actual trading behavior under varying behavioral, market, and financial conditions (Nguyen et al., 2022). Collectively, these variables indicate that investment decisions are shaped by an integrated behavioral market financial system rather than by isolated financial indicators, particularly in technology firms characterized by rapid innovation, speculative trading, and high market uncertainty.

Integrated Perspective: Causal and Predictive Approach

Previous studies generally employ either explanatory approaches, such as regression and Structural Equation Modeling, or predictive approaches based on Machine Learning. Machine Learning algorithms, including Random Forest and XGBoost, effectively capture nonlinear relationships and improve predictive accuracy (Fischer & Krauss, 2018; Gu et al., 2020; Nti et al., 2023), yet they provide limited explanation regarding causal mechanisms. Conversely, Fuzzy DEMATEL effectively identifies causal relationships and interdependencies among variables (Gabus & Fontela, 1972; Wu & Lee, 2007; Tzeng & Huang, 2011), but it does not evaluate predictive importance. To overcome these limitations, this study integrates Fuzzy DEMATEL and Machine Learning within a hybrid analytical framework that simultaneously explains the causal structure among behavioral, market, and financial variables while evaluating their predictive contribution to investment decision-making.

Conceptual Development (Implicit Hypothesis Logic)

Behavioral Finance Theory suggests that investment decisions emerge from the interaction of psychological, market, and financial factors rather than from rational financial considerations alone (Tversky & Kahneman, 1974; Thaler, 2016; Barberis et al., 2021). Within this perspective, investor sentiment is expected to function as the primary behavioral driver because it shapes investors' expectations and market reactions (Baker & Wurgler, 2007; Huang et al., 2022). Its influence is reinforced by market volatility, which amplifies uncertainty and behavioral responses (Bouri et al., 2022; Vo et al., 2024). These conditions subsequently affect herding behavior, overconfidence, and risk perception, which together influence investment decision-making (Barber & Odean, 2001; Chang et al., 2000; Kumar & Goyal, 2021).

At the same time, stock return and financial leverage provide firm-specific information regarding investment performance and financial risk (Fama & French, 2015; Modigliani & Miller, 1958). Rather than acting independently, these financial factors interact dynamically with behavioral and market variables, particularly within technology firms characterized by rapid innovation and high uncertainty. Accordingly, this study conceptualizes investment decision-making as an integrated behavioral market financial system. Fuzzy DEMATEL is employed to identify the causal relationships among the variables, whereas Machine Learning evaluates their predictive importance. Integrating these complementary approaches provides a more comprehensive explanation of investment decision-making by simultaneously revealing the causal structure and predictive contribution of each variable.

Conceptual Framework

Figure 2 illustrates the conceptual framework of this study, which reconceptualizes investment decision-making as a complex, dynamic, and interdependent system. Unlike conventional financial models that assume linear and independent relationships among variables, this framework emphasizes the simultaneous interaction between behavioral, market, and financial factors.

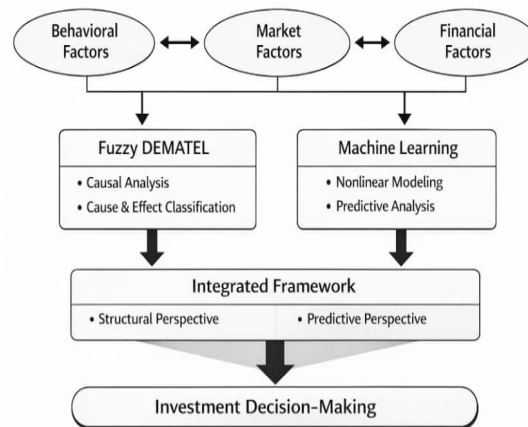


Figure 2. Conceptual Framework

Developed by the authors based on Baker and Wurgler (2007), Barberis et al. (2021), and Vo et al. (2024).

This framework is grounded in behavioral finance theory and prior empirical findings emphasizing the interaction between sentiment, volatility, and investment behavior (Baker & Wurgler, 2007; Barberis et al., 2021; Vo et al., 2024). Behavioral factors particularly investor sentiment, overconfidence, and herding behavior are positioned as central drivers that actively shape market dynamics. Market factors, such as volatility and stock returns, are not treated as exogenous determinants but as variables that both influence and are influenced by investor behavior. Similarly, financial factors reflect firm-level conditions that interact within this system rather than acting as isolated inputs.

To address the limitations of existing approaches, this study introduces a hybrid analytical framework that integrates Fuzzy DEMATEL and Machine Learning. Fuzzy DEMATEL provides a structural perspective by identifying causal relationships and distinguishing between driving and dependent variables, while machine learning captures nonlinear interactions and evaluates predictive importance. The novelty of this framework lies in its ability to simultaneously capture causal structure and predictive dynamics within a unified model, thereby overcoming the limitations of prior studies that rely on either explanatory or predictive approaches alone. This dual perspective enables a more comprehensive understanding of investment decision-making, particularly in volatile and sentiment-driven markets. Consequently, the framework offers both theoretical and methodological contributions by advancing behavioral finance research and providing an integrated approach for analyzing complex financial systems.

RESEARCH METHOD

Research Design

This study adopts a hybrid analytical approach by integrating Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) and Machine Learning to investigate investor behavior and investment decision-making. Fuzzy DEMATEL, originally developed from the DEMATEL method introduced by the Battelle Memorial Institute and later extended with fuzzy logic (Wu & Lee, 2007), is particularly suitable for analyzing complex causal relationships under uncertainty (Tzeng & Huang, 2011). Recent studies have demonstrated its effectiveness in identifying key influencing factors and distinguishing cause effect relationships in financial and decision-making contexts (Govindan et al., 2020; Kumar & Dixit, 2022).

Machine Learning complements Fuzzy DEMATEL by providing predictive capabilities for complex and nonlinear financial data. Algorithms such as Random Forest and XGBoost have been widely adopted because of their high predictive accuracy and ability to capture nonlinear interactions among financial

variables (Fischer & Krauss, 2018; Gu et al., 2020). Recent studies further confirm that Machine Learning significantly improves financial forecasting performance compared with conventional econometric approaches (Nti et al., 2023; Vo et al., 2024).

To support the hybrid analytical framework, this study employs a mixed-data approach. Primary data were collected through expert judgment from finance academics and investment practitioners to construct the Fuzzy DEMATEL model and identify the causal relationships among behavioral, market, and financial variables. Secondary data were obtained from technology companies listed on the Indonesia Stock Exchange (IDX) during the 2020–2024 period and were used to develop the Machine Learning models for predictive analysis. The integration of these complementary data sources provides a comprehensive framework for explaining causal relationships while simultaneously evaluating predictive performance in investment decision-making.

Data and Sample

This study employed a mixed-data approach consisting of primary and secondary data. Primary data were collected through expert judgment to construct the Fuzzy DEMATEL model, whereas secondary data were used to develop the Machine Learning models. The population consisted of technology companies listed on the Indonesia Stock Exchange (IDX) during the 2020–2024 period. A purposive sampling technique was employed using the following criteria: (1) firms continuously listed on the IDX during the observation period; (2) firms publishing complete annual financial statements; (3) firms with complete stock price and trading data required for the analysis; and (4) firms with no missing observations for the research variables. Based on these criteria, 22 technology firms were selected, resulting in 110 firm year observations over the five year observation period. Secondary data were obtained from the Indonesia Stock Exchange (IDX), firms annual reports, and publicly available financial databases. These data were used to develop the Random Forest and XGBoost models for predictive analysis. Primary data obtained through expert judgment were used exclusively to construct the Fuzzy DEMATEL model for identifying the causal relationships among the research variables.

Expert Panel

Primary data for the Fuzzy DEMATEL analysis were collected using a purposive sampling technique involving seven experts, comprising three finance academics, two certified investment practitioners, and two senior capital market analysts. All experts had more than ten years of professional experience in behavioral finance, investment analysis, or capital markets and were selected based on their expertise and familiarity with the research variables.

Table 2. Profile of Expert Panel

Expert Category	Number	Experience
Finance academics	3	>10 years
Investment practitioners	2	>10 years
Capital market analysts	2	>10 years
Total	7	—

Source: Processed by the authors (2026).

The use of seven experts is consistent with previous Fuzzy DEMATEL studies, which recommend panels of five to ten experts to ensure reliable causal evaluations (Okoli & Pawlowski, 2004; Wu & Lee, 2007; Govindan et al., 2020). Each expert independently assessed the influence among variables using the predefined linguistic scale, and the individual judgments were aggregated into a fuzzy direct-relation matrix for further analysis. The expert panel was used exclusively for the Fuzzy DEMATEL analysis, whereas

the Machine Learning models were developed using secondary financial data from technology companies listed on the Indonesia Stock Exchange during 2020–2024.

Expert Judgment Procedure

Expert judgments were collected using a structured questionnaire designed to evaluate the causal relationships among the research variables. Each expert independently assessed the degree of influence of one variable on another using a five level linguistic scale ranging from "No Influence" to "Very High Influence." The linguistic assessments were then converted into Triangular Fuzzy Numbers (TFNs) in accordance with the standard Fuzzy DEMATEL methodology. The individual expert evaluations were aggregated to construct the initial fuzzy direct-relation matrix. Subsequently, the matrix was normalized and transformed into the total relation matrix to identify both direct and indirect causal relationships among the variables. This procedure enables Fuzzy DEMATEL to accommodate uncertainty and subjectivity in expert judgments while providing a systematic representation of the causal structure among behavioral, market, and financial variables. The causal relationships identified through Fuzzy DEMATEL were subsequently integrated with the Machine Learning analysis. While Fuzzy DEMATEL explains the structural cause effect relationships among the variables, the Machine Learning models evaluate their predictive importance using secondary financial data. The integration of these two analytical approaches provides a more comprehensive understanding of investment decision-making in Indonesia's technology sector.

Variable Measurement

The variables in this study are classified into three categories: behavioral, market, and financial factors, as presented in Table 3. This classification is consistent with Behavioral Finance Theory, which emphasizes that investment decisions are influenced by the interaction of psychological, market, and firm-specific factors (Barberis et al., 2021). To ensure construct validity, each variable was measured using a distinct proxy that reflects its conceptual definition. Investor sentiment was proxied by Trading Volume Activity (TVA) because higher trading activity relative to outstanding shares reflects stronger market participation and investor sentiment (Baker & Wurgler, 2006, 2007; Vo et al., 2024). Overconfidence was measured using Abnormal Trading Volume (ATV), which captures deviations of current trading volume from its historical average and reflects excessive trading associated with investor overconfidence (Barber & Odean, 2001; Kumar & Goyal, 2021).

Table 3. Variables and Proxies

Variable	Proxy	Formula	Reference
Investor Sentiment	Trading Volume Activity (TVA)	Trading Volume / Outstanding Shares	Baker & Wurgler (2006); Brown & Cliff (2004); Vo et al. (2024)
Herding Behavior	Cross-sectional Absolute Deviation (CSAD)	$CSAD = (1/N) \sum R_{i,t} - R_{m,t} $	Chang et al. (2000)
Overconfidence	Trading Volume Growth (TVG)	Current Trading Volume – Historical Average Trading Volume	Statman, Thorley, & Vorkink (2006); Gervais & Odean (2001)
Risk Perception	Negative Return	Semi-standard deviation of negative returns	Bouri et al. (2022)
Market Volatility	Absolute Return	Standard deviation of daily returns	Vo et al. (2024)

Variable	Proxy	Formula	Reference
Stock Return	Annual Return	Stock Annual return	Fama (1970); Ross, Westerfield, & Jaffe (2022) Gu et al. (2020)
Financial Leverage	Debt-to-Equity Ratio (DER)	Total Debt / Total Equity	Brigham & Ehrhardt (2022); Ross, Westerfield, & Jaffe (2022)
Investment Decision	Trading Intensity	Trading Frequency/ Trading Days	Nguyen et al., (2022); Barber & Odean (2000); Glaser & Weber (2007)

Source: Processed data (2026)

Herding behavior was measured using the Cross-Sectional Absolute Deviation (CSAD), which reflects the convergence of individual stock returns toward market returns and has been widely adopted in behavioral finance research (Chang et al., 2000). Risk perception was measured using downside volatility, defined as the semi standard deviation of negative stock returns, because it captures investors' sensitivity to adverse market movements and perceived downside risk (Bouri et al., 2022). In contrast, market volatility was measured by the standard deviation of daily stock returns, representing the overall fluctuation of stock prices in the market (Vo et al., 2024).

Herding behavior was measured using the Cross-Sectional Absolute Deviation (CSAD) proposed by Chang et al. (2000). CSAD was calculated using the daily stock returns of all sampled technology firms listed on the Indonesia Stock Exchange during 2020–2024. Daily stock prices were obtained from the Indonesia Stock Exchange database and firms' historical trading records. The CSAD measure captures the degree of return convergence across firms and serves as an indicator of collective investor behavior during periods of market uncertainty.

Stock return was measured as the annual percentage return, while financial leverage was represented by the Debt to Equity Ratio (DER). Investment decision-making was proxied by trading intensity, reflecting investors' actual trading behavior in response to behavioral, market, and financial conditions (Nguyen et al., 2022).

Fuzzy DEMATEL Method

Prior to constructing the Fuzzy DEMATEL model, primary data were collected through expert judgment using a purposive sampling technique. The expert panel consisted of seven experts, including three finance academics, two certified investment practitioners, and two senior capital market analysts, each with more than ten years of professional experience in behavioral finance, investment analysis, or capital markets. The experts independently evaluated the causal influence among the research variables using a predefined linguistic scale. Their individual assessments were aggregated into a fuzzy direct relation matrix, which served as the basis for identifying the causal relationships among the variables.

Fuzzy DEMATEL is a decision-making approach designed to analyze complex causal relationships among interrelated variables. By integrating fuzzy logic into the conventional DEMATEL framework, the method effectively accommodates uncertainty and ambiguity in expert judgments, making it particularly suitable for behavioral finance and investment research (Wu & Lee, 2007; Tzeng & Huang, 2011; Govindan et al., 2020). The causal relationships were evaluated using pairwise comparisons based on a five level linguistic scale: No Influence (N), Low Influence (L), Moderate Influence (M), High Influence (H), and Very High Influence (VH). Each linguistic assessment was converted into a corresponding Triangular Fuzzy Number (TFN), as presented in Table 4.

Table 4. Linguistic Scale and Triangular Fuzzy Numbers

Linguistic Term	Abbreviation	Triangular Fuzzy Number
No Influence	N	(0,00; 0,00; 0,25)
Low Influence	L	(0,00; 0,25; 0,50)
Moderate Influence	M	(0,25; 0,50; 0,75)
High Influence	H	(0,50; 0,75; 1,00)
Very High Influence	VH	(0,75; 1,00; 1,00)

Source: Adapted from Govindan et al. (2020), Kumar and Dixit (2022), and Wu and Lee (2007).

The aggregated fuzzy direct relation matrix was normalized to ensure comparability among influence values, and the total relation matrix was calculated as:

$$T = X(I - X)^{-1}$$

where: (T) = total relation matrix, (I) = identity matrix

This formulation allows the model to account for feedback loops and indirect influences, which are essential in complex financial systems (Wu & Lee, 2007). The total influence of each variable is calculated using row and column sums:

$$D_i = \sum_{j=1}^n t_{ij}$$

$$R_i = \sum_{j=1}^n t_{ji}$$

where: (D_i) = total influence given by variable (i) and (R_i) = total influence received by variable (i).

The prominence ($D + R$) value indicates the overall importance of each variable within the system, whereas the relation ($D - R$) value classifies variables into cause ($D - R > 0$) and effect ($D - R < 0$) groups. Variables with positive relation values are considered the primary driving factors, while negative values indicate variables that are mainly influenced by other factors. This procedure enables the identification of the key determinants and causal structure underlying investment decision-making. This classification is crucial for identifying key drivers in investment decision-making (Govindan et al., 2020).

Machine Learning Method

Machine Learning was employed to evaluate the predictive importance of behavioral, market, and financial variables affecting investment decisions. Two ensemble learning algorithms, namely Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were selected because of their ability to capture nonlinear relationships, interactions among predictors, and high dimensional financial data, making them widely applied in financial prediction studies (Breiman, 2001; Chen & Guestrin, 2016; Fischer & Krauss, 2018; Gu et al., 2020; Nti et al., 2023; Vo et al., 2024).

The analysis utilized secondary panel data obtained from technology companies listed on the Indonesia Stock Exchange (IDX) during the 2020–2024 period. Prior to model development, the dataset underwent preprocessing, including data cleaning, feature selection, and normalization to improve model performance. Subsequently, the data were randomly divided into 80% training data and 20% testing data. To enhance model generalization and minimize overfitting, five fold cross validation and grid search were applied during the hyperparameter optimization process.

For the Random Forest model, the optimized hyperparameters included the number of trees ($n_estimators$), maximum tree depth (max_depth), and the minimum number of samples required for node splitting ($min_samples_split$). For the XGBoost model, the optimized hyperparameters included the

learning rate (*learning_rate*), maximum tree depth (*max_depth*), number of trees (*n_estimators*), and subsampling ratio (*subsample*). The Random Forest prediction model is expressed as:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^B T_b(x)$$

where $T_b(x)$ denotes the prediction generated by the b -th decision tree and B is the total number of trees. For XGBoost, the objective function is:

$Obj = \sum l(y_i, \hat{y}_i) + \sum \Omega(f_k)$, where l represents the loss function and Ω is the regularization term controlling model complexity.

The machine learning models were developed using panel data from technology firms listed on the Indonesia Stock Exchange during 2020–2024. After data preprocessing, the dataset was divided into training and testing subsets. Five-fold cross-validation and grid search were employed to optimize model performance, while prediction accuracy was evaluated using R^2 , RMSE, and MAE.

Table 5. Machine Learning Model Configuration

Component	Specification
Dataset	Technology firms listed on IDX, 2020–2024
Data preprocessing	Data cleaning, feature selection, normalization
Training data	80%
Testing data	20%
Validation	Five-fold cross-validation
Hyperparameter tuning	Grid search
Algorithms	Random Forest (RF) and XGBoost
Performance metrics	R^2 , RMSE, MAE
Output	Prediction performance and feature importance

Source: Processed by the authors (2026).

Figure 3 illustrates the integrated research workflow. The process begins with expert judgment to construct the Fuzzy DEMATEL model, followed by machine learning modelling using secondary financial data. Finally, the causal relationships identified by Fuzzy DEMATEL are integrated with the predictive results obtained from Random Forest and XGBoost to provide a comprehensive understanding of investment decision-making.

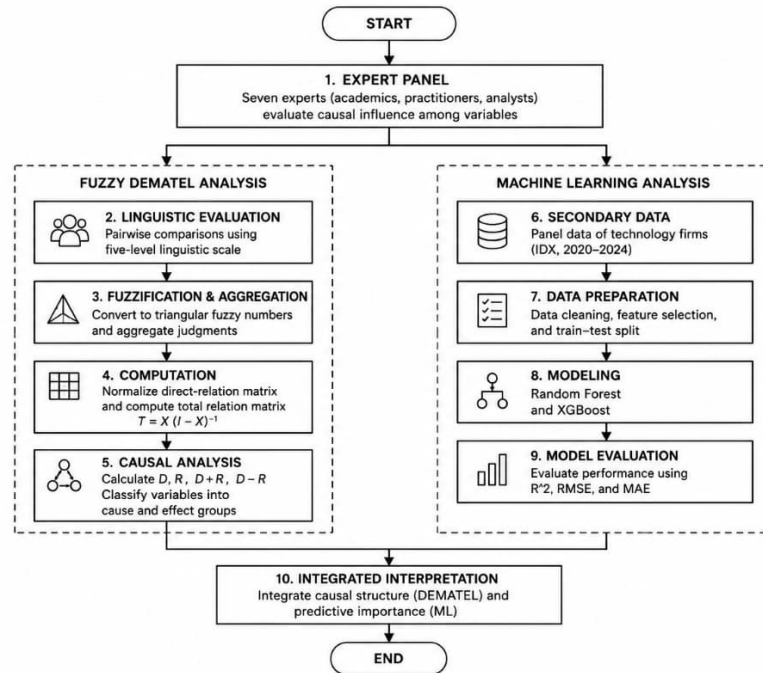


Figure 3: The research workflow

Source: Processed data (2026)

Feature Importance Analysis

Feature importance analysis was conducted to determine the relative contribution of each predictor in the Machine Learning models. Variable importance scores generated by Random Forest and XGBoost were used to identify the most influential behavioral, market, and financial factors affecting investment decisions. These results were subsequently compared with the causal relationships identified by Fuzzy DEMATEL to provide complementary insights into the determinants of investment decision-making (Gu et al., 2020; Vo et al., 2024).

Integration of Analytical Results

The findings obtained from Fuzzy DEMATEL and Machine Learning were integrated during the interpretation stage. Fuzzy DEMATEL identified the causal structure among behavioral, market, and financial variables, whereas Machine Learning evaluated their predictive importance. The integration of these complementary approaches enabled a more comprehensive understanding of investment decision-making by simultaneously explaining the causal mechanisms and predictive performance of the research variables.

RESULTS AND DISCUSSION

Descriptive Statistics Analysis

Table 6 presents the descriptive statistics of the variables used in this study. The results show that investor sentiment and market volatility have moderate average values, indicating dynamic market conditions. Stock returns exhibit a negative average, suggesting a market correction during the observation period. Behavioral variables such as herding and overconfidence show noticeable variation, reflecting the presence of collective and individual investor biases. Risk perception also demonstrates variability, indicating differing levels of investor sensitivity to market uncertainty. Meanwhile, financial leverage

remains relatively stable, suggesting a limited role in short-term investment decisions. The descriptive statistics indicate substantial variability across behavioral and market variables, suggesting heterogeneous investment behavior among Indonesian technology firms. Such variability provides an appropriate basis for applying both causal and predictive analyses.

Table 6. Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Sentiment	0,487	0,112	0,221	0,731
Volatility	0,039	0,017	0,006	0,094
Overconfidence	0,183	0,094	-0,091	0,462
Herding (CSAD)	0,027	0,011	0,004	0,058
Risk Perception	0,031	0,015	0,006	0,079
Return	0,146	0,284	-0,482	0,691
Leverage	1,482	0,794	0,231	4,587
Investment Decision	0,352	0,117	0,101	0,698

Source: Processed data (2026)

Fuzzy DEMATEL Results

Table 7 presents the results of the Fuzzy DEMATEL analysis based on the prominence (D+R) and relation (D-R) indices. The prominence values indicate the relative importance of each variable within the investment decision-making system, whereas the relation values distinguish variables into cause and effect groups. Variables with positive relation values function as causal drivers, while negative values represent variables primarily influenced by other factors.

Table 7. DEMATEL Results

Variable	D	R	D+R	D-R	Role
Investor Sentiment	4,921	3,684	8,605	1,237	Cause
Market Volatility	4,687	4,301	8,988	0,386	Cause
Herding	3,952	4,176	8,128	-0,224	Effect
Overconfidence	3,821	4,015	7,836	-0,194	Effect
Risk Perception	3,734	4,486	8,220	-0,752	Effect
Stock Return	3,482	4,103	7,585	-0,621	Effect
Leverage	3,281	3,914	7,195	-0,633	Effect
Investment Decision	4,176	4,375	8,551	-0,199	Effect

Source: Processed data (2026)

The Fuzzy DEMATEL results indicate that investor sentiment has the highest positive relation value ($D-R = 1,237$), identifying it as the primary causal factor driving the interactions among behavioral, market, and financial variables. This finding suggests that changes in investor sentiment initiate the behavioral and market dynamics that subsequently influence investment decision-making in Indonesia's technology sector. Market volatility also belongs to the cause group ($D-R = 0,386$) and records the highest prominence value ($D+R = 8,988$), indicating that it serves as the central connecting variable linking behavioral and financial factors within the system.

Conversely, herding behavior, overconfidence, risk perception, stock return, financial leverage, and investment decision belong to the effect group because their $D-R$ values are negative, indicating that these variables are influenced more by other variables than they influence the system. Among them, risk perception records the lowest relation value ($D-R = -0,752$), suggesting that it is the variable most strongly affected by the interactions among behavioral and market factors. Meanwhile, financial leverage has the

lowest prominence value ($D+R = 7,195$), indicating that its overall role in the investment decision-making system is relatively limited compared with the behavioral and market variables.

These findings indicate that behavioral variables dominate the causal structure of investment decision-making in Indonesia's technology sector.

Interpretation of the DEMATEL Cause Effect Diagram

Figure 4 illustrates the cause effect relationships among the research variables based on the Fuzzy DEMATEL analysis. The horizontal axis represents the relation index ($D-R$), which distinguishes variables into the cause group (positive values) and the effect group (negative values), whereas the vertical axis represents the prominence index ($D+R$), indicating the overall importance of each variable within the system.

The figure shows that investor sentiment and market volatility are positioned in the cause group, confirming their roles as the primary driving variables. Investor sentiment exhibits the highest positive relation value, indicating that it exerts the strongest causal influence on the other variables. Meanwhile, market volatility records the highest prominence value, suggesting that it functions as the central variable connecting behavioral and financial factors within the investment decision-making process. In contrast, herding behavior, overconfidence, risk perception, stock return, financial leverage, and investment decision are located in the effect group, indicating that they are primarily influenced by the causal variables. Overall, the cause effect diagram confirms that investment decision-making in Indonesia's technology sector is predominantly driven by behavioral dynamics, with investor sentiment acting as the principal causal driver and market volatility serving as the key connecting mechanism between behavioral and financial factors.

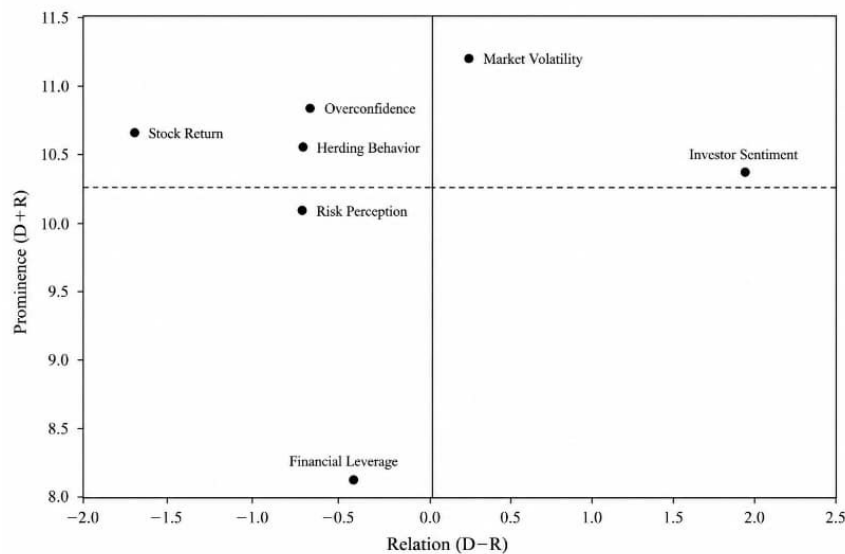


Figure 4. Cause Effect Diagram of Behavioral, Market, and Financial Variables Based on Fuzzy DEMATEL Analysis

Source: Processed data (2026)

Machine Learning Results

Table 8 presents the predictive performance of the Machine Learning models. XGBoost outperformed Random Forest across all evaluation metrics, achieving a higher coefficient of determination (R^2) and lower RMSE and MAE values. These results indicate that XGBoost provides superior predictive accuracy for modelling investment decision-making in Indonesia's technology sector.

Table 8. Machine Learning Model Performance

Model	Train R ²	Test R ²	RMSE	MAE
Random Forest	0,952	0,917	0,028	0,022
XGBoost	0,969	0,942	0,021	0,016

Source: Processed data (2026)

The evaluation results indicate that XGBoost consistently outperforms Random Forest across all performance metrics, suggesting that the algorithm is more effective in capturing the complex nonlinear relationships among behavioral, market, and financial variables. These findings support the robustness of the proposed hybrid analytical framework and provide the basis for the subsequent feature importance analysis.

Feature Importance Analysis

Table 9 presents the feature importance scores obtained from the best performing machine learning model, namely XGBoost. The results indicate that investor sentiment is the most influential predictor of investment decision-making, with the highest importance score (0,281). This finding is followed by market volatility (0,224), suggesting that behavioral and market related factors contribute more substantially to prediction accuracy than conventional financial variables.

Among the remaining variables, overconfidence (0,145) and risk perception (0,126) also demonstrate relatively high predictive importance, indicating that investors' psychological characteristics play a meaningful role in explaining investment decisions. Herding behavior (0,102) exhibits a moderate contribution, whereas stock return (0,073) and financial leverage (0,049) provide comparatively smaller contributions to the predictive model.

Table 9. Feature Importance Ranking (XGBoost)

Variable	Importance
Investor Sentiment	0,281
Market Volatility	0,224
Overconfidence	0,145
Risk Perception	0,126
Herding	0,102
Stock Return	0,073
Financial Leverage	0,049

Source: Processed data (2026)

Overall, the feature importance analysis confirms that behavioral variables dominate the prediction of investment decision-making, while financial variables contribute to a lesser extent. These findings complement the Fuzzy DEMATEL results by demonstrating that investor sentiment is not only the primary causal driver but also the strongest predictor within the proposed hybrid analytical framework.

Integrated Discussion (DEMATEL + Machine Learning)

Table 10 integrates the findings obtained from the Fuzzy DEMATEL and Machine Learning analyses, demonstrating a high degree of consistency between the causal structure and predictive performance of the proposed hybrid analytical framework. The Fuzzy DEMATEL results identify investor sentiment as the primary causal driver influencing the interactions among behavioral, market, and financial variables, whereas the Machine Learning analysis ranks investor sentiment as the strongest predictor of investment decision-making. Likewise, market volatility consistently emerges as the principal connecting mechanism within the investment decision-making system, indicating that uncertainty amplifies the transmission of behavioral responses into market outcomes. These complementary findings demonstrate that the

integration of causal modelling and predictive analytics provides a more comprehensive explanation of investment decision-making than either analytical approach alone.

Table 10. Integrated Causal and Predictive Findings

Variable	DEMATEL Role	ML Importance	Interpretation
Sentiment	Cause	Highest	Core driver
Volatility	Cause	High	Amplifier
Overconfidence	Effect	Medium	Behavioral response
Herding	Effect	Medium	Collective investor reaction driven by market sentiment
Risk Perception	Effect	Medium	Investor sensitivity toward uncertainty
Return	Effect	Medium	Outcome
Leverage	Effect	Low	Structural factor

Source: Processed data (2026)

The integrated findings presented in Table 10 provide the basis for interpreting how causal relationships identified by Fuzzy DEMATEL correspond with the predictive importance estimated by Machine Learning. The results strongly support Behavioral Finance Theory, which argues that investors do not always make decisions based on rational evaluation of financial information but are also influenced by psychological biases, heuristics, and market expectations (Tversky & Kahneman, 1974; Thaler, 2016; Barberis et al., 2021). The dominant role of investor sentiment is consistent with the findings of Baker and Wurgler (2007), Huang et al. (2022), and Vo et al. (2024), who reported that investor optimism and pessimism significantly influence trading activity, market volatility, and stock price movements. Similarly, the identification of market volatility as the central connecting variable is consistent with Bouri et al. (2022), who emphasized that volatility reflects investors' responses to uncertainty, and with Vo et al. (2024), who demonstrated that volatility strengthens the relationship between investor sentiment and stock market performance. Collectively, these findings reinforce the proposition that behavioral factors act as the initial driving forces that subsequently shape market dynamics and financial outcomes.

The findings are particularly relevant to Indonesia's technology sector because the valuation of technology firms depends heavily on innovation capability, future growth expectations, and intangible assets rather than current accounting performance. Under these conditions, investors tend to respond more rapidly to changes in market sentiment and uncertainty than to conventional financial indicators. Consequently, behavioral variables exert greater influence on investment decision-making than stock returns or financial leverage. This evidence is consistent with previous studies showing that technology firms are more vulnerable to behavioral reactions due to rapid innovation cycles and higher market uncertainty (Bouri et al., 2022; Vo et al., 2024). Therefore, investor sentiment and market volatility should be regarded as strategic indicators for understanding investment behavior in emerging technology markets.

The analysis also demonstrates that overconfidence, herding behavior, and risk perception belong to the effect group within the causal structure while still exhibiting meaningful predictive importance in the Machine Learning model. This finding suggests that these behavioral biases are not independent determinants but emerge as responses to changes in investor sentiment and market conditions. Such evidence supports the arguments of Barber and Odean (2001), Chang et al. (2000), and Kumar and Goyal (2021), who proposed that excessive trading behavior, collective decision-making, and investors' perceptions of risk become more pronounced during periods of heightened uncertainty. Accordingly, investment decisions should be understood as the outcome of dynamic interactions among behavioral, market, and financial factors rather than isolated effects of individual variables.

From a theoretical perspective, this study extends Behavioral Finance Theory by conceptualizing investment decision-making as an integrated behavioral–market–financial system instead of a collection of independent determinants. From a methodological perspective, the study contributes by integrating Fuzzy DEMATEL and Machine Learning within a unified analytical framework capable of simultaneously identifying causal relationships and evaluating predictive importance. Unlike previous studies that generally relied on either explanatory analysis or predictive modelling alone (Gu et al., 2020; Nti et al., 2023; Govindan et al., 2020; Kumar & Dixit, 2022), the proposed framework provides complementary structural and predictive insights into complex investment behavior. Practically, the findings offer valuable implications for investors, portfolio managers, financial analysts, and policymakers by emphasizing the importance of monitoring investor sentiment and market volatility to improve portfolio allocation, risk assessment, and investment strategy formulation in technology-oriented capital markets.

CONCLUSION

This study investigated investment decision-making in Indonesia's technology sector by integrating Fuzzy DEMATEL and Machine Learning within a hybrid analytical framework. The findings consistently indicate that investor sentiment is both the principal causal driver and the strongest predictor of investment decisions, while market volatility functions as the central mechanism connecting behavioral and financial variables. These results demonstrate that investment decision-making is shaped primarily by the interaction of behavioral and market factors rather than by conventional financial indicators alone.

The study contributes to Behavioral Finance Theory by conceptualizing investment decision-making as an integrated behavioral market financial system and contributes methodologically through the combination of causal modelling and predictive analytics within a unified analytical framework. The proposed approach provides complementary insights that improve understanding of complex investment behavior and offers practical implications for investors, portfolio managers, financial analysts, and policymakers operating in technology-intensive and highly uncertain market environments.

Despite these contributions, this study has several limitations. The empirical analysis is limited to technology companies listed on the Indonesia Stock Exchange during 2020–2024, which may restrict the generalizability of the findings to other industries and capital markets. In addition, the causal analysis relies on expert judgment within the Fuzzy DEMATEL framework, whereas the predictive analysis is based on historical financial and market data. Future research is encouraged to examine other industrial sectors and international capital markets, incorporate additional behavioral indicators such as social media sentiment or news-based sentiment, and integrate explainable artificial intelligence (XAI) techniques to enhance the transparency and interpretability of machine learning models in behavioral finance.

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