

Psychological Biases and Portfolio Decisions: Empirical Study on Gen-Z Stock Investors in Daerah Istimewa Yogyakarta

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Abstract

The rapid growth of Generation Z retail investors in Indonesia's stock market highlights the growing relevance of behavioral finance in explaining investment decision-making. Moving beyond the assumption of full investor rationality, this study examines the effects of herding, overconfidence, anchoring bias, and financial literacy on portfolio decisions among Generation Z stock investors in Yogyakarta (DIY), Indonesia. A quantitative explanatory design was employed, using primary data collected via purposive sampling through a structured questionnaire distributed to active Generation Z retail investors on the Indonesia Stock Exchange, yielding 250 valid responses, analyzed using PLS-SEM via SmartPLS. The results indicate that herding, driven by digital information flows, overconfidence, and anchoring bias significantly and negatively influence portfolio decisions, while financial literacy significantly contributes to more rational and disciplined portfolio decision-making among young investors. These findings contribute to behavioral finance literature in emerging markets and offer practical implications for policymakers, brokerages, and financial educators in designing literacy programs and behaviorally informed digital platforms for Generation Z investors in DIY.

Keywords: *Behavioral Finance, Portfolio Decisions, Financial Literacy, Gen-Z Investors, Stock Market.*

INTRODUCTION

Standard financial theory assumes investors act rationally, processing all available information to maximize utility (Statman, 2014; Yurttadur & Ozcelik, 2019). Real markets rarely operate that cleanly. Persistent anomalies and biased choices reveal that classical models miss much of what actually drives investment behavior (Statman, 2014). Behavioral finance emerged from this gap, treating investors as ordinary people whose decisions are shaped by emotion, social pressure, and cognitive limits, not just risk and return calculations (Statman, 2014; Yurttadur & Ozcelik, 2019). Investors often lean on heuristics and shortcuts, especially under uncertainty or fast-changing conditions (Hamurcu et al., 2025; Statman, 2014), a pattern confirmed across many investor groups by recent reviews of herding, overconfidence, and anchoring biases (Kumar & Prince, 2023).

Digital finance and Buy Now Pay Later (BNPL) platforms have facilitated market access for younger demographics (Cervellati et al., 2026; Wang et al., 2021). However, BNPL utilization frequently compounds existing debt, raising concerns regarding repayment capacity (Guttman-Kenney et al., 2023) and stimulating increased consumption (Kumar et al., 2024). Broadened access does not guarantee prudent financial behavior; young investors globally continue to exhibit overconfidence, engage in high-risk investments, and resort to aggressive borrowing (Berlinger et al., 2025; Cervellati et al., 2026; Ramírez-Montoya et al., 2026).

Indonesia illustrates this tension clearly. Digital investment platforms have grown fast alongside rising Generation Z participation, and social media has turned investing into something

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almost instant, where information and trading signals spread within seconds. Evidence from Indonesian retail investors shows many follow influencer advice without checking it first, reflecting overconfidence in secondhand information (Dalimunthe et al., 2023), and lab-based trading experiments find people shift toward the crowd once they see "leading traders" act, a clear manifestation of herding (Chmura et al., 2022). Investors exposed to such rapid, fragmented information flows also tend to anchor their judgments on early or salient reference points rather than adjusting fully to new information. Yet younger investors often have limited financial literacy and complex thinking skills, leaving them more open to shortcuts and emotional decisions (Hamurcu et al., 2025; Shaheen & Faraz, 2026; Vrdoljak et al., 2026). This is a paradox where market access outpaces behavioral readiness.

Financial literacy alone cannot eliminate cognitive biases (Mahmood et al., 2024; Ashfaq et al., 2024). Biases often interact (Bai & Khan, 2023) and compound (Shunmugasundaram & Sinha, 2025), with their strength varying across cultures and generations (Altaf & Jan, 2023). However, prior literature mostly examines isolated biases in Western contexts. Addressing this gap, the novelty of this study lies in being among the first to empirically examine how herding, overconfidence, anchoring, and financial literacy jointly shape portfolio decisions specifically among Generation Z stock investors in Indonesia. It provides novel evidence from Yogyakarta that financial literacy outweighs these combined biases as a primary cognitive defense.

LITERATURE REVIEW

Behavioral Finance Theory

Grounded in Kahneman and Tversky (1979), extended by Shiller (2003) and Barberis and Thaler (2003), this theory challenges rational-agent assumptions like the Efficient Market Hypothesis (EMH) and Modern Portfolio Theory, explaining how cognitive limits, heuristics, and emotion drive Gen Z investors' portfolio choices away from optimal allocation. Recent evidence reinforces this critique: biases continue generating anomalies inconsistent with EMH (Kanapickiene et al., 2024) and push investors toward suboptimal diversification, such as home bias (Matei & Buz, 2023).

Prospect Theory and Heuristics

Prospect Theory (Kahneman & Tversky, 1979) shows investors feel losses more painfully than equivalent gains, unlike expected utility theory's linear assumptions. In fast-moving markets, investors rely on heuristics that simplify decisions but systematically bias risk perception and portfolio adjustments. Recent studies confirm anchoring's relevance to risk assessments (Al Rahaleh, 2024) and its interaction with herding in shaping investment decisions (Othman et al., 2023).

Human Capital Theory

Drawing on Schultz (1961), Becker (1964), and Heckman (2006), this theory frames financial literacy as domain-specific human capital equipping investors to analyze statements and manage risk, acting as a cognitive defense against biases. Recent research confirms literacy significantly moderates biases' effects on portfolio decisions among Gen Y and Z investors (Patiu et al., 2024) and shapes Gen Z's financial behavior (Khan et al., 2024).

Hypothesis Development and Relationships Among Variables

The Effect of Herding Behaviour on Portfolio Decisions

Herding occurs when investors set aside their own analysis and instead mimic the trades of others, a tendency that intensifies once social cues signal that other traders are already moving

in a given direction ([Chmura et al., 2022](#)). Among Indonesian retail investors this pattern is amplified by social media, where influencer opinions travel faster than fundamental analysis and are frequently acted upon without independent verification. Because Gen Z investors are heavy users of these digital channels, herding is expected to leave a visible mark on how they build and rebalance their portfolios ([Dalimunthe et al., 2023](#)).

H₁: Herding behaviour has a significant effect on portfolio decisions.

The Effect of Overconfidence Bias on Portfolio Decisions

Overconfident investors overrate the precision of their own judgment, trade more frequently, and underestimate risk, a pattern documented across a wide range of investor populations ([Kumar & Prince, 2023](#)). In a market where information now moves in real time, that overestimation can push investors toward concentrated positions or frequent portfolio churn rather than diversification. Evidence from Indonesian samples confirms that overconfidence measurably shifts investment decision-making even alongside other biases such as herding ([Prasetyo et al., 2023](#)).

H₂: Overconfidence bias has a significant effect on portfolio decisions.

The Effect of Anchoring Bias on Portfolio Decisions

Anchoring bias leads investors to fixate on an initial reference point, such as a purchase price or a recent high, and to adjust their subsequent decisions insufficiently away from it ([Kahneman & Tversky, 1979](#)). This reference dependence can result in premature selling, reluctance to realize losses, or misjudging fair value, all of which distort portfolio allocation. Gen Z investors typically hold shorter trading histories and fewer independent valuation anchors of their own, which may leave them more reliant on whatever figure they encountered first ([Dalimunthe et al., 2023](#)).

H₃: Anchoring bias has a significant effect on portfolio decisions.

The Effect of Financial Literacy on Portfolio Decisions

Financial literacy equips investors with analytical skills to interpret financial information and resist emotionally driven decisions, functioning as domain-specific human capital ([Schultz, 1961](#); [Becker, 1964](#); [Heckman, 2006](#)). It strengthens risk-tolerance-portfolio alignment ([Hamurcu et al., 2025](#)), saving habits ([Shaheen & Faraz, 2026](#)), and cryptocurrency decisions ([Vrdoljak et al., 2026](#)). However, literacy does not fully eliminate bias, as effects persist despite adequate literacy ([Mahmood et al., 2024](#)) and cognitive shortcuts remain ([Ashfaq et al., 2024](#)), so literacy only partially counteracts bias-driven decisions.

H₄: Financial literacy has a significant effect on portfolio decisions.

RESEARCH METHODOLOGY

Research Design and Data Collection

This study used a quantitative explanatory design testing causal relationships among behavioral biases, financial literacy, and portfolio decisions ([Sekaran & Bougie, 2016](#)). Purposive sampling targeted Gen Z stock investors in DIY born between 1997–2012 ([Dimock, 2019](#)). Respondent screening criteria required: (1) Gen Z status, (2) actively investing in stock, (3) minimum investment experience of one year or more, and (4) possessing a valid Single Investor Identification (SID) from the Indonesia Stock Exchange (IDX). Data were gathered via Google Forms shared through investor Telegram/WhatsApp groups and offline QR codes at university investment galleries. Initial filter questions automatically screened ineligible respondents. Ultimately, 250 valid responses were analyzed, exceeding [Hair et al.'s \(2021\)](#) recommended PLS-SEM threshold.

Respondent Profile

Based on data collected from 250 Generation Z active investors who met all screening criteria, the demographic and behavioral profile of respondents was analyzed descriptively to provide an overview of the sample in terms of gender, age, education, occupation, and investment experience, as summarized in Table 1.

Table 1. Respondent Profile

Variable	Category	Amount	Percentage
Gender	Male	145	58%
	Female	105	42%
Age	< 20 years	105	42%
	20–29 years	145	58%
Education	High School	30	12%
	Bachelor Degree	67	26.8%
	Master Degree	153	61.2%
Occupation	Student	100	40%
	Employed	100	40%
	Unemployed	50	20%
Investment experience	1 year	167	66.8%
	>1 year	83	33.2%

Note: gender and age were measured on a two-point coded scale (1–2); category labels follow the original coding of the survey instrument.

The sample of 250 respondents (Table 1) leaned male, 58% (n=145) against 42% (n=105) female, a gap narrow enough that gender carries no substantive weight in the structural analysis. Most fell into the 20–29 bracket (58%, n=145), the remainder under 20 (42%, n=105), pointing to an older Gen Z cohort. Education skewed advanced: 61.2% (n=153) held a Master's degree, 26.8% (n=67) a Bachelor's, and 12% (n=30) finished only high school. Occupation split evenly between students and employed respondents (40% each, n=100), with 20% (n=50) unemployed. Two-thirds (66.8%, n=167) had traded a year or less, reflecting a sample early in its investing career.

Data Analysis Technique

Data were analyzed using PLS-SEM in SmartPLS, following [Hair et al.'s \(2021\)](#) two-stage procedure: measurement model first, then structural model. PLS-SEM suited this prediction-oriented, reflective-indicator research, where unified theory remains underdeveloped ([Hair et al., 2021](#)). Convergent validity used outer loadings and AVE ([Fornell & Larcker, 1981](#)); discriminant validity used HTMT ([Henseler et al., 2015](#)). The structural model was evaluated via R^2 , f^2 , VIF, and

bootstrapped path significance.

Research Model and Structural Equation

Figure 1 presents the research model tested in this study. Four exogenous constructs, herding behaviour (measured by four indicators, X1.1–X1.4), overconfidence bias (X2.1–X2.4), anchoring bias (X3.1–X3.4), and financial literacy (X4.1–X4.5), are modeled as reflective first-order constructs predicting portfolio decision (Y1–Y4), the single endogenous construct. All constructs are specified as reflective, consistent with the assumption that the observed indicators are manifestations of the underlying latent trait rather than its causes (Hair et al., 2021).

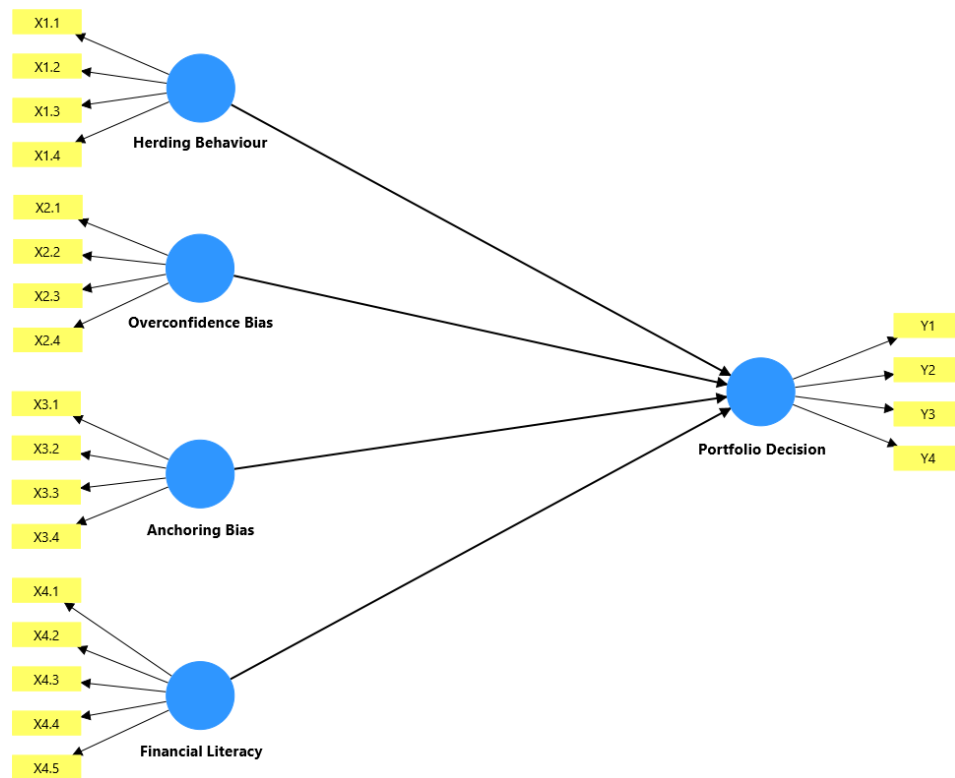


Figure 1. Research Model

The structural equation for the model estimated in this study is expressed as:

$$PD = \beta_1 HB + \beta_2 OCB + \beta_3 AB + \beta_4 FL + \zeta$$

Where:

- PD** = Portfolio Decision
- HB** = Herding Behaviour
- OCB** = Overconfidence Bias
- AB** = Anchoring Bias
- FL** = Financial Literacy
- β_1 – β_4** = Path coefficients
- ζ** = Residual variance

Where β_1 through β_4 denote the path coefficients estimated for HB, OCB, AB, and FL, respectively, while ζ represents the residual variance in PD not explained by the model. Hypotheses H1–H4, developed in Section 2, correspond directly to β_1 through β_4 , respectively. The estimated path coefficients and their statistical significance are reported in Section 4.3.

FINDINGS AND DISCUSSION

Evaluation of the Measurement Model (Outer Model Analysis)

The measurement model was evaluated on two criteria: convergent validity and discriminant validity. Convergent validity was examined through outer loadings and average variance extracted (AVE). As shown in Table 2, every indicator loaded above the commonly cited 0.70 threshold, ranging from 0.778 (X2.4, an overconfidence-bias item) to 0.885 (X1.4, a herding-behaviour item), and every loading was significant at $p < 0.001$, with bootstrapped t-statistics well above 1.96. This indicates that each indicator captures a substantial share of the variance in its intended construct (Hair et al., 2021).

Table 2. Outer Loadings

Indicator	Loading (O)	STDEV	T Statistics	P Values
X1.1 <- Herding Behaviour	0.843	0.021	41.043	0
X1.2 <- Herding Behaviour	0.847	0.021	39.448	0
X1.3 <- Herding Behaviour	0.858	0.018	46.584	0
X1.4 <- Herding Behaviour	0.885	0.014	63.574	0
X2.1 <- Overconfidence Bias	0.873	0.018	49.704	0
X2.2 <- Overconfidence Bias	0.814	0.03	26.913	0
X2.3 <- Overconfidence Bias	0.782	0.034	23.328	0
X2.4 <- Overconfidence Bias	0.778	0.033	23.517	0
X3.1 <- Anchoring Bias	0.864	0.017	49.574	0
X3.2 <- Anchoring Bias	0.848	0.019	45.031	0
X3.3 <- Anchoring Bias	0.83	0.027	31.114	0
X3.4 <- Anchoring Bias	0.819	0.025	32.642	0
X4.1 <- Financial Literacy	0.856	0.017	49.25	0
X4.2 <- Financial Literacy	0.816	0.024	34.55	0
X4.3 <- Financial Literacy	0.845	0.021	41.086	0
X4.4 <- Financial Literacy	0.828	0.021	40.177	0
X4.5 <- Financial Literacy	0.825	0.023	35.557	0
Y1 <- Portfolio Decision	0.854	0.017	50.332	0
Y2 <- Portfolio Decision	0.862	0.015	57.317	0
Y3 <- Portfolio Decision	0.813	0.026	31.432	0
Y4 <- Portfolio Decision	0.801	0.024	33.38	0

Table 3 reports the average variance extracted for each construct. AVE values ranged from 0.660 (overconfidence bias) to 0.736 (herding behaviour), all comfortably above the 0.50 minimum proposed by [Fornell and Larcker \(1981\)](#). Combined with the loading pattern in Table 2, this confirms that convergent validity holds across all five constructs.

Table 3. Average Variance Extracted (AVE)

Construct	AVE
Anchoring Bias	0.706
Financial Literacy	0.696
Herding Behaviour	0.736
Overconfidence Bias	0.660
Portfolio Decision	0.693

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT), following [Henseler et al. \(2015\)](#). All HTMT values were below the conservative 0.85 threshold, ranging from 0.122 between financial literacy and anchoring bias to 0.569 between portfolio decision and financial literacy. Thus, the five constructs are empirically distinct. Indicator-level collinearity was also acceptable, with outer VIF values ranging from 1.614 to 2.487, below the cut-off of 5 ([Hair et al., 2021](#)).

Table 4. Discriminant Validity (HTMT)

Construct Pair	HTMT
Financial Literacy <-> Anchoring Bias	0.122
Herding Behaviour <-> Anchoring Bias	0.195
Herding Behaviour <-> Financial Literacy	0.247
Overconfidence Bias <-> Anchoring Bias	0.358
Overconfidence Bias <-> Financial Literacy	0.171
Overconfidence Bias <-> Herding Behaviour	0.359
Portfolio Decision <-> Anchoring Bias	0.429
Portfolio Decision <-> Financial Literacy	0.569
Portfolio Decision <-> Herding Behaviour	0.543
Portfolio Decision <-> Overconfidence Bias	0.467

Evaluation of the Structural Model (Inner Model Analysis)

The structural model was evaluated through R^2 , f^2 , and collinearity diagnostics. Portfolio decision recorded an R^2 of 0.485 (adjusted $R^2 = 0.476$), meaning the four predictors jointly explain roughly 48.5% of variance, just below the moderate threshold noted by [Hair et al. \(2021\)](#), a respectable result for purely psychological predictors. Effect sizes showed financial literacy carrying the largest effect ($f^2 = 0.268$, medium), followed by herding ($f^2 = 0.143$), anchoring bias ($f^2 = 0.089$), and overconfidence bias ($f^2 = 0.054$), all small-to-medium per [Hair et al.'s \(2021\)](#) cut-offs. Financial literacy thus outweighs any single bias individually, though the biases collectively remain meaningful. Collinearity was not a concern across predictors.

Table 5. R-Square and Effect Size (f^2)

Construct / Path	Value
Portfolio Decision (R^2)	0.485
Portfolio Decision (R^2 adjusted)	0.476
Anchoring Bias -> Portfolio Decision (f^2)	0.089
Financial Literacy -> Portfolio Decision (f^2)	0.268
Herding Behaviour -> Portfolio Decision (f^2)	0.143
Overconfidence Bias -> Portfolio Decision (f^2)	0.054

Hypothesis Testing

Bootstrapping confirmed all four hypotheses: herding ($\beta = -0.292$, $p < 0.001$), overconfidence ($\beta = -0.182$, $p < 0.001$), and anchoring bias ($\beta = -0.226$, $p < 0.001$) were significantly negative, while financial literacy ($\beta = 0.383$, $p < 0.001$) was significantly positive. Higher bias levels associate with less disciplined, reactive portfolio decisions; stronger literacy associates with more disciplined ones.

Table 6. Hypothesis Testing Results

Hyp. Path	Original Sample (O)	T Statistics	P Values	Decision
H1 Herding Behaviour -> Portfolio Decision	-0.292	5.952	0	Supported
H2 Overconfidence Bias -> Portfolio Decision	-0.182	4.009	0	Supported
H3 Anchoring Bias -> Portfolio Decision	-0.226	4.948	0	Supported
H4 Financial Literacy -> Portfolio Decision	0.383	8.403	0	Supported

Table 7. Statistic Description

Indicator	Missing	Mean	Median	Min	Max	SD	Excess Kurtosis	Skewness	CvM p-value
X1.1	0	2.936	3.000	1	5	1.010	-0.329	0.129	0.000
X1.2	0	2.940	3.000	1	5	0.930	-0.346	0.090	0.000
X1.3	0	2.956	3.000	1	5	0.973	-0.420	0.089	0.000
X1.4	0	2.952	3.000	1	5	1.061	-0.585	0.056	0.000
X2.1	0	3.016	3.000	1	5	1.054	-0.656	0.030	0.000
X2.2	0	3.116	3.000	1	5	0.942	-0.388	-0.031	0.000
X2.3	0	3.088	3.000	1	5	0.863	-0.001	0.130	0.000
X2.4	0	3.036	3.000	1	5	0.891	-0.281	-0.037	0.000
X3.1	0	2.984	3.000	1	5	0.938	-0.296	0.003	0.000
X3.2	0	3.044	3.000	1	5	1.033	-0.545	0.043	0.000
X3.3	0	3.052	3.000	1	5	0.939	-0.540	-0.133	0.000

Indicator	Missing	Mean	Median	Min	Max	SD	Excess Kurtosis	Skewness	CvM p-value
X3.4	0	3.060	3.000	1	5	1.004	-0.392	0.141	0.000
X4.1	0	3.416	3.000	1	5	1.154	-0.863	-0.202	0.000
X4.2	0	3.456	3.000	1	5	0.921	-0.066	-0.256	0.000
X4.3	0	3.468	3.000	1	5	0.960	-0.394	-0.182	0.000
X4.4	0	3.400	3.000	1	5	0.972	-0.544	-0.190	0.000
X4.5	0	3.424	3.000	1	5	1.002	-0.456	-0.162	0.000
Y1	0	3.376	3.000	1	5	1.017	-0.431	-0.188	0.000
Y2	0	3.260	3.000	1	5	0.964	-0.397	-0.137	0.000
Y3	0	3.284	3.000	1	5	0.948	-0.237	-0.001	0.000
Y4	0	3.328	3.000	1	5	0.874	-0.512	0.139	0.000

Descriptive statistics were computed for the twenty-one indicators representing Anchoring Bias (X1.1–X1.4), Overconfidence Bias (X2.1–X2.4), Herding Behaviour (X3.1–X3.4), Financial Literacy (X4.1–X4.5), and Portfolio Decision (Y1–Y4), measured on a five-point Likert scale, with no missing values recorded across the entire dataset. Means ranged from 2.936 to 3.468 while medians remained consistently at 3.000, indicating responses clustered near the scale midpoint. Skewness (–0.256 to 0.141) and excess kurtosis (–0.863 to –0.001) fell within the accepted normality threshold (Hair et al., 2019); however, the Cramér-von Mises test rejected normality for every indicator ($p = 0.000$), supporting non-parametric PLS-SEM (Hair et al., 2019).

Discussion

The negative path from herding behaviour to portfolio decision shows Gen Z investors prone to following crowds make less disciplined choices. Beyond merely supporting prior findings, this result highlights a novel dynamic among Indonesian Generation Z investors: the unique vulnerability to digital herding in an emerging market. This aligns with laboratory evidence of traders shifting toward the crowd, abandoning their own analysis (Chmura et al., 2022), and Indonesian field evidence of retail investors blindly following influencer recommendations (Dalimunthe et al., 2023). Digital platforms compress reflection time, weakening discipline. Overconfidence bias also reduced portfolio decision quality, matching systematic reviews (Kumar & Prince, 2023) and Indonesian evidence (Prasetyo et al., 2023). With two thirds having minimal trading experience, overconfident investors likely underdiversify before accumulating corrective feedback. Anchoring bias produced the second strongest negative effect, reflecting reference-dependent judgment where investors adjust insufficiently to new information (Kahneman & Tversky, 1979). Conversely, financial literacy was the only positive predictor, acting as human capital (Schultz, 1961; Becker, 1964; Heckman, 2006) that strengthens risk tolerance portfolio links (Hamurcu et al., 2025) and consistent saving behaviour (Shaheen & Faraz, 2026). It functions as a buffer against bias (Mahmood et al., 2024; Ashfaq et al., 2024), supporting behavioural finance premises (Statman, 2014; Yurttadur & Ozcelik, 2019).

While compelling, this study acknowledges certain boundaries. Fundamentally, our sample exclusively targets Generation Z investors in Yogyakarta. As an educational hub, Yogyakarta fosters a unique socioeconomic environment. Therefore, these investment behaviors might not perfectly reflect realities in faster-paced, highly commercialized centers like Jakarta or Surabaya, restricting national generalizability. Additionally, relying on cross-sectional data limits our ability to observe

behavioral evolution across different market cycles. Future longitudinal research is needed to track this learning curve and verify if early financial literacy provides a lasting shield against long-term volatility. Furthermore, self-reported questionnaires introduce subjectivity, as respondents might downplay crowd-following tendencies. Future studies should pair survey responses with actual brokerage records to observe real-world portfolio execution.

CONCLUSION AND FURTHER RESEARCH

This study examined how herding, overconfidence, and anchoring biases influence portfolio decisions among Generation Z stock investors in the Special Region of Yogyakarta, alongside the role of financial literacy. Using PLS-SEM with 250 active Gen Z investors, all four hypothesized relationships were supported. Herding, overconfidence, and anchoring negatively affected portfolio-decision quality, while financial literacy had a positive effect and was the strongest predictor. These findings support behavioural finance in explaining digitally native investors beyond rational-agent assumptions (Statman, 2014; Kahneman & Tversky, 1979). The study extends research on individual biases and Western settings by examining these factors jointly with financial literacy (Altaf & Jan, 2023; Shunmugasundaram & Sinha, 2025). Financial literacy as a direct predictor also challenges the assumption that literacy alone neutralizes bias (Mahmood et al., 2024; Ashfaq et al., 2024). Practical implications highlight literacy initiatives and bias-aware platforms. Limitations include geographic scope, purposive sampling, and cross-sectional design, while future research could examine moderation and personality, cognitive ability, and complex-thinking competency (Goldberg, 1990; McCrae & Costa, 1999; Gladstone & Barrett, 2023; Ramírez-Montoya et al., 2026).

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