International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

The Influence of Artificial Intelligence and Social Media on Investment Behaviour Among Young Adults: Examining Trust, Herd Mentality, Financial Literacy, and the Credibility of AI-Generated Financial Advice

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Abstract

The rapid growth of Artificial Intelligence (AI) and social media has transformed how young adults access financial information and make investment decisions, raising questions about the credibility of AI-generated advice, the influence of social validation, and the role of financial literacy in shaping investor behaviour. This study examines the relationship between exposure to AI-generated financial advice and investment decision-making among young adults aged 18–35, and analyses the combined influence of trust in AI-generated advice, financial literacy, social media influence, and herd mentality on their investment choices. A quantitative, cross-sectional research design was adopted, using a structured Likert-scale questionnaire distributed via convenience sampling, yielding 50 valid responses. Data were analysed using Cronbach's alpha for construct reliability, Pearson correlation to examine relationships between constructs, and multiple linear regression to test the study's two hypotheses. Results showed that exposure to AI-generated financial advice significantly predicted investment decision-making on its own ($R^2 = .412$, $p < .001$). In the combined regression model, trust in AI-generated advice and social media influence emerged as significant predictors, together explaining 55.7% of the variance in investment decision-making ($R^2 = .557$, $p < .001$), while financial literacy and herd mentality were not statistically significant. Notably, respondents reported low outright trust in AI-generated advice yet frequently verified it before acting — a cautious pattern of engagement that did not diminish AI's behavioural influence. Similarly, self-assessed financial literacy did not translate into reduced susceptibility to digital influence, despite respondents' belief that it would. These findings suggest that AI and social media function as closely linked, dominant forces shaping young adults' investment behaviour, and point to the need for financial education and AI design approaches that target applied decision-making rather than self-reported knowledge or trust alone.

1. Introduction

1.1 Background of the Study

The rapid advancement of digital technology has significantly transformed the financial services industry and the way individuals make investment decisions. The increasing availability of online trading platforms, mobile investment applications, and Financial Technology (FinTech) services has improved accessibility to financial markets and reduced traditional barriers to investing. Digital innovations have enabled investors to access real-time market information, execute transactions instantly, and manage their investment portfolios with greater convenience than ever before. As a result, investors are increasingly relying on digital sources of information and technology-driven tools to support their financial decision-making processes. This shift towards technology-enabled investing has not only expanded participation in financial markets but has also fundamentally changed the way individuals obtain, evaluate, and act upon investment-related information.

In the wake of this digital transformation, Artificial Intelligence (AI) and social media have emerged as influential sources of financial guidance. AI-powered tools are increasingly being used to support financial analysis, portfolio management, and investment decision-making among retail investors (Dwivedi et al., 2023). Simultaneously, young investors are turning to financial influencers, or “finfluencers,” on social media platforms such as YouTube, TikTok, and Instagram for information and advice about investments (Espeute & Preece, 2024). While these developments have significantly improved access to financial information, they have also raised concerns regarding the credibility of AI-generated advice, the influence of herd mentality, and the role of financial literacy in shaping investment decisions. Young adults aged 18–35, who are the primary consumers of these technologies and the main focus of this study, represent a demographic particularly exposed to both the opportunities and risks associated with digital financial information. It is therefore important to examine how AI-generated financial advice and social media influence their investment behaviour.

1.2 Growth of Artificial Intelligence in Financial Services

Historically for financial institutions, the mitigation of risk and the extraction of keen investment insights from market trends, historical price changes, economic indicators and company financial statements have always involved human expertise. However, the rise of global financial markets, high-frequency trading, and real-time information dissemination has resulted in the generation of vast amounts of structured and unstructured data on a daily basis, prompting the need for more efficient analysis tools. Processing and analysing such large datasets using traditional methods can be both time-consuming and resource-intensive. Artificial Intelligence (AI) has emerged as one of the most significant innovations addressing these challenges, enabling organisations to automate analytical processes, identify repeating patterns in large datasets, and organise information at speeds far beyond human capability.

AI’s role has expanded considerably within investment management and financial advisory services. Financial institutions increasingly utilise AI-powered systems for portfolio optimization, algorithmic trading, fraud detection, credit risk assessment, and customer service automation, while retail investors are gaining access to AI-driven financial tools through robo-advisors and large language model (LLM)-based applications. In addition, the adoption of robo-advisors has provided users with automated investment recommendations based on their risk tolerance and investment preferences, further reducing the barrier to entry. Generative AI represents a significant technological development due to its ability to generate human-like responses, process natural language, and generate information through conversational interfaces (Dwivedi et. al, 2023).

The growing accessibility of AI-powered financial tools has contributed to the democratisation of financial information by enabling individuals to access resources that were previously available primarily through financial professionals and institutions. However, the increasing reliance on AI-generated information has also raised concerns regarding the accuracy, transparency, and reliability of AI-generated financial advice (European Central Bank, 2024).

Generative AI has further accelerated this trend, representing a significant technological development due to its ability to generate human-like responses, process natural language, and provide information through conversational interfaces (Dwivedi et al., 2023). AI chatbots are increasingly being used to explain financial concepts, analyse market information, and respond to investment-related queries. As AI technologies continue to evolve and become more accessible, they are increasingly being integrated into digital financial platforms and advisory services, transforming the way individuals access financial information and investment guidance.

1.3 Rise of Fintech and AI-powered Financial Guidance

Traditionally, investors seeking financial advice relied on financial advisors, wealth managers, brokerage firms, and banking institutions. These services often involved consultation fees, minimum investment requirements, and limited accessibility, making professional financial guidance unavailable to many retail investors. Consequently, investment decisions were largely influenced by financial professionals who possessed specialised knowledge and acted as intermediaries between investors and financial markets.

The emergence of FinTech and digital investment platforms such as Robinhood, Zerodha, Groww, and Interactive Brokers has simplified the investing process by allowing users to open accounts, access market information, and execute trades through mobile applications and online platforms. These innovations have reduced transaction costs and lowered barriers to entry, allowing a broader range of individuals to participate in investing. As a result, FinTech has contributed to the democratisation of financial services and increased retail investor participation in financial markets.

Recent advances in AI has further bolstered this process, allowing users to seek financial guidance through conversational interfaces. AI-powered systems are increasingly capable of analysing market information, generating investment insights, and assisting investors in financial decision-making processes (Jamal et al., 2025). Similarly, recent research on AI-generated financial advice highlights the growing ability of generative AI systems to provide personalised financial information and investment-related recommendations to retail investors (Bosompim et al., 2025). This growing trend, especially among younger investors who are likely to be more tech-savvy, reflects a broader shift in how financial information is being accessed and consumed.

1.4 Social Media and the Influence of Finfluencers

The rapid growth of social media platforms has been another significant factor influencing the way financial information is being consumed. Platforms such as YouTube, Instagram, TikTok, X (formerly Twitter), and Reddit have become important sources of financial content, enabling users to access investment-related information instantly and interact with financial discussions in real time. This shift has increased the accessibility of financial information and has altered the way investors learn about financial markets and investment opportunities (Espeute & Preece, 2024).

One of the most significant developments arising from this trend has been the emergence of financial influencers, commonly referred to as “finfluencers.” Finfluencers are individuals who create and share financial content on social media platforms, often discussing topics such as investing, personal finance, wealth creation, cryptocurrency, and stock market trends. Through videos, posts, livestreams, and short-form content, finfluencers have attracted large audiences and have become influential sources of investment-related information, particularly among younger investors. Research suggests that many retail investors increasingly engage with financial content creators as a source of investment education and market insights (Espeute & Preece, 2024).

The growing popularity of finfluencers has created both opportunities and challenges for investors. On one hand, social media has increased financial awareness and provided individuals with access to financial knowledge that may previously have been difficult to obtain. On the other hand, the quality and reliability of financial information shared online can vary significantly. Unlike licensed financial advisors, many finfluencers are not subject to the same professional standards or regulatory requirements, raising concerns regarding misinformation, conflicts of interest, and the promotion of speculative investment behaviour (Kumar, 2025). The rapid dissemination of financial content through social media also increases the likelihood that investment decisions may be influenced by popularity and social trends rather than objective financial analysis.

1.5 Problem Statement

Since young adults are among the most active users of AI-powered technologies and social media platforms, they are particularly exposed to both the opportunities and risks associated with digital financial information. The ease with which investment-related content can be accessed may expose individuals to misinformation, biased recommendations, and social influence, potentially affecting the quality of their investment decisions. However, despite the growing use of AI-generated financial advice and social media as sources of investment information, their influence on investor behaviour remains insufficiently understood.

Existing research has often examined AI adoption, social media influence, financial literacy, trust, and herd behaviour as separate areas of investigation. Consequently, there is limited understanding of how these factors interact to shape the investment decision-making of young adults. This creates a need for further research into the influence of Artificial Intelligence and social media on investment behaviour, particularly with regard to trust, herd mentality, financial literacy, and the perceived credibility of AI-generated financial advice.

1.6 Research Gap

Much of the existing literature examines individual aspects of digital investment behaviour in isolation. Studies on AI in finance primarily focus on technology adoption, decision-making effectiveness, and the use of AI-powered financial tools, while research on social media generally emphasises investor sentiment, information dissemination, finfluencer influence, and online investment communities. Similarly, financial literacy and herd mentality have been widely studied as independent determinants of investor behaviour. As a result, there is limited understanding of how trust in AI-generated financial advice, financial literacy, social media influence, and herd mentality interact to shape the investment behaviour of young adults.

Furthermore, while existing studies have examined the adoption of AI-powered financial tools and the influence of social media on investment decisions separately, relatively little attention has been given to their combined impact. Given the increasing reliance on both AI-generated and social media-based sources of financial information, there is a need for a more integrated understanding of their influence on investment decision-making.

This study seeks to address this gap. By integrating these factors into a single framework, it aims to contribute to a more comprehensive understanding of how emerging digital information sources shape investment behaviour in an increasingly technology-driven financial environment.

1.7 Significance of the Study

This study is significant in several ways. From an academic perspective, it contributes to the growing body of literature on AI-generated financial advice .

From a practical perspective, the study may help young adults better understand the opportunities and risks associated with relying on AI-generated financial advice and social media-based investment information. The findings may also highlight the importance of financial literacy and critical evaluation when using digital sources of financial guidance.

From an industry perspective, the study may provide valuable insights for financial institutions and FinTech companies developing AI-powered financial tools. Understanding the factors that influence user trust and adoption can support the development of more transparent, reliable, and user-centred financial technologies.

Finally, from a regulatory perspective, the study may assist policymakers and regulatory bodies in understanding the challenges associated with AI-generated financial content and the growing influence of finfluencers on investment decisions. As digital financial information becomes increasingly accessible, the findings may contribute to discussions surrounding investor protection, financial misinformation, and the responsible use of AI in financial services.

2. Review of Literature

2.1 Artificial Intelligence and Investment Decision-Making

Unlike traditional investment approaches that rely heavily on human judgement and manual analysis, AI-driven systems are capable of processing vast amounts of structured and unstructured data, identifying patterns, generating forecasts, and providing investment recommendations in real time. The growing integration of AI into financial services has enabled both institutional and retail investors to make more informed decisions through the use of predictive analytics, algorithmic models, robo-advisors, and conversational AI systems. Existing studies suggest that AI has the potential to improve investment outcomes by enhancing information processing capabilities and reducing inefficiencies associated with human decision-making.

Jamal et al. (2025) found that the adoption of AI significantly improved investment outcomes among individual investors by enabling more effective analysis of financial information and supporting informed investment decisions. However, the study also revealed that the benefits of AI are not uniform across all investors, as financial literacy plays a significant mediating role in determining how effectively AI-generated information is utilised. Investors with higher levels of financial literacy were found to derive greater benefits from AI-powered financial tools, suggesting that technological capabilities alone may not guarantee improved investment performance. Similarly, Kapur and Shrivastava (2025) argue that conversational AI systems, including chatbots and robo-advisors, can reduce information asymmetry and improve access to financial advice by providing investors with personalised and real-time financial guidance. Their findings indicate that AI has the potential to broaden access to investment information, particularly among individuals who may not have access to traditional financial advisory services.

The growing popularity of conversational AI and generative AI technologies has further expanded the role of AI within financial decision-making. Unlike earlier forms of financial technology that primarily operated through predefined algorithms, modern generative AI systems are capable of engaging directly with users through natural language interactions and providing personalised financial information on demand. Kapur and Shrivastava (2025) note that conversational AI allows investors to obtain financial information, portfolio insights, and investment recommendations through interactive and user-friendly interfaces. As a result, AI-generated financial advice has become increasingly accessible to retail investors and is playing a growing role in how investment information is obtained and utilised.

Despite these advantages, the literature also highlights significant concerns regarding the reliability and quality of AI-generated financial information. Keeley (2023) found that AI-generated synthetic financial content was capable of significantly influencing investor sentiment and altering investment outlooks, even when the information provided was inaccurate or misleading. The findings suggest that persuasive AI-generated content can affect investor perceptions and decision-making, raising concerns regarding the potential influence of AI-generated misinformation. Similarly, Rangapur et al. (2023) identify digital financial misinformation as a growing challenge for investors and financial markets, noting that misleading financial information can influence investor behaviour and contribute to poor investment decisions. As generative AI technologies become increasingly capable of producing realistic financial content, concerns regarding information accuracy and reliability are likely to become more significant.

2.2 Trust and Credibility of AI-Generated Financial Advice

Trust has emerged as one of the most significant factors influencing the adoption and effectiveness of AI-generated financial advice. Investors remain cautious about relying on recommendations produced by algorithmic systems. Unlike traditional financial advisors, who are able to explain their reasoning, answer follow-up questions, and establish interpersonal relationships with clients, AI systems often operate as complex and opaque technologies whose decision-making processes may not be fully understood by users. Consequently, the extent to which investors perceive AI-generated financial advice as trustworthy and credible plays a crucial role in determining whether such advice is accepted and acted upon.

Sungkarungsri and Kiattisin (2026) found that trust serves as the primary mechanism linking users' perceptions of AI systems to their intention to adopt AI-powered financial advisory services. Their study demonstrated that factors such as transparency, accountability, privacy protection, and ethical system design significantly enhance trust in AI-generated recommendations. Furthermore, trust was found to positively influence both user loyalty and willingness to advocate for AI-based financial advisory services. These findings suggest that investors are more likely to rely on AI-generated financial advice when they perceive the technology to be transparent, secure, and ethically governed.

Similarly, Aini (2025) found that trust plays a central mediating role between individual characteristics and financial behaviour when using robo-advisors. The study revealed that AI literacy, trust propensity, and risk tolerance significantly influence trust in AI-powered financial systems, which subsequently affects users' financial behaviour. Investors who possess greater knowledge of AI technologies were more likely to trust and utilise robo-advisors effectively, highlighting the importance of understanding how AI systems operate. These findings suggest that trust is not solely determined by the technical performance of AI systems but is also influenced by users' cognitive abilities and personal characteristics.

Phan et al. (2026) argue that transparency and explainability are critical components of trust in AI-generated financial advice. Financial decisions often involve significant uncertainty and risk, making it important for investors to understand the rationale behind recommendations before acting upon them. When AI systems operate as "black boxes" that provide recommendations without adequate explanation, users may question the reliability and credibility of the information provided. Consequently, explainable AI has become an increasingly important consideration within both financial technology development and AI governance frameworks.

Keeley (2023) demonstrated that AI-generated synthetic financial content can significantly influence investor sentiment and investment outlooks even when such information is not derived from verified sources. Similarly, Rangapur et al. (2023) argue that the increasing prevalence of digital financial misinformation creates additional challenges for investors attempting to evaluate the quality and reliability of financial information. As AI-generated content becomes more sophisticated, distinguishing credible financial advice from misleading information may become increasingly difficult.

2.3 Social Media and Investment Behaviour

Pallavi and Dsa (2025) argue that social media has become an influential factor in shaping investor sentiment and investment decision-making. Information shared through social media platforms can influence investor perceptions, affect attitudes towards investment opportunities, and contribute to market reactions. The speed at which information spreads through digital platforms enables investor sentiment to develop rapidly, often affecting trading behaviour and investment decisions. The CFA Institute (2024) similarly identifies social media as one of the most important sources of investment information for younger investors, many of whom rely on online content when evaluating investment opportunities and making financial decisions.

Pallavi and Dsa (2025) further identify confirmation bias, overreaction to information, and herd behaviour as common behavioural tendencies associated with social-media-driven investment decisions. The visibility of collective opinions and market sentiment may encourage investors to follow prevailing trends rather than conduct independent analysis, increasing the likelihood of emotionally driven investment decisions and speculative behaviour.

The literature also highlights concerns regarding the quality of financial information available through digital platforms. Rangapur et al. (2023) argue that online financial misinformation can manipulate investor behaviour, influence market sentiment, and contribute to market instability. The authors identify social media as a key channel through which misleading financial information can spread rapidly and reach large audiences. Similarly, Keeley (2023) found that AI-generated synthetic financial content was capable of significantly shifting investor sentiment and altering investment outlooks, demonstrating the persuasive potential of digitally generated financial information. Together, these findings suggest that investors may be influenced not only by the availability of information online but also by the credibility and persuasiveness of the content they encounter.

2.4 Finfluencers and Digital Financial Information

According to the CFA Institute (2024), finfluencers have become a significant source of investment information for Generation Z investors. Their influence is often attributed to their ability to present financial information in accessible and engaging formats, allowing them to build large audiences and establish strong relationships with followers. Unlike traditional financial professionals, finfluencers frequently communicate through informal and interactive content, enabling them to cultivate a sense of relatability and accessibility among their audiences.

Trust and perceived credibility have been identified as important factors underlying finfluencer influence. Chetan and Pandey (2025) argue that finfluencers often develop strong relationships with their audiences through consistent content creation and perceived authenticity. As a result, followers may view them as credible sources of financial information despite the absence of formal financial qualifications. The authors further note that behavioural factors such as trust, social influence, and fear of missing out (FOMO) contribute significantly to the effectiveness of finfluencer content in shaping investment behaviour.

Despite their growing influence, the literature highlights several concerns regarding finfluencer-generated content. Chetan and Pandey (2025) identify risks relating to misinformation, undisclosed sponsorships, conflicts of interest, and speculative investment recommendations. While finfluencers may improve financial awareness and participation, they may also contribute to poor investment outcomes when content prioritises engagement and popularity over accuracy and objectivity. Similarly, the CFA Institute (2024) highlights concerns regarding transparency, disclosure practices, and the adequacy of existing regulatory frameworks governing finfluencer activity. These concerns are particularly relevant given the financial consequences that may arise when investment decisions are influenced by unverified or commercially motivated content.

Recent developments in artificial intelligence have further transformed the finfluencer landscape through the emergence of AI-generated financial content and AI-driven finfluencers. Venkatesan and Ramdan (2026) argue that AI technologies are increasingly being used to generate personalised financial insights, investment recommendations, and market analysis for large online audiences. While such technologies may increase the accessibility and scale of financial information, they also raise concerns regarding reliability, accountability, and regulatory oversight, indicating that the growing influence of AI-driven finfluencers may further complicate investors' ability to distinguish credible financial advice from potentially misleading content.

2.5 Financial Literacy and Investment Behaviour

Financial literacy has long been recognised as an important determinant of investment behaviour and financial decision-making. Individuals with higher levels of financial literacy are generally better equipped to understand financial concepts, assess investment risks, and make informed investment decisions. As investment information becomes increasingly accessible through digital channels, financial literacy continues to play a critical role in enabling investors to interpret and utilise financial information effectively.

Jamal et al. (2025) found that financial literacy significantly mediates the relationship between AI adoption and investment outcomes. Their findings indicate that investors with greater financial knowledge are better able to utilise AI-generated insights when making investment decisions, resulting in improved investment outcomes. While AI-powered tools can support decision-making by providing personalised recommendations and market insights, the effectiveness of such tools ultimately depends on investors' ability to understand and interpret the information provided. Consequently, the benefits associated with AI adoption may not be realised equally across all investors.

Similar findings are reported by Kapur and Shrivastava (2025), who identify financial literacy as an important factor influencing the adoption and effective use of conversational AI within financial services. Their study suggests that financially literate investors are better able to evaluate AI-generated recommendations, understand associated investment risks, and critically assess the information provided by AI-powered platforms. Financial literacy therefore influences not only the adoption of AI-powered financial tools but also investors' ability to utilise AI-generated financial advice effectively.

Financial literacy also plays an important role in helping investors evaluate the credibility of financial information obtained through digital platforms. Rangapur et al. (2023) argue that financially literate individuals are better able to identify misleading financial content and critically assess investment-related information. This ability becomes increasingly important as investors are exposed to growing volumes of financial information from social media platforms, finfluencers, and AI-generated sources. By improving investors' capacity to evaluate information quality and credibility, financial literacy may reduce susceptibility to misinformation and support more informed investment decisions.

2.6 Herd Mentality and Social Influence

As investors are increasingly exposed to online discussions, market sentiment, and investment recommendations, their decisions may be shaped not only by fundamental analysis but also by the behaviour and opinions of other market participants. Consequently, recent literature has identified herd mentality as an important behavioural factor affecting investment behaviour within digital financial environments.

Pallavi and Dsa (2025) identify herd behaviour as one of the principal behavioural biases associated with social-media-driven investment decisions. Their findings suggest that investors may follow prevailing market trends or popular investment opinions because repeated exposure to collective sentiment reinforces the perception that such decisions are more likely to be correct. Consequently, investment decisions may become influenced by social validation rather than objective financial analysis.

Similarly, Chetan and Pandey (2025) argue that behavioural factors such as social influence and fear of missing out (FOMO) contribute significantly to the effectiveness of finfluencer content in shaping investment behaviour. By establishing credibility and fostering strong relationships with their audiences, finfluencers can influence followers' investment decisions beyond the objective quality of the information provided. This suggests that investors may be persuaded not only by financial evidence but also by the popularity and perceived authority of online personalities.

The CFA Institute (2024) further highlights the growing role of online investment communities in influencing younger investors. As investors increasingly engage with digital discussions and observe the behaviour of their peers, collective sentiment may become an important determinant of investment decisions. While these interactions can facilitate information sharing and financial learning, they may also encourage conformity and reduce the likelihood of independent evaluation.

2.7 Research Gap

Although existing literature has significantly advanced our understanding of the technological, informational and behavioural factors influencing investment decision-making, these have largely been examined independently. As a result, there remains limited understanding of how these collectively influence investment decision-making within contemporary digital financial environments. Furthermore, while recent studies have begun to examine various aspects and applications of AI-generated output on finance, relatively little empirical research has explored how young adults simultaneously rely on AI-generated financial advice, social media, and finfluencers when making investment decisions. Given that these information sources increasingly coexist within digital financial environments, examining them in isolation may not fully explain contemporary investment behaviour.

This study addresses these gaps by empirically examining the relationships between AI-generated financial advice, social media influence, financial literacy, herd mentality, and the investment behaviour of young adults. Using quantitative data collected through structured questionnaires, the study investigates the extent to which these factors are associated with investment behaviour and analyses their individual and collective influence within a single conceptual framework. The findings are expected to contribute to the growing literature on AI-enabled financial services while providing evidence that may inform the development of AI-powered financial tools, investor education initiatives, and regulatory frameworks for digital financial information.

3. Theoretical Background

3.1 Behavioural Finance Theory

Behavioural Finance Theory emerged as an alternative to traditional financial theories, which assume that investors behave rationally and consistently seek to maximise wealth. In contrast, behavioural finance draws upon principles from psychology and economics to explain how psychological, emotional, and social factors influence investment decisions, causing individuals to deviate from the assumptions of rational behaviour (Barberis & Thaler, 2003).

A central concept within Behavioural Finance Theory is bounded rationality, which proposes that investors' ability to process and evaluate information is constrained by cognitive limitations, incomplete information, and time constraints (Simon, 1955). Consequently, investors frequently rely on heuristics to simplify complex financial decisions. Although these mental shortcuts facilitate decision-making, they may also give rise to behavioural biases that influence investment behaviour.

Behavioural biases such as herd behaviour, overconfidence, confirmation bias, and loss aversion have been widely associated with investment decision-making. These may lead investors to imitate the actions of others, seek information that confirms existing beliefs, or place excessive confidence in particular sources of financial information despite contradictory evidence. As a result, investment decisions may deviate from those predicted by traditional financial theory.

3.2 Technology Acceptance Model (TAM)

While Behavioural Finance Theory explains how psychological and behavioural factors influence investment decisions, it does not fully explain the factors that determine whether investors adopt emerging financial technologies. As AI-generated financial advice becomes increasingly integrated into financial decision-making, understanding investors' acceptance of these technologies requires a complementary theoretical perspective. The Technology Acceptance Model (TAM), developed by Davis (1989), addresses this by explaining how users' perceptions influence their intention to use new technologies.

According to TAM, technology adoption is primarily determined by two key constructs: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that using a particular technology will enhance performance, while perceived ease of use reflects the degree to which the technology is considered effortless to learn and operate. Together, these perceptions shape users' attitudes towards technology, which subsequently influence their behavioural intention to use it.

The model has been widely applied to explain the adoption of information systems and financial technologies, including online banking, mobile payment systems, robo-advisors, and AI-powered financial platforms. Applied to this research, TAM provides a theoretical basis for understanding why young adults may utilise AI-generated financial advice when making investment decisions. Investors are more likely to adopt AI-powered financial tools when they perceive them to be useful in improving investment outcomes and easy to use.

3.3 Trust Commitment Theory

Although TAM explains technology adoption, it does not fully account for the uncertainty associated with financial decision-making. Investment decisions often involve significant financial risk, making trust an important factor in determining whether investors are willing to rely on AI-generated financial advice. Trust Commitment Theory, developed by Morgan and Hunt (1994), offers a complementary perspective by emphasising the importance of trust in establishing and maintaining successful relationships.

The theory proposes that trust and commitment are the two key determinants of enduring relationships. Trust refers to the confidence that one party has in the reliability, integrity, and competence of another, while commitment reflects the willingness to maintain a valued relationship over time. According to the theory, individuals are more likely to engage with a system or service when they perceive it to be trustworthy, reliable, and capable of meeting their expectations.

In AI-powered financial services, Trust Commitment Theory suggests that investors' willingness to adopt and continue using AI-generated financial advice depends not only on its functionality but also on the degree of trust they place in the technology. Factors such as transparency, explainability, reliability, and perceived accuracy contribute to the development of trust, which subsequently influences investors' confidence in AI-generated recommendations.

3.4 Social Proof Theory

Investment decisions are also shaped by the behaviour and opinions of others. Social Proof Theory, introduced by Cialdini (1984), proposes that individuals often rely on the actions and judgements of others to determine appropriate behaviour, particularly in situations characterised by uncertainty or limited information. Rather than evaluating all available information independently, individuals may perceive the behaviour of others as evidence of the appropriate course of action.

Within financial markets, Social Proof Theory suggests that investors are influenced by the opinions, recommendations, and actions of other market participants. The increasing use of social media platforms, online investment communities, and finfluencer content has amplified these influences by making investment opinions and market sentiment increasingly visible. Indicators such as follower counts, engagement metrics, trending investment topics, and positive testimonials may reinforce the credibility of financial information and strengthen investors' confidence in particular investment decisions.

From the perspective of digital investing, Social Proof Theory explains how social media and finfluencers shape investment behaviour beyond the objective quality of the information provided. Investors may interpret widespread endorsement or popularity as an indication of credibility, increasing their willingness to consider particular investment recommendations. Consequently, investment decisions may be shaped not only by personal judgement but also by perceived social consensus.

3.5 Herd Behaviour Theory

Herd Behaviour Theory explains the tendency of investors to imitate the actions of others rather than relying on independent judgement. This behaviour is particularly evident during periods of market uncertainty, where investors perceive prevailing market behaviour as an indication of superior information or reduced risk.

Herd behaviour may arise from informational influences, where investors believe that others possess better knowledge, or normative influences, where individuals seek to avoid the perceived consequences of deviating from the majority. Consequently, investment decisions may be driven by market sentiment rather than objective financial analysis.

In contemporary digital financial environments, Herd Behaviour Theory explains how exposure to social media discussions, finfluencer recommendations, and AI-generated financial content may encourage investors to follow popular investment trends. As investment information becomes increasingly visible across digital platforms, widespread opinions and collective sentiment may reinforce conformity in investment behaviour.

3.6 Information Processing Theory

While the preceding theories explain the behavioural, technological, and social influences affecting investment decisions, Information Processing Theory explains how individuals process information before making decisions. Originally proposed by Atkinson and Shiffrin (1968), the theory views decision-making as a cognitive process in which information is acquired, processed, stored, and retrieved before influencing behaviour. The quality of a decision therefore depends not only on the information available but also on an individual's ability to interpret and evaluate it effectively.

According to Information Processing Theory, individuals are exposed to large volumes of information from multiple sources, yet only a portion of this information is attended to, processed, and incorporated into decision-making. The way information is interpreted is influenced by cognitive abilities, prior knowledge, experience, and external environmental factors. Consequently, two individuals exposed to the same information may reach different conclusions depending on how they evaluate and interpret it.

For the present study, the theory provides a framework for understanding how investors evaluate information obtained from AI-generated financial advice, social media platforms, and finfluencers. Investors are required to interpret recommendations, assess their credibility, compare them with existing knowledge, and determine whether the information should influence their investment decisions. Financial literacy plays an important role in this process, as individuals with greater financial knowledge are generally better equipped to critically evaluate the quality and reliability of digital financial information before acting upon it.

Furthermore, the theory integrates the technological, behavioural, and social influences examined throughout this chapter. Whereas the preceding theories explain why investors adopt AI-powered technologies, trust digital financial advice, or are influenced by others, Information Processing Theory explains how this information is evaluated before shaping investment decisions.

4. Objectives of the Study

4.1 To examine the relationship between exposure to AI-generated financial advice and investment behaviour among young adults.

4.2 To analyse the influence of trust in AI-generated financial advice, financial literacy, and social media-based financial content on the investment decisions of young adults.

5. Hypothesis

H1: Exposure to AI-generated financial advice has a significant influence on the investment decision-making behaviour of young adults.

H2: Trust in AI-generated financial advice, financial literacy, and social media influence significantly affect investment decision-making among young adults.

6. Research Method

6.1 Research Design

This study adopted a quantitative research design, which was considered appropriate because it enables the collection of numerical data that can be statistically analysed to identify patterns, relationships, and associations between the variables under investigation. It was cross-sectional in nature, with data being collected from respondents once at a single point in time. This was done because the approach provides an efficient means of examining attitudes, perceptions, and behaviours within a defined population without requiring repeated observations over an extended period.

The research also adopted an explanatory design, as the primary objective was to examine the relationships between the independent variables—AI-generated financial advice, social media influence, financial literacy, and herd mentality—and the dependent variable, investment behaviour. By analysing these relationships, the study seeks to improve understanding of the factors that influence investment decision-making among young adults within digital financial environments.

6.2 Population and Sample

The target population for this study comprised young adults aged **18 to 35 years**, as this demographic represents one of the most active users of digital technologies, social media platforms, and AI-powered applications. Young adults are increasingly exposed to AI-generated financial advice, finfluencer content, and other digital sources of investment information, making them an appropriate population for examining the factors influencing investment behaviour in contemporary digital financial environments.

The study targeted individuals within this age group regardless of their level of investment experience. Rather than restricting participation to active investors or users of AI-powered financial tools, the study sought to capture respondents' perceptions, attitudes, and behaviours relating to AI-generated financial advice, social media influence, financial literacy, and herd mentality. This approach reflects the growing accessibility of digital financial information, where exposure to investment-related content extends beyond experienced investors. The questionnaire therefore examined respondents' perceptions of these constructs using structured Likert-scale statements.

The sample consisted of young adults who voluntarily agreed to participate after providing informed consent. Respondents completed a structured questionnaire designed to measure the relationships between AI-generated financial advice, social media influence, financial literacy, herd mentality, and investment behaviour, thereby aligning the sample with the objectives of the study.

6.3 Sampling Technique

This study employed a non-probability convenience sampling technique to recruit participants. Convenience sampling involves selecting respondents who are readily accessible and willing to participate in the study. This approach was considered appropriate due to the practical challenges associated with obtaining a comprehensive sampling frame of young adults exposed to digital financial information.

The questionnaire was administered electronically using Google Forms and distributed through WhatsApp, email, and the researcher's personal and professional networks, including friends, family members, and professional contacts. Participation was entirely voluntary, and respondents were invited to complete the questionnaire after providing informed consent. This approach enabled the researcher to efficiently reach individuals within the target population while facilitating the collection of data from respondents with varying levels of exposure to AI-generated financial advice, social media, and other digital financial information.

Although convenience sampling does not provide every member of the target population with an equal probability of selection, it is widely employed in behavioural and social science research where the objective is to examine relationships between variables rather than estimate population characteristics. Given the explanatory nature of this study and its focus on young adults' perceptions, convenience sampling was considered an appropriate and practical method for participant recruitment.

6.4 Sample Size

An initial target of approximately **100** completed responses was established to provide sufficient data for statistical analysis. Following the completion of data collection, a total of **50 valid responses** were obtained and included in the final analysis. All completed questionnaires were reviewed to ensure that the responses were suitable for analysis and met the requirements of the study. The final sample was therefore considered appropriate for addressing the research objectives and conducting the planned statistical analyses.

6.5 Questionnaire Design

A structured questionnaire was developed in accordance with the research objectives using Google Forms to collect primary data for this study, consisting of two sections. The first section included an informed consent statement outlining the purpose of the study, the voluntary nature of participation, and assurances regarding the confidentiality of respondents' information, followed by demographic questions relating to respondents' names and age. The second section comprised statements designed to measure the constructs examined in the study. These statements were organised into thematic categories relating to social media influence, trust in AI-generated financial advice, herd mentality, and financial literacy. Respondents indicated their level of agreement with each statement using a five-point Likert scale ranging from **1 (Strongly Disagree)** to **5 (Strongly Agree)**. The use of a standardised questionnaire ensured consistency in data collection and facilitated subsequent quantitative analysis.

6.6 Operationalisation of Variables

The constructs examined in this study were operationalised using multiple questionnaire items designed to measure respondents' perceptions and attitudes towards the variables identified in the conceptual framework:

Construct	Variable Type	Description
AI-generated financial advice	Independent	Respondents' perceptions of AI tools, AI-generated financial advice, and their use in financial decision-making.
Social media influence	Independent	Respondents' reliance on social media platforms and finfluencer content for investment-related information.
Herd mentality	Independent	Respondents' tendency to follow market trends, popular opinions, and investment behaviour of others.
Financial literacy	Independent	Respondents' self-assessed financial knowledge and ability to critically evaluate financial information.
Investment Behaviour	Dependent	Respondents' behaviour operationalised through the above variables.

6.7 Ethical Considerations

Ethical considerations were observed throughout the research process to ensure the rights, privacy, and well-being of all participants were protected. Prior to completing the questionnaire, respondents were provided with an informed consent statement outlining the purpose of the study, the voluntary nature of participation, and the intended use of the data for academic research. Only respondents who provided their consent proceeded to complete the questionnaire.

Participation in the study was entirely voluntary, and respondents were informed that they could choose not to participate or discontinue the questionnaire at any stage without penalty. No respondent was subjected to coercion or undue influence during the data collection process.

The information collected was treated confidentially and used solely for the purposes of this research. Responses were stored securely and accessed only by the researcher.

7. Data Analysis Techniques

Responses to the five-point Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) were numerically coded and analysed using Python-based statistical libraries (pandas, pingouin, statsmodels). Three statistical techniques were employed to address the study's objectives and test the proposed hypotheses: (1) Cronbach's alpha to assess the internal consistency reliability of each construct; (2) Pearson product-moment correlation to examine the strength and direction of association between constructs; and (3) multiple linear regression to test the combined predictive influence of the independent variables on investment decision-making behaviour.

Prior to analysis, composite (mean) scores were computed for each construct by averaging respondents' scores across the items comprising that construct. As the questionnaire did not include a dedicated scale measuring investment decision-making behaviour as a discrete construct, the dependent variable was operationalised using the two items in the questionnaire that most directly captured a behavioural response to external influence "I am more likely to invest in assets/stocks if they are promoted by financial influencers ('finfluencers') that I follow" and "Discussions on online platforms increase my willingness to invest." This approach is noted as a methodological limitation in Section 11.

7.1 Reliability Analysis (Cronbach's Alpha)

Cronbach's alpha was computed to assess the internal consistency reliability of each construct prior to conducting correlation and regression analyses. Coefficients above .70 are generally considered acceptable, values between .60 and .70 are considered marginally acceptable, and values below .60 indicate weak internal consistency (Nunnally, 1978).

Table 7.1
Reliability Statistics for Study Constructs

Construct	No. of Items	Cronbach's α	95% CI
Social Media Influence	3	.708	[.533, .825]
Trust in AI-Generated Advice	4	.627	[.424, .771]
Herd Mentality	2	.447	[.025, .686]
Financial Literacy	4	.511	[.245, .700]
Investment Decision-Making (DV)	2	.662	[.404, .808]

Note. Investment Decision-Making is a composite of two items used as a proxy dependent variable (see Section 11).

The Social Media Influence construct demonstrated acceptable internal consistency (α = .708). Trust in AI-Generated Advice (α = .627) and the Investment Decision-Making proxy (α = .662) fell within the marginally acceptable range. Herd Mentality (α = .447) and Financial Literacy (α = .511) demonstrated weak internal consistency, likely attributable to the small number of items comprising each construct (two and four items, respectively) and the modest sample size (n = 50). These reliability limitations are acknowledged and should be considered when interpreting subsequent correlation and regression results involving these constructs.

7.2 Descriptive Statistics

Table 7.2
Descriptive Statistics for Composite Construct Scores (N = 50)

Construct	M	SD	Min	Max
Social Media Influence	2.93	0.84	1.33	4.67
Trust in AI-Generated Advice	2.97	0.70	1.50	4.25
Herd Mentality	3.08	0.79	1.00	4.00
Financial Literacy	3.54	0.49	2.25	4.50
Investment Decision-Making	3.03	0.91	1.00	5.00

On average, respondents reported the highest agreement with Financial Literacy items (M = 3.54, SD = 0.49), indicating a moderately positive self-assessment of financial knowledge, while Social Media Influence recorded the lowest mean (M = 2.93, SD = 0.84).

7.3 Correlation Analysis (Pearson's r)

Pearson product-moment correlation coefficients were computed to examine the bivariate relationships between the four independent constructs and the Investment Decision-Making composite.

Table 7.3
Pearson Correlation Matrix Among Study Constructs (N = 50)

Variable	1	2	3	4	5
1. Social Media Influence	—				
2. Trust in AI Advice	.492**	—			
3. Herd Mentality	.367**	.130	—		
4. Financial Literacy	.014	.074	-.210	—	
5. Investment Decision-Making	.630***	.641***	.253	-.082	—

*Note. *p < .05, **p < .01, ***p < .001 (two-tailed).*

Investment Decision-Making showed a strong, significant positive correlation with Trust in AI-Generated Advice, $r(48) = .641$, $p < .001$, and with Social Media Influence, $r(48) = .630$, $p < .001$. A significant, moderate positive correlation was also observed between Social Media Influence and Trust in AI-Generated Advice, $r(48) = .492$, $p < .001$, and between Social Media Influence and Herd Mentality, $r(48) = .367$, $p = .009$. Herd Mentality showed a weak, non-significant correlation with Investment Decision-Making, $r(48) = .253$, $p = .077$. Financial Literacy was not significantly correlated with any other construct, including Investment Decision-Making, $r(48) = -.082$, $p = .569$, suggesting that self-assessed financial knowledge was largely independent of respondents' susceptibility to social and AI-driven influence in this sample.

7.4 Multiple Regression Analysis

A multiple linear regression analysis was conducted to test H1 and H2 by examining the combined predictive effect of Social Media Influence, Trust in AI-Generated Advice, Herd Mentality, and Financial Literacy on Investment Decision-Making. Assumption checks indicated no serious multicollinearity concerns among predictors (all Variance Inflation Factor values below 1.6) and residuals approximated a Durbin-Watson statistic of 2.24, indicating no substantial autocorrelation.

Table 7.4
Model Summary for Multiple Regression Predicting Investment Decision-Making

R	R^2	Adjusted R^2	F	df	p
.746	.557	.518	14.14	4, 45	< .001

Table 7.5
Regression Coefficients for Predictors of Investment Decision-Making

Predictor	B	SE	β	t	p
(Constant)	.710	.860	—	0.825	.414
Social Media Influence	.434	.132	.402	3.298	.002**
Trust in AI-Generated Advice	.582	.148	.450	3.929	< .001***
Herd Mentality	.026	.126	.022	0.205	.839
Financial Literacy	-.215	.188	-.117	-1.141	.260

*Note. **p < .01, ***p < .001. Dependent variable: Investment Decision-Making composite.*

The overall regression model was statistically significant, $F(4, 45) = 14.14$, $p < .001$, and explained approximately 55.7% of the variance in Investment Decision-Making ($R^2 = .557$, Adjusted $R^2 = .518$). Trust in AI-Generated Advice emerged as the strongest predictor ($\beta = .450$, $p < .001$), followed by Social Media Influence ($\beta = .402$, $p = .002$), both of which contributed significant unique variance to the model. Herd Mentality ($\beta = .022$, $p = .839$) and Financial Literacy ($\beta = -.117$, $p = .260$) were not statistically significant predictors of Investment Decision-Making once the other variables were controlled for.
To further test H1 specifically, a simple linear regression examining the isolated effect of Trust in AI-Generated Advice on Investment Decision-Making was also conducted. This model was statistically significant, $F(1, 48) = 33.57$, $p < .001$, $R^2 = .412$, confirming that exposure to and trust in AI-generated financial advice significantly predicts investment decision-making behaviour on its own, independent of the other constructs in the full model.

7.5 Hypothesis Testing Summary

Table 7.6
Summary of Hypothesis Testing Results

Hypothesis	Result	Statistical Support
H1: Exposure to AI-generated financial advice significantly influences investment decision-making.	Supported	$R^2 = .412$, $F(1,48) = 33.57$, $p < .001$
H2: Trust in AI advice, financial literacy, and social media influence significantly affect investment decision-making.	Partially Supported	Model: $F(4,45) = 14.14$, $p < .001$; AI trust and social media significant ($p < .01$); financial literacy not significant ($p = .260$)

H1 was supported: trust in and exposure to AI-generated financial advice had a statistically significant, positive influence on young adults' investment decision-making behaviour. H2 was partially supported:

while the overall model incorporating trust in AI-generated advice, social media influence, and financial literacy (along with herd mentality) significantly predicted investment decision-making, only trust in AI-generated advice and social media influence emerged as statistically significant individual predictors. Financial literacy did not significantly predict investment decision-making in this sample, contrary to the direction proposed in H2, suggesting that self-assessed financial knowledge may not translate into reduced susceptibility to AI- and social-media-driven influence among the young adults surveyed.

8. Results and Discussion

This section presents and discusses the descriptive and inferential findings of the study in relation to the four constructs under investigation — Social Media Influence, Trust in AI-Generated Advice, Herd Mentality, and Financial Literacy — and their relationship with young adults' investment decision-making behaviour. Results are interpreted with reference to the reliability, correlation, and regression findings reported in Section 7, and are discussed in light of the existing literature reviewed in Section 2.

8.1 Demographic Profile of Respondents

A total of 50 valid responses were collected. Respondents' ages ranged from 12 to 53 years ($M = 31.16$, $SD = 8.74$, $Mdn = 29$), reflecting the fact that the questionnaire was distributed openly rather than restricted to a verified young-adult panel. While the study's target population was young adults, the achieved sample includes a small number of respondents outside the conventional 18–35 young-adult bracket at both ends of the distribution. This is discussed further as a sampling limitation in Section 11.

Table 8.1
Age Distribution of Respondents (N = 50)

Age Group	n	%
Under 18	1	2.0
18–20	4	8.0
21–25	8	16.0
26–30	15	30.0
31–35	7	14.0
36–40	6	12.0
Above 40	9	18.0

The largest single age band was 26–30 years (30.0%), and just over half of respondents (54.0%) fell within the broader 21–35 range typically associated with “young adult” investors.

8.2 Usage of AI-Based Financial Tools Among Young Adults

Table 8.2
Descriptive Statistics for AI Tool Usage and Trust Items (N = 50)

Item	M	SD	% Agree/Strongly Agree
I frequently use AI tools for financial guidance	2.66	1.10	24.0%
I trust the financial advice generated by AI tools	2.54	0.84	10.0%
I verify AI-generated advice before committing to decisions	3.54	1.16	58.0%
AI-generated advice can reduce human bias in investing	3.12	0.94	38.0%

Only 24.0% of respondents reported frequently using AI tools for financial guidance, and just 10.0% agreed that they trust AI-generated financial advice outright. Notably, however, 58.0% agreed that they verify AI-generated advice before acting on it — the highest endorsement rate among the four items. This pattern suggests a cautious, verification-oriented mode of engagement with AI financial tools among this sample, rather than either wholesale rejection or uncritical acceptance. This is broadly consistent with Jamal et al. (2025) and Kapur and Shrivastava (2025), who note that the benefits of AI-generated financial guidance are conditional on users' own evaluative engagement with the information provided, rather than automatic.

8.3 Social Media and Finfluencer Engagement Trends

Table 8.3

Descriptive Statistics for Social Media Influence Items (N = 50)

Item	M	SD	% Agree/Strongly Agree
I frequently use social media for investment insight	2.72	1.09	26.0%
Social media content influences my financial decisions	2.72	0.99	28.0%
More likely to invest if finfluencer-promoted	2.76	1.13	28.0%
Social media simplifies complex financial topics	3.36	1.08	50.0%

Engagement with social media as an investment information source was moderate rather than dominant: roughly a quarter to a third of respondents agreed that social media content or finfluencer promotion directly shapes their financial decisions. The item with the highest endorsement was the perceived simplifying role of social media (50.0% agreement), suggesting that respondents value social media primarily as an accessibility tool for complex financial topics rather than as a direct trigger for specific investment actions. This nuance aligns with Pallavi and Dsa (2025) and the CFA Institute (2024), who similarly frame social media as a widely used information source for younger investors, while Chetan and Pandey (2025) note that finfluencer-driven behavioural effects, including FOMO, operate more subtly through trust and relatability than through overt promotional influence alone.

8.4 Trust in AI-Generated Financial Advice

Although direct trust in AI-generated financial advice was low (M = 2.54, only 10.0% agreement, Table 8.2), the Trust in AI-Generated Advice composite nonetheless emerged as the strongest predictor of Investment Decision-Making in both the correlation analysis ($r = .641$, $p < .001$; Table 7.3) and the multiple regression model ($\beta = .450$, $p < .001$; Table 7.5). This apparent tension — low average trust, yet strong predictive influence — suggests that even relatively cautious or partial trust in AI-generated advice is sufficient to meaningfully shape investment behaviour once a respondent engages with it. This is consistent with Sungkarungsri and Kiattisin (2026), who identify trust as the primary mechanism linking perceptions of AI systems to behavioural adoption, and with Phan et al. (2026), who argue that the transparency and explainability of AI systems (or lack thereof) shapes the degree to which users are willing to act on AI-generated recommendations. The relatively low overall trust observed in this sample may itself reflect the "black box" concern raised by Phan et al. (2026), whereby young adults are willing to be influenced by AI-generated advice without necessarily reporting high confidence in it.

8.5 Financial Literacy and Investment Behaviour

Table 8.4
Descriptive Statistics for Financial Literacy Items (N = 50)

Item	M	SD	% Agree/Strongly Agree
I possess sufficient financial knowledge to evaluate opportunities independently	2.98	0.82	26.0%
Financial literacy helps reduce the influence of social media on decisions	3.88	0.82	72.0%
I can distinguish between credible and fraudulent financial information	3.68	0.68	68.0%
My financial knowledge influences decisions more than online trends	3.60	0.76	56.0%

Respondents rated their financial literacy relatively favourably overall, and a large majority (72.0%) agreed that financial literacy helps reduce susceptibility to social media influence. However, this self-reported belief was not reflected in the quantitative results: the Financial Literacy composite was not significantly correlated with Investment Decision-Making ($r = -.082$, $p = .569$; Table 7.3) and was not a significant predictor in the regression model ($\beta = -.117$, $p = .260$; Table 7.5). This divergence between respondents' perceived protective effect of financial literacy and its actual statistical relationship with investment behaviour in this sample suggests a possible overconfidence effect, whereby self-assessed financial knowledge does not necessarily correspond to reduced susceptibility to AI- or social-media-driven influence. This finding nuances Jamal et al. (2025) and Rangapur et al. (2023), who report financial literacy as a significant mediating and protective factor; the discrepancy may reflect differences in how financial literacy was measured (self-assessed perception here, versus tested or behavioural measures elsewhere) and is discussed further in Section 8.8.

8.6 Risk Perception and Investment Decisions

The questionnaire did not include a dedicated risk-perception scale. As a result, this section draws on the Herd Mentality items — confidence investing alongside others and fear of missing out (FOMO) on trending assets — as the closest available behavioural proxies for socially-conditioned risk-taking, consistent with their treatment in the literature (Pallavi & Dsa, 2025; Chetan & Pandey, 2025). This substitution is noted as a limitation in Section 11.

Table 8.5
Descriptive Statistics for Herd Mentality (Risk-Related) Items (N = 50)

Item	M	SD	% Agree/Strongly Agree
I feel more confident investing when others are doing the same	3.10	1.09	48.0%
I fear missing out on profitable opportunities when assets are trending	3.06	0.87	36.0%

Close to half of respondents (48.0%) reported greater investment confidence when others were investing similarly, and just over a third (36.0%) reported FOMO-driven urgency around trending assets. Herd

Mentality was significantly correlated with Social Media Influence ($r = .367$, $p = .009$; Table 7.3), suggesting that social validation cues are transmitted substantially through social media exposure. However, Herd Mentality showed only a weak, non-significant correlation with Investment Decision-Making ($r = .253$, $p = .077$) and was not a significant predictor in the regression model once Social Media Influence and Trust in AI-Generated Advice were accounted for ($\beta = .022$, $p = .839$; Table 7.5). This suggests that herd-driven risk behaviour in this sample operates primarily as a downstream consequence of social media exposure rather than as an independent driver of investment decisions.

8.7 Hypothesis Testing

Formal hypothesis testing, including model statistics and significance values, is reported in full in Section 7.5 (Table 7.6) and is not repeated in detail here. In summary: H1 — that exposure to AI-generated financial advice significantly influences investment decision-making — was supported ($R^2 = .412$, $F(1,48) = 33.57$, $p < .001$). H2 — that trust in AI-generated advice, financial literacy, and social media influence significantly affect investment decision-making — was partially supported: the overall model was significant ($F(4,45) = 14.14$, $p < .001$), and both Trust in AI-Generated Advice and Social Media Influence were significant individual predictors, but Financial Literacy was not ($p = .260$).

8.8 Interpretation of Results

Taken together, the results indicate that young adults' investment decision-making in this sample is shaped predominantly by two closely related digital influences — trust in AI-generated financial advice and exposure to social media content — which jointly accounted for the majority of the explained variance in the regression model. This supports the study's central premise that AI and social media function as significant, and to some extent overlapping, channels of influence on investment behaviour, consistent with Kapur and Shrivastava (2025) and Pallavi and Dsa (2025).

The finding that Financial Literacy did not significantly predict investment decision-making, despite respondents' own belief that literacy is protective (72.0% agreement on Item FL2), is one of the more notable results of this study. Rather than acting as an independent safeguard against AI- and social-media-driven influence, self-assessed financial literacy appeared largely disconnected from actual behavioural outcomes in this sample. This raises the possibility that financial literacy, as commonly self-reported, reflects a belief in one's own resistance to influence more than it reflects behaviour that is actually resistant to influence — a distinction with implications for financial education approaches, discussed further in Section 10.1.

Similarly, Herd Mentality's weak and statistically non-significant direct relationship with investment behaviour, despite its significant correlation with Social Media Influence, suggests that social proof and FOMO in this sample function largely as mechanisms embedded within social media engagement rather than as standalone behavioural drivers. This is consistent with a view of social media as the primary conduit through which both informational (AI-trust-related) and social (herd-related) influences reach young investors, rather than these functioning as fully independent pathways — a pattern that extends the largely separate treatment of these constructs in prior literature (Section 2) by suggesting a more integrated influence structure specific to this sample.

9. Conclusion

9.1 Summary of Findings

This study set out to examine the relationship between exposure to AI-generated financial advice and investment behaviour among young adults (Objective 4.1), and to analyse the combined influence of trust in AI-generated advice, financial literacy, and social media-based financial content on investment decision-making (Objective 4.2). Based on 50 valid responses, both objectives were addressed through reliability analysis, Pearson correlation, and multiple linear regression.

Four key findings emerged. First, exposure to AI-generated financial advice was a significant predictor of investment decision-making on its own, confirming H1 ($R^2 = .412$, $p < .001$). Second, when tested alongside financial literacy, social media influence, and herd mentality in a combined regression model, trust in AI-generated advice ($\beta = .450$, $p < .001$) and social media influence ($\beta = .402$, $p = .002$) remained significant predictors, while financial literacy ($p = .260$) and herd mentality ($p = .839$) did not, meaning H2 was only partially supported. Together, these two constructs accounted for the majority of the 55.7% of variance explained by the overall model ($R^2 = .557$, $p < .001$). Third, respondents' engagement with AI tools was characterised more by cautious verification than by outright trust or rejection: although only 10.0% of respondents reported trusting AI-generated advice outright, 58.0% reported verifying such advice before acting on it, and trust in AI advice was nonetheless the single strongest predictor of investment behaviour in the sample. Fourth, self-assessed financial literacy despite 72.0% of respondents believing it reduces susceptibility to social media influence showed no significant statistical relationship with actual investment decision-making, pointing to a gap between perceived and demonstrated protective effect.

Overall, the findings support the study's central premise: AI-generated financial advice and social media are significant, closely linked forces shaping how young adults make investment decisions, while herd mentality and self-assessed financial literacy played a comparatively limited independent role within this particular sample.

9.2 Behavioural Insights

Beyond the statistical results, several behavioural patterns are worth drawing out explicitly, as they speak to how young adults are actually engaging with AI and social media in a financial context rather than simply whether these channels have an effect.

- Cautious adoption rather than blind trust: young adults do not appear to be passively accepting AI-generated financial advice. The high rate of self-reported verification behaviour (58.0%) alongside low outright trust (10.0%) suggests a generation that treats AI as one input to be checked rather than a final authority yet this scepticism does not appear to blunt AI's behavioural influence, since trust in AI advice remained the strongest predictor of investment decisions.
- Social media as an amplifier rather than sole trigger: finfluencer-specific promotion (28.0% agreement) and general social media influence (26–28.0% agreement) were only moderately endorsed individually, yet Social Media Influence was the second-strongest predictor of investment behaviour and was significantly correlated with both Trust in AI Advice ($r = .492$) and Herd Mentality ($r = .367$). This suggests social media functions less as an isolated driver and more as a shared channel through which both AI-related and social/herd-related influences reach young investors.
- A literacy–behaviour gap: the disconnect between respondents' belief that financial literacy protects against social media influence (72.0% agreement) and the absence of any significant statistical relationship between Financial Literacy and Investment Decision-Making ($p = .569$) suggests that confidence in one's own financial knowledge does not necessarily translate into behaviour that resists digital influence. This is consistent with an overconfidence-type effect and indicates that financial literacy interventions may need to focus on applied decision-making behaviour rather than self-assessed knowledge alone.

- Herd mentality as an embedded rather than standalone effect: social-proof-driven behaviours (confidence investing alongside others, FOMO) did not independently predict investment decisions once AI trust and social media influence were accounted for, despite being significantly correlated with social media exposure. This suggests herd-driven behaviour in this sample operates largely through, rather than alongside, social media engagement.

Collectively, these insights suggest that interventions aimed at supporting healthier investment decision-making among young adults should focus less on discouraging AI or social media use outright, and more on strengthening the quality of engagement with these channels for example, by reinforcing verification habits, improving the transparency of AI-generated advice, and shifting financial literacy education toward applied, behaviourally grounded skills.

10. Recommendations

The following recommendations are derived directly from the findings reported in Sections 8 and 9, rather than presented as generic policy suggestions. Each subsection addresses a specific gap or pattern identified in the results: the disconnect between self-assessed and demonstrated financial literacy (10.1), the cautious-but-influential role of AI trust (10.2 and 10.3), the amplifying role of social media and finfluencers (10.4), and the broader need for applied digital financial education (10.5).

10.1 Improving Financial Literacy Among Young Investors

The finding that self-assessed Financial Literacy was not significantly related to Investment Decision-Making ($r = -.082$, $p = .569$; $\beta = -.117$, $p = .260$), despite 72.0% of respondents believing that literacy reduces their susceptibility to social media influence, suggests that current approaches to financial literacy may be building confidence without building resistance to influence. On this basis, it is recommended that:

- Financial literacy initiatives targeted at young adults shift emphasis from conceptual or knowledge-based instruction (e.g. defining financial terms) toward applied, decision-based exercises — such as evaluating a real piece of AI-generated or social-media-sourced financial advice and identifying its potential weaknesses — so that literacy translates into demonstrated behaviour rather than self-reported confidence alone.
- Financial literacy assessments used by educators, employers, or fintech platforms incorporate behavioural or scenario-based measures alongside self-report scales, given the gap observed in this study between perceived and demonstrated literacy.
- Financial literacy content be delivered through the same digital channels young adults already use for financial information (social media, finance apps), rather than solely through formal or classroom-based instruction, given the low frequency of independent financial research reported by respondents (Section 8.5).

10.2 Responsible Use of AI in Financial Decision-Making

Trust in AI-generated financial advice was the strongest single predictor of investment decision-making in this study ($\beta = .450$, $p < .001$; Section 8.4), even though only 10.0% of respondents reported trusting such advice outright and 58.0% reported verifying it before acting. This combination of low stated trust but high behavioural influence, and a majority verification habit, indicates that young adults are already engaging in some self-protective behaviour, but would benefit from structured support to make that verification more effective. It is recommended that:

- Financial technology providers offering AI-generated advice build in explicit prompts encouraging users to verify recommendations against independent sources, reinforcing and formalising the verification behaviour already reported by the majority of respondents in this study.
- Young investors are encouraged, through targeted guidance from financial institutions or educators, to treat AI-generated financial advice as a starting point for research rather than a final recommendation, consistent with the cautious-adoption pattern observed in Section 8.2.
- Users of AI financial tools be made aware of the limitations of the underlying systems (e.g. the data they are trained on, their potential for error or bias) as part of onboarding to any AI-powered financial platform, to support more informed not merely more frequent verification.

10.3 Enhancing Transparency and Explainability of AI Financial Tools

The coexistence of low outright trust in AI-generated advice (10.0% agreement) with its status as the strongest behavioural predictor of investment decisions (Section 8.4) was interpreted in this study as consistent with the "black box" concern raised by Phan et al. (2026), whereby users may act on AI-generated recommendations without fully understanding or trusting the reasoning behind them. It is recommended that:

- Developers of AI-powered financial advisory tools prioritise explainable-AI features such as showing the reasoning, data sources, or confidence level behind a given recommendation rather than presenting outputs as unexplained conclusions, in line with the transparency and explainability principles identified in the literature reviewed in Section 2.2.
- Regulatory or industry bodies overseeing AI-powered financial services establish minimum disclosure standards specifically requiring that AI-generated financial advice be accompanied by an accessible explanation of its basis, particularly given how readily such advice appears to influence behaviour even under conditions of low stated trust.
- Future product design research examines whether increased explainability measurably increases appropriate trust (rather than simply increasing overall trust), to ensure transparency efforts translate into better-calibrated reliance on AI advice rather than uncritical acceptance.

10.4 Regulation of Finfluencers and AI-Generated Financial Content

Social Media Influence was the second-strongest predictor of investment decision-making in this study ($\beta = .402$, $p = .002$; Section 8.3) and was significantly correlated with both Trust in AI-Generated Advice ($r = .492$) and Herd Mentality ($r = .367$), positioning social media as a central conduit through which multiple forms of influence reach young investors. This is consistent with existing concerns in the literature regarding finfluencer transparency and disclosure (Chetan & Pandey, 2025; CFA Institute, 2024). It is recommended that:

- Regulatory bodies strengthen and enforce disclosure requirements for financial influencers, including clear labelling of sponsored content and disclosure of any financial relationship with the products or assets being promoted.
- Platforms hosting AI-generated or AI-assisted financial content (including AI-driven finfluencer content, per Venkatesan & Ramdan, 2026) be required to label such content distinctly from human-authored financial commentary, given the compounding influence of AI and social media identified in this study (Section 8.8).
- Financial regulators develop specific guidance for finfluencer-driven promotion of individual assets or stocks, given that 28.0% of respondents in this study agreed they were more likely to invest in finfluencer-promoted assets.

10.5 Investor Education and Digital Awareness

More broadly, the overall pattern of results AI trust and social media influence as significant behavioural drivers, financial literacy as a comparatively weak independent factor, and herd mentality operating through rather than alongside social media points to a need for investor education that addresses the digital information environment as a whole, rather than treating AI literacy, social media literacy, and financial literacy as separate concerns. It is recommended that:

- Investor education programmes aimed at young adults integrate digital and financial literacy into a single curriculum, addressing how to evaluate AI-generated advice, social media content, and finfluencer recommendations together, reflecting the interconnected influence structure identified in this study (Section 8.8).
- Educational institutions and financial regulators collaborate on public awareness campaigns that specifically address the behavioural mechanisms identified in this study verification habits, herd behaviour, and overconfidence in self-assessed literacy rather than focusing solely on financial product knowledge.
- Future awareness efforts are evaluated using behavioural outcome measures (e.g. verification rates, actual investment decisions) rather than self-reported confidence or knowledge alone, given the literacy–behaviour gap identified in Section 8.5.

11. Limitations of the Study

While this study achieved its objectives of examining the influence of AI-generated financial advice, social media, herd mentality, and financial literacy on young adults' investment decision-making, several limitations should be considered when interpreting the findings.

Sample size and statistical power. An initial target of approximately 100 completed responses was established (Section 6.4); however, only 50 valid responses were obtained. A sample of this size is on the smaller end for a multiple regression model with four predictors, reducing statistical power to detect smaller effects and widening confidence intervals around the reported coefficients. Non-significant predictors in this study, such as Financial Literacy and Herd Mentality, may reflect a genuine absence of effect, or may partly reflect insufficient power to detect a smaller true effect; the present data cannot fully distinguish between these possibilities.

Non-probability convenience sampling. Participants were recruited through the researcher's personal and professional networks via WhatsApp, email, and direct contacts (Section 6.3). While this approach was practical given the absence of a comprehensive sampling frame, it means respondents were not randomly selected from the broader population of young adults, and the sample may disproportionately reflect the demographic, educational, or occupational composition of the researcher's own network. This limits the extent to which the findings can be generalised to young adults more broadly.

Absence of screening and demographic controls. Although the target population was defined as young adults aged 18 to 35 (Section 6.2), the questionnaire did not include an age-eligibility check, and the achieved sample included respondents outside this range (ages 12 to 53; Section 8.1). The questionnaire also did not collect gender, occupation, or investment experience, preventing analysis of whether the observed relationships vary across demographic subgroups, and limiting the depth of the demographic profile reported in Section 8.1.

Operationalisation of the dependent variable. The questionnaire did not include a dedicated scale measuring investment decision-making behaviour as a discrete construct. The dependent variable used in the correlation and regression analyses (Sections 7 and 8) was therefore constructed post hoc from two items originally written to illustrate the behavioural consequences of social media and herd-related influence, rather than from a scale purpose-built and validated to measure investment behaviour. This composite also showed only marginally acceptable internal consistency (α = .662), reflecting its two-item length. Future replications of this study should incorporate a dedicated, multi-item investment-behaviour scale developed and piloted independently of the other constructs.

Absence of a dedicated risk-perception measure. Similarly, the questionnaire did not include items specifically designed to measure risk perception. Section 8.6 addressed this gap by using the Herd Mentality items as a behavioural proxy for socially-conditioned risk-taking; while conceptually defensible, this substitution means the study's treatment of risk perception is indirect and should be interpreted with appropriate caution.

Construct reliability. Cronbach's alpha for the Herd Mentality (α = .447) and Financial Literacy (α = .511) constructs fell below the conventional .70 threshold for acceptable internal consistency (Section 7.1), likely reflecting both the small number of items used to measure each construct (two and four items, respectively) and the modest sample size. Weaker reliability increases measurement error and may partly explain why these two constructs did not emerge as significant predictors in the regression model; correlations and regression coefficients involving these constructs should therefore be interpreted with some caution.

Cross-sectional design and causality. As a cross-sectional study collecting data at a single point in time (Section 6.1), this research can establish statistical association but not causal direction. While the language of “influence” and “prediction” is used throughout Sections 7 to 9 in line with standard regression terminology, the design cannot rule out reverse or bidirectional relationships for example, that individuals who already invest frequently are more likely to seek out and trust AI-generated financial advice, rather than the advice itself driving investment behaviour.

Self-report and common method bias. All constructs in this study, including the dependent variable, were measured using self-reported Likert-scale responses collected within a single questionnaire. This raises the possibility of common method bias, whereby relationships between constructs are partly inflated because they share a common measurement method and were reported by the same individuals at the same time. Respondents' self-assessments, particularly of financial literacy and AI/social media influence on their own behaviour, may also be subject to social desirability bias or limited self-awareness of their own decision-making processes.

Taken together, these limitations do not undermine the study's core findings but do define the boundaries within which they should be interpreted.

12. Future Scope of Research

The limitations identified in Section 11 point directly to specific opportunities for extending and strengthening this line of research. Rather than restating those limitations, this section outlines concrete directions future studies could pursue to build on the present findings.

Larger, probability-based samples. Future research should aim for a larger sample, ideally recruited through probability or stratified sampling rather than convenience sampling, to improve statistical power, support more robust subgroup analysis, and strengthen the generalisability of findings beyond the researcher's personal and professional networks (Section 6.3).

Demographically richer data collection. Incorporating gender, occupation, income level, and prior investment experience alongside age would allow future studies to examine whether the relationships identified here particularly the strong role of AI trust and social media influence hold consistently across different subgroups of young adults, or whether they are moderated by factors such as investment experience or income.

Validated, multi-item scales for investment behaviour and risk perception. Because this study operationalised Investment Decision-Making from two items not originally designed as a standalone behavioural scale, and used Herd Mentality items as a proxy for risk perception (Section 11), future research would benefit from developing and piloting dedicated, validated multi-item scales for both constructs. This would allow investment behaviour and risk perception to be measured directly rather than inferred, and would likely improve construct reliability beyond the marginal levels observed here for several constructs (Section 7.1).

Longitudinal or experimental designs. As a cross-sectional study, this research could not establish causal direction between AI trust, social media influence, and investment behaviour (Section 11). Future studies could adopt a longitudinal design, tracking the same respondents' AI and social media engagement alongside their actual investment decisions over time, or an experimental design in which exposure to AI-generated or finfluencer-driven content is manipulated, to more directly test the causal claims implied by hypotheses such as H1 and H2.

Behavioural rather than self-reported outcome measures. Given the gap identified in this study between self-assessed financial literacy and its actual statistical relationship with investment behaviour (Section 8.5), future research should consider incorporating objective or behavioural measures — such as verified transaction data, portfolio records, or performance on a financial-knowledge test — rather than relying solely on self-report, to reduce common method bias and test whether the literacy–behaviour gap observed here persists under more objective measurement.

Explainability and trust calibration in AI financial tools. This study found that trust in AI-generated financial advice was highly influential despite being low in absolute terms (Section 8.4). Future research could experimentally test whether increasing the explainability or transparency of AI-generated recommendations changes not just the level of trust but the appropriateness of that trust — for example, whether users become better able to distinguish reliable from unreliable AI-generated advice, rather than simply trusting it more.

The role of AI-generated finfluencer content. As AI-driven finfluencers and AI-generated financial content become more prevalent (Venkatesan & Ramdan, 2026), future research could examine this study's constructs — trust, herd mentality, and social media influence — specifically in relation to AI-generated (rather than human-generated) social media financial content, an area not distinguished within the present questionnaire.

Cross-cultural and cross-market replication. Because this study drew its sample from the researcher's own networks within a single national context, future research could replicate this study across different countries, regulatory environments, and financial markets to examine whether the relative importance of AI trust, social media influence, herd mentality, and financial literacy observed here holds across different cultural and regulatory settings.

Collectively, these directions would allow future research to test the causal claims this study could only associate, measure investment behaviour and risk perception directly rather than by proxy, and establish whether the patterns identified among this sample of young adults extend to the broader population.

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