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Digital Financial Decisions: Evidence on Social Influence, Technology, and Herd Behavior in Emerging Financial Ecosystems

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ABSTRACT
The rapid growth of digital financial ecosystems has transformed how individuals make investment and consumption decisions within socially connected and technology-driven environments. This study examines the influence of psychological, social, and technological factors on herd behavior and digital investment decisions, as well as their implications for perceived market impact. Using a quantitative approach, data were collected from 105 active users of digital financial platforms in East Java, Indonesia, including cryptocurrency investors, paylater users, and digital investment application users. The data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The findings reveal that social and technological factors positively and significantly influence investment and consumption decisions, while psychological factors significantly affect herd behavior but do not directly influence investment decisions. Herd behavior also does not significantly moderate the relationships between psychological, social, and technological factors and investment decisions. Furthermore, investment and consumption decisions significantly contribute to perceived market impact. These findings indicate that digital financial behavior is increasingly shaped by social interaction and technological facilitation rather than solely by internal psychological mechanisms. This study contributes to behavioral finance literature by extending herd behavior analysis into digitally mediated financial environments.

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INTRODUCTION

The rapid expansion of the digital financial ecosystem has fundamentally transformed economic behavior, particularly in investment and consumption decision-making (Breidbach et al., 2020; Palmié et al., 2020). The proliferation of fintech platforms, cryptocurrency exchanges, peer-to-peer lending services, and pay-later systems has significantly lowered market entry barriers, enabling broader participation across demographic groups (Ediagbonya & Tioluwani, 2023). While this technological democratization enhances financial inclusion, it simultaneously introduces behavioral complexities that challenge traditional assumptions of rational economic decision-making (Gabor & Brooks, 2020; Wang et al., 2023). In digitally connected markets, information spreads rapidly through social media, online communities, and algorithm-driven recommendations, amplifying collective responses to trends (Theodorakopoulos et al., 2025). One

critical behavioral phenomenon emerging from this environment is herd behavior, defined as the tendency of individuals to imitate the actions of others without conducting independent analysis (Chen et al., 2025; Kameda & Hastie, 2015; Komalasari et al., 2022; Rook, 2006). In highly volatile digital markets, such behavior may intensify price fluctuations, contribute to speculative bubbles, and increase systemic risk, particularly in emerging economies (Kyriazis et al., 2020; Osman et al., 2024; Perepelitsa & Timofeyev, 2022).

Previous research has extensively examined herd behavior in traditional financial markets such as stock exchanges and foreign exchange markets (Chang et al., 2000). Early foundational studies conceptualized herding as informational cascades and reputational behavior under uncertainty (Ali et al., 2021; Doherty, 2018; Komalasari et al., 2022). Subsequent empirical research confirmed the presence of herding during crisis periods and high-volatility phases (Balcilar & Demirer, 2015; Galariotis et al., 2016b; Jirasakuldech & Emekter, 2021; Nguyen & Vo, 2024; Schmitt & Westerhoff, 2017; Zhang & Giouvris, 2022). More recent studies have incorporated behavioral finance perspectives, highlighting the roles of cognitive bias, overconfidence, and risk perception in shaping investment decisions (Ahmad & Shah, 2022; Ahmed et al., 2022; Almansour et al., 2023, 2025; Badola et al., 2024; Duxbury, 2015). In parallel, emerging research has begun to explore the influence of digital platforms and social media sentiment on market behavior (Arvidsson, 2011; Dwivedi et al., 2023; Hadi et al., 2024; Hays et al., 2013; Kapoor et al., 2018; Kim et al., 2023; Lamberton & Stephen, 2016; Liu, 2020; Onyeje et al., 2022; Puschmann & Powell, 2018; Rapp et al., 2013; Rodríguez-Ibánez et al., 2023; Stieglitz & Dang-Xuan, 2013; Thies et al., 2016; Valenzuela, 2013; Vrontis et al., 2021; Wolny & Mueller, 2013; Yu et al., 2013). These studies collectively demonstrate that psychological, social, and technological dimensions are increasingly intertwined in shaping modern financial decision-making (Gärling et al., 2009; Ilugbusi & Adisa, 2024; Kumar et al., 2023; Saini et al., 2026).

Despite the growing body of literature on herd behavior and digital financial participation, several important research gaps remain unresolved. First, prior studies tend to examine psychological, social, and technological determinants separately, resulting in fragmented explanations of digital financial behavior (Barone et al., 2024; Dar & Kumar, 2023; Palmié et al., 2020). Behavioral finance studies largely emphasize internal cognitive bias and emotional responses, while digital economy research focuses more on technological adoption and platform accessibility. Consequently, limited research has integrated these multidimensional determinants within a unified framework capable of explaining herd-driven financial behavior in digital ecosystems.

Second, most herd behavior studies are still concentrated on conventional financial markets such as stock exchanges and foreign exchange markets (Chang et al., 2000; Galariotis et al., 2016a; Nguyen & Vo, 2024). Although recent studies have begun exploring cryptocurrency markets and fintech environments, herd behavior is still predominantly conceptualized as a direct determinant of investment decisions. Such an approach may be insufficient for explaining decision-making patterns in digitally mediated environments where platform architecture, algorithmic recommendations, and social media interaction increasingly shape investor behavior (Akanfe et al., 2025; Dwivedi et al., 2023; Manser Payne et al., 2021). Therefore, there remains limited understanding regarding whether herd behavior functions as an independent predictor or as a context-dependent mechanism embedded within technological and social systems.

Third, empirical evidence from Southeast Asian countries, particularly Indonesia, remains relatively limited despite the rapid expansion of digital financial participation in the region (Fahlevi et al., 2024; Rahayu et al., 2023). Indonesia represents one of the fastest-growing digital financial markets, characterized by increasing fintech adoption, cryptocurrency participation, and social-media-driven investment activity. However, existing studies in Indonesia mainly focus on financial

literacy, technology adoption, or digital payment systems, while research examining herd behavior within integrated digital financial ecosystems remains scarce.

Based on these gaps, this study develops an integrated behavioral framework that examines the influence of psychological, social, and technological factors on herd behavior and investment decisions within digital financial environments. Unlike previous studies that primarily treat herd behavior as a universally dominant predictor, this study positions herd behavior as a contextual behavioral mechanism shaped by digital social interaction and technological facilitation. By extending herd behavior analysis into Indonesia's digital financial ecosystem, this study contributes to the refinement of behavioral finance theory in the era of financial digitalization.

This study aims to develop and empirically test an integrated model examining the influence of psychological, social, and technological factors on herd behavior and their subsequent impact on investment and consumption decisions, as well as market stability. This research contributes theoretically by extending herd behavior analysis into the digital finance ecosystem through a multidimensional perspective. Practically, the findings offer policy-relevant insights for regulators, fintech platforms, and financial educators to strengthen digital financial literacy, mitigate speculative risk, and promote more stable and rational participation in digital markets. By bridging behavioral finance theory with digital economy dynamics, this study provides a comprehensive framework for understanding and managing collective decision-making in the era of financial digitalization.

LITERATURE REVIEW

Behavioral Finance Theory

This study is primarily grounded in Behavioral Finance Theory, which explains that financial decision-making is not always driven by rational economic considerations but is also influenced by psychological, social, and contextual factors (Duxbury, 2015; Gärling et al., 2009). Unlike classical financial theory that assumes investors behave rationally and process information objectively, behavioral finance emphasizes that individuals are susceptible to cognitive bias, emotional responses, heuristic thinking, and social influence when making financial decisions (Barberis & Thaler, 2003; Kahneman & Tversky, 2013; Thaler, 1999). Such behavioral tendencies become increasingly relevant in digital financial environments characterized by rapid information diffusion, social-media interaction, and technology-driven investment platforms (Dwivedi et al., 2023; Siering et al., 2017).

Behavioral Finance Theory provides an overarching framework for understanding how psychological tendencies, social exposure, and technological facilitation collectively shape herd behavior and investment decisions (Duxbury, 2015; Gärling et al., 2009). Digital platforms not only accelerate information access but also restructure how individuals perceive risk, evaluate trends, and respond to market signals (Kumar et al., 2023; Wang et al., 2023). Consequently, investor behavior in digital ecosystems may deviate further from purely rational decision-making models (Kavitha et al., 2023; Yadav & Pavlou, 2020).

To complement this grand theoretical perspective, this study also incorporates Social Influence Theory and Diffusion of Innovation Theory as supporting theories. Behavioral Finance Theory primarily explains how cognitive bias, emotional responses, and irrational tendencies influence financial decision-making. However, this perspective alone may be insufficient for explaining investor behavior within digitally connected financial ecosystems, where social interaction and technological systems increasingly shape decision-making processes. Therefore, additional supporting theories are required to explain the external social and technological mechanisms influencing digital financial participation.

Social Influence Theory explains how group norms, peer interaction, and informational conformity shape individual behavior under uncertainty (Smith et al., 2007). This theory complements Behavioral Finance Theory by explaining how external social pressure and online interaction influence conformity behavior beyond individual psychological tendencies. Meanwhile, Diffusion of Innovation Theory explains how technological accessibility, perceived usefulness, and ease of use accelerate digital financial participation and behavioral adoption (Sahin & Thompson, 2006). Unlike Behavioral Finance Theory, which primarily focuses on cognitive and emotional aspects of decision-making, Diffusion of Innovation Theory emphasizes the role of technological systems and innovation adoption in shaping behavioral participation. Integrating these theories allows the study to develop a multidimensional framework capable of explaining herd-driven financial behavior within digitally mediated environments.

Although several foundational theories adopted in this study originate from earlier literature, these theories remain highly relevant and continue to be widely applied in recent behavioral finance, digital finance, and technology adoption research. Behavioral Finance Theory continues to provide an important framework for explaining cognitive bias and investor behavior in digitally mediated financial environments (Kavitha et al., 2023; Saini et al., 2026). Similarly, Social Influence Theory remains relevant for understanding conformity behavior and digital peer interaction within online financial communities (Kawai et al., 2023; Ooi, 2025a) . In addition, Diffusion of Innovation Theory continues to be extensively utilized in studies examining fintech adoption, AI-driven financial systems, and digital financial participation (Akanfe et al., 2025; Del Sarto & Ozili, 2025). Therefore, these classical theories remain theoretically robust and contextually appropriate for explaining behavioral dynamics in contemporary digital financial ecosystems.

The Influence of Psychological Factors on Herd Behavior

Behavioral Finance Theory explains that individuals are often influenced by cognitive bias, emotional reactions, and heuristic thinking when making financial decisions under uncertainty (Duxbury, 2015; Gärling et al., 2009). In highly uncertain digital financial environments, investors may rely more heavily on intuitive judgment and collective market signals rather than objective analysis. Such psychological tendencies may increase susceptibility to conformity behavior and imitation within financial markets. Parveen et al. (2020) emphasizes that overconfidence, representativeness bias, and loss aversion influence how individuals process financial information, particularly under uncertainty. When investors experience Fear of Missing Out (FoMO), they are more likely to rely on heuristic shortcuts and follow majority actions (Gupta & Shrivastava, 2022). Bhutto et al. (2025) show that herding behavior is significantly associated with psychological bias through risk perception mechanisms. In addition, Yadav et al. (2026) demonstrate that limited financial literacy increases reliance on heuristic-based decision-making, which may foster conformity behavior. These findings indicate that psychological factors may function as antecedents of herd behavior, particularly in uncertain and digitally connected financial environments. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:

H1: Psychological factors positively influence herd behavior.

The Influence of Social Factors on Herd Behavior

Social Influence Theory explains that individuals tend to adjust their behavior according to group norms, social validation, and collective expectations, particularly under conditions of uncertainty (Smith et al., 2007). In digital financial ecosystems, social-media interaction and online investment communities may intensify informational conformity, encouraging individuals to imitate the behavior of others when making financial decisions. Kawai et al. (2023) and Matsumoto

et al. (2025) demonstrate that digital interaction among investors creates informational contagion effects, where investment recommendations spread rapidly across online communities. Ooi (2025) further show that real-time public sentiment strengthens herding behavior in stock markets. In digital financial ecosystems, influencer endorsements and community discussions amplify perceived consensus, increasing conformity pressure (Cardoso et al., 2024). These empirical findings indicate that social exposure in online environments may stimulate herd behavior among retail investors. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:
H2: Social factors positively influence herd behavior.

The Influence of Technological Factors on Herd Behavior

Diffusion of Innovation Theory explains that technological accessibility, perceived usefulness, and ease of use influence behavioral adoption and participation patterns (Sahin & Thompson, 2006). Within digital financial ecosystems, technological systems such as AI-based recommendations, real-time notifications, and algorithmic investment features may accelerate collective responses to market trends and increase synchronized financial behavior among users. Al-Rahmi et al. (2018) explains that perceived ease of use and usefulness accelerate technology adoption. In digital finance, algorithmic recommendations, AI-based analytics, and real-time notifications influence investor responsiveness to market trends (Belanche et al., 2019; Lee et al., 2021). Hu and Liu (2025) find that digital financial integration increases household risk-taking behavior. Similarly, He & Li (2020) show that digital participation intensifies synchronized financial activity. The structure of digital platforms may therefore accelerate collective responses and reinforce herd tendencies by reducing cognitive barriers and increasing information speed. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed.
H3: Technological factors positively influence herd behavior.

The Influence of Psychological Factors on Investment and Consumption Decisions

Behavioral Finance Theory explains that financial decision-making is often influenced by cognitive bias, emotional reactions, and heuristic judgment rather than purely rational evaluation (Duxbury, 2015; Gärling et al., 2009). Psychological tendencies such as overconfidence, Fear of Missing Out (FoMO), and intuitive thinking may shape how individuals assess investment opportunities and consumption behavior, particularly in uncertain financial environments. Behavioral finance literature suggests that psychological bias influences financial decision-making (Loerwald & Stemmann, 2016). Nazem (2025) argues that cognitive bias affects risk assessment and investment preference. However, Kumar et al (2024) show that psychological traits may influence investment decisions indirectly rather than directly, depending on contextual mediators. In digitally mediated environments, investor decisions may be shaped more strongly by external stimuli such as social exposure and technological interfaces than by internal psychological processes (Yadav et al., 2020). Although classical theory predicts a direct influence, empirical findings suggest contextual variability. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:
H4: Psychological factors positively influence investment and consumption decisions.

The Influence of Social Factors on Investment and Consumption Decisions

Social Influence Theory explains that individuals tend to adjust their behavior according to social norms, peer interaction, and collective expectations, especially under conditions of uncertainty (Smith et al., 2007). Within digital financial ecosystems, social-media exposure, online

investment communities, and influencer recommendations may directly shape investment preferences and consumption behavior through informational conformity and social validation mechanisms. Social validation plays a crucial role in shaping financial decisions (Patwa et al., 2024). Akhtar et al. (2018) show that social influence significantly affects investment decisions among young investors. Sudaryanto et al. (2025) argue that digital peer recommendations influence investor confidence and transaction behavior. In social-media-driven markets, individuals may directly adjust their investment and consumption decisions based on perceived majority opinion and viral trends (Motoki et al., 2020). These findings indicate that social exposure can directly shape economic behavior. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:
H5: Social factors positively influence investment and consumption decisions.

The Influence of Technological Factors on Investment and Consumption Decisions

Diffusion of Innovation Theory explains that technological accessibility, perceived usefulness, and ease of use encourage behavioral adoption and participation (Sahin & Thompson, 2006). In digital financial ecosystems, investment applications, AI-assisted systems, and mobile financial technologies may simplify financial transactions and increase participation intensity by reducing information and transaction barriers. Technological advancement lowers transaction costs and simplifies access to financial markets (Domowitz, 2002). Sahin and Thompson (2006) explains that technology adoption increases behavioral participation. Nguyen-Thi-Phuong et al find that digital financial engagement increases transaction frequency and market participation. Automated investment tools and AI-based systems may influence investment speed and perceived objectivity (Chua et al., 2023). Therefore, technological facilitation is expected to directly influence investment and consumption decisions in digital markets. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:
H6: Technological factors positively influence investment and consumption decisions.

The Influence of Herd Behavior on Investment and Consumption Decisions

Behavioral Finance Theory explains that under conditions of uncertainty, individuals may rely on collective market behavior and observable actions of others when making financial decisions (Duxbury, 2015). Herd behavior emerges when investors imitate majority actions rather than conducting independent analysis, potentially influencing synchronized investment and consumption patterns within financial markets. Herd behavior has traditionally been considered a determinant of synchronized trading decisions (Singhania et al., 2025). Doherty (2018) argue that informational cascades lead investors to follow majority actions, influencing financial transactions. Tlili et al (2023) finds that herding increases during market turbulence. However, Srivastava & Moid (2025) suggest that herding may influence investment decisions indirectly through mediating factors rather than as a direct predictor. In digital financial environments, structural technological and social mechanisms may dominate over pure imitation behavior (Li et al., 2023). This suggests that while classical theory predicts a direct relationship, empirical strength may vary depending on contextual digital factors. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:
H7: Herd behavior positively influences investment and consumption decisions.

The Influence of Investment and Consumption Decisions on Market Impact

Behavioral Finance Theory explains that aggregated individual financial decisions may collectively influence broader market dynamics and stability (Gärling et al., 2009). When investment and consumption decisions become increasingly synchronized within digital financial

ecosystems, collective participation may intensify market volatility, speculative behavior, and systemic financial risk. Market stability is shaped by the aggregation of individual financial decisions (Fenzl & Pelzmann, 2012). Mukherjee & Tiwari (2022) argue that correlated trading behavior may result in mispricing and speculative bubbles. Belhouichet et al (2025) demonstrates that synchronized investor participation increases market volatility. Rieger et al (2022) show that collective trend-following behavior intensifies price fluctuations during economic uncertainty. In digital markets, He & Li (2020) indicate that increased digital financial participation amplifies transaction intensity and systemic exposure. These findings suggest that aggregated investment and consumption decisions may directly influence perceived market impact and stability. Based on the theoretical arguments and previous empirical findings, the following hypothesis is proposed:

H8: Investment and consumption decisions positively influence perceived market impact.

The Moderating Role of Herd Behavior (Revised and Expanded Version)

Herd behavior does not only function as a direct determinant of financial decisions but may also operate as a contextual amplifier that alters the strength of other behavioral relationships (Rook, 2006). Classical informational cascade theory Sachdeva et al (2023) argues that conformity pressure can override individual cognitive evaluation, particularly when uncertainty is high. Under such conditions, individuals may rely less on private judgment and more on observable majority actions. This suggests that herd behavior can intensify the influence of psychological bias, social exposure, or technological stimuli on investment decisions.

From a psychological perspective, individuals with cognitive biases such as overconfidence or Fear of Missing Out (FoMO) may be more susceptible to conformity pressure when herd intensity is high. In such cases, herd behavior could strengthen the relationship between psychological tendencies and investment decisions by accelerating imitation behavior. Ahmed et al (2022) indicate that risk perception and behavioral bias interact in shaping investment outcomes, implying that collective pressure may magnify internal bias under certain conditions. From a social standpoint, herd behavior may reinforce social influence mechanisms. When digital communities exhibit strong consensus, conformity pressure may intensify the impact of social exposure on individual investment behavior. Urena et al (2019) show that online investment networks generate credibility through repetition and group validation, which may amplify decision alignment. Thus, herd behavior could strengthen the relationship between social factors and investment decisions when conformity pressure is dominant.

Regarding technological factors, digital platforms equipped with algorithmic recommendations and trend notifications may structurally embed herding dynamics within decision architecture. However, unlike classical herding driven by observational imitation, digital herding may be mediated by platform design. In this case, herd behavior may either strengthen technological influence by accelerating collective response or weaken it if algorithmic decision aids substitute for pure imitation behavior. This contextual variability justifies examining herd behavior as a moderating construct rather than assuming a universally dominant direct effect. Therefore, herd behavior may function as a conditional mechanism that either amplifies or attenuates the influence of psychological, social, and technological determinants on investment and consumption decisions. To empirically examine these possibilities, the following moderation hypotheses are proposed:

H9: Herd behavior strengthens the relationship between psychological factors and investment decisions.

H10: Herd behavior strengthens the relationship between social factors and investment decisions

H11: Herd behavior strengthens the relationship between technological factors and investment

decisions.

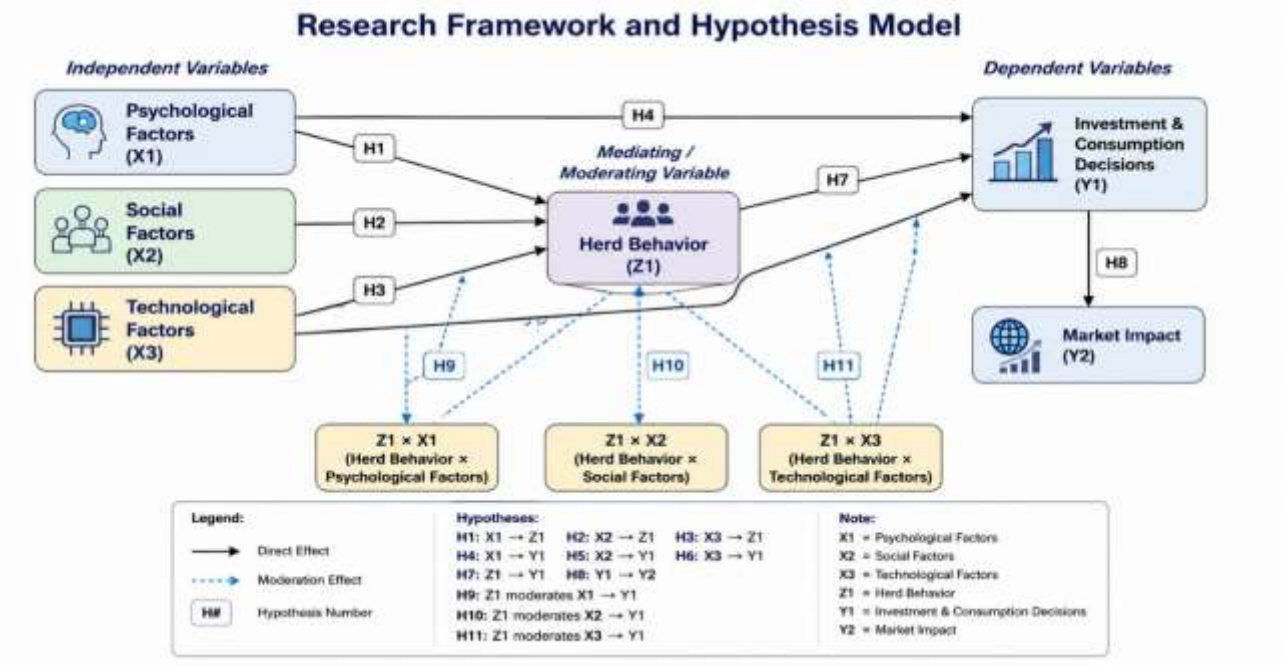


Figure 1. Research framework
Source: Processed Data, 2025

Figure 1 illustrates the conceptual research framework developed to examine the determinants of herd behavior and its impact on investment decision-making within the digital financial ecosystem. The framework positions psychological factors (X1), social factors (X2), and technological factors (X3) as exogenous variables that influence herd behavior (Z1) as well as investment and consumption decisions (Y1). Psychological factors represent internal cognitive and emotional drivers such as Fear of Missing Out (FoMO), intuitive judgment, and cognitive bias. Social factors reflect external social influence, including online community interaction, social media exposure, and majority opinion. Technological factors capture digital platform characteristics such as ease of use, AI-based recommendations, and real-time notifications that may accelerate financial participation.

Herd behavior (Z1) is modeled both as an endogenous variable influenced by psychological, social, and technological factors, and as a moderating variable that may strengthen or weaken the relationship between these determinants and investment decisions. This dual positioning allows the model to examine whether conformity behavior functions as a direct driver or merely as an amplifier within digital financial environments. Investment and consumption decisions (Y1) are treated as behavioral outcomes shaped by multidimensional influences and are further hypothesized to affect perceived market impact (Y2). Market impact reflects aggregated consequences such as volatility, speculative bubbles, and systemic risk arising from collective financial actions. Overall, the framework integrates behavioral finance theory, social influence theory, and diffusion of innovation theory to explain how digital-era investment behavior is formed and how it contributes to broader market dynamics.

RESEARCH METHOD

This study employs a quantitative research design to examine the structural relationships among psychological factors, social factors, technological factors, herd behavior, investment and

consumption decisions, and perceived market impact within the digital financial ecosystem. A variance-based Structural Equation Modeling approach using Partial Least Squares (SEM-PLS) was applied to test both direct and moderating relationships among latent constructs. SEM-PLS was selected because the study aims to predict behavioral relationships within a relatively complex exploratory model involving multiple constructs and interaction effects. In addition, SEM-PLS is considered appropriate for prediction-oriented research with relatively limited sample sizes and non-normal data distribution assumptions (Batra, 2025; Hair & Alamer, 2022; Tama et al., 2023).

The target population consists of individuals actively involved in digital financial activities, including: (1) paylater users, (2) cryptocurrency investors, and (3) digital investment application users. Because this population is not formally recorded and difficult to enumerate, non-probability sampling was applied. The study used purposive sampling combined with snowball sampling. The inclusion criteria were: (1) Individuals aged 15 years or older, (2) Active users of at least one digital financial platform (paylater, cryptocurrency exchange, or digital investment application). Data collection was conducted through online questionnaires distributed via digital platforms and community networks. A total of 500 responses were initially collected. After eliminating incomplete and ineligible responses, 360 valid responses remained. Following the screening process based on predefined inclusion criteria, 105 respondents met all requirements and were included in the final analysis. Although the final sample size is relatively limited, SEM-PLS is considered appropriate for exploratory and prediction-oriented models with small-to-medium sample sizes (Hair & Alamer, 2022). Furthermore, the sample size exceeds the minimum requirement based on the ten-times rule, as the most complex construct in the model contains fewer than ten structural paths and indicators. Therefore, the sample size is considered adequate for estimating the structural relationships in this study.

The research instrument was developed based on the operational definitions of each construct derived from behavioral finance theory (Duxbury, 2015), social influence theory (Smith et al., 2007), and diffusion of innovation theory (Sahin & Thompson, 2006). All constructs were measured using reflective indicators and structured into a closed-ended questionnaire. Responses were recorded using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The instrument consists of six latent variables: Psychological Factors (X1), Social Factors (X2), Technological Factors (X3), Herd Behavior (Z1), Investment and Consumption Decisions (Y1), and Perceived Market Impact (Y2). The detailed measurement indicators are presented in table 1.

The measurement items used in this study were adapted and modified from previous studies related to behavioral finance, herd behavior, digital financial participation, social influence, and technology adoption. Although several foundational theories and measurement approaches originate from earlier literature, they remain widely recognized and continue to be extensively applied in recent behavioral finance and digital financial research. To ensure contextual relevance, several indicators were refined and contextually adjusted to reflect investor behavior within digitally mediated financial ecosystems.

Table 1. Research Instrument

Variable	Code	Measurement Item
Psychological Factors (X1) Ahmad & Shah (2022); Gupta & Shrivastava (2022)	X1.1	I feel left behind if I do not invest when others start investing.
	X1.2	I worry about missing profitable investment trends.
	X1.3	I often decide to invest because many people are doing it.
	X1.4	I feel anxious when I am not involved in viral investments.

	X1.5	I rely more on intuition than data analysis when investing.
	X1.6	I tend to ignore information that contradicts my investment beliefs.
	X1.7	I believe that I can easily replicate others' investment success.
	X1.8	I assume that popular investments are generally profitable.
Social Factors (X2) Akhtar et al. (2018); Kawai et al. (2023)	X2.1	I frequently obtain investment information from social media platforms.
	X2.2	Investment influencers on social media affect my decisions.
	X2.3	I follow investment trends based on viral content.
	X2.4	I trust investment information widely shared on social media.
	X2.5	I discuss investment matters in online communities or groups.
	X2.6	The majority opinion in my investment community influences my decisions.
	X2.7	I feel more confident investing after seeing many others do it.
	X2.8	I prefer following community investment strategies rather than creating my own.
Technological Factors (X3) Sahin & Thompson (2006); Chua et al. (2023)	X3.1	Easy-to-use investment applications increase my investment activity.
	X3.2	I feel comfortable investing using only a smartphone.
	X3.3	I started investing because the digital process is fast and practical.
	X3.4	Notifications and promotions from investment apps motivate me to invest.
	X3.5	I trust AI-based investment recommendations provided by applications.
	X3.6	Technology helps me make faster investment decisions.
	X3.7	I prefer platforms that use AI for market analysis.
	X3.8	AI-based decisions are more objective than personal intuition.
Herd Behavior (Z1) Rook (2006); Komalasari et al. (2022)	Z1.1	I often follow majority investment decisions without deep analysis.
	Z1.2	If many people buy a particular asset, I tend to buy it as well.
	Z1.3	I feel safer making the same investment decisions as others.
	Z1.4	I consider my investment decision correct if many people make the same choice.
Investment & Consumption Decisions (Y1) Kumar et al. (2024); Nguyen-Thi-Phuong et al. (2026)	Y1.1	I tend to invest based on trends rather than long-term needs.
	Y1.2	My consumption decisions change after following certain investment trends.
	Y1.3	I have purchased goods influenced by investment gains.
	Y1.4	I sometimes invest without fully understanding the associated risks.

	Y2.1	Trend-following behavior can trigger unreasonable asset price increases.
Market Impact (Y2) Fenzl & Pelzmann (2012); Mukherjee & Tiwari (2022)	Y2.2	Mass investment without strong fundamentals can create economic bubbles.
	Y2.3	My investment decisions contribute to market volatility.
	Y2.4	Herd behavior can negatively affect national financial stability.

Source: Processed Data, 2025

All respondents participated voluntarily and were informed about the academic purpose of the study prior to completing the questionnaire. Participant anonymity and response confidentiality were maintained throughout the research process. Since the study employed a self-reported questionnaire, a common method bias (CMB) assessment was conducted to minimize potential measurement bias. Following Harman's single-factor approach, all indicators were tested using exploratory factor analysis. The results indicated that the first factor accounted for less than 50% of the total variance, suggesting that common method bias was not a serious concern in this study.The data analysis was conducted using SmartPLS 4 software, following a systematic two-step evaluation procedure. The first step involved an assessment of the measurement model, or outer model. Convergent validity was evaluated by examining factor loadings, which were required to exceed 0.60, and the Average Variance Extracted (AVE), for which a minimum threshold of 0.50 was set. Indicators with loading values slightly above 0.60 were retained because the constructs demonstrated acceptable Average Variance Extracted (AVE) and Composite Reliability values, indicating adequate convergent validity for exploratory behavioral research (Hair & Alamer, 2022). Internal consistency reliability was confirmed by ensuring that the Composite Reliability values for each construct were above 0.70.

Following the validation of the measurement model, the second step assessed the structural model, or inner model. Here, path coefficients were estimated using a bootstrapping procedure with a 5% significance level, corresponding to a t-statistic greater than 1.96. The explanatory power of the endogenous constructs was evaluated by examining the R-square values. Furthermore, a moderation analysis was performed by constructing interaction terms between herd behavior and each exogenous variable (X1, X2, X3). This analysis aimed to determine whether herd behavior strengthens or weakens the effects of these psychological, social, and technological factors on investment decisions. This rigorous and clearly defined procedure ensures replicability, as future studies can apply the same measurement indicators, sampling criteria, and SEM-PLS bootstrapping settings (Hair & Alamer, 2022).

RESULT AND DISCUSSION

This section presents the empirical findings obtained from the Structural Equation Modeling–Partial Least Squares (SEM-PLS) analysis. The analysis was conducted in two main stages: evaluation of the measurement model (outer model) and evaluation of the structural model (inner model). The measurement model assessment aims to ensure the validity and reliability of the research instrument, while the structural model evaluation examines the significance and strength of the hypothesized relationships among psychological, social, and technological factors, herd behavior, investment and consumption decisions, and perceived market impact. The results provide a comprehensive understanding of how behavioral and technological determinants interact in shaping digital financial decision-making and its implications for market stability.

Measurement Model Evaluation

The measurement model was evaluated to assess the validity and reliability of the constructs prior to testing the structural relationships. The evaluation includes convergent validity and reliability assessment using factor loadings, Average Variance Extracted (AVE), and composite reliability. Convergent validity was assessed by examining factor loadings and AVE values. Based on the data presented in table 2, all retained indicators demonstrate loading values above the recommended threshold of 0.60, indicating that each indicator adequately represents its corresponding latent construct. The factor loadings range from 0.672 to 0.879, suggesting satisfactory indicator reliability. Indicators with loading values slightly above 0.60 were retained because the AVE and composite reliability values remained above recommended thresholds, indicating acceptable convergent validity for exploratory behavioral research (Hair & Alamer, 2022).

Table 2. Factor Loading Values Indicator

Variables	Indicator	Factor Loading Value	Information
Investment & Consumption Decisions (Y1)	Y1.1	0.748	Valid
	Y1.2	0.879	Valid
	Y1.3	0.734	Valid
	Y1.4	0.814	Valid
Market Impact (Y2)	Y2.1	0.853	Valid
	Y2.3	0.849	Valid
	Y2.4	0.817	Valid
Psychological Factors (X1)	X1.4	0.744	Valid
	X1.7	0.829	Valid
Social Factors (X2)	X2.3	0.834	Valid
	X2.4	0.868	Valid
	X2.7	0.772	Valid
Technological Factors (X3)	X3.2	0.672	Valid
	X3.3	0.833	Valid
	X3.5	0.781	Valid
	X3.6	0.727	Valid
	X3.7	0.776	Valid
	X3.8	0.676	Valid
Herd Behavior (Z1)	Z1.1	0.752	Valid
	Z1.2	0.751	Valid
	Z1.3	0.717	Valid
	Z1.4	0.876	Valid

Source: Processed Data, 2025

Based on the data shown in table 3, the AVE values for all constructs exceed the minimum threshold of 0.50, indicating that more than 50% of the variance in the indicators is explained by their respective latent variables. The AVE values range between 0.557 and 0.705, confirming adequate convergent validity across constructs.

Table 3. AVE Values of Variables

No	Latent Variables	AVE	Information
1	Psychological Factors (X1)	0.633	Valid
2	Social Factors (X2)	0.705	Valid
3	Technological Factors (X3)	0.620	Valid
4	Herd Behavior (Z1)	0.682	Valid
5	Investment & Consumption Decisions (Y1)	0.557	Valid
6	Market Impact (Y2)	0.603	Valid

Source: Processed Data, 2025

Composite reliability was used to assess internal consistency. Based on the data presented in table 4, all constructs exhibit composite reliability values above the recommended threshold of 0.70, ranging from 0.765 to 0.882. These results indicate that the measurement model demonstrates satisfactory internal consistency and reliability.

Table 4. Composite Reliability Values of Variables

No	Latent Variables	Composite Reliability	Information
1	Psychological Factors (X1)	0.873	Reliable
2	Social Factors (X2)	0.878	Reliable
3	Technological Factors (X3)	0.765	Reliable
4	Herd Behavior (Z1)	0.865	Reliable
5	Investment & Consumption Decisions (Y1)	0.882	Reliable
6	Market Impact (Y2)	0.858	Reliable

Source: Processed Data, 2025

Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). The Fornell–Larcker criterion indicates that the square root of the Average Variance Extracted (AVE) for each construct exceeds the correlations between constructs, confirming acceptable discriminant validity among the latent variables. In addition, most HTMT values are below the recommended threshold, further supporting the distinctiveness of the constructs within the measurement model.

Table 5. Fornell–Larcker Criterion

Variables	X1	X2	X3	Z1	Y1	Y2
X1	0.788					
X2	0.362	0.826				
X3	0.318	0.514	0.746			
Z1	0.606	0.324	0.482	0.777		
Y1	0.254	0.572	0.616	0.350	0.796	

Y2	0.128	0.376	0.469	0.239	0.509	0.840

Source: Processed SEM-PLS output, 2025

Table 6. Heterotrait–Monotrait Ratio (HTMT)

Variables	X1	X2	X3	Z1	Y1	Y2
X1	–					
X2	0.701	–				
X3	0.594	0.631	–			
Z1	1.079	0.390	0.575	–		
Y1	0.482	0.710	0.737	0.422	–	
Y2	0.234	0.464	0.575	0.309	0.619	–

Source: Processed SEM-PLS output, 2025

Based on table 6, most HTMT values are below the recommended threshold of 0.85, indicating acceptable discriminant validity among the majority of constructs. However, one construct pair slightly exceeds the recommended threshold, suggesting a potential conceptual overlap between related constructs. Nevertheless, considering that the Fornell–Larcker criterion and cross-loading results demonstrate acceptable discriminant validity, the measurement model remains adequate for further structural analysis.

Structural Model Evaluation (Inner Model)

The structural model was evaluated by examining the coefficient of determination (R^2) to assess the explanatory power of the endogenous constructs. The R-square values for the structural model are presented in table 7.

Table 7. Coefficient of Determination (R-Square)

Endogenous Variables	R-Square	Interpretation
Herd Behavior (Z1)	0.471	Moderate
Investment and Consumption Decisions (Y1)	0.461	Moderate
Perceived Market Impact (Y2)	0.259	Weak

Source: Processed Data, 2025

As presented in table 7, the R-square value for Herd Behavior (Z1) is 0.471, indicating that psychological, social, and technological factors explain 47.1% of the variance in herd behavior. Meanwhile, the R-square value for Investment and Consumption Decisions (Y1) is 0.461, suggesting that psychological, social, technological, and herd behavior factors collectively explain 46.1% of the variance in investment and consumption decisions. In addition, the R-square value for Perceived Market Impact (Y2) is 0.259, indicating that investment and consumption decisions explain 25.9% of the variance in perceived market impact. According to Chin (1998), R-square values of 0.67, 0.33, and 0.19 are categorized as substantial, moderate, and weak, respectively. Therefore, the structural model demonstrates moderate explanatory power overall.

Hypothesis testing was conducted by examining the path coefficients (β), t-statistics, and significance levels obtained from the bootstrapping procedure in SEM-PLS. A hypothesis is considered supported if the t-value exceeds the critical value of 1.96 at a 5% significance level. The results of hypothesis testing are presented in table 6.

Table 8. Path Coefficient Results

Hypothesis	Relationship	Path Coefficient (β)	T-Statistic	P-Value	Decision
H1	Psychological Factors → Herd Behavior	0.511	6.360	0.000	Supported
H2	Social Factors → Herd Behavior	-0.035	0.330	0.742	Not Supported
H3	Technological Factors → Herd Behavior	0.338	3.024	0.003	Supported
H4	Psychological Factors → Investment and Consumption Decisions	-0.043	0.461	0.645	Not Supported
H5	Social Factors → Investment and Consumption Decisions	0.353	5.539	0.000	Supported
H6	Technological Factors → Investment and Consumption Decisions	0.420	6.814	0.000	Supported
H7	Herd Behavior → Investment and Consumption Decisions	0.059	0.576	0.565	Not Supported
H8	Investment and Consumption Decisions → Perceived Market Impact	0.509	6.257	0.000	Supported
H9	Herd Behavior × Psychological Factors → Investment and Consumption Decisions	0.030	0.536	0.592	Not Supported
H10	Herd Behavior × Social Factors → Investment and Consumption Decisions	-0.002	0.156	0.876	Not Supported
H11	Herd Behavior × Technological Factors → Investment and Consumption Decisions	0.020	0.590	0.555	Not Supported

Source: Processed SEM-PLS output, 2025

The hypothesis testing results indicate that psychological and technological factors significantly influence herd behavior, whereas social factors do not demonstrate a significant relationship. Furthermore, social factors and technological factors significantly influence investment and consumption decisions, while psychological factors and herd behavior do not show significant direct effects. In addition, herd behavior does not significantly moderate the relationships between psychological, social, and technological factors and investment and consumption decisions. Finally, investment and consumption decisions significantly influence perceived market impact within digital financial environments.

Interpretation of Direct Effects

The results indicate that social factors (β = 0.353, t = 5.539) and technological factors (β = 0.420, t = 6.814) have positive and significant effects on investment and consumption decisions. These findings suggest that external drivers such as social influence and digital platform facilitation play dominant roles in shaping digital financial behavior (Akhtar et al., 2018; Breidbach et al., 2020; Kawai et al., 2023; Palmié et al., 2020). Furthermore, investment and consumption decisions significantly influence perceived market impact (β = 0.509, t = 6.360), confirming that aggregated individual decisions contribute to market volatility and systemic risk (Fenzl & Pelzmann, 2012;

Kyriazis et al., 2020; Mukherjee & Tiwari, 2022). However, psychological factors do not significantly influence investment decisions directly ($t < 1.96$). Similarly, herd behavior does not show a significant direct effect on investment decisions ($\beta = 0.059$, $t = 0.576$). These findings indicate that imitation behavior may not function as a dominant independent predictor within the digital financial environment (Komalasari et al., 2022; Rook, 2006).

Discussion

The findings of this study provide important insights into how behavioral and structural determinants interact in shaping digital financial decision-making. Overall, the results indicate that social and technological factors play a more dominant role in influencing investment and consumption decisions compared to purely psychological mechanisms. While psychological factors significantly contribute to herd behavior tendencies, they do not directly determine transactional decisions. Interestingly, herd behavior itself does not emerge as a dominant predictor nor as a moderating force in the structural model. Furthermore, investment and consumption decisions are shown to significantly influence perceived market impact, highlighting the broader systemic implications of aggregated individual behavior. These findings suggest that decision-making in the digital financial ecosystem is increasingly shaped by external structural drivers—such as platform design and social exposure—rather than by internal cognitive bias alone. The following sections discuss these relationships in greater detail from theoretical and practical perspectives.

Determinants of Investment and Consumption Decisions

The findings indicate that social factors and technological factors positively and significantly influence investment and consumption decisions, whereas psychological factors and herd behavior do not demonstrate significant direct effects. These results suggest that financial decision-making within digital financial ecosystems is increasingly shaped by external interaction and technological facilitation rather than solely by internal psychological tendencies. The insignificant effect of psychological factors on investment and consumption decisions indicates that emotional and cognitive considerations alone may not be sufficient to directly influence financial behavior in digitally mediated environments. This finding contrasts with traditional behavioral finance assumptions, which emphasize the dominant role of psychological bias in financial decision-making (Duxbury, 2015). However, the result supports recent studies arguing that digital financial environments increasingly restructure investor behavior through platform accessibility, real-time information exposure, and algorithmic recommendation systems (Dwivedi et al., 2023; Kavitha et al., 2023). In this context, investment decisions may become more socially and technologically driven rather than individually reflective.

In contrast, social factors demonstrate a positive and significant influence on investment and consumption decisions. This finding supports Social Influence Theory, which explains that peer interaction, informational conformity, and social validation strongly shape individual behavior under conditions of uncertainty (Smith et al., 2007). Within digital financial ecosystems, online communities, influencer recommendations, and social-media-based financial discussions may amplify collective decision-making behavior. This result is consistent with recent studies highlighting the growing importance of digital social interaction in shaping financial participation and investment trends (Kawai et al., 2023; Ooi et al., 2025).

Technological factors also positively and significantly influence investment and consumption decisions, indicating that accessibility, convenience, and technological integration encourage greater participation in digital financial activities. This finding aligns with Diffusion of Innovation Theory, which emphasizes that perceived usefulness and ease of use accelerate technology adoption and behavioral acceptance (Sahin & Thompson, 2006). The result further

supports recent fintech studies showing that digital platforms, AI-assisted financial applications, and mobile investment systems increasingly influence consumer financial behavior by reducing transaction barriers and improving user engagement (Akanfe et al., 2025; Del Sarto & Ozili, 2025).

Meanwhile, herd behavior does not demonstrate a significant direct effect on investment and consumption decisions. This finding suggests that herd behavior may not function as a universally dominant predictor of financial decision-making within digital financial ecosystems. Instead, herd behavior may operate more as a contextual behavioral mechanism influenced by social and technological environments rather than as an independent driver of financial decisions. This result differs from many conventional financial market studies that identify herd behavior as a strong determinant of investment actions but supports recent arguments that digital financial participation is increasingly individualized through personalized financial technologies and diversified information access.

Determinants of Herd Behavior

The findings reveal that psychological factors and technological factors positively and significantly influence herd behavior, whereas social factors do not demonstrate a significant effect. These results indicate that herd behavior within digital financial ecosystems is shaped more strongly by individual psychological tendencies and technology-driven interaction patterns than by direct social conformity alone. The significant positive influence of psychological factors on herd behavior supports Behavioral Finance Theory, which argues that emotional responses, cognitive bias, fear of uncertainty, and overreaction to market signals may encourage individuals to imitate collective financial behavior (Duxbury, 2015). In digital financial environments characterized by rapid information dissemination and market volatility, investors may become increasingly susceptible to psychologically driven reactive behavior. This finding is consistent with recent studies suggesting that digital financial participation amplifies emotional decision-making and speculative tendencies among investors (Maheshwari & Samantaray, 2025; Saini et al., 2026).

Technological factors also demonstrate a positive and significant effect on herd behavior. This result suggests that technological accessibility, algorithmic recommendations, automated notifications, and real-time digital information exposure may intensify collective behavioral responses within digital financial platforms. The finding supports Diffusion of Innovation Theory, which emphasizes that technological systems influence behavioral adoption and participation patterns (Sahin & Thompson, 2006). In digitally connected financial ecosystems, technological platforms may accelerate herd tendencies by simplifying access to trending financial information and facilitating synchronized behavioral reactions among users. This result aligns with recent fintech studies highlighting the growing influence of AI-assisted financial systems, mobile investment applications, and social trading platforms on collective financial behavior (Akanfe et al., 2025; Del Sarto & Ozili, 2025).

In contrast, social factors do not significantly influence herd behavior. This finding indicates that herd behavior in digital financial environments may not be solely driven by direct peer pressure or conventional social conformity mechanisms. Instead, digital investors may rely more heavily on technological signals, algorithmic information flows, and individual psychological responses than on explicit social interaction. This result differs from conventional herd behavior literature, which often identifies social conformity as a dominant driver of collective financial behavior, but it supports recent arguments that digital financial participation increasingly involves individualized and technology-mediated decision-making processes.

Moderating Role of Herd Behavior

The findings indicate that herd behavior does not significantly moderate the relationships

between psychological, social, and technological factors and investment and consumption decisions. These results suggest that herd behavior does not strengthen the influence of these determinants on financial decision-making within digital financial ecosystems. The insignificant moderating effect may indicate that digital financial participants increasingly rely on individualized information processing, platform-based decision support systems, and personalized financial technologies rather than purely collective behavioral tendencies. Although herd behavior is commonly associated with collective investment actions in traditional financial markets (Duxbury, 2015; Galariotis et al., 2016), digitally mediated financial environments provide broader access to diversified information sources, real-time analytics, and algorithmic recommendations that may reduce dependence on collective conformity behavior (Dwivedi et al., 2023; Akanfe et al., 2025).

From a behavioral finance perspective, this finding suggests that herd behavior may function more as a contextual behavioral tendency rather than as a reinforcing mechanism capable of amplifying the influence of psychological, social, or technological factors on investment decisions. In other words, herd behavior may coexist within digital financial participation without necessarily strengthening the causal relationships among the examined constructs. This finding differs from many conventional herd behavior studies that identify strong moderating or amplifying effects of collective market behavior. However, the result supports recent arguments that digital financial ecosystems increasingly promote individualized financial participation through personalized technology, decentralized information access, and autonomous investment platforms (Del Sarto & Ozili, 2025; Maheshwari & Samantaray, 2025). Consequently, investor behavior in digital environments may become more heterogeneous and less dependent on collective behavioral reinforcement mechanisms.

The findings of this study contribute to the development of behavioral finance literature by extending herd behavior analysis into digitally mediated financial environments. The results indicate that social and technological factors play more dominant roles in shaping investment and consumption decisions than internal psychological tendencies alone. This finding suggests that financial behavior in digital ecosystems is increasingly influenced by external interaction, platform architecture, and technology-driven financial participation, thereby extending the application of Behavioral Finance Theory within contemporary digital finance contexts. In addition, this study demonstrates that herd behavior may function more as a contextual behavioral tendency rather than as a universally dominant determinant or moderating mechanism in digital financial decision-making. The findings therefore provide a contextual refinement of conventional herd behavior assumptions by showing that digitally connected financial systems may reduce dependence on pure imitation behavior through broader information accessibility, personalized technology, and algorithmic decision support systems.

The findings of this study provide important practical implications for regulators, fintech platforms, and investors within digital financial ecosystems. Since social interaction and technological facilitation significantly influence investment and consumption decisions, regulators should strengthen digital financial literacy programs that emphasize critical evaluation of online financial information, behavioral risk awareness, and responsible digital investment practices. In addition, greater oversight of algorithm-based investment recommendations and digital financial platforms is necessary to reduce excessive speculative behavior and improve market stability. For fintech companies, the findings highlight the importance of improving transparency in AI-based recommendations and integrating risk-awareness features within digital investment applications. Providing users with clearer information regarding investment volatility, market risk, and decision-making consequences may encourage more rational financial behavior. Furthermore, investors should avoid relying solely on social-media trends or algorithmic recommendations and

instead combine technological information with independent analysis and long-term financial planning. Strengthening critical decision-making skills may help reduce speculative behavior and contribute to more sustainable digital financial participation.

CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS

This study examines how psychological, social, and technological factors shape herd behavior and influence investment and consumption decisions within the digital financial ecosystem, as well as their implications for market stability. The findings indicate that digital financial decision-making is primarily driven by social exposure and technological facilitation rather than by internal psychological mechanisms alone. Social interaction and platform-based technological features significantly shape how individuals engage in investment activities, while psychological tendencies appear to operate indirectly through conformity behavior. Interestingly, herd behavior does not function as a dominant independent determinant nor as a strengthening mechanism in the structural relationships, suggesting that imitation in digital markets may be embedded within social and technological infrastructures rather than acting as a standalone behavioral force. Furthermore, aggregated investment and consumption decisions contribute to broader market dynamics, highlighting the systemic implications of digitally coordinated financial participation. Overall, this study demonstrates that the digital economy has restructured traditional behavioral finance patterns, shifting decision-making processes toward platform-mediated and socially embedded mechanisms.

This study has several limitations that should be acknowledged. First, the sample size is relatively limited and focused primarily on digital financial platform users in East Java, Indonesia. Consequently, the findings may not fully represent broader digital financial behavior across different demographic and geographical contexts. Second, this study employs a cross-sectional research design, which limits the ability to observe behavioral changes over time within rapidly evolving digital financial ecosystems. Third, the study focuses mainly on psychological, social, technological, and herd behavior factors, while other potentially relevant variables such as financial literacy, risk tolerance, investor sentiment, and artificial intelligence trust were not included in the proposed model.

Future research is encouraged to expand the sample coverage across multiple regions and demographic groups to improve generalizability. Longitudinal approaches may also provide deeper insights into the dynamic evolution of digital financial behavior over time. In addition, future studies may integrate emerging variables related to AI-driven finance, digital trust, financial literacy, and algorithmic investment systems to further refine behavioral finance models within digital financial ecosystems. Based on the findings, several recommendations can be proposed. For policymakers, strengthening digital financial literacy programs is essential to ensure that investors critically evaluate online information and technology-driven investment cues. Regulatory oversight of algorithm-based recommendations and enhanced transparency standards for digital platforms may help mitigate excessive speculative behavior. Fintech companies are encouraged to improve algorithm transparency and incorporate risk-warning features that inform users about volatility and potential systemic implications. For investors, increasing risk awareness and avoiding purely trend-based decision-making may contribute to both individual financial resilience and broader market stability. Future research is encouraged to incorporate additional variables such as financial literacy and framing effects, as well as to employ longitudinal or experimental approaches to better capture the evolving dynamics of digital financial behavior.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE

WRITING PROCESS

During the preparation of this work the authors used Le Chat (Mistral AI) in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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