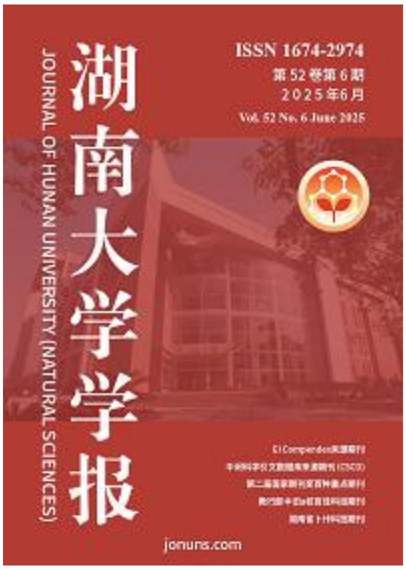

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The Role of Social Media and Social Interaction in Investment Decision-Making in the Digital Era: The Mediating Role of Risk Tolerance

Heni Safitri[1*], Giriati[2], Wendy[3]

[1]**Universitas Muhammadiyah Pontianak, Indonesia**

[2,3] **Universitas Tanjungpura Pontianak, Indonesia**

* Corresponding author: heni.safitri@unmuhpnk.ac.id

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Abstract: Understanding how digital information sources influence retail investor behaviour in emerging markets is critical for financial stability and inclusion. This study examined whether social media use and offline social interaction shape equity investment decisions among Indonesian retail investors and whether risk tolerance mediates these relationships. We surveyed 300 self-directed stock investors and analysed the data with partial least-squares structural equation modelling (SmartPLS). The measurement model satisfied all reliability and validity thresholds and the structural model achieved good fit, high predictive relevance and no multicollinearity. Investment decisions were explained. Social interaction increased investment propensity and elevated risk tolerance; the mediated component represented 35 % of the total effect. Social media exposure produced neither direct nor indirect influence. Risk tolerance strongly predicted investment behaviour, whereas loss aversion dampened it. These results demonstrate that interpersonal networks, rather than digital feeds, are the primary conduit through which Indonesian investors acquire actionable information, and that building appropriate risk tolerance is pivotal for translating social learning into market participation. The findings isolate context-specific drivers within behavioural finance and suggest that policy efforts should focus on investor communities and risk-education initiatives rather than generic social-media campaigns. Future research should replicate the model in other emerging economies and incorporate real-time sentiment analytics to clarify boundary conditions as algorithmic trading and social platforms continue to converge.

Keywords: social media; investment decision-making; risk tolerance; behavioural finance social interaction; retail investors; Indonesia.

社交媒体和社交互动在数字时代投资决策中的作用 ：受风险承受能力的调节

摘要：了解数字信息源如何影响新兴市场散户投资者的行为，对维护金融稳定与提升普惠金融至关重要。本研究考察了社交媒体使用与线下社会互动是否影响印尼散户的股票投资决策，以及风险承受能力在其中是否发挥中介作用。研究团队对300名自主决策的股票投资者进行问卷调查，并采用偏最小二乘结构方程模型（SmartPLS）进行数据分析。测量模型满足所有可靠性与效度阈值，结构模型亦表现出良好拟合度、高预测相关性且不存在多重共线性。结果显示，社会互动不仅提高了投资倾向，还提升了风险承受能力；中介效应占总效应的35%。社交媒体曝光无直接或间接影响。风险承受能力对投资行为具有强预测力，而损失厌恶则抑制投资行为。研究表明，人际网络而非数字信息流是印尼投资者获取可操作信息的主要渠道，培养适当的风险承受能力是将社会学习转化为市场参与的关键。结论揭示了行为金融中情境特定的驱动因素，建议政策重点应放在投资者社区建设与风险教育计划，而非泛化的社交媒体宣传。未来研究可在其他新兴经济体复制本模型，并结合实时情绪分析，以厘清算法交易与社交平台进一步融合过程中的边界条件。

关键词：社交媒体；投资决策制定；风险承受能力；行为金融；社会互动；散户投资者；印尼

1. Introduction

One driver of the recent surge in stock investment is the ready availability of information on social media. Such openness has attracted investors from diverse backgrounds, including students, homemakers and salaried workers. Companies now leverage social media both to convey corporate information and to engage with stakeholders. Digital investment platforms also enable young and novice investors to begin with modest sums, further broadening market participation. The growing enthusiasm among Millennials and Generation Z is largely attributable to open-access investment content on websites, news portals and social-media channels. Investment-focused accounts including “finfluencers” [1-5] have become key sources of financial advice.

The Fig.1. shows the number of social media users in Indonesia, namely:

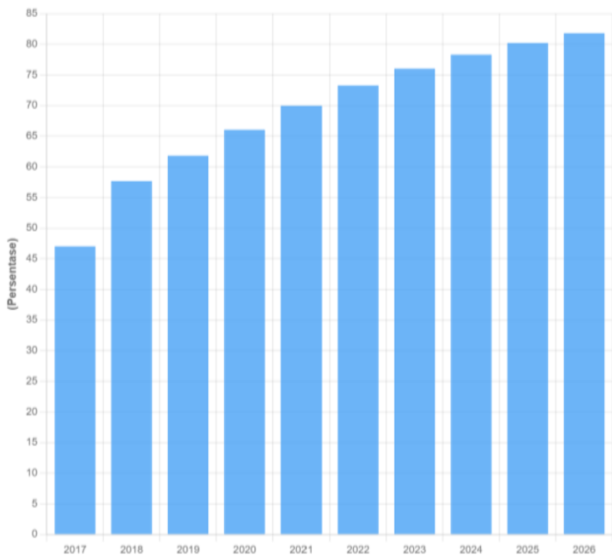

Figure 1. Data (Trends) and Predictions of Internet and Social Media Users in Indonesia 2017-2026 Source: (https://data.goodstats.id, 2023)

By 2026, 81.82% of Indonesians are expected to have their own social media. This figure has doubled from 2017, which amounted to 47.03%. Social media users in Indonesia are only 47.03% of the population. This figure is expected to double by 2026 with a total of 81.82% users. Not only that, 78.5% of internet users are estimated to use at least 1 social media account. This value is predicted to continue to grow in the coming years.

Meanwhile, based on the results of the 2023 survey, in terms of age alone, social media users are dominated by 18-34 year olds (54.1%), with female gender (51.3%) while male (48.7%). Indonesians spend an average of 3 hours and 14 minutes per day and 81% access it every day. Activities that are often carried out also vary from sharing photos / videos (81%), communication (79%), news / information (73%), entertainment (68%), online shopping (61%) (https://www.rri.co.id, n.d.).

The digital revolution has fundamentally changed the way information is disseminated, where the internet facilitates users to share their insights and perspectives instantly to a global audience through social media platforms such as Facebook, Twitter, LinkedIn and Instagram. The proliferation of these social media platforms has significantly minimized information gaps in the investment decision-making process [6-9].

Continuous media exposure plays an important role in shaping an individual's perception of reality. In the investment context, social media platforms influence investors' understanding of market dynamics, investment trends and economic opportunities, ultimately impacting their investment choices. This relationship between social media and investment decision- making can be understood through cultivation theory, which explains that individuals who consistently consume media content tend to adopt the worldview presented by those media sources. Based on this theoretical framework, investors as individuals tend to follow what they observe and hear through media channels. This phenomenon is particularly prominent in today's digital age, where access to social media is easy and widespread.

Social factors are recognized as powerful influences and can have a significant impact on investors' decision-making process. Recent studies on investment decision-making reveal that individual investors do not make financial decisions independently; instead, they rely on information gathered through social interactions with others [10-15]. Social interactions with family, friends, and through social media have become vital channels for sharing information and ideas [1; 16-17]. These social interactions show that individuals engage with others to obtain information needed to make the right investment decisions [18-20].

Research on the influence of social factors on investment decisions is crucial to do because it can deepen our understanding of real investor behavior. Social factors are believed to have a significant role in influencing investment decisions made by investors. By understanding these social concepts, investors can make better investment decisions through a thoughtful understanding of their social media usage and social environment interactions.

This understanding will help investors to maintain their long-term investment strategies and be more prudent in their investment decisions without being easily swayed by pressures or opinions from their social environment. Thus, it is important to conduct research that considers the influence of these social factors so that a more realistic and accurate investment decision-making model can be developed in accordance with the social dynamics that occur in society.

2. Method

2.1 Type of Research

The approach used in this research is a quantitative approach. The quantitative approach views human behavior as predictable and social reality, objective and measurable [21]. This quantitative research uses a survey approach. Survey is a quantitative study used to examine the symptoms of a group or individual behavior. In general, surveys use questionnaires as data collection tools [22].

2.2. Place and Time of Research

This research was conducted in Indonesia using research objects, namely retail investors who invest in the Indonesian capital market, namely stock investment. This research was conducted in 2025 using data on the number of active retail investors until December 2024 obtained from the Indonesia Stock Exchange.

2.3 Types and Sources of Data

The types of data used are primary and secondary data. Primary data in this study were obtained from questionnaires distributed to respondents in this study, namely stock investors. Secondary data in this study were obtained from the Indonesia Stock Exchange in the form of documents and articles taken from the website.

2.4 Population and Sample

The population in this study is spread across Indonesia and invests in stocks in the Indonesian capital market. The total population in this study is 4,915,744 stock investors on the Indonesia Stock Exchange. The sampling technique used in this study was proportional stratified random sampling. According to (Ferdinand, 2002) , SEM requires the number of samples that must be met is at least 100 or the number of parameters multiplied by 5-10. In this study, the number of parameters is 13 and if multiplied by 10, the number is 130. So that the minimum sample size that must be met is 130 respondents. The more the number of samples, the better it will be for a study. The number of samples used in this study were 300 retail stock investors in Indonesia. In the sample that was drawn, the researcher determined several criteria so that the sample used as the object of the study could provide appropriate answers and become a valid source of data. The criteria determined in drawing the sample were:

a. Investors are active investors and have invested for at least 1 year
b. Investors are retail investors who independently manage their investments
c. Investors who invest in shares on the Indonesia Stock Exchange

2.5 Operational Definition of Variables

The variables and each indicator in this study can be seen in the following table.

Table 1. Operational Definition of Variables

Variable	Measurement Item
Exogenous Variable	
Social Interaction	1. Family members
	2. Reference group
	(Akhtar et al., 2018; Shanmugham & Ramya, 2012)
Social Media	1. Content on social media
	2. Influencers in social media
	(Zhang & Choi, 2022)
Mediating Variable	
Risk Tolerance	1. Readiness to take risks
	2. Fund allocation
	3. Investment experience
	(Grable & Roszkowski, 2008; Harahap et al., 2022; Kishor, 2020)
	(Alzoubi & Aziz, 2021)
Endogenous Variable	
Investment Decision	1. Investment rate of return
	2. Investment risk
	3. Investment period
	(Armansyah, 2022; Rahman & Gan, 2020)
Control Variable	
Loss aversion	1. Avoiding the risk of loss
	2. Sensitivity to loss
	3. Recovery after loss
	(Jain et al., 2019; Zahera & Bansal, 2018)

Source : Developed by Authors

2.6 Data Analysis Technique

The analysis technique used in this research is Structural Equation Modeling (SEM) with SmartPLS. SEM is a set of statistical testing techniques that can test a series of relatively complex relationships between variables. The advantage of this analytical technique is its ability to simultaneously test the structural model and measurement model.

2.6.1 Indicator Reliability

The level of reliability can be seen in the outer loading value of each indicator. Outer Loadings are used to see the loading factor of each indicator used. According to Chin, the loading factor value of 0.5-0.6 is considered sufficient for early stage research . If the loading factor value is more than 0.7, the indicator is very valid and suitable for use.

2.6.2 Convergent Validity

An indicator is considered valid when the indicator has an AVE (average variance extranced) value above 0.5. The AVE value is the average percentage of variance scores extracted from a set of latent variables estimated through the Standarized loading of their indicators in the process of iterating the algorithm in PLS.

2.6.3 Internal Consistency Reliability

Internal Consistency Reliability is an index that shows the extent to which a measuring device can be trusted to be relied upon. The tool used is to know the value of composite reliability, namely the construction is considered reliable if the composite reliability value is> 0.7.

2.6.4 Variance Inflation Factor (VIF)

VIF is done to avoid multicollinearity, namely the phenomenon of two or more independent variables being highly correlated, causing the model's predictive ability to be poor. According to (Sarstedt & Cheah, 2019) multicollinearity in SmartPLS can be seen in the Variance Inflation Factor (VIF) value where the VIF value must be <5.

2.6.5 Coefficient of Determination (R^2)

The structural model (Inner model) is evaluated by looking at the percentage of variance explained, namely by looking at R2which is a way to assess how much endogenous construction can be explained by exogenous construction. SmartPLS presents the results of calculating the coefficient of determination (R2) value, which is expected to be between 0 and 1. The criteria for $R^2 \geq 0.75$ (0.75 or more) are referred to as strong construction, $R^2 \geq 0.50$ (0.50 to 0.74) is referred to as moderate and $R^2 \geq 0.25$ (0.25 to 0.49) as weak.

2.6.6 Effect Size (f^2)

In the context of analysis using SmartPLS, the level of influence between variables is represented by the f^2 value. The interpretation of the f^2 value is as follows: $f^2 = 0.02$: indicates a small effect, $f^2 = 0.15$: indicates a moderate effect, and $f^2 = 0.35$: indicates a large effect. In addition, (Hair et al., 2021) adds that f^2 values less than 0.02 can be ignored or considered to have no significant effect. Thus, analyzing the f^2 value provides a clearer picture of the strength of the relationship between variables in the model under study.

2.6.7 Goodness of Fit

Measuring the right model with Standardized Root Mean Square Residual (SRMR). The goodness of fit (GoF) value of 0.1 is interpreted that the level of fit of the model is small, 0.25 as medium, and 0.38 as large.

2.6.8 Hypothesis Testing

Hypothesis testing is a procedure that uses evidence from a sample to determine the feasibility of a hypothesis. Through this process, we can decide whether the hypothesis is plausible enough to be accepted or too implausible to be rejected. In other words, this indicates a significant effect of the exogenous variables on the endogenous variables being tested. This hypothesis is tested at a significant level of 0.05 (95% confidence level). To determine the decision to test the hypothesis, it is done by comparing the significant level and alpha (0.05) with the following conditions: If the probability ≤ 0.05 (P-value) or t count (t Statistic) ≥ t table, then the null hypothesis (H0) is rejected and the alternative hypothesis (H1) is accepted. This means that the independent variable partially has a significant effect on the dependent variable at 5% error (α = 0.05). However, if the probability ≥ 0.05 (P- value) or t count (t Statistic) ≤ t table, then the null hypothesis (H0) is accepted and the alternative hypothesis (H1) is rejected, meaning that the independent variable partially has no significant effect on the dependent variable at 5% error (α
= 0.05).

3. Results

3.1. Respondent Profile

The respondent profile data used in this study are as follows:

Table 2. Respondent Profile

Profile	N	Percentage
Gender		
Male	205	68
Female	95	32
Age		
20-29	170	56
30-39	100	33
40-49	30	11
Last Education		
S1	262	87
S2	38	13
Job		
Private Employee	166	62
Civil Servant	37	12
Entrepreneur	78	26
Income Per Month (IDR)		
1.000.000-3.999.999	70	23
4.000.000-6.999.999	110	37
7.000.000-9.999.999	52	17
>10.000.000	68	23

Source: Developed by the Authors

3.2 Indicator Reliability and Coherent Validity

Outer loadings showed the loading factor for each indicator, which is considered highly valid and appropriate when the loading factor surpassed 0.7. The validity was also determined when the AVE exceeded 0.5. In order to assess Internal Consistency Reliability, the composite reliability value was determined. A construct was considered reliable if the composite reliability value was greater than 0.7. Meanwhile, 0.7 is the minimum acceptable value, with 0.8 or 0.9 considered as ideal scores. The following are the results of outer loading, construct reliability and validity.

Table 3. Indicator Reliability and Coherent Validity

Variable/ Item	Loading	Cronbach α	CR	AVE
Social Interaction		0,825	0,881	0,681
S1	0,781			
S2	0,656			
S3	0,887			
S4	0,884			
Social Media		0,889	0,893	0,652
SM1	0,970			
SM2	0,887			
SM3	0,675			
SM4	0,736			
Risk Tolerance		0,854	0,896	0,682
RT1	0,810			
RT2	0,848			
RT3	0,843			
RT4	0,803			
Loss Aversion		0,784	0,856	0,599
LA1	0,723			
LA2	0,733			
LA3	0,829			
LA4	0,805			
Investment Decision		0,794	0,866	0,617
ID1	0,771			
ID2	0,806			
ID3	0,777			
ID4	0,788			

Source: Prepared by the Authors

The factor loadings for all constructs-whether exogenous, endogenous, or mediating- exceeded the 0.7 threshold, indicating that all measurement indicators demonstrated validity and appropriateness for the analysis. Additionally, Cronbach's alpha coefficients and Average Variance Extracted (AVE) values surpassed the recommended benchmarks of 0.6 and 0.5 respectively, suggesting adequate convergent validity. This means that each latent construct accounts for over half of the variance observed in its corresponding measurement indicators. Furthermore, composite reliability values for all constructs exceeded 0.8, confirming that the variables possess strong reliability and are well-suited for the study. These findings collectively demonstrate that the measurement instruments employed in this research exhibit satisfactory reliability and validity characteristics.

3.3 Variance Inflation Factor (VIF)

Sarstedt & Cheah (2019), stated that multicollinearity using SmartPLS can be observed in the VIF value <5. The following are the results of the test conducted.

Table 4. VIF

Variable	Investment Decision	Risk Tolerance
Social Media	1,008	1,002
Social Interaction	1,192	1,002
Risk Tolerance	1,386	
Loss Aversion	1,293	

Source: SmartPLS 3 (Prepared by the Authors)

The Variance Inflation Factor (VIF) analysis revealed that all relationships between exogenous and endogenous variables fell below the threshold of 5, indicating the absence of multicollinearity issues or excessive intercorrelations among variables. The lack of multicollinearity is crucial for statistical analysis as it ensures reliable estimation of regression coefficients, establishes a robust model structure, allows for accurate evaluation of individual independent variable contributions, and preserves the statistical validity of results by eliminating potential bias in the analysis.

3.4 Coefficient od Determination (R^2)

Chin stated that R^2 values of 0.67, 0.33 and 0.19 were referred to as strong, moderate and weak construction, respectively.

Table 5. R Square and Adjusted R Square

	R Square	R Square Adjusted
Investment Decision	0,482	0,475
Risk Tolerance	0,147	0,141

Source: SmartPLS 3 (Prepared by the Authors)

The coefficient of determination showed that investment decisions could be analyzed using social interaction, social media, and loss aversion variables with an R^2 value of 0.482, showing moderate relationship. In addition, the risk tolerance variable was explained using social interaction and social media with an R^2 value of 0.147, implying a weak relationship.

3.5 Effect Size (f^2)

The interpretation of the f2value was reported as follows f2= 0.02, 0.15, and 0.35 showing small, moderate, and large effect, respectively.

Table 6. Effect Size (f^2)

Variable	Investment Decision	Effect Size (f2)	Loss Aversion	Effect Size (f2)
Social Media	0,000	**Small Effect**	0,168	**Moderate Effect**
Social Interaction	0,012	**Small Effect**	0,002	**Small Effect**
Risk Tolerance	0,378	**Large Effect**		
Loss Aversion	0,076	**Small Effect**		

Source: SmartPLS 3 (Prepared by the Authors)

Based on the f2value, social media, social interaction and loss aversion had a small effect on investment decisions, while risk tolerance had a large effect. Social media and social interaction variables had moderate and small effects on risk tolerance.

3.6 Goodness of Fit

The Standardized Root Mean Square Residual (SRMR) is evaluated based on its numerical value, with thresholds below 0.10 or 0.08 typically deemed acceptable for model fit. Henseler proposed SRMR in 2014 as a goodness-of-fit measure specifically for Partial Least Squares Structural Equation Modeling (PLS-SEM), intended to serve as a safeguard against model misspecification issues.

Table 7. Model Fit

	Saturated Model	Estimated Model
SRMR	0,069	0,075
Criteria	**Model Fit**	**Model Fit**

Source: SmartPLS 3 (Prepared by the Authors)

The findings revealed that both saturated and estimated model SRMR values fell below the 0.10 or 0.08 thresholds, demonstrating that an appropriate model fit was achieved and model specification errors were avoided. Furthermore, the structural model exhibited strong explanatory power for the data and proved to be dependable for informing decision-making processes.

3.7 Direct and Indirect Effect Analysis

In statistical analysis, the relationship between P-values and the established significance threshold is commonly set at 5% ($\alpha = 0.05$). When P-values are at or below 0.05, this indicates that the independent variable exerts a statistically significant partial influence on the dependent variable, with a 5% probability. Conversely, when P-values exceed 0.05, this suggests that the independent variable does not demonstrate a statistically significant partial effect on the dependent variable at the 5% significance level.

Table 8. Direct Effect and Indirect Effect

	Original Sample (O)	Sample Mean (M)	P Values	Result
Social Media -> Investment Decision	0,030	0,031	**0,607**	**Not Significant**
Social Media -> Risk Tolerance	0,044	0,038	**0,525**	**Not Significant**
Social Interaction -> Investment Decision	0,282	0,282	**0,000**	**Positive Significant**
Social Interaction -> Risk Tolerance	0,379	0,389	**0,000**	**Positive Significant**
Loss Aversion -> Investment Decision	0,226	0,231	**0,006**	**Positive Significant**
Risk Tolerance -> Investment Decision	0,521	0,519	**0,000**	**Positive Significant**
Social Media -> Risk Tolerance -> Investment Decision	0,023	0,020	**0,531**	**Not Significant**
Social Interaction -> Risk Tolerance -> Investment Decision	0,197	0,202	**0,000**	**Positive Significant**

Source: Source: SmartPLS 3 (Prepared by the Authors)

From the results of direct effect testing, it shows that Social media has no significant effect on investment decision making and risk tolerance with a p value of 0.607 and 0.525 respectively. From these results it can be seen that H1 in this study is rejected. Meanwhile, social interaction has a positive and significant effect on both investment decision and risk tolerance with each p value of 0.000. From these results, H2 in this study is accepted. Loss Aversion as a control variable also has a positive significant effect on investment decision making with a p value of 0.006. Risk tolerance as a mediating variable directly also has a positive and significant effect on investment decision making with a p value of 0.000.

The results of indirect effect testing show that social media has no effect on investment decision making with risk tolerance as a mediating variable with a p value of 0.531. Meanwhile, social interaction has a positive and significant effect on investment decision making with risk tolerance as a mediating variable with a p value of 0.000. These results indicate that H3 in this study is rejected and H4 is accepted.

3.8 Research Model

The framework for the research model is shown in the following figure:

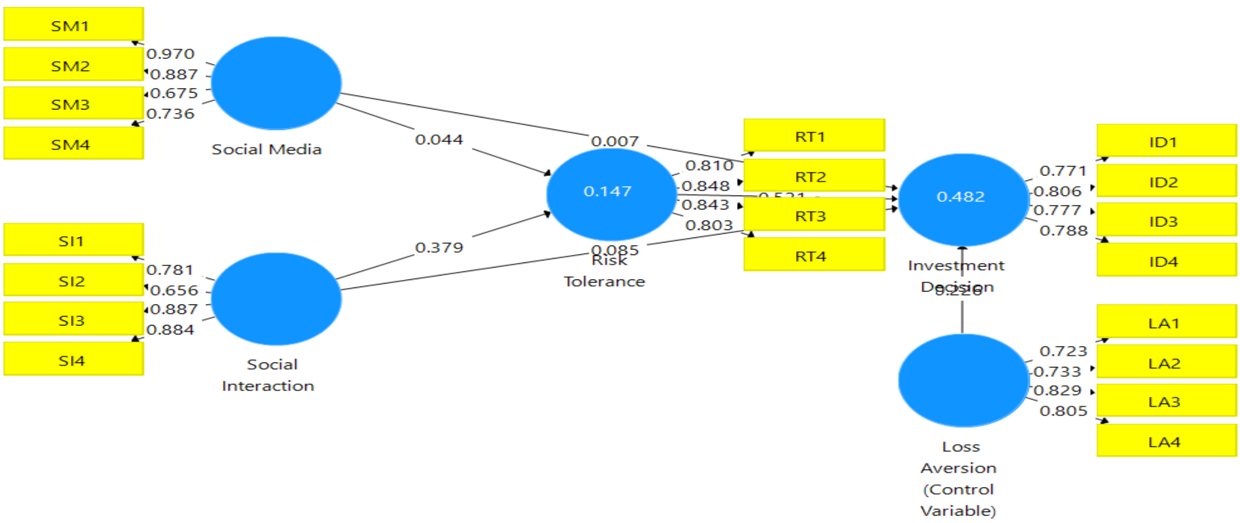

Figure 2. Research Model
Source : Developed by the Authors

4. Discussion

4.1 Social Interaction to Investment Decision

The research findings demonstrated that social interaction variables significantly influenced investment decision-making processes. The study revealed that social dynamics substantially shaped individual viewpoints, with conversations and interactions among members of one's social network-encompassing friends, family members, and professional contacts-serving as key influencers of personal perspectives. Individuals demonstrated a mutual influence pattern, both shaping and being shaped by prevailing opinions within their immediate social circles. Consequently, social interactions emerged as determinants of investment decision- making behavior, thereby confirming H1. These findings aligned with previous studies conducted by [1; 23-26].

4.2 Social Media to Investment Decision

The study found that social media variables did not influence investment decisions, as information disseminated across various platforms often lacked verification, contained bias, or was potentially misleading. This situation led experienced investors to develop skepticism, causing them to rely more heavily on credible and authenticated information sources. Moreover, the overwhelming volume of information available on social media platforms created challenges in identifying accurate and pertinent content. Sentiment expressed on social media frequently failed to accurately represent underlying market fundamentals and actual performance metrics. Despite social media's extensive reach and accessibility, it demonstrated minimal impact on investment decision-making, particularly among seasoned investors. These findings resulted in the rejection of H1, which corresponded with research conducted by [27-35].

4.3 Risk Tolerance as Mediated

The research further revealed that risk tolerance functioned as a mediating factor in the relationship between social interaction and investment decisions. Social exchanges with peers, family members, or industry professionals influenced how individuals conceptualized and evaluated investment-related risks. Through discussions, knowledge sharing, and exposure to others' investment experiences, personal risk perceptions regarding various investment alternatives underwent modification. These altered perceptions subsequently increased or decreased individual risk tolerance levels. Additionally, through interpersonal interactions, risk tolerance functioned as an evaluative criterion for investment decision- making, supporting H4. These outcomes were consistent with research findings from [36-56].

The study also determined that risk tolerance failed to serve as a mediating variable between social media exposure and investment decisions. Experienced investors maintained skepticism toward information obtained from social platforms, meaning such content did not substantially alter their risk perceptions. This lack of influence on risk assessment contributed to the rejection of H3, indicating that the pathway from social media through risk tolerance to investment decisions was not statistically significant among the study participants.

5. Conclusion

The research results indicate that social interactions have an influence on investment decision-making. Joining investor communities can provide valuable learning through sharing experiences and knowledge. Discussions with mentors or experienced investors can help broaden insights and improve investment strategies. Meanwhile, to avoid negative impacts from social interactions in investing, the most important thing is to build strong information filters. Every investment recommendation or tip needs to be validated with independent research and adjusted to personal financial goals.

The findings on social interaction influence provide strong empirical support for Social Capital Theory and Network Theory of Social Capital, demonstrating how social networks function as valuable resources in investment decision-making through information exchange and social learning. Future research can add other social factors that may influence an investor's investment decision-making. Additionally, future research can also collaborate other factors such as psychological conditions and socio-demographics to examine their influence on investment decision-making.

Limitations

Despite methodological rigour and a reasonably representative sample, several limitations temper the interpretability of our results. First, the analysis relies on self-reported questionnaires, which expose the data to social-desirability bias and recall error—respondents may, for instance, overstate their financial knowledge or under-report impulsive trades. Second, the cross-sectional design precludes temporal ordering; social interaction and risk tolerance were measured simultaneously, leaving causal direction inferential rather than demonstrable. Third, the sampling frame is confined to Indonesian retail investors, most of whom hold tertiary degrees and enjoy reliable internet access; findings may not generalise to markets with different digital infrastructures or collectivist norms. Fourth, the model controls for only one psychological covariate—loss aversion—while omitting overconfidence, endowment effects and other biases that could attenuate or inflate the mediating pathway. Fifth, exposure to social media is treated as an aggregate construct, without distinguishing platform type, content quality or algorithmic curation, thereby obscuring granular mechanisms. Finally, although partial least-squares structural-equation modelling is appropriate for exploratory work, it is generally less powerful for detecting small effects than covariance-based SEM and may therefore underestimate weak but meaningful relationships. Recognising these constraints invites future validation through multilevel, longitudinal and cross-cultural designs with finer operationalisations.

Future Directions

Future inquiries could, first, adopt longitudinal panel designs that track shifts in risk tolerance and network structure following exogenous shocks—regulatory or macroeconomic—to establish causal dynamics. Second, expanding the geographic scope to an ASEAN comparison would permit tests of cultural moderators such as individualism scores or informal-institution strength. Third, combining traditional surveys with digital ethnography and big-data analytics—mining public tweets, YouTube comments and forum posts—would enable objective sentiment measurement and content verification. Fourth, researchers should model non-linear and threshold effects; social influence may surface only beyond a critical network density or under high volumes of negative noise. Fifth, cohort heterogeneity deserves attention: Generation Z may respond to influencers differently from millennials, whereas older investors might rely more on offline advice. Sixth, incorporating cognitive and affective mediators—financial self-efficacy, fear of missing out—would allow multi-step mechanism tests. Finally, agent-based simulations in which agents receive heterogeneous social signals could conduct virtual experiments free from ethical constraints, clarifying the network parameters that tip markets toward irrational dynamics.

Practical Implications and Recommendations

The evidence offers actionable insights for regulators, brokers and educators. First, because offline communities enhance investment propensity, the Indonesian Stock Exchange should subsidise certified investor clubs at universities and tech parks, financing expert seminars and mentoring schemes. Second, given the mediating role of risk tolerance, brokerage apps ought to embed interactive risk-profiling tools and tailor dashboards accordingly: conservative users see capital-preservation scenarios; aggressive users view portfolio volatility projections. Third, the null effect of social media underscores a need for media literacy. Fourth, tax incentives for accredited risk-management courses would encourage uptake of CFA Institute modules or local equivalents. Fifth, commercial banks might integrate moderated client forums into their digital channels, employing peer-review mechanisms so that investment tips pass expert screening. Finally, industry bodies should develop insight panels to monitor which forms of social engagement raise client confidence, enabling firms to personalise services and reduce account churn.

Theoretical Contribution

This study advances behavioural-finance scholarship in three ways. First, it refines the concept of social capital by disentangling offline networks from online feeds, thereby supporting the view that information channels are context-specific rather than fungible. Second, it extends risk-behaviour models by demonstrating that risk tolerance is the pivotal conduit through which social interaction translates into market participation, adding a social layer to the individual utility focus of prospect theory. Third, the null finding for social-media exposure constitutes a meaningful boundary condition, signalling that content quality and format must be considered before attributing explanatory power to digital channels. In addition, the work confirms the suitability of PLS-SEM for complex behavioural models in emerging markets and supplies a validated indicator set for future cross-cultural comparisons. Collectively, these insights integrate network sociology with financial rationality frameworks, offering a more nuanced understanding of how social structures steer individual investment decisions in the era of digital transformation.

Declarations

Author Contributions

The following statements should be used:

Conceptualization, H.S. and W.; methodology, H.S.; software, H.S; validation, G., W.; formal analysis, H.S; investigation, W.; resources, G.; data curation, H.S.; writing—original draft preparation, all authors; writing—review and editing, H.S.; visualization, H.S.; supervision, G.; project administration, H.S.; funding acquisition, W. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and was approved by the review committee of Research Center of the Universitas Muhammadiyah Pontianak, Indonesia.

Conflicts of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript.

References

[1] AGARWAL, S., & SINGH, S. Biases in Capital Market Instrument Investing Decisions: A Study from India. Australasian Business. Accounting and Finance Journal, 2024, 18(3), 307–330. https://doi.org/10.14453/aabfj.v18i3.16

[2] AKHTAR, F., THYAGARAJ, K. S., & DAS, N. The impact of social influence on the relationship between personality traits and perceived investment performance of individual investors. International Journal of Managerial Finance, 2017, 14(1), 130–148. https://doi.org/10.1108/ijmf-05-2016-0102

[3] ALMANSOUR, B. Y., ELKRGHLI, S., & ALMANSOUR, A. Y. Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, 2023, *11* (2), 2239032. https://doi.org/10.1080/23322039.2023.2239032

[4] ALZOUBI, H. M., & AZIZ, R. Does Emotional Intelligence Contribute to Quality of Strategic Decisions? The Mediating Role of Open Innovation. *Journal of Open Innovation: Technology, Markets, and Complexity*, 2021, *7* (2), 130. https://doi.org/10.3390/joitmc7020130

[5] ARMANSYAH, R. F. Herd Instinct Bias, Emotional Biases, And Information Processing Biases In Investment Decisions. *Journal of Management Entrepreneurship*, 2022, *24* (2), 105-117. https://doi.org/10.9744/jmk.24.2.105-117

[6] AUSAT, A. M. A. The Role of Social Media in Shaping Public Opinion and Its Influence on Economic Decisions. *Technology and Society Perspectives (TACIT)*, 2023, *1* (1), 35-44. https://doi.org/10.61100/tacit.v1i1.37

[7] DE CASTRO, P. A. L., Barreto Teodoro, A. R., De Castro, L. I., & Parsons, S. Expected utility or prospect theory: Which better fits agent-based modeling of markets? *Journal of Computational Science*, 2016, *17*, 97-102. https://doi.org/10.1016/j.jocs.2016.10.002

[8] DHAMI, S., & AL-NOWAIHI, A. Why do people pay taxes? Prospect theory versus expected utility theory. *Journal of Economic Behavior & Organization*, 2007, *64* (1), 171-192. https://doi.org/10.1016/j.jebo.2006.08.006

[9] DITA, R. D. R. T., HERYANA, T., & BASUKI, T. I. Investment Decision-Making Behavior in the Era of Covid-19: An Analysis on the Basis of Mental Accounting, Loss Aversion Bias, and Risk Tolerance. *HOLISTICA Journal of Business and Public Administration*, 2023, *14* (2), 33-42. https://doi.org/10.2478/hjbpa-2023-0014

[10] FERDINAND, A. SEM in Management Research. *Semarang: BP-UNDIP*. 2002.

[11] GASPAR, R. M., & SILVA, P. M. Investors' perspective on portfolio insurance: Expected utility vs prospect theories. *Portuguese Economi Journal*, 2023, *22*(1), 49-79. https://doi.org/10.1007/s10258-021-00200-z

[12] GRABLE, J. E., & ROSZKOWSKI, M. J. The influence of mood on the willingness to take financial risks. *Journal of Risk Research*, 2008, *11* (7), 905-923. https://doi.org/10.1080/13669870802090390

[13] HÄCKEL, B., PFOSSER, S., & TRÄNKLER, T. Explaining the energy efficiency gap-Expected Utility Theory versus Cumulative Prospect Theory. *Energy Policy*, 2017, *111*,414-426. https://doi.org/10.1016/j.enpol.2017.09.026

[14] HAIR, J. F., HULT, G. T. M., RINGLE, C. M., SARSTEDT, M., DANKS, N. P., & RAY, S. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. 2021. https://doi.org/10.1007/978-3-030-80519-7

[15] HAN, B., HIRSHLEIFER, D., & WALDEN, J. *Social Transmission Bias and Investor Behavior*. 2021.

[16] HARAHAP, S., THOYIB, A., SUMIATI, S., & DJAZULI, A. The Impact of Financial Literacy on Retirement Planning with Serial Mediation of Financial Risk Tolerance and Saving Behavior: Evidence of Medium Entrepreneurs in Indonesia. *International Journal of Financial Studies*, 2022, *10* (3), 66. https://doi.org/10.3390/ijfs10030066

[17] HARTONO, J. *Data Collection Methods and Analysis Techniques*. Andi Publisher. 2018.

[18] HASSELGREN, B., CHRYSOULAS, C., PITROPAKIS, N., & BUCHANAN, W. J. Using Social Media & Sentiment Analysis to Make Investment Decisions. *Future Internet*, 2022, *15* (1),5. https://doi.org/10.3390/fi15010005

[19] HEO, W., GRABLE, J. E., NOBRE, L., & RUIZ-MENJIVAR, J. An Estimate of the Mediation Effect of Risk Tolerance among Marital Status, Gender, and Investing Behavior. *International Journal of Human Ecology*, 2016, *17* (1), 1-14. https://doi.org/10.6115/ijhe.2016.17.1.1

[20] HONG, H., KUBIK, J. D., & STEIN, J. C. Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers. *The Journal of Finance*. 2005.

[21] HOSSAIN, T., & SIDDIQUA, P. Exploring the

influence of behavioral aspects on stock investment decision-making: A study on Bangladeshi individual investors. *PSU Research Review*, 2024, *8* (2), 467-483. https://doi.org/10.1108/PRR-10-2021-0054

[22] https://data.goodstats.id. *A look at Indonesia's Social Media Users 2017-2026*. GoodStats Data. 2023. https://data.goodstats.id/statistic/agneszefanyayonatan/menilik- pengguna-media-sosial-indonesia-2017-2026-xUAlp

[23] https://www.rri.co.id. (n.d.). *This is the Statistical Data of Indonesian Social Media Usage in 2024*. Rri.Co.Id - The Most Trusted News Portal. Retrieved July 28, 2024, from https://www.rri.co.id/iptek/721570/ini-data-statistik-penggunaan-media-sosial- masyarakat-indonesia-tahun-2024

[24] HVIDE, H. K., & ÖSTBERG, P. *Stock Investments at Work*. 2014.

[25] ISMAIL, S., NAIR, R. K., SHAM, R., & WAHAB, S. N. Impacts of online social media on investment decision in Malaysia. *Indian Journal of Public Health Research & Development*, 2018, *9* (11), 1241. https://doi.org/10.5958/0976 5506.2018.01627.3

[26] JAIN, J., WALIA, N., & GUPTA, S. Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process. *Review of Behavioral Finance*, 2019, *12* (3), 297-314. https://doi.org/10.1108/RBF-03- 2019-0044

[27] JOSE, J., & KUMAR, I. M. A Study On The Influence Of Loss Aversion Among Day Traders In Stock Exchange. *Turkish Journal of Computer and Mathematics Education*, 2021, *12*(11), 6789–6796.

[28] KAHNEMAN, D., & TVERSKY, A. On the interpretation of intuitive probability: A reply to Jonathan Cohen. *Cognition*, 1979, *7* (4), 409-411. https://doi.org/10.1016/0010- 0277(79)90024-6

[29] KAMIL, H. H., & TANNO, A. The Influence of Social Media as a Source of Information in Making Investor Investment Decisions, Educational Background and Income as Control Variables. *Journal of Accounting*, 2022, *6*.

[30] KISHOR, N. Risk preferences for financial decision: Do emotional biases matter? 2020.

[31] KUMAR, S., & CHAURASIA, A. The relationship between emotional biases and investment decisions: A meta-analysis. *IIMT Journal of Management*, 2024, *1* (2), 171-185. https://doi.org/10.1108/IIMTJM-03-2024-0034

[32] LAL, S., SULEMANA, A.-S., NGUYEN, T. X. T., KHAN, M. S. R., & KADOYA, Y. Information Sources for Investment Decisions: Evidence from Japanese Investors. *International Journal of Financial Studies*, 2023, *11* (4), 117.mhttps://doi.org/10.3390/ijfs11040117

[33] LATAN, H. *Structural Equation Modeling: Amos 21.0 Implementation Theory*. 2014. Alfabeta. https://openlibrary.telkomuniversity.ac.id/pustaka/18645/model- persamaan-struktural-teori-implementasi-amos-21-0.html

[34] LIANG, P., & GUO, S. Social interaction, Internet access and stock market participation-An empirical study in China. *Journal of Comparative Economics*, 2015, *43* (4), 883-901. https://doi.org/10.1016/j.jce.2015.02.003

[35] LU, T. (JUN), & TANG, N. Social interactions in asset allocation decisions: Evidence from 401(k) pension plan investors. *Journal of Economic Behavior & Organization*, 2019, *159* , 1-14. https://doi.org/10.1016/j.jebo.2019.01.009

[36] MASSAR, S. A. A., PU, Z., CHEN, C., & CHEE, M. W. L. Losses Motivate Cognitive Effort More Than Gains in Effort-Based Decision Making and Performance. *Frontiers in Human Neuroscience. 2020.* https://doi.org/10.3389/fnhum.2020.00287

[37] MOUEED, A., & HUNJRA, A. I. Use anger to guide your stock market decision-making: Results from Pakistan. *Cogent Economics & Finance*, 2020, *8* (1), 1733279. https://doi.org/10.1080/23322039.2020.1733279

[38] NORMASYHURI, K., SAPUTRI, Y. D., & ANGGRAENI, E. Generation Z Sharia investment decision patterns: Does information media matter? *Journal of Islamic Economics and Finance*, 2023, *9* (2), 246-262. https://doi.org/10.20885/JEKI.vol9.iss2.art7

[39] OLAJIDE, O., PANDEY, S., & PANDEY, I. Social Media for Investment Advice and Financial Satisfaction: Does Generation Matter? *Journal of Risk and Financial Management*, 2024, *17* (9), 410. https://doi.org/10.3390/jrfm17090410

[40] OSTROVSKY-BERMAN, E., & LITWIN, H. Social Network and Financial Risk Tolerance Among Investors Nearing and During Retirement. *Journal of Family and Economic Issues*, 2019, *40* (2), 237-249. https://doi.org/10.1007/s10834-018-9592-5

[41] PANDEY, L. K., SINGH, R., BAKER, H. K., & LASKAR, H. R. Beyond the Screen: How YouTube Influencers Shape Equity Investment Decisions. *Journal of Theoretical and Applied Electronic Commerce Research*, 2025, *20* (1), 15. https://doi.org/10.3390/jtaer20010015

[42] PANDIT, K., & VAIDYA, R. *Adoption of Scoial Media in Investment Decsion at Stock Market: A Qualitative Analysis Among Nepali Investors*. 2022, *11*(1).

[43] RAHMAN, M., & GAN, S. S. Generation Y investment decision: An analysis using behavioral factors. *ManagerialFinance*, 2020, *46* (8), 1023-1041. https://doi.org/10.1108/MF-10-2018-0534

[44] RIZKIANA, A. *Can Investor Sentiment in Social Media Be Used to Make Investment Decision in Stock Market*. 2021, *25*(1).

[45] SADIQ, M., & AMNA, H. Impact of Personality

Traits on Risk Tolerance and Investors' Decision Making: *International Journal of Applied Behavioral Economics*, 2019, *8* (1), 1-20. https://doi.org/10.4018/IJABE.2019010101

[46] SARSTEDT, M., & CHEAH, J.-H. Partial least squares structural equation modeling using SmartPLS: A software review. *Journal of Marketing Analytics*, 2019, *7* (3), 196-202. https://doi.org/10.1057/s41270-019-00058-3

[47] SAUTMA, R. B., TARIGAN, Z. J. H., SIAGIAN, H., & FERRY, J. The Impact of Personality Traits on Financial Decisions through Financial Knowledge and Investment Risk. *Journal of Competitiveness*, 2024, *16* (2), 262-279. https://doi.org/10.7441/joc.2024.02.13

[48] SHANMUGHAM, R., & RAMYA, K. Impact of Social Factors on Individual Investors' Trading Behavior. *Procedia Economics and Finance*, 2012, *2*, 237-246. https://doi.org/10.1016/S2212-5671(12)00084-6

[49] SHIVE, S. An Epidemic Model of Investor Behavior. *Journal of Financial and Quantitative Analysis*, 2010, *45* (1), 169-198. https://doi.org/10.1017/S0022109009990470

[50] SHRESTHA, S. K., KARKI, T. B., MAHAT, D., & NEUPANE, D. Analyzing the impact of Social Interaction on Stock Market Participation: A Qualitative Study Using NVivo. *Nepal Journal of Multidisciplinary Research*, 2024, *7*(2), 57-69. https://doi.org/10.3126/njmr.v7i2.68245

[51] SIGIT, H., & AMIRULLAH, S. *Business Research Methods: Quantitative & Qualitative Approaches*. Media Nusa Creative (MNC Publishing). 2021

[52] ULLAH, K., KAKAKHEL, S. J., & AKHTER, M. *How does Social Interaction affect the Individual Investor's Investment Decision? .2021*

[53] YUSUF, M. *Quantitative, Qualitative & Combined Research Methods*. Prenada Media. Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, 2016, *10* (2), 210-251. https://doi.org/10.1108/QRFM-04-2017-0028

[54] ZHANG, X., & CHOI, J. The Importance of Social Influencer-Generated Contents for User Cognition and Emotional Attachment: An Information Relevance Perspective. *Sustainability*, 2022, *14* (11), 6676. https://doi.org/10.3390/su14116676

[55] ZHAO, J. C., FU, W.-T., ZHANG, H., ZHAO, S., & DUH, H. To Risk or Not to Risk: Improving Financial Risk Taking of Older Adults by Online Social Information. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 2015, 95-104. https://doi.org/10.1145/2675133.2685033

[56] ZHENG, R., OSPINA-FORERO, L., & CHEN, Y. Implications of social network structures on socially influenced decision-making. *Decision*, 2024, *51* (1), 85-103. https://doi.org/10.1007/s40622-024-00380-5

参考文:

[1] AGARWAL, S., & SINGH, S. 资本市场工具投资决策中的偏见：来自印度的研究。澳大拉西亚商业、会计与金融期刊，2024年，18(3)，307–330。https://doi.org/10.14453/aabfj.v18i3.16

[2] AKHTAR, F., THYAGARAJ, K. S., & DAS, N. **社会影响**对个人投资者人格特质与感知投资绩效关系的影响。国际管理金融期刊，2017年，14(1)，130–148。https://doi.org/10.1108/ijmf-05-2016-0102

[3] ALMANSOUR, B. Y., ELKRGHLI, S., & ALMANSOUR, A. Y. **行**为金融因素与投资决策：风险感知的中介作用。认知经济学与金融期刊，2023年，11(2)，2239032。https://doi.org/10.1080/23322039.2023.2239032

[4] ALZOUBI, H. M., & AZIZ, R. **情商是否有助于**战略决策质量？开放创新的中介作用。开放创新期刊：技术、市场与复杂性，2021年，7(2)，130。https://doi.org/10.3390/joitmc7020130

[5] ARMANSYAH, R. F. **投**资决策中的从众本能偏见、情绪偏见和信息处理偏见。管理创业期刊，2022年，24(2)，105-117。https://doi.org/10.9744/jmk.24.2.105-117

[6] AUSAT, A. M. A. **社交媒体在塑造公众**舆论及其对经济决策影响中的作用。技术与社会视角期刊，2023年，1(1)，35-44。https://doi.org/10.61100/tacit.v1i1.37

[7] DE CASTRO, P. A. L., Barreto Teodoro, A. R., De Castro, L. I., & Parsons, S. 期望效用理论还是前景理论：哪个更适合市场的基于代理的建模？计算科学期刊，2016年，17，97-102。https://doi.org/10.1016/j.jocs.2016.10.002

[8] DHAMI, S., & AL-NOWAIHI, A. 人们为什么纳税？前景理论与期望效用理论的比较。经济行为与组织期刊，2007年，64(1)，171-192。https://doi.org/10.1016/j.jebo.2006.08.006

[9] DITA, R. D. R. T., HERYANA, T., & BASUKI, T. I. 新冠疫情时代的投资决策行为：基于心理账户、损失厌恶偏见和风险容忍度的分析。全息商业与公共管理期刊，2023年，14(2)，33-42。https://doi.org/10.2478/hjbpa-2023-0014

[10] FERDINAND, A. 管理研究中的结构方程模型。三宝垄：BP-UNDIP出版社。2002年。

[11] GASPAR, R. M., & SILVA, P. M. 投资者对投资组合保险的看法：期望效用理论与前景理论。葡萄牙经济期刊，2023年，22(1)，49-79。https://doi.org/10.1007/s10258-021-00200-z

[12] GRABLE, J. E., & ROSZKOWSKI, M. J. 情绪对承担金融风险意愿的影响。风险研究期刊，2008年，11(7)，905-923。https://doi.org/10.1080/13669870802090390

[13] HÄCKEL, B., PFOSSER, S., & TRÄNKLER, T. 解释能源效率差距——期望效用理论与累积前景理论。能源政策期刊，2017年，111，414-426。https://doi.org/10.1016/j.enpol.2017.09.026

[14] HAIR, J. F., HULT, G. T. M., RINGLE, C. M., SARSTEDT, M., DANKS, N. P., & RAY, S. 使用R的偏最小二乘结构方程建模(PLS-SEM)：工作手册。施普林格国际出版社。2021年。https://doi.org/10.1007/978-3-030-80519-7

[15] HAN, B., HIRSHLEIFER, D., & WALDEN, J. 社会传播偏见与投资者行为。2021年。

[16] HARAHAP, S., THOYIB, A., SUMIATI, S., & DJAZULI, A. 金融素养对退休规划的影响：金融风险容忍度和储蓄行为的串行中介作用——来自印度尼西亚中等企业家的证据。国际金融研究期刊，2022年，10(3)，66。https://doi.org/10.3390/ijfs10030066

[17] HARTONO, J. 数据收集方法与分析技术。安迪出版社。2018年。

[18] HASSELGREN, B., CHRYSOULAS, C., PITROPAKIS, N., & BUCHANAN, W. J. 使用社交媒体和情感分析进行投资决策。未来互联网期刊，2022年，15(1)，5。https://doi.org/10.3390/fi15010005

[19] HEO, W., GRABLE, J. E., NOBRE, L., & RUIZ-MENJIVAR, J. 婚姻状况、性别与投资行为中风险容忍度中介效应的估计。国际人类生态学期刊，2016年，17(1)，1-14。https://doi.org/10.6115/ijhe.2016.17.1.1

[20] HONG, H., KUBIK, J. D., & STEIN, J. C. 邻居的投资组合：资金管理者持股和交易中的口碑效应。金融期刊。2005年.

[21] HOSSAIN, T., & SIDDIQUA, P. 探索行为因素对股票投资决策的影响：对孟加拉国个人投资者的研究。PSU研究评论，2024年，8(2)，467-483。https://doi.org/10.1108/PRR-10-2021-0054

[22] https://data.goodstats.id. 印度尼西亚社交媒体用户概览2017-2026年。GoodStats数据。2023年。https://data.goodstats.id/statistic/agneszefanyayonatan/menilik- pengguna-media-sosial-indonesia-2017-2026-xUAlp

[23] https://www.rri.co.id. (未注明日期). 2024年印度尼西亚社交媒体使用统计数据。Rri.Co.Id - 最受信赖的新闻门户。检索于2024年7月28日，来源：

https://www.rri.co.id/iptek/721570/ini-data-statistik-penggunaan-media-sosial-masyarakat-indonesia-tahun-2024

[24] HVIDE, H. K., & ÖSTBERG, P. 工作场所的股票投资。2014年。

[25] ISMAIL, S., NAIR, R. K., SHAM, R., & WAHAB, S. N. 在线社交媒体对马来西亚投资决策的影响。印度公共卫生研究与发展期刊，2018年，9(11)，1241。https://doi.org/10.5958/0976-5506.2018.01627.3

[26] JAIN, J., WALIA, N., & GUPTA, S. 使用模糊层次分析法评估影响个人股票投资者投资决策的行为偏见。行为金融评论，2019年，12(3)，297-314。https://doi.org/10.1108/RBF-03- 2019-0044

[27] JOSE, J., & KUMAR, I. M. 股票交易所日内交易者损失厌恶影响的研究。土耳其计算机与数学教育期刊，2021年，12(11)，6789–6796。

[28] KAHNEMAN, D., & TVERSKY, A. 关于直觉概率的解释：对乔纳森·科恩的回应。认知期刊，1979年，7(4)，409-411。https://doi.org/10.1016/0010- 0277(79)90024-6

[29] KAMIL, H. H., & TANNO, A. 社交媒体作为信息来源对投资者投资决策制定的影响，教育背景和收入作为控制变量。会计期刊，2022年，6。

[30] KISHOR, N. 金融决策的风险偏好：情绪偏见重要吗？2020年

[31] KUMAR, S., & CHAURASIA, A. 情绪偏见与投资决策之间的关系：元分析。IIMT管理期刊，2024年，1(2)，171-185。https://doi.org/10.1108/IIMTJM-03-2024-0034

[32] LAL, S., SULEMANA, A.-S., NGUYEN, T. X. T., KHAN, M. S. R., & KADOYA, Y. 投资决策的信息来源：来自日本投资者的证据。国际金融研究期刊，2023年，11(4)，117。https://doi.org/10.3390/ijfs11040117

[33] LATAN, H. 结构方程建模：Amos 21.0实施理论。2014年。Alfabeta出版社。https://openlibrary.telkomuniversity.ac.id/pustaka/18645/model- persamaan-struktural-teori-implementasi-amos-21-0.html

[34] LIANG, P., & GUO, S. 社会互动、互联网接入与股市参与——中国的实证研究。比较经济学期刊，2015年，43(4)，883901。https://doi.org/10.1016/j.jce.2015.02.003

[35] LU, T. (JUN), & TANG, N. 资产配置决策中的社会互动：来自401(k)养老金计划投资者的证据。经济行为与组织期刊，2019年，159，1-14。https://doi.org/10.1016/j.jebo.2019.01.009

[36] MASSAR, S. A. A., PU, Z., CHEN, C., & CHEE, M. W. L. 在基于努力的决策制定和绩效中，损失比收益更能激发认知努力。人类神经科学前沿。2020年。https://doi.org/10.3389/fnhum.2020.00287

[37] MOUEED, A., & HUNJRA, A. I. 利用愤怒指导股市决策：来自巴基斯坦的结果。认知经济学与金融期刊，2020年，8(1)，1733279。https://doi.org/10.1080/23322039.2020.1733279

[38] NORMASYHURI, K., SAPUTRI, Y. D., & ANGGRAENI, E. Z世代伊斯兰投资决策模式：信息媒体重要吗？伊斯兰经济与金融期刊，2023年，9(2)246262。https://doi.org/10.20885/JEKI.vol9.iss2.art7

[39] OLAJIDE, O., PANDEY, S., & PANDEY, I. 社交媒体投资建议与财务满意度：世代重要吗？风险与金融管理期刊，2024年，17(9)，410。https://doi.org/10.3390/jrfm17090410

[40] OSTROVSKY-BERMAN, E., & LITWIN, H. 临近和处于退休期投资者的社交网络与金融风险容忍度。家庭与经济问题期刊，

2019年，40(2)，237-249。 https://doi.org/10.1007/s10834-018-9592-5

[41] PANDEY, L. K., SINGH, R., BAKER, H. K., & LASKAR, H. R. 屏幕之外：YouTube影响者如何影响股票投资决策。理论与应用电子商务研究期刊，2025年，20(1)，15。 https://doi.org/10.3390/jtaer20010015

[42] PANDIT, K., & VAIDYA, R. 股票市场投资决策中社交媒体的采用：尼泊尔投资者的定性分析。2022年，11(1)。

[43] RAHMAN, M., & GAN, S. S. Y世代投资决策：使用行为因素的分析。管理金融期刊，2020年，46(8)，1023-1041。 https://doi.org/10.1108/MF-10-2018-0534

[44] RIZKIANA, A. 社交媒体中的投资者情绪能否用于股票市场投资决策。2021年，25(1)。

[45] SADIQ, M., & AMNA, H. 人格特质对风险容忍度和投资者决策的影响。国际应用行为经济学期刊，2019年，8(1)，1-20。 https://doi.org/10.4018/IJABE.2019010101

[46] SARSTEDT, M., & CHEAH, J.-H. 使用SmartPLS的偏最小二乘结构方程建模：软件评述。营销分析期刊，2019年，7(3)，196-202。 https://doi.org/10.1057/s41270-019-00058-3

[47] SAUTMA, R. B., TARIGAN, Z. J. H., SIAGIAN, H., & FERRY, J. 人格特质通过金融知识和投资风险对金融决策的影响。竞争力期刊，2024年，16(2)262279。 https://doi.org/10.7441/joc.2024.02.13

[48] SHANMUGHAM, R., & RAMYA, K. 社会因素对个人投资者交易行为的影响。经济学与金融论文集，2012年，2，237-246。 https://doi.org/10.1016/S2212-5671(12)00084-6

[49] SHIVE, S. 投资者行为的流行病模型。金融与定量分析期刊，2010年，45(1)，169-198。 https://doi.org/10.1017/S0022109009990470

[50] SHRESTHA, S. K., KARKI, T. B., MAHAT, D., & NEUPANE, D. 分析社会互动对股市参与的影响：使用NVivo的定性研究。尼泊尔多学科研究期刊，2024年，7(2)，57-69。 https://doi.org/10.3126/njmr.v7i2.68245

[51] SIGIT, H., & AMIRULLAH, S. 商业研究方法：定量与定性方法。Media Nusa Creative (MNC Publishing)出版社。2021年

[52] ULLAH, K., KAKAKHEL, S. J., & AKHTER, M. 社会互动如何影响个人投资者的投资决策？2021年

[53] YUSUF, M. 定量、定性与混合研究方法。Prenada Media出版社。Zahera, S. A., & Bansal, R. (2018). 投资者在投资决策中是否表现出行为偏见？系统性综述。金融市场定性研究期刊，2016年，10(2)，210-251。 https://doi.org/10.1108/QRFM-04-2017-0028

[54] ZHANG, X., & CHOI, J. 社交影响者生成内容对用户认知和情感依恋的重要性：信息相关性视角。可持续发展期刊，2022年，14(11)，6676。 https://doi.org/10.3390/su14116676

[55] ZHAO, J. C., FU, W.-T., ZHANG, H., ZHAO, S., & DUH, H. 冒险还是不冒险：通过在线社交信息改善老年人的金融风险承担。第18届ACM计算机支持协作工作与社会计算会议论文集，2015年，95-104。 https://doi.org/10.1145/2675133.2685033

[56] ZHENG, R., OSPINA-FORERO, L., & CHEN, Y. 社交网络结构对社会影响决策的影响。决策期刊，2024年，51(1)，85-103。 https://doi.org/10.1007/s40622-024-00380-5

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