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The Influence of Finfluencer Credibility and Algorithmic Literacy on Stock Investment Decisions via Herding Behavior among Generation Z Investors

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Abstract: This study examines how finfluencer credibility and algorithmic literacy influence the quality of stock investment decisions among Generation Z investors, focusing on the mediating role of herding behavior. It explores how recommendation algorithms shape investment-content exposure and how awareness affects responses to financial influencers. A quantitative, explanatory study was conducted using a cross-sectional survey of 200 Generation Z stock investors in Makassar, Indonesia, selected through purposive sampling. Data were analyzed using partial least squares structural equation modeling (PLS-SEM), with 5,000 bootstrap subsamples to assess direct and indirect effects. The results support all seven hypotheses. Finfluencer credibility positively affects herding behavior and investment decision quality, whereas algorithmic literacy negatively affects herding behavior and positively affects decision quality. Herding behavior, in turn, has a significant negative effect on decision quality. Mediation analysis indicates that herding behavior competitively mediates the relationship between finfluencer credibility and decision quality, while complementarily mediating the relationship between algorithmic literacy and decision quality. The total effect of algorithmic literacy is substantially greater than that of finfluencer credibility. These findings extend the Elaboration Likelihood Model by integrating the Persuasion Knowledge Model into behavioral finance and establish algorithmic literacy as a relevant capability in financially consequential decisions. The study highlights the importance of investor education that develops critical awareness of recommendation systems alongside conventional financial knowledge in digital investment markets.

Keywords: Finfluencer Credibility; Algorithmic Literacy; Herding Behavior; Stock Investment Decisions; Generation Z.

1. Introduction

The Indonesian capital market has experienced substantial growth in recent years, accompanied by a significant expansion in retail investor participation, particularly among younger demographic groups. The Indonesian Central Securities Depository (Kustodian Sentral Efek Indonesia [KSEI]) reported that the number of Single Investor Identification (SID) accounts reached 30.30 million as of August 7, 2026, representing a 49% increase from 20.34 million at the end of 2025 (KSEI, 2026). This expansion has been largely driven by younger investors, with individuals below the age of 30 accounting for 52.59% of capital market investors at the end of 2025 (KSEI, 2025). This demographic shift indicates that Generation Z and younger millennials are becoming increasingly influential participants in Indonesia's capital market, with their investment decisions increasingly shaped by digital information environments.

Beyond changes in investor demographics, the sources and mechanisms through which investment information is acquired have also undergone considerable transformation. Traditional information channels, including prospectuses, financial statements, and securities research reports, increasingly coexist with social media platforms that distribute financial information through short-form videos, discussion threads, and algorithmically curated content. Within this environment, financial influencers (finfluencers) have emerged as influential information intermediaries who disseminate financial knowledge, market interpretations, and investment recommendations to online audiences. Their influence is particularly relevant to younger investors, whose investment-related information consumption is frequently embedded in social media interactions. Evidence from emerging markets suggests that perceived credibility, audience engagement, and platform trust significantly influence Generation Z's investment decisions (Malombe & Kowero, 2026). Similarly, finfluencer opinions have been found to exert significant effects on young investors' investment decisions (Batool et al., 2026).

These developments suggest that investment decisions are increasingly influenced not only by the informational quality of financial content but also by the perceived characteristics of the individuals communicating it.

The growing influence of finfluencers has also attracted regulatory attention, particularly concerning investor protection and the potential consequences of unqualified financial recommendations. In Indonesia, the Financial Services Authority (Otoritas Jasa Keuangan [OJK]) introduced Financial Services Authority Regulation No. 6 of 2026 concerning the Conduct of Financial Information Providers, which establishes regulatory provisions for finfluencers, content creators, affiliates, and analysts disseminating investment recommendations (OJK, 2026). The regulation addresses disclosure of economic benefits, risk warnings for high-risk financial products, and regulatory authority over inappropriate financial content. This regulatory development demonstrates that finfluencer-related activities have evolved beyond conventional digital marketing concerns and increasingly constitute an important issue in financial consumer protection. Nevertheless, regulatory oversight alone may be insufficient to address the behavioral mechanisms through which financial information influences individual investment decisions, particularly when investors encounter persuasive content repeatedly through personalized recommendation systems.

The vulnerability of younger investors is further complicated by the disparity between financial inclusion and financial literacy. Indonesia's 2026 National Survey of Financial Literacy and Inclusion reported a national financial literacy index of 69.57% and a financial inclusion index of 93.61% (OJK & Statistics Indonesia, 2026). Among individuals aged 18–25, financial literacy reached 73.32%, while financial inclusion stood at 95.69%. Although these figures indicate considerable progress in financial accessibility, they also highlight the continuing gap between access to financial products and the knowledge required to evaluate them effectively. Consequently, younger investors may possess relatively unrestricted access to digital investment platforms without necessarily having sufficient analytical capabilities to assess the credibility, relevance, and potential risks of the information they encounter. This condition creates an environment in which external recommendations can become influential determinants of investment behavior.

Importantly, financial content does not necessarily reach Generation Z because individuals actively search for it. Rather, social media recommendation algorithms increasingly determine which information becomes visible through users' personalized feeds. These systems select and prioritize content based on previous interactions, viewing patterns, and engagement histories, potentially reinforcing exposure to similar opinions while reducing the visibility of alternative perspectives. Research involving Indonesian Generation Z users has demonstrated that perceptions of recommendation algorithms are positively associated with filter bubble formation, which subsequently relates to information-seeking behavior (Megawati et al., 2026). In investment contexts, repeated exposure to similar financial recommendations may create the perception that particular investment opinions represent broader market consensus. However, such apparent agreement may reflect algorithmic content selection rather than independent agreement among investors. This distinction is important because it may encourage individuals to interpret repeated recommendations as evidence of superior information, thereby increasing their susceptibility to herding behavior.

The geographical distribution of Indonesian capital market investors provides an additional justification for examining this phenomenon in Eastern Indonesia. Although Java accounts for 64.44% of national capital market investors, Sulawesi represents only 5.66%, with investment assets valued at approximately IDR 26 trillion (KSEI, 2026). This relatively smaller investor base provides an important regional context for investigating the development of digital investment behavior outside Indonesia's dominant financial centers. Makassar, as a major educational and economic center in Eastern Indonesia, offers a relevant setting for examining young investors who increasingly access capital market

information through university investment galleries, investor communities, and social media platforms. Nevertheless, the specific mechanisms through which finfluencer credibility and algorithmically curated information shape investment decision quality among Generation Z investors in this regional context remain insufficiently understood.

Despite the growing body of research on digital financial information and investment behavior, several important theoretical and empirical gaps remain. First, previous findings concerning the relationship between herding behavior and investment decisions remain inconsistent. Some studies report a positive and significant relationship between herding behavior and investment decisions (Zainordin et al., 2025; Pramesti & Graciafernandy, 2024; Maharani et al., 2025), whereas others identify statistically insignificant relationships (Saridona et al., 2026; Runtuwene & Sibilang, 2024; Sucipto et al., 2026). One possible explanation for these inconsistencies concerns differences in the operationalization of investment decisions. Studies measuring investment decisions through investment activity or transaction intensity may capture a different behavioral outcome from studies examining the quality of investment judgment. Moreover, herding behavior has predominantly been examined as a direct predictor rather than as an intervening mechanism through which external information influences investment decision quality. This limitation leaves the underlying behavioral process insufficiently explained.

Second, the existing literature provides limited examination of finfluencer credibility as a multidimensional antecedent of herding behavior. Previous Indonesian studies have generally emphasized finfluencer exposure or social media usage as explanatory variables (Bachmid et al., 2026; Sholikhah & Takarini, 2026). However, exposure to financial content does not necessarily indicate that investors perceive its source as credible. Source credibility theory suggests that persuasive effectiveness depends substantially on the perceived characteristics of the information source rather than merely on its presence or frequency of exposure (Ohanian, 1990). Consequently, examining finfluencer credibility through dimensions of expertise, trustworthiness, and attractiveness or homophily may provide a more comprehensive explanation of how financial influencers shape investors' behavioral responses.

Third, an important conceptual limitation concerns the capabilities examined as protective factors against external financial influence. Previous studies have primarily employed financial literacy, digital financial literacy, or financial knowledge to explain investors' ability to make informed decisions (Saridona et al., 2026; Yu & Yusbardini, 2025; Sugianto et al., 2024). Although these constructs capture knowledge of financial products, services, and risks, they do not necessarily explain whether investors understand how digital recommendation systems determine the information presented to them. This distinction becomes particularly important when investment information is distributed through algorithmically curated environments. The capability required to evaluate financial products may differ from the capability required to critically interpret the mechanisms through which financial information is selected and repeatedly presented.

Fourth, a theoretical gap remains between algorithmic literacy research and behavioral finance. Algorithmic literacy has developed as an established construct in media and communication studies, encompassing cognitive, affective, and behavioral dimensions (Oeldorf-Hirsch & Neubaum, 2025; Gagrčin et al., 2024). Validated measurement instruments have also been developed to assess individuals' understanding of algorithmic systems and their implications for information consumption (Dogruel et al., 2022). Nevertheless, its explanatory relevance to financially consequential decisions, particularly stock investment behavior, remains insufficiently examined. This gap is noteworthy because algorithmic recommendation systems increasingly influence the information environments in which young investors evaluate financial opportunities. Integrating algorithmic literacy into behavioral finance may therefore provide a more contextually relevant explanation of how investors recognize and respond to digitally mediated financial persuasion.

To address these gaps, this study develops an integrated research framework that examines the effects of finfluencer credibility and algorithmic literacy on stock investment decision quality, with herding behavior serving as a mediating variable. The framework conceptualizes finfluencer credibility and algorithmic literacy as two distinct antecedents operating through opposing behavioral mechanisms. Drawing on the Elaboration Likelihood Model (ELM), finfluencer credibility represents a peripheral cue that may influence investors' judgments and encourage reliance on external recommendations. Conversely, the Persuasion Knowledge Model (PKM) provides a theoretical explanation of how individuals recognize persuasive mechanisms and develop responses to external influence. In this study, algorithmic literacy is conceptualized as a form of persuasion knowledge that enables investors to recognize, understand, critically evaluate, and respond to algorithmic content-selection mechanisms. Accordingly, the central proposition is that understanding how recommendation algorithms operate may reduce investors' reliance on perceived social consensus and consequently mitigate herding behavior.

Based on this framework, the study addresses seven research questions concerning the direct effects of finfluencer credibility and algorithmic literacy on herding behavior and stock investment decision quality, the effect of herding behavior on investment decision quality, and the mediating roles of herding behavior in both relationships. Specifically, the study examines whether herding behavior mediates the relationship between finfluencer credibility and investment decision quality and whether it similarly mediates the relationship between algorithmic literacy and investment decision quality. By examining these relationships simultaneously, the study seeks to clarify how source-related persuasive cues and users' understanding of algorithmic information selection jointly influence the quality of investment decisions.

This study offers three principal contributions. First, its theoretical contribution lies in extending the application of ELM through integration with PKM in the context of behavioral finance. This integration provides a framework for understanding not only how perceived source credibility influences investment behavior but also how awareness of algorithmic persuasion mechanisms may help investors resist externally induced behavioral tendencies. Second, its methodological contribution involves adapting and validating an Indonesian-language algorithmic literacy instrument for the context of investment-related social media content. This provides an empirical foundation for examining algorithmic literacy beyond its conventional application in media and information studies. Third, its practical contribution concerns the development of investor education and financial consumer protection initiatives. The findings may inform the OJK and the Indonesia Stock Exchange in incorporating algorithmic literacy into investor education programs, encourage digital investment platforms to improve transparency regarding recommendation mechanisms, and support university investment galleries and investor communities in developing educational interventions that strengthen critical evaluation of financial content.

The remainder of this article is organized as follows. Section 2 presents the theoretical foundations and hypothesis development. Section 3 describes the research methodology. Section 4 reports and discusses the empirical findings. Finally, Section 5 presents the conclusions, research limitations, and recommendations for future research.

2. Research Methodology

3.1. Research Design

This study employed an explanatory quantitative approach using a cross-sectional survey design and primary data. The explanatory approach was adopted to examine the theoretically established relationships among the research constructs and to investigate the underlying mechanisms through which finfluencer credibility and algorithmic literacy influence stock investment decision

quality, particularly through the mediating role of herding behavior. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The selection of PLS-SEM was based on several methodological considerations. First, the study emphasizes prediction and theory development, particularly by introducing algorithmic literacy into the context of investment decision-making. Second, the proposed structural model incorporates multiple direct and indirect relationships that require simultaneous estimation. Third, PLS-SEM accommodates data distributions that may not satisfy multivariate normality assumptions. Finally, the study employs non-probability sampling, and its analytical objectives are aligned with the variance-based estimation approach (Hair et al., 2022).

3.2. Research Setting, Population, and Sample

3.2.1. Research Setting

The study was conducted in Makassar City, Indonesia, which was selected based on three considerations. First, Makassar represents an important center of economic and capital market development in Eastern Indonesia. Although Sulawesi accounts for only 5.66% of Indonesia's total capital market investors, with investment assets valued at approximately IDR 26 trillion (Kustodian Sentral Efek Indonesia, 2026), the region provides a relevant context for examining the emerging participation of younger retail investors. Second, the concentration of higher education institutions and university-based Investment Galleries in Makassar provides an important entry point for Generation Z investors into the capital market. These institutions and investor communities facilitate access to investment information, financial education, and social media-based investment networks. Third, the geographical concentration of the target population enables a more controlled implementation of purposive sampling. Nevertheless, the selection of a single research location may limit the generalizability of the findings to other geographical settings. This limitation is acknowledged in interpreting the empirical results.

3.2.2. Population and Respondent Eligibility Criteria

The target population comprised Generation Z stock investors residing, studying, or working in Makassar City. Respondents were selected using five inclusion criteria:

1. Individuals born between 1997 and 2012, corresponding to an age range of 18–28 years at the time of the study.
2. Individuals residing, studying, or working in Makassar City.
3. Individuals holding an active Single Investor Identification (SID) for at least six months.
4. Individuals who had conducted at least three stock transactions during the preceding six months.
5. Individuals following at least one finfluencer account on social media.

These eligibility requirements were established to ensure that respondents possessed sufficient investment experience and direct exposure to financial influencer content. The minimum SID ownership period and transaction frequency ensured that participants had practical experience in stock investment, while the social media requirement provided a concrete reference for evaluating perceived finfluencer credibility.

3.2.3. Sample Size Determination

The minimum sample size was determined exclusively using the inverse square root method proposed by Kock and Hadaya (2018). This approach was selected because it estimates the minimum sample size required to detect a specified minimum path coefficient in structural equation models without requiring an exact population size. The total number of Generation Z stock investors in Makassar City could not be established precisely because publicly available KSEI and Indonesia Stock

Exchange statistics did not provide a cross-tabulation of investor age and geographical location. Consequently, a complete sampling frame was unavailable.

The minimum sample size was calculated using the following formula:

where (n_{\min}) represents the minimum required sample size and (\beta_{\min}) denotes the minimum path coefficient expected to be detected at a 5% significance level and 80% statistical power. The minimum path coefficient was set at 0.18. This threshold was established with reference to previously reported relationships in related studies, including the effect of digital financial literacy on investment decisions (β = 0.602) reported by Saridona et al. (2026) and the relationship between recommendation algorithm perceptions and filter bubble formation (β = 0.544) reported by Megawati et al. (2026). Substituting the selected coefficient into the formula produces the following calculation:

$$n_{\min} = \left(\frac{2.486}{|\beta_{\min}|} \right)^2$$

Where:

- $n_{\min}$ = minimum required sample size;
- 2.486 = constant corresponding to the specified significance level and statistical power;
- $\beta_{\min}$ = minimum expected path coefficient.

The resulting minimum sample size was rounded upward to 191 respondents. To provide an adequate margin for incomplete responses, screening exclusions, and potentially unreliable questionnaire submissions, the final target sample was established at 200 valid respondents. Accordingly, 230 questionnaires were distributed, representing an additional allocation of approximately 13% above the required final sample. Table 2 presents the sensitivity of the minimum sample size to different assumptions regarding the minimum path coefficient.

Table 2. Sample Size Scenarios Based on the Inverse Square Root Method

Minimum β	Calculation	Minimum Sample Size	Interpretation
0.15	(2.486 / 0.15)²	275	Detects relatively weak path relationships but requires a larger sample
0.17	(2.486 / 0.17)²	214	Provides a more conservative sample size
0.18	(2.486 / 0.18)²	191	Selected threshold, rounded upward to 200 respondents
0.20	(2.486 / 0.20)²	155	May be insufficient for detecting weaker relationships

All scenarios in Table 2 were calculated using the same inverse square root formula. The sensitivity analysis is presented to illustrate how different minimum path coefficient assumptions influence the required sample size rather than to compare alternative sample size estimation techniques.

3.2.4. Sampling Technique and Data Collection

This study employed purposive sampling to recruit respondents through three primary channels: university Investment Galleries, investor communities, and selected online networks operating within Makassar City. The questionnaire incorporated screening questions to verify

compliance with all five respondent eligibility criteria. Individuals who failed to satisfy any of the inclusion requirements were excluded from the survey process. Geographical eligibility was assessed through questions concerning respondents' subdistricts of residence, study, or employment.
A total of 230 questionnaires were distributed, with 200 valid responses ultimately retained for the final analysis.

3.3. Variable Operationalization and Measurement

All research constructs were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). All measurement items were positively worded, and no reverse-coded items were included. Four principal constructs were examined: finfluencer credibility, algorithmic literacy, herding behavior, and stock investment decision quality. Their operational definitions, dimensions, measurement items, and adaptation sources are presented in Table 3.

Table 3. Operationalization of Research Variables

Variable	Operational Definition	Dimensions	Items	Measurement Sources
Finfluencer Credibility (X1)	Investors' perceptions of the credibility and trustworthiness of financial influencers as sources of investment information	Expertise; trustworthiness; attractiveness/homophily	6	Ohanian (1990); McCroskey et al. (1975)
Algorithmic Literacy (X2)	Investors' ability to recognize, understand, critically evaluate, and respond to recommendation algorithms that select investment-related content	Algorithmic awareness; knowledge of mechanisms; critical evaluation; coping strategies	6	Dogruel et al. (2022); Oeldorf-Hirsch and Neubaum (2023); Gagrčin et al. (2024)
Herding Behavior (M)	Investors' tendency to imitate the investment decisions of other market participants without sufficient independent analysis	Buying and selling decisions; stock selection; transaction speed; transaction volume	6	Bikhchandani et al. (1992); Bikhchandani and Sharma (2000)
Stock Investment Decision Quality (Y)	The quality of investors' judgments when selecting stocks, allocating investment funds, and determining transaction timing	Investment selection; fund allocation; timing; risk–return considerations	6*	Developed from the investment decision dimensions of Rahayu and Ekawanti (2026)

Note: One indicator (KI6) was removed during measurement model evaluation because its outer loading did not meet the required threshold. Consequently, 23 indicators were retained for the final analysis. All items were measured using a five-point Likert scale.

The measurement instruments originally developed in English were adapted into Indonesian using a back-translation procedure. First, the original items were translated into Indonesian by an initial

translator. Subsequently, an independent second translator, who had not been exposed to the original instrument, translated the Indonesian version back into English. Both versions were then compared to identify and resolve potential differences in meaning and conceptual interpretation.

Additional validation procedures were implemented for the algorithmic literacy construct because its application to investment-related contexts had not previously been established in the research setting. Four stages were undertaken:

1. **Translation and contextual adaptation:** Measurement items were translated from existing English-language instruments (Dogruel et al., 2022; Oeldorf-Hirsch & Neubaum, 2023) and adapted from general social media contexts to investment-related content.
2. **Expert content validation:** The adapted items were evaluated by three experts representing behavioral finance, digital communication, and capital market practice.
3. **Content Validity Index assessment:** The Content Validity Index (CVI) was calculated to evaluate the relevance of individual measurement items, followed by revisions to items that did not meet the established criteria.
4. **Cognitive interviews:** Interviews were conducted with five prospective respondents to assess the clarity, comprehensibility, and consistency of interpretation of technical terms, including social media feeds, recommendation systems, and content preferences.

A pilot test was subsequently conducted involving 30 respondents who met the eligibility criteria but were excluded from the final analytical sample. The pilot assessment employed a corrected item-total correlation threshold of 0.30 and a minimum Cronbach's alpha coefficient of 0.70 to evaluate preliminary item quality and internal consistency.

3.4. Data Analysis Techniques

The empirical analysis was conducted using SmartPLS 4 and followed four analytical stages. First, descriptive statistical analysis was performed to examine respondent characteristics and the distribution of measurement item responses. The analysis included means, standard deviations, minimum and maximum values, skewness, and kurtosis. This preliminary assessment provided an overview of the respondent profile and the distributional characteristics of the observed data. Second, the measurement model (outer model) was evaluated to establish the reliability and validity of the research constructs. Indicator reliability was assessed through outer loadings, with a recommended threshold of 0.70. Internal consistency reliability was examined using Cronbach's alpha, rho_A, and composite reliability, with minimum acceptable values of 0.70. Convergent validity was assessed using the Average Variance Extracted (AVE), with a minimum threshold of 0.50. Discriminant validity was evaluated through the Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait (HTMT) ratio, using 0.90 as the maximum acceptable HTMT threshold (Henseler et al., 2015).

Third, the structural model (inner model) was assessed to examine the relationships among the latent constructs. Collinearity was evaluated using the Variance Inflation Factor (VIF), with values below 5 indicating the absence of critical multicollinearity concerns. Hypothesized relationships were tested using path coefficients and bootstrapping with 5,000 subsamples. The explanatory and predictive capabilities of the model were examined through the coefficient of determination (R^2), effect size (f^2), and PLSpredict procedures (Shmueli et al., 2019). Fourth, mediation analysis was conducted to investigate the indirect effects of finfluencer credibility and algorithmic literacy on stock investment decision quality through herding behavior. The classification of mediation effects followed the approach proposed by Zhao et al. (2010), distinguishing among complementary mediation, competitive

mediation, and indirect-only mediation based on the statistical significance and directional relationships of direct and indirect effects.

3.5. Common Method Bias and Ethical Considerations

Common method bias was addressed through both procedural and statistical measures. Procedurally, respondent anonymity was maintained, construct labels were not disclosed in the questionnaire, and measurement items from different constructs were presented in randomized order to minimize response patterns associated with common measurement sources. Statistically, Harman's single-factor test was conducted to assess whether a single factor accounted for a substantial proportion of the total variance. Additionally, full collinearity VIF was examined using a threshold of 3.3, following the approach recommended by Kock (2015). Ethical considerations were incorporated into the data collection process through an informed consent statement presented on the first page of the questionnaire. The statement explained the research objectives, assured respondents of anonymity, emphasized the voluntary nature of participation, and informed them of their right to discontinue participation at any stage of the survey.

3. Results and Discussion

3.1. Research Results

3.1.1. Respondent Characteristics

A total of 200 respondents met all the inclusion criteria and completed the questionnaire. Table 4 presents the demographic and investment-related characteristics of the respondents, while Table 5 reports the item-level descriptive statistics.

Table 4. Respondent Characteristics (N = 200)

Characteristics	Category	f	%
Age (Mean = 22.16; SD = 2.47)	18–20 years	60	30.0
	21–23 years	86	43.0
	24–26 years	39	19.5
	27–28 years	15	7.5
Gender	Female	102	51.0
	Male	98	49.0
Educational attainment	Senior high school/equivalent	120	60.0
	Bachelor's degree (S1)	53	26.5
	Diploma (D3)	20	10.0
	Master's degree (S2)	7	3.5
Employment status	University students	138	69.0
	Private-sector employees	35	17.5
	Entrepreneurs	16	8.0
	Freelancers	8	4.0
	Civil servants/state-owned enterprise employees	3	1.5
Monthly income/allowance	Below IDR 1 million	35	17.5
	IDR 1–2.49 million	93	46.5
	IDR 2.5–4.99 million	53	26.5
	IDR 5 million or above	19	9.5
Duration of SID ownership	6–12 months	65	32.5

	More than 1–2 years	81	40.5
	More than 2–3 years	41	20.5
	More than 3 years	13	6.5
Transaction frequency in the previous six months	3–10 transactions	64	32.0
	11–25 transactions	87	43.5
	26–50 transactions	35	17.5
	More than 50 transactions	14	7.0
Primary securities platform	Ajaib	49	24.5
	Stockbit	45	22.5
	IPOT	28	14.0
	Mirae Asset	22	11.0
	BNI Sekuritas	18	9.0
	Mandiri Sekuritas	18	9.0
	Others	20	10.0
Primary social media platform for investment content	Instagram	64	32.0
	TikTok	58	29.0
	YouTube	40	20.0
	X (Twitter)	31	15.5
	Telegram	7	3.5
Primary type of followed finfluencer	Analysts/practitioners	71	35.5
	Educational content creators	60	30.0
	Traders/signal providers	46	23.0
	Celebrities	13	6.5
	Stock investment communities	10	5.0
Number of followed finfluencer accounts	1 account	43	21.5
	2–3 accounts	78	39.0
	4–5 accounts	48	24.0
	More than 5 accounts	31	15.5
Respondent recruitment channel	University Investment Galleries	89	44.5
	Investor communities	61	30.5
	Online channels in Makassar	50	25.0

The respondent profile reveals four characteristics that are particularly relevant to interpreting the findings. First, respondents were predominantly aged 21–23 years (43.0%), with a mean age of 22.16 years, indicating that the sample primarily represents young investors in the capital market. Second, most respondents were university students (69.0%), while 44.5% were recruited through university Investment Galleries. This distribution is consistent with the role of university-based investment communities as an important entry point for young investors in Makassar. Third, respondents generally had relatively limited investment experience, with 73.0% having held a Single Investor Identification (SID) for no more than two years. This characteristic is relevant because less-experienced investors may rely more heavily on external information sources when making investment decisions. Fourth, Instagram (32.0%) and TikTok (29.0%) were the dominant platforms for accessing investment-related content. These platforms are particularly relevant to the present study because

content exposure is substantially influenced by algorithmic recommendation systems rather than solely by users' explicit choices of followed accounts.

4.1.2. Descriptive Statistics

Table 5 presents the descriptive statistics for each measurement item, including the mean, standard deviation, skewness, and kurtosis.

Table 5. Item-Level Descriptive Statistics (N = 200)

Code	Mean	SD	Skewness	Kurtosis	Code	Mean	SD	Skewness	Kurtosis
KF1	3.570	0.894	−0.447	0.170	HB1	3.190	0.926	0.034	−0.312
KF2	3.475	0.924	−0.119	−0.160	HB2	2.905	0.928	0.152	−0.409
KF3	3.410	0.858	−0.176	−0.265	HB3	3.315	0.905	0.072	−0.283
KF4	3.165	0.867	−0.046	−0.053	HB4	3.360	0.924	0.109	−0.324
KF5	3.305	0.947	−0.035	−0.295	HB5	3.090	0.952	0.066	−0.542
KF6	3.535	0.826	−0.032	−0.520	HB6	2.910	0.963	0.011	−0.309
LA1	3.625	0.910	−0.316	−0.485	KI1	3.700	0.962	−0.325	−0.377
LA2	3.570	0.877	−0.126	−0.237	KI2	3.700	0.956	−0.376	−0.307
LA3	3.685	0.922	−0.304	−0.356	KI3	3.775	0.927	−0.570	0.074
LA4	3.470	0.907	−0.297	−0.269	KI4	3.485	0.913	−0.195	−0.272
LA5	3.380	0.927	−0.026	−0.400	KI5	3.580	0.915	−0.259	−0.201
LA6	3.065	0.972	−0.065	−0.292	KI6[a]	3.305	0.936	−0.162	−0.335

Note: [a] Indicator KI6 was removed during the measurement model assessment because its outer loading was below 0.70. All items were measured on a five-point scale.

As shown in Table 5, the skewness and kurtosis values indicate no substantial departures from the observed distributional patterns. Absolute skewness values did not exceed 0.58, while absolute kurtosis values remained below 0.55. At the construct level, stock investment decisions recorded the highest mean score (3.648; SD = 0.764), followed by algorithmic literacy (3.466; SD = 0.745), finfluencer credibility (3.410; SD = 0.671), and herding behavior (3.128; SD = 0.735). An important pattern emerged within the algorithmic literacy construct. The items representing awareness and critical evaluation recorded relatively high mean scores (LA1 = 3.625; LA3 = 3.685), whereas the items associated with counteracting algorithmic influence recorded lower scores (LA5 = 3.380; LA6 = 3.065). This pattern suggests that respondents were more aware of algorithmic content curation than they were likely to take practical steps to manage its influence. This distinction provides an important basis for interpreting the practical implications of the findings.

4.1.3. Common Method Bias Assessment

Common method bias (CMB) was assessed using Harman's single-factor test and the full collinearity variance inflation factor (VIF) approach. The Harman single-factor test, based on 23 measurement indicators, showed that the first unrotated factor accounted for 29.27% of the total variance, substantially below the commonly applied 50% threshold. Furthermore, principal component analysis identified four components with eigenvalues greater than one, collectively explaining 63.59% of the total variance. This result corresponds to the four constructs included in the proposed research model. The full collinearity VIF values were 1.219 for finfluencer credibility, 1.323 for algorithmic literacy, 1.561 for herding behavior, and 1.225 for stock investment decisions. All values were below the 3.3 threshold. Taken together, these results suggest that common method bias is unlikely to represent a serious concern in the present dataset.

4.1.4. Measurement Model Assessment

During the measurement model assessment, one indicator, KI6 ("I establish a maximum acceptable loss and a profit target before conducting a transaction"), was removed because its outer loading was below the recommended threshold of 0.70. Its removal did not substantially compromise the conceptual coverage of the construct, as the risk–return consideration dimension remained represented by indicator KI5. Consequently, the subsequent analyses were conducted using 23 indicators.

Table 6. Measurement Model Assessment

Construct	Indicator	Outer Loading	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Finfluencer Credibility (X1)	KF1	0.746	0.852	0.854	0.890	0.574
	KF2	0.794				
	KF3	0.756				
	KF4	0.753				
	KF5	0.727				
	KF6	0.769				
Algorithmic Literacy (X2)	LA1	0.828	0.896	0.901	0.920	0.657
	LA2	0.805				
	LA3	0.831				
	LA4	0.788				
	LA5	0.837				
	LA6	0.772				
Herding Behavior (M)	HB1	0.800	0.878	0.885	0.908	0.621
	HB2	0.800				
	HB3	0.812				
	HB4	0.785				
	HB5	0.815				
	HB6	0.715				
Stock Investment Decisions (Y)	KI1	0.857	0.875	0.889	0.909	0.668
	KI2	0.842				
	KI3	0.846				
	KI4	0.705				
	KI5	0.826				

Note: Recommended thresholds: outer loading ≥ 0.70; Cronbach's alpha, rho_A, and composite reliability ≥ 0.70; AVE ≥ 0.50.

As reported in Table 6, all retained indicators exhibited outer loadings ranging from 0.705 to 0.857, exceeding the recommended threshold of 0.70. Internal consistency reliability was also established. Cronbach's alpha values ranged from 0.852 to 0.896, rho_A values ranged from 0.854 to 0.901, and composite reliability values ranged from 0.890 to 0.920. All values exceeded the minimum recommended threshold of 0.70. Convergent validity was assessed using the average variance extracted (AVE). The AVE values ranged from 0.574 to 0.668, exceeding the recommended threshold of 0.50. These

findings indicate that the measurement indicators adequately represent their respective latent constructs and demonstrate satisfactory internal consistency and convergent validity.

Discriminant validity was further examined using the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT), and cross-loading assessment.

Table 7. Discriminant Validity Assessment

Panel A. Fornell–Larcker Criterion

Construct	HB (M)	KI (Y)	KF (X1)	LA (X2)
Herding Behavior (M)	0.788			
Stock Investment Decisions (Y)	−0.336	0.817		
Finfluencer Credibility (X1)	0.381	0.053	0.758	
Algorithmic Literacy (X2)	−0.441	0.354	−0.062	0.811

Panel B. Heterotrait–Monotrait Ratio (HTMT)

Construct	HB (M)	KI (Y)	KF (X1)	LA (X2)
Herding Behavior (M)	—			
Stock Investment Decisions (Y)	0.372	—		
Finfluencer Credibility (X1)	0.434	0.099	—	
Algorithmic Literacy (X2)	0.492	0.389	0.092	—

Note: In Panel A, diagonal values represent the square root of AVE, while off-diagonal values represent inter-construct correlations. In Panel B, all HTMT values are below the recommended threshold of 0.90.

The Fornell–Larcker assessment indicates that the square root of AVE for each construct (0.758–0.817) exceeded its correlations with the other constructs. Similarly, the HTMT values ranged from 0.092 to 0.492, remaining well below the recommended threshold of 0.90. Cross-loading assessment also indicated that each indicator loaded more strongly on its associated construct than on the other constructs. Therefore, the results provide consistent evidence supporting the discriminant validity of the measurement model.

4.1.5. Structural Model Assessment

The structural model was evaluated by examining collinearity, model explanatory power, predictive relevance, effect sizes, and model fit. The inner VIF values ranged from 1.003 to 1.456, substantially below the threshold of 5. This indicates that multicollinearity among the predictor constructs was not a substantial concern. The model fit assessment produced an SRMR value of 0.058, which was below the recommended threshold of 0.08. The other reported fit measures were NFI = 0.852, d_ULS = 0.926, and d_G = 0.321. Regarding explanatory power, the model accounted for 32.1% of the variance in herding behavior (adjusted R^2 = 0.314) and 19.4% of the variance in stock investment decisions (adjusted R^2 = 0.182). Predictive relevance was also supported by positive Q^2predict values of 0.300 for herding behavior and 0.104 for stock investment decisions.

The effect size assessment showed that algorithmic literacy had the largest contribution to explaining herding behavior (f^2 = 0.258), followed by finfluencer credibility (f^2 = 0.185). Both effects fall within the moderate range based on the commonly used effect-size classification.

Table 8. Summary of Structural Model Assessment

Endogenous Construct	R^2	Adjusted R^2	Q^2predict	RMSE	MAE
Herding Behavior (M)	0.321	0.314	0.300	0.847	0.697
Stock Investment Decisions (Y)	0.194	0.182	0.104	0.957	0.764

Note: Effect sizes (f^2): X1 → M = 0.185 (moderate); X2 → M = 0.258 (moderate); M → Y = 0.078 (small); X1 → Y = 0.035 (small); X2 → Y = 0.053 (small). Inner VIF values ranged from 1.003 to 1.456 (< 5). Model fit indices: SRMR = 0.058; NFI = 0.852; d_ULS = 0.926; d_G = 0.321.

Figure 2 presents the estimated structural model, including path coefficients and outer loadings obtained using SmartPLS 4.

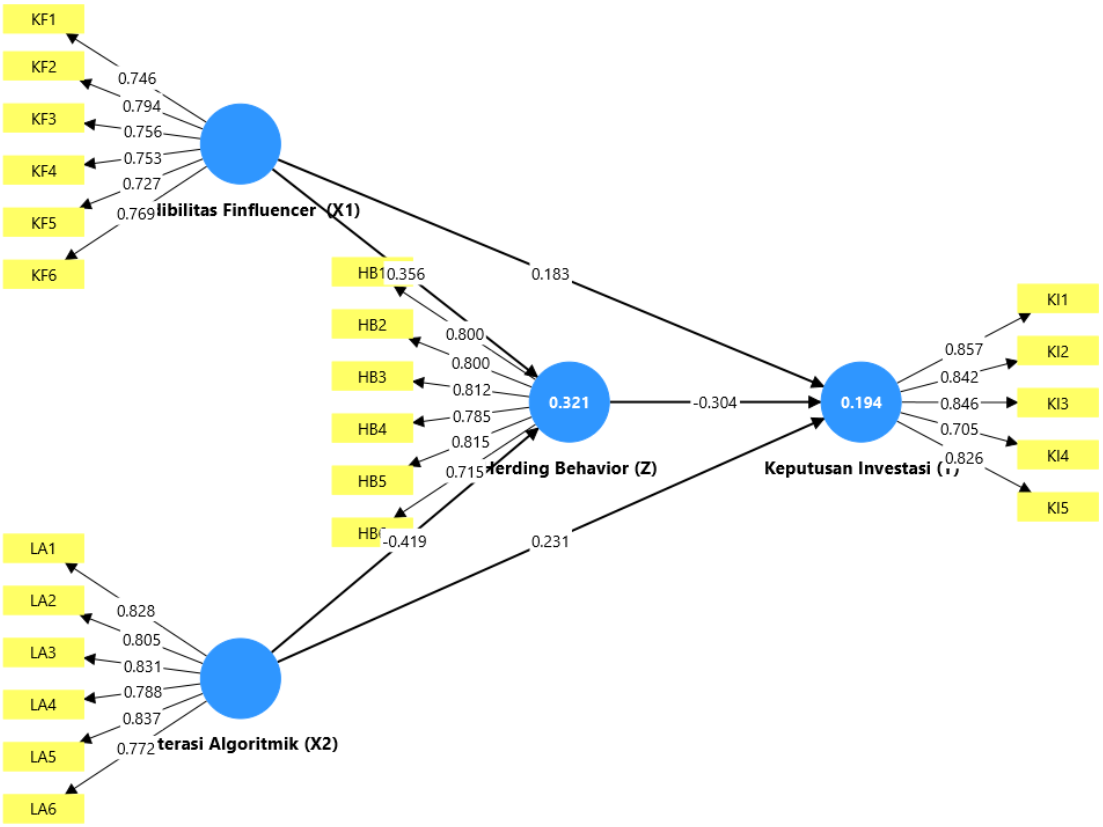


Figure 2. Structural Model with Path Coefficients and Outer Loadings

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 subsamples. Table 9 presents the results of the direct-effect assessment.

Table 9. Direct Effect Hypothesis Testing Results (5,000 Bootstrap Subsamples)

Hypothesis	Structural Path	Original Sample (O)	Sample Mean (M)	SD	t-statistic	p-value	Decision
H1	Finfluencer Credibility (X1) → Herding Behavior (M)	0.356	0.362	0.057	6.229	<0.001	Supported
H2	Finfluencer Credibility (X1) → Stock Investment Decisions (Y)	0.183	0.186	0.066	2.776	0.006	Supported
H3	Algorithmic Literacy (X2) → Herding Behavior (M)	−0.419	−0.422	0.059	7.091	<0.001	Supported

H4	Algorithmic Literacy (X2) → Stock Investment Decisions (Y)	0.231	0.237	0.079	2.938	0.003	Supported
H5	Herding Behavior (M) → Stock Investment Decisions (Y)	−0.304	−0.308	0.078	3.898	<0.001	Supported

Note: Statistical significance was assessed at $p < 0.05$. Values originally reported as $p = 0.000$ are expressed as $p < 0.001$.

All five direct-effect hypotheses were supported. Finfluencer credibility had a positive and statistically significant effect on herding behavior (β = 0.356; t = 6.229; p < 0.001), supporting H1. Finfluencer credibility also positively influenced stock investment decisions (β = 0.183; t = 2.776; p = 0.006), supporting H2. In contrast, algorithmic literacy had a negative and statistically significant effect on herding behavior (β = −0.419; t = 7.091; p < 0.001), supporting H3. Its effect on stock investment decisions was positive and statistically significant (β = 0.231; t = 2.938; p = 0.003), supporting H4. Finally, herding behavior negatively influenced stock investment decisions (β = −0.304; t = 3.898; p < 0.001), supporting H5.

Figure 3 presents the same structural model with the corresponding p-values obtained from the bootstrapping procedure.

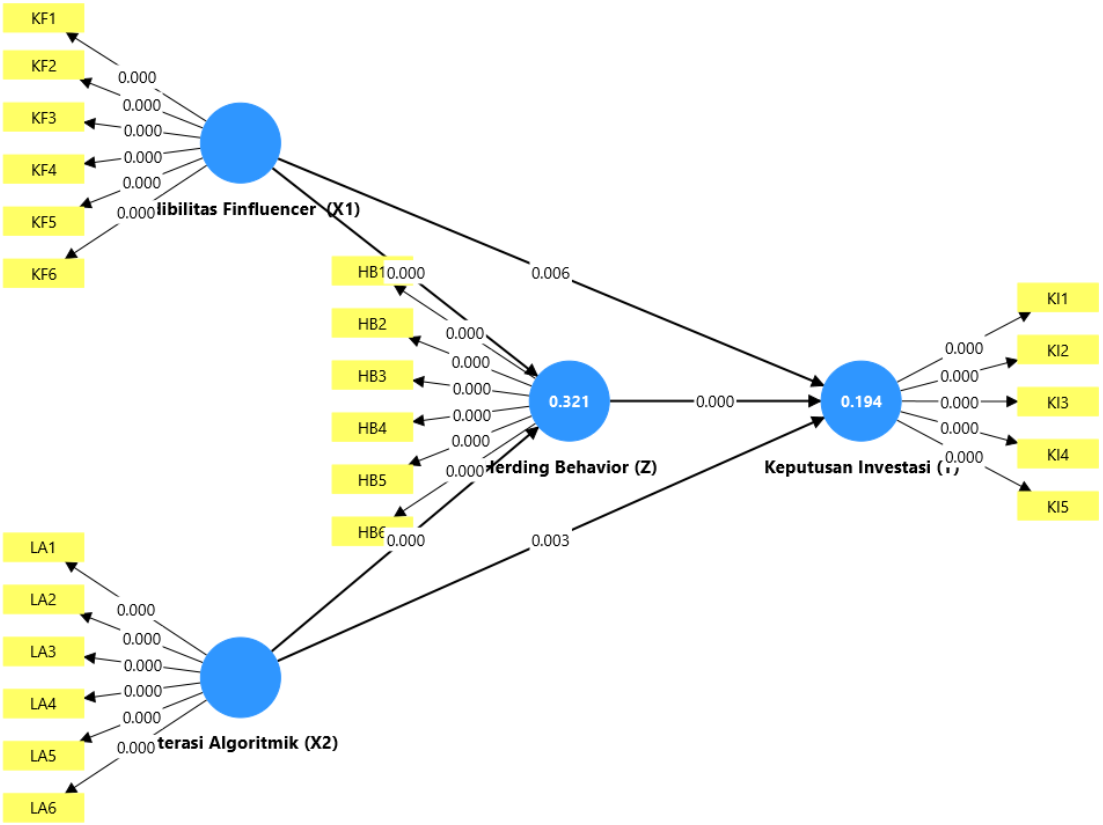


Figure 3. Structural Model with Bootstrapped p-values

The indirect effects and mediation classifications are reported in Table 10.

Table 10. Indirect Effect and Mediation Assessment

Hypothesis	Structural Path	Indirect Effect	t-statistic	p-value	Direct Effect	Total Effect	Mediation Type
H6	X1 → M → Y	−0.108	3.169	0.002	0.183*	0.075	Competitive mediation
H7	X2 → M → Y	0.127	3.385	0.001	0.231*	0.358	Complementary mediation

*Note: * Direct effects are statistically significant at p < 0.05. Mediation classifications follow Zhao et al. (2010): competitive mediation occurs when significant direct and indirect effects have opposite signs, whereas complementary mediation occurs when both effects are significant and have the same sign.*

Both mediation hypotheses were supported, although they exhibited different mediation patterns. The indirect effect of finfluencer credibility on stock investment decisions through herding behavior was negative and statistically significant (β = −0.108; t = 3.169; p = 0.002). Because the direct effect was positive and significant (β = 0.183), while the indirect effect was negative and significant, the relationship represents competitive mediation. Consequently, the total effect of finfluencer credibility on stock investment decisions was relatively small (β = 0.075). Conversely, the indirect effect of algorithmic literacy on stock investment decisions through herding behavior was positive and statistically significant (β = 0.127; t = 3.385; p = 0.001). This effect was consistent in direction with its positive direct effect (β = 0.231), indicating complementary mediation. The resulting total effect was 0.358, suggesting that algorithmic literacy contributes to stock investment decisions through both direct and indirect pathways.

Table 11 summarizes the outcomes of all seven hypotheses.

Table 11. Summary of Hypothesis Testing Results

Hypothesis	Proposed Relationship	Hypothesized Direction	Empirical Result	Decision
H1	Finfluencer credibility positively influences herding behavior	Positive	β = 0.356; p < 0.001	Supported
H2	Finfluencer credibility positively influences stock investment decisions	Positive	β = 0.183; p = 0.006	Supported
H3	Algorithmic literacy negatively influences herding behavior	Negative	β = −0.419; p < 0.001	Supported
H4	Algorithmic literacy positively influences stock investment decisions	Positive	β = 0.231; p = 0.003	Supported
H5	Herding behavior negatively influences stock investment decisions	Negative	β = −0.304; p < 0.001	Supported
H6	Herding behavior mediates the relationship between finfluencer credibility and stock investment decisions	Mediation	β = −0.108; p = 0.002	Supported
H7	Herding behavior mediates the relationship between algorithmic literacy and stock investment decisions	Mediation	β = 0.127; p = 0.001	Supported

3.2. Discussion

3.2.1. Finfluencer Credibility and the Formation of Herding Behavior

The positive and significant relationship between finfluencer credibility and herding behavior (β = 0.356) highlights the relevance of the peripheral route described by the Elaboration Likelihood Model (ELM) in the context of stock investment decisions. This finding suggests that perceived source credibility may encourage investors to rely on recommendations from financial influencers rather than independently evaluating investment information. More specifically, when finfluencers are perceived as knowledgeable, competent, and trustworthy, their recommendations may become persuasive cues that reduce investors' perceived need to conduct independent assessments. Consequently, source credibility may unintentionally reinforce imitation-based investment behavior. This finding illustrates that credibility does not necessarily translate into more autonomous or analytically rigorous investment decisions; its implications depend partly on how investors process and respond to the information provided.

The magnitude of the coefficient is consistent with findings from other emerging-market contexts (Malombe & Kowero, 2026; Batool et al., 2026) and reinforces the relevance of treating credibility as an antecedent of herding behavior rather than merely as a direct determinant of investment decisions. However, the finding differs from Rianda and Adiati (2025), who reported no significant direct effect of stock influencer credibility on herding behavior. Several methodological differences may help explain this divergence. The present study involved a larger sample (200 respondents compared with 138) and operationalized finfluencer credibility as a latent construct measured through six indicators representing three dimensions. In contrast, differences in construct operationalization and model specification may influence the relationships identified across studies. Accordingly, the measurement approach adopted in the present study provides a possible explanation for the different empirical results, although further comparative research is needed to establish this explanation more conclusively.

3.2.2. Algorithmic Literacy as Persuasion Knowledge

One of the most prominent findings is that algorithmic literacy is a stronger predictor of herding behavior than finfluencer credibility. Its path coefficient is greater in absolute magnitude (−0.419 compared with 0.356), and its effect size is also larger (f^2 = 0.258 compared with 0.185). This indicates that, within the proposed model, the capacity to recognize and critically evaluate algorithmically curated content plays a particularly important role in limiting imitation-based investment behavior. The theoretical explanation lies in the different mechanisms through which the two constructs operate. Finfluencer credibility operates at the source level by shaping investors' perceptions of a particular information provider. Algorithmic literacy, in contrast, operates at the content-selection level by influencing how investors interpret the broader information environment presented on their social media feeds.

An information cascade may emerge when investors interpret the repeated appearance of similar recommendations as evidence that other market participants possess superior information. However, when investors recognize that repeated exposure may result from algorithmic content curation rather than independent confirmation from multiple information sources, the persuasive influence of such repetition may be weakened. In this respect, algorithmic literacy can help investors distinguish between genuine informational consensus and algorithmically amplified visibility. This mechanism is consistent with the Persuasion Knowledge Model (PKM) proposed by Friestad and Wright (1994). The model suggests that individuals become better equipped to respond critically to persuasive attempts when they recognize the strategies and mechanisms underlying those attempts. Applied to algorithmically curated investment content, this implies that recognizing the role of recommendation

systems may reduce the likelihood that investors interpret repeated exposure as sufficient justification for following a particular investment recommendation. The findings also extend the application of algorithmic literacy beyond its established use in studies of digital information and news consumption (Oeldorf-Hirsch & Neubaum, 2023; Swart, 2021; Huang et al., 2025). Specifically, the results provide empirical evidence that algorithmic literacy is relevant to financial decision-making, where information exposure may have direct implications for investment behavior and financial risk.

3.2.3. Comparing Algorithmic Literacy with Established Literacy Constructs

A comparison with studies employing digital financial literacy highlights the distinctive contribution of algorithmic literacy. Saridona et al. (2026), for example, reported that digital financial literacy had a substantial positive effect on investment decisions (β = 0.602), while herding behavior did not have a significant effect. Their findings also indicated that digital financial literacy did not mitigate the influence of finfluencers. The present study identifies a different pattern. Algorithmic literacy has a moderate positive effect on stock investment decisions (β = 0.231), but its stronger contribution emerges through its negative relationship with herding behavior (β = −0.419). This distinction suggests that the two literacy constructs may perform different functions in the investment decision-making process.

Digital financial literacy primarily strengthens investment decisions by improving individuals' knowledge of digital financial products and services. Algorithmic literacy, on the other hand, may improve decision quality by reducing excessive dependence on socially amplified information cues. The constructs therefore address different dimensions of the digital investment environment. This distinction is particularly important because investment-related information on social media is not presented solely through users' deliberate information-seeking activities. It is also filtered, ranked, and recommended through algorithmic systems. Consequently, the ability to understand these systems may provide a form of protection that is more directly aligned with the mechanism through which investors are exposed to persuasive investment content.

The findings of Rianda and Adiati (2025), who reported that financial knowledge did not moderate the relationship between influencer credibility and herding behavior, provide further context for this interpretation. A possible explanation is that financial knowledge and algorithmic literacy address different sources of influence. Knowledge of financial concepts does not necessarily enable investors to recognize how recommendation algorithms shape their information exposure. Thus, literacy interventions may be more effective when their content corresponds directly to the mechanisms underlying the risks they seek to address.

3.2.4. Herding Behavior and Investment Decision Quality: Addressing Inconsistencies in Previous Research

The present study identifies a negative and statistically significant relationship between herding behavior and stock investment decision quality (β = −0.304). This finding contributes to the ongoing debate in the literature, where previous studies have reported positive relationships (Zainordin et al., 2025; Pramesti & Graciafernandy, 2024; Maharani et al., 2025), negative relationships, or statistically insignificant effects (Saridona et al., 2026; Runtuwene & Sibilang, 2024; Sucipto et al., 2026). One possible explanation for these inconsistent findings concerns how the dependent variable is operationalized. When investment decisions are measured in terms of transaction frequency or investment activity, herding may produce a positive association because following the majority can encourage additional transactions. In contrast, when investment decisions are conceptualized as the quality of the underlying assessment process, as in the present study and Rahayu and Ekawanti (2026),

herding may have a negative effect because imitation can replace independent evaluation and informed judgment.

Studies reporting insignificant relationships may employ operational definitions that combine elements of investment activity and decision quality. When these dimensions are not clearly distinguished, their potentially opposing relationships with herding behavior may weaken the estimated overall effect. This interpretation has an important methodological implication for future research. The expected direction of the relationship between herding behavior and investment decisions should be established only after clarifying whether the dependent construct measures investment activity, decision-making quality, or both. Such conceptual precision is necessary to improve comparability across empirical studies and to explain why herding behavior may have different implications in different investment contexts.

3.2.5. Two Mediation Patterns and Their Implications

The mediation findings represent an important substantive contribution of this study. Herding behavior mediates the relationships between both antecedent variables and stock investment decisions, but the mediation patterns differ in direction and implication. For finfluencer credibility, the results indicate competitive mediation. The positive direct effect (β = 0.183) is partially offset by the negative indirect effect through herding behavior (β = −0.108), resulting in a relatively small total effect of 0.075. This finding challenges the assumption that credible financial influencers necessarily improve the quality of investors' decisions. A more nuanced interpretation is that credible finfluencers may exert two simultaneous influences. On the one hand, their expertise and trustworthiness may provide useful financial information. On the other hand, the same credibility may encourage followers to imitate recommendations without sufficient independent assessment. The negative indirect pathway therefore offsets a substantial proportion of the positive direct effect. Based on the estimated coefficients, the magnitude of the indirect effect is approximately 59% of the direct effect. This comparison illustrates how imitation-based behavior may substantially weaken the potential benefits associated with credible financial information.

From an investor-protection perspective, these findings suggest that credibility alone should not be treated as a sufficient indicator of the quality or safety of financial recommendations. Investors must also be encouraged to evaluate the underlying information and maintain independent judgment. For algorithmic literacy, the findings demonstrate complementary mediation. Its positive direct effect (β = 0.231) is reinforced by a positive indirect effect through reduced herding behavior (β = 0.127), producing a total effect of 0.358. This pattern suggests that algorithmic literacy may improve stock investment decisions through two mutually reinforcing pathways: strengthening investors' capacity for independent evaluation and reducing their tendency to imitate recommendations presented through algorithmically curated content. The comparison of total effects further highlights the relative importance of algorithmic literacy in the proposed model. Its total effect (0.358) is approximately 4.8 times the total effect of finfluencer credibility (0.075). This result suggests that investors' ability to critically interpret their digital information environment may be more consequential for investment decision quality than the perceived credibility of the sources they follow.

3.2.6. Interpreting the Explanatory Power of the Model

The explanatory power of the model for stock investment decisions is relatively modest, with an R^2 value of 0.194. This indicates that the two antecedents included in the model account for 19.4% of the variance in stock investment decisions. Such a result should be interpreted in light of the model's specific theoretical scope. The study focuses on factors associated with digital information exposure and persuasion mechanisms rather than attempting to incorporate every established determinant of

investment decisions. Other factors that may influence investment decision quality include risk tolerance, overconfidence, investment experience, financial objectives, and individual financial circumstances. Their exclusion means that a substantial proportion of the variance remains attributable to factors beyond the scope of the present model.

Nevertheless, the positive Q^2predict values for both endogenous constructs indicate predictive relevance within the assessment framework employed. The higher explanatory power for herding behavior (R^2 = 0.321) also suggests that finfluencer credibility and algorithmic literacy are relevant predictors of imitation-based investment behavior. This is consistent with the central theoretical objective of the study, which is to examine how source credibility and algorithmic awareness shape investors' susceptibility to herding. Overall, the model provides evidence that digital persuasion mechanisms are relevant to understanding herding behavior and stock investment decisions, while also indicating the need for future models to incorporate additional individual and contextual determinants.

3.3. Implications

3.3.1. Theoretical Implications

This study extends the application of the Elaboration Likelihood Model (ELM) through the integration of the Persuasion Knowledge Model (PKM) in the context of behavioral finance. Its principal theoretical contribution is the demonstration that persuasion knowledge in digital environments extends beyond awareness of the motives and credibility of information providers. It also encompasses awareness of the technological systems that determine which information providers and messages are presented to users.

By incorporating algorithmic literacy into the behavioral finance framework, the study broadens the understanding of how investors process financial information in algorithmically curated environments. The findings indicate that investors' ability to recognize content-selection mechanisms may influence their susceptibility to social information cues and imitation-based behavior. This integration provides a foundation for examining similar mechanisms in other technology-mediated financial behaviors, including the use of buy-now-pay-later services, online lending platforms, and cryptocurrency investments. Future research may investigate whether algorithmic literacy also reduces vulnerability to persuasive digital content in these financial contexts.

3.3.2. Methodological Implications

Methodologically, this study provides an Indonesian-language algorithmic literacy instrument adapted to the context of investment-related content. The instrument consists of six indicators that satisfy the reliability and validity criteria, with Cronbach's alpha of 0.896, rho_A of 0.901, composite reliability of 0.920, and AVE of 0.657. These results provide initial empirical support for the instrument's use in examining algorithmic literacy in the context of investment information consumption. The instrument may serve as a basis for further validation and application in different populations, geographical settings, and digital financial environments. Nevertheless, subsequent studies should examine its measurement properties across different investor groups and platforms to establish its broader applicability and measurement consistency.

3.3.3. Practical and Policy Implications

The findings offer four practical and policy implications for stakeholders involved in investor education, digital platforms, financial regulation, and university-based investment communities. First, for the Financial Services Authority (OJK) and the Indonesia Stock Exchange (IDX), algorithmic literacy should be considered as a complementary component of investor education programs. Rather than focusing exclusively on financial products, investment instruments, and risk assessment, educational

initiatives should also equip investors with the ability to understand how social media recommendation systems curate and amplify investment-related content. In practical terms, this involves teaching investors how to critically interpret their social media feeds and distinguish repeated algorithmic exposure from independent confirmation of investment information. Second, social media and securities platform providers should consider improving transparency regarding their recommendation systems. The findings support the importance of providing users with accessible explanations of why particular investment-related content is recommended or displayed. Greater transparency may help users recognize the role of algorithmic curation in shaping their information exposure and reduce the risk of interpreting repeated content visibility as evidence of investment consensus.

Third, in relation to the implementation of POJK No. 6 of 2026, the competitive mediation finding suggests that disclosure of conflicts of interest and investment risk warnings may need to be complemented by interventions targeting information recipients. The negative indirect effect of finfluencer credibility operates through herding behavior, indicating that regulating the conduct of information providers alone may not fully address imitation-based investment risks. Investor education should therefore strengthen users' ability to critically evaluate recommendations and maintain independent decision-making. Fourth, university Investment Galleries and young investor communities in Makassar should emphasize practical behavioral training rather than relying exclusively on the dissemination of conceptual knowledge. The descriptive results reveal a gap between awareness of algorithmic curation and the ability to respond to it: respondents reported relatively high awareness (LA1 = 3.625), but a lower score on the item associated with adjusting content preferences (LA6 = 3.065). This suggests that educational programs should include practical activities, such as reviewing recommendation settings, diversifying information sources, identifying repeated content patterns, and independently verifying investment claims before making transactions.

4. Conclusions

4.1. Main Findings

This study examined the influence of finfluencer credibility and algorithmic literacy on stock investment decision quality, with herding behavior serving as a mediating variable among Generation Z investors in Makassar, Indonesia. The findings demonstrate that finfluencer credibility positively influences both herding behavior and stock investment decisions, whereas algorithmic literacy negatively influences herding behavior and positively influences stock investment decisions. Furthermore, herding behavior has a negative and significant effect on stock investment decision quality. These findings indicate that credible financial information sources may simultaneously provide investment benefits and encourage imitation-based behavior, while algorithmic literacy may help investors maintain greater independence in their decision-making processes.

4.2. Theoretical Contributions

The study contributes to behavioral finance by integrating the Elaboration Likelihood Model (ELM) and the Persuasion Knowledge Model (PKM) to explain investment behavior in algorithmically curated digital environments. Specifically, the findings highlight algorithmic literacy as an important dimension of investors' ability to recognize and critically evaluate how financial information is selected and presented. The study also provides a possible explanation for inconsistencies in previous research concerning herding behavior and investment decisions by distinguishing investment activity from investment decision quality. This distinction emphasizes the importance of conceptual precision when examining the behavioral consequences of herding.

4.3. Mediation Contributions

An important contribution of this study is the identification of two different mediation mechanisms through herding behavior. First, herding behavior competitively mediates the relationship between finfluencer credibility and stock investment decisions, as the negative indirect effect partially offsets the positive direct effect. Second, herding behavior complementarily mediates the relationship between algorithmic literacy and stock investment decisions, reinforcing its positive direct effect. The comparison of total effects further indicates that algorithmic literacy has a substantially stronger overall relationship with investment decision quality than finfluencer credibility. These findings suggest that investors' capacity to critically interpret algorithmically curated information is particularly important in reducing excessive reliance on social investment cues.

4.4. Practical and Policy Implications

The findings underscore the importance of incorporating algorithmic literacy into investor education programs. Financial regulators, securities institutions, and university Investment Galleries should develop educational initiatives that encourage investors to recognize algorithmic content curation, diversify information sources, critically evaluate financial recommendations, and verify investment information before conducting transactions. Social media and securities platform providers should also consider improving transparency regarding the recommendation mechanisms that influence users' exposure to investment-related content. Such initiatives may strengthen investor autonomy and support more informed investment decisions, particularly among Generation Z investors.

4.5. Limitations and Future Research Directions

This study has several limitations. First, the cross-sectional survey design and the sample of 200 Generation Z investors in Makassar limit the generalizability of the findings and do not establish causal relationships among the examined constructs. Second, the use of self-reported questionnaire data may introduce response-related biases. Third, the research model focuses on finfluencer credibility and algorithmic literacy without incorporating other potential determinants of investment decision quality, such as risk tolerance, overconfidence, investment experience, and financial objectives. Future research should employ longitudinal or experimental approaches to examine the development of algorithmic literacy and its influence on herding behavior over time. Studies involving larger and more geographically diverse samples are also recommended to assess the generalizability of the findings across different investor populations and digital platforms. Further validation of the algorithmic literacy instrument in other digital financial contexts would strengthen its measurement applicability and contribute to the development of a broader behavioral finance framework.

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