Social media exposure and its influence on individual investment decisions

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ABSTRACT,

In today's digital age, social media has become not only a central communication tool, but also a means of accessing information on various topics, including finance. Behavioural finance suggests that personality traits may determine how exposure to social media influences investment decisions. While previous research has examined this connection, no studies have focused on Dutch investors, and none have examined the moderating effects of two variables: tie strength - the degree of connectedness between individuals on social media - and the role of financial influencers, individuals who specialise in financial content on social platforms. This study seeks to assess the influence of social media exposure on investment decisions among Dutch investors, considering the moderating role of tie strength and financial influencers. Data was collected from 142 respondents through a questionnaire measuring their perceptions of the influence of social media exposure on investment behaviour. The results show that exposure to social media has a significant impact on investors' propensity to invest and the amount they are willing to allocate to investments. Respondents feel that other investors are more influenced by social media exposure than themselves, a phenomenon known as the third-person effect. This study offers valuable insights for investors and financial advisers who want to understand the role of social media in investment behaviour.

Keywords
Social media exposure, Investment decisions, Tie strength, Financial influencers, behavioral finance, Traditional finance

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Content

1. Introduction

This chapter provides background information on the key research areas of this study, social media exposure, investment decisions, tie strength and financial influencers. Following this, the research objective, and research gaps are highlighted. By highlighting these aspects, the aim is to clarify the context and importance of the study within the existing literature. Finally, the research question, together with some sub-questions, will be formulated.

1.1 Background

In today's world, the influence of social media has become a powerful tool and has influence on almost every facet of modern life, changing the way individuals communicate, access information and engage with various aspects of their lives (van Dijck & Poell, 2013). What began as a means of social contact has now also influenced things like consumer behavior and decision-making processes (Eisenbeiss et al., 2023). Social media plays a role in shaping their perceptions of investment risks, affecting both their thoughts and emotions (Yang et al., 2022). One area where the impact of social media is increasingly evident is the financial market, also in relation to individuals' investment decisions.

From a traditional finance perspective, investors within financial markets behave rationally, objective and seek to maximize profits, while they tend to be risk averse. Rationality means that investors make decisions based on logical reasoning and the available information. Rational decision-makers seek to maximize expected returns while minimizing risk. They aim for the highest possible return for a given level of risk or the lowest possible risk for a given return (Kamoune & Ibenrissoul, 2022). However, recent scientific research has challenged this assumption and exposed the inherent human tendency towards irrationality. This realization led to the emergence of the behavioral finance field (Bikas et al., 2013). This field of research challenges the idea that individuals consistently make rational decisions, opting instead for a more nuanced understanding of investors who may be influenced by psychological traits (Niehaus & Shrider, 2014). It also aims to understand how emotions and cognitive biases have an impact on investors decisions (Bakar & Yi, 2016). Previous studies have indicated that investors' decisions are influenced by their beliefs and preferences, which affect their risk-taking behavior (Bakar & Yi, 2016).

In the financial markets, digital platforms, including social media channels, have a significant impact on decisions made in investments (Lal et al., 2023). Social media channels such as LinkedIn and Twitter have led to new insights regarding company-specific analyst recommendations, and analyst price targets among investors (Bollen et al., 2011; Gu & Kurov, 2020). Given the abundance of financial information, expert opinions and real-time trend updates available on social media channels, it is not surprising that potential investors are using the rapid expansion of social media to their advantage in recent decades (Nghiem et al., 2021). The accessibility of financial knowledge has empowered individuals who were previously excluded from traditional channels of financial advice and analysis. As a result, an increasing number of people are turning to social media platforms to gain insights into financial market and potentially reap financial rewards (Alexander & Gentry, 2013). Through social media, individuals can seek for validation, share opinions, and engage in discussions that shape their investment decisions.

Additionally, social media has fostered the rise of influencer marketing within the financial sector (Joshi et al., 2023). Financial influencers, individuals who have both a significant social media following and expertise in finance, may influence their followers' investment choices through their analysis and recommendations. They use their social media platforms to provide valuable insights and advice on financial market investments and manage to attract their audiences with their knowledge and engaging personalities (Arora et al., 2019; Lou & Yuan, 2018). The phenomenon of financial influencers represents a potential moderating factor in the relationship between social media exposure and investment decisions.

Financial advice provided by financial influencers on social media has the potential to enhance the financial literacy of people (Geenen, 2023). Financial behavior within investment decisions is further highlighted by the emergence of tie strength as a potential moderating factor in the relationship. Tie strength refers to a measure of depth and intimacy within relationships (Granovetter, 1973). When individuals encounter financial information shared intimate friends or family members or shared by a role model, they may perceive this information as more credible, impacting their financial behavior. Tie strength, when emerging via online social media platforms, could play a significant role in the relationship between social media exposure and investment decisions.
Examining the influence of social media exposure on investment decisions coupled with the moderating variables of tie strength and financial influencers, carries remarkable practical implications. In today's digital world, where social media serves as a widely used source of information and communication, understanding its influence on investment choices could be relevant. The findings of this study can offer practical insights for individual investors, and financial advisers. For individual investors, being aware of how exposure to social media can influence their investment decisions offers the opportunity to make more informed and strategic choices (Naveed et al., 2020). Recognizing the potential impact of the strength of ties - the strength of their social connections - and the influence of financial influencers can help investors assess the reliability and relevance of the information they encounter on social media platforms (Sun et al., 2021). On the other hand, financial advisers can benefit from insights into their clients' decision-making process (Pallavi & Kusum, 2024). By understanding how clients' social connections and external influencers interact with social media exposure, advisers can tailor their advice to potential biases and offer personalized strategies that align with clients' financial goals. This not only improves the quality of advice, but also helps reduce biases in investment behavior, which can ultimately contribute to better financial outcomes for clients.

1.2 Research Objective and research gap

The primary research objective of this thesis is to understand the relationship between social media exposure and investment decisions among investors. Specifically, this research focuses on whether the degree of exposure to social media platforms affects Dutch investors' investment propensities and the amount of resources invested. In addition, this research focuses on the possible moderating influence of tie strength and financial influencers on the relationship between social media exposure and investment decisions. Through a theorical explanation and empirical analysis, this research seeks to shed light on the investment decision making process in the social media age and offer implications for both theory and practice in the field of finance, behavioral finance, and social media.

Existing studies have examined the influence of media on various aspects of financial markets. Jiao et al., (2020) conducted research in which they studied the effect on stock volatility and turnover of coverage by traditional news media and social media. Their findings reveal that traditional news media coverage is associated with decreased volatility and turnover in subsequent periods, while social media coverage is linked to increased volatility and turnover.

Also, there are existing studies that have studied the impact of social media on individual investors decisions. For example, Khadka and Chapagain (2023) conducted a study exploring the relationship between social media and investment decisions within the context of the Nepali stock market. Their findings revealed significant positive relationships between social media and investment decision-making. The same applies to research conducted by Ismail et al., (2018). In this study, the researchers investigate the impact of online social media on the investment decisions of investors in Malaysia. The specific focus is on understanding how various aspects of online social media, like information from social media, online community behavior, influence investment decisions. Their findings also revealed significant positive relationships between social media and investment decisions. To investigate the role of emotional sentiment in investment decisions, Sul et al. (2016) analyzed the cumulative sentiment of 2.5 million tweets about S&P 500 firms. They found that tweets from users with fewer than 171 followers significantly affected a firm's stock returns not only on the following trading day but also over the subsequent 10 and 20 days. A study performed by Hasselgren et al., (2023) explores the use of social media sentiment data for investment decisions. In their approach, the authors focused on S&P 500 stocks, which resulted that they could develop a system for measuring and visualizing collective sentiment. The results showed that the trend of social media sentiment reflected stock market performance for the assets studied, which suggested that users could use this sentiment to inform their investment decisions.

Recent research highlights the role of emotional sentiment in investment decisions, showing that sentiment spread through social media affects stock prices. Rapidly spreading sentiment is quickly reflected in stock prices, while slower-spreading sentiment predicts future prices. Analyzing 2.5 million tweets about S&P 500 firms, we found that sentiment from users with fewer than 171 followers significantly impacted stock returns on the next trading day, and over the following 10 and 20 days.

Although the existing literature has extensively investigated the link between social media and investment decisions, there remains a research gap in determining if there is any significant positive influence of social media exposure on investment propensity or the likelihood of investing more resources into assets within the Dutch population. To the best of knowledge, no previous studies have delved into this specific aspect, leaving an important gap in research that we hope to fill with this study. Gaining a deeper understanding of how exposure to social media influences investment decisions among Dutch investors is potentially important for the Dutch economic landscape. By clarifying this connection, this research can provide valuable insights into investors' incentives for buying or not buying equities, and how much they invest in. In addition, existing research has not explored the potential moderating role of tie strength and financial influencers in this relationship. While some studies have pointed out the moderating role of tie strength and financial influences in other contexts, their specific influence on investment decisions remains unexplored. This research aims to fill these gaps by providing insight into the influence of the exposure of social media on investment decisions among Dutch investors and by exploring the potential moderating effects of tie strength and financial influencers, to contribute to a better understanding in the field of social media and finance.

1.3 Research questions

In this study, we pose one research question:

- How does exposure to social media influence individuals' propensity to invest in financial assets such as stocks and bonds and the amount of their investments?

In addition, two sub-questions are introduced to check whether there is a possible moderating effect on this relationship:

- Does tie strength affect the relationship between exposure to social media and investment decision-making?
- Do financial influencers affect the relationship between exposure to social media and investment decision-making?

2. Literature review

The evolving field of financial decision-making has undergone a thorough transformation with the widespread adoption of social media platforms (Guijarro et al., 2019). As people increasingly rely on social media platforms for information, connection and conversation, the influence of social media in shaping investment decisions has received much attention in research. This paragraph aims to provide a thorough synthesis of existing research, highlighting the coherence between social media exposure and the decision-making processes that contribute to individuals' investment choices. Furthermore, the objective is to provide a description of tie strength and financial influencers, exploring whether the strength of ties and the presence of financial influencers play a moderating role in this relationship.

2.1 Schools of thought

2.1.1 Traditional finance

There are two fundamental theories that comprise the financial market, namely the traditional finance theory, also known as conventional finance theory, and the emerging field of behavioral finance. In principle, traditional finance was based on theories such as the efficient market hypothesis (EMH) and portfolio theory, notably developed by Harry Markowitz. Markowitz's contributions paved the way for modern portfolio theory, which emphasizes factors such as expected return, standard deviation, and correlation within investment portfolios. Within finance, research focused on creating a theoretical framework to better understand market dynamics. Traditional finance theory, successfully developed formulas, including the well-known CAPM formula and the Black-Scholes formula (Kamoune & Ibenrissoul, 2022). Traditional finance assumes that investors behave rationally and seek to maximize profits while being risk averse. Rationality in this context refers to investors making decisions that are logically and in line with their financial interests. However, this assumption is challenged by market anomalies arising from speculation and unpredictability. These anomalies suggest deviations from rational behavior, where investors may make decisions based on factors that are not purely rational, such as emotions or imperfect information (Bakshi, 2020).

As said before the traditional finance theory shares significant relevance with the efficient market hypothesis, which gained prominence in the mid-1960s. The efficient market hypothesis is built upon three arguments. First and foremost, it is assumed that investors in the market are rational and can rationally assess and value securities within the market (Fama, 1970; Tseng, 2006). Second, the efficient market hypothesis addresses that investors could deviate from rationality. If this is the case and investors do not act rationally, the efficient market hypothesis states that their trading activities will cancel each other out or will be arbitraged away (Shleifer, 2000). Lastly, the efficient market hypothesis states that decision-makers consistently prioritize their self-interest, highlighting the persistent influence of individual motivations and goals in the decision-making process (Fama, 1970; Tseng, 2006). The forms of the Efficient Market Hypothesis vary in their assumptions about the incorporation of information in asset prices. The weak form of EMH suggests that asset prices move randomly and reflect all historical price data. The semi-strong form of EMH states that prices adjust rapidly based on market and public information, while the strong form of EMH suggests that prices incorporate all types of information, including private information (Khalil & Nilsson, 2021).

The EMH has implications for financial managers as it emphasizes the importance of information in predicting future price movements of financial assets. However, the theory has been exposed to criticism, especially with regard to its assumptions on investor rationality and market efficiency. Critics claim that EMH does not take into account factors such as excessive price volatility and the influence of behavioral biases on market outcomes. In response to these criticisms, behavioral finance emerged as an alternative to traditional finance. Behavioral finance seeks to understand how psychological factors influence financial decisions and market behavior, challenging the assumptions of rationality and market efficiency inherent in traditional finance (Malkiel, 2003).

2.1.2 Behavioral finance

Behavioral finance is one of the other fundamental theories within the field of financial markets. It is a field of study that integrates principles from both economics and psychology into financial theory and practice (Belsky & Gilovich, 2000; Prosad et al., 2015). It seeks to understand how psychological factors influence individuals' financial decisions, market dynamics and the behavior of financial markets. In essence, it recognizes that human behavior in financial contexts is often driven by emotions, cognitive biases and heuristics rather than strict rationality (Niehaus & Shrider, 2014).Traditional financial theories, such as the EMH and modern portfolio theory, assume that investors are perfectly rational, always act in their best interests and have access to all relevant information. Behavioral finance, however, challenges these assumptions by pointing out the various ways in which individuals deviate from rational behavior when making financial decisions (Statman, 1999).

Prospect theory, which is an important theory within the behavioral finance field, posits that people have a stronger aversion to losses than an equal preference for gains. This means that individuals are more likely to take risks to avoid losses than to pursue gains of equal value. It serves as a behavioral framework that clarifies how people make decisions when faced with uncertainty and risk, such as estimating the probability of potential gains or losses. Originally formulated by the experimental research of Daniel Kahneman and Amos Tversky, prospect theory emphasizes the presence of consistent biases that shape decision-making under conditions of uncertainty, influenced by psychological factors. According to this theory, people tend to process information in ways that deviate from strict logic, meaning that people tend to process information in ways that differ from purely rational approaches. This deviation from strict logic illustrates how human decision-making is influenced by subjective perceptions, personal experiences, and emotional responses (Alam, 2022; Kahneman & Tversky, 1988).

Another important concept in behavioral finance is bounded rationality. Bounded rationality is a term used to describe the concept of rational decision making while recognizing the cognitive limitations of the decision maker. These limitations include both the amount of knowledge available to the decision maker and his ability to process information. This principle underlies the behavioral approach to economics, which looks deeply at how the actual decision-making process affects the outcomes of decisions. Unlike traditional economic models that assume perfect rationality, bounded rationality recognizes that individuals are often unable to fully analyze all available information and make optimal decisions. Instead, decision makers rely on heuristics, or mental shortcuts, to simplify complex decision-making problems. While these heuristics can help decision-making, they can also lead to systematic biases and errors (Simon, 1997, p. 291; Tseng, 2006). Biases like overconfidence, herding, and anchoring are recognized as fundamental biases within behavioral finance. These biases play a role in shaping the decision making process of individual investors (Singh & Nag, 2016; Thaler & Shefrin, 1988). Overconfidence involves an individual's excessive belief in their ability to predict outcomes (Prosad et al., 2018). Herding refers to the tendency to blindly follow the actions of a crowd (Mello et al., 2010). Anchoring involves relying too heavily on the first piece of information encountered when making decision. This tendency can lead individuals to prioritize this initial information, even if it may not be directly relevant to the decision-making context (Shin & Park, 2018). Another important bias, perhaps one of the most intriguing, is known as the disposition effect. Within this effect, investors tend to sell winning investments early while persistently holding onto losing investments. The underlying goal is to maximize returns and delay losses. This bias stands out as one of the most prominent tendencies in investor behavior (Syed & Bansal, 2019).

In general, behavioral finance offers valuable insights into the complexity of human decision-making in financial contexts. By understanding the psychological factors that drive financial behavior, practitioners and policymakers can develop strategies to reduce the negative effects of cognitive biases and improve financial decision-making processes.

2.2 Independent variable

2.2.1 Social media exposure

At the core of social media's influence on investment decisions lies its role as a powerful source of financial information (Agarwal et al., 2021). The financial information provided does not always meet factual standards but is sometimes also some sort of noise in world of trading, identifying a category of investors known as noise traders. These so-called noise traders are investors whose decisions are not based on fundamental analysis or rational assessment of information. Instead, they may be driven by emotions, market trends or speculative behavior (Shleifer & Summers, 1990). A study performed by Baklaci et al., (2011) studies the behavioral aspects and emotions of investors in Turkish stock market. It shows that as volume increases, prices move closer together, suggesting that more active traders may be reacting to short-term trends rather than long-term factors. This behavior may briefly increase market volatility before stabilizing again (Baklaci et al., 2011). Another study conducted by Vamossy (2024) examines how investor emotions expressed on social media relate to asset prices. The study finds that specific investor emotions, like being happy or anxious can predict daily asset price movements. Li et al., (2018) and Allen et al., (2019) highlight that the stock market volatility is closely linked to the release, distribution and the reception of information by the public. The increase in volume and speed of social media activity contributes to the effects of financial information on the stock market.

The term social media exposure can be divided into two different terms, namely social media, and exposure. Social media is interactive and networked (Bechmann & Lomborg, 2013; Park et al., 2018). Many individuals are motivated towards participating in virtual communities in exchange for rewards in the form of friendship, appreciation, knowledge, financial support, collective creation, and many more. Individuals on social media are both producers and consumers of information (Grover et al., 2022). Social media gives individuals empowerment in the decision-making process (Bulut & Karabulut, 2018; Sadovykh et al., 2015)

In the existing literature social media can be defined as many things as possible. Social media is as “a technology-centric—but not entirely technological—ecosystem in which a diverse and complex set of behaviors, interactions, and exchanges involving various kinds of interconnected actors (individuals and firms, organizations, and institutions) can occur” (Appel et al., 2020, p. 80). More straightforward definitions of social media exist. Kaplan and Haenlein (2010) define social media as a group of internet-based applications that build and enable the creation and exchange of user-generated content. This term encompasses various collaborative applications, including, blogs/microblogs (e.g. Twitter/X), content communities (e.g. YouTube), and social networking sites (e.g. LinkedIn).

Dellaracas et al., (2010) and Mangold & Faulds (2009) explain social media, also known as user-generated media, as online information sources generated, initiated, disseminated and used by consumers to inform each other about products, brands, services, personalities and issues. Kapoor et al., (2018) explain social media as various user-driven online platforms that enable the dissemination of information, the creation of dialogue and communication with each other and a wider audience. Basically, it is a digital environment that provides an environment conducive to interactions and networking at different levels, including professional, business, and personal. Applications like X, LinkedIn, and other specialized forums serve as these online platforms where investors engage in discussions, share insights, and access a wide range of information (Valle-Cruz et al., 2022).

Many researchers have explored areas at the intersection of social media and investing. Bukovina (2016) found that online social platforms offer the benefit of mutual education and gathering investment-related opinions in the stock market. Tan and Tan (2012) found that the behavior of social media users significantly and positively influences social development and the investment decision-making process. Chen et al., (2013) examine how social media affects investor sentiment within financial markets, specifically analyzing whether articles posted on social media can predict future stock returns and profits. The authors identify three motivations for sharing investment insights, including feeling more useful because of attention and recognition, getting paid for reviews that led to profits, and expecting market prices to match the true values by people because of the information getting exchanged on such platforms (Chen et al., 2013).

Exposure, in principle, is a more straightforward concept. Michael Slater (2004) refers to exposure as the degree to which the audience have come across specific messages or categories of messages. In the context of this study, exposure relates to the frequency with which individuals encounter financial-related messages. In research, exposure on social media is often categorized into intentional exposure and incidental exposure (Matthes et al., 2020; Nanz et al., 2022). An example of intentional exposure related to investment decisions could be an individual actively seeking financial information, market updates, or investment strategies on social media platforms to make informed decisions. On the other hand, incidental exposure in the context of investment decisions might occur when individuals, while casually browsing social media, come across financial news, stock market trends, or investment-related content without actively seeking it. The extent to which an individual is exposed to financial information on social media could influence investment decisions. Recognizing the value of this wealth of information on social media, practitioners have developed sentiment analysis tools to make effective use of it. These tools automatically distinguish opinions and emotions in texts and extract positive or negative sentiments from social media data (Pang & Lee, 2004). A study conducted by He et al., (2016) examined the importance of social media sentiment in predicting stock prices, especially on platforms such as Twitter/X. The findings suggest that negative sentiment is a particularly influential factor in predicting future stock prices. Interestingly, the study also shows that tweet volume and positive sentiment have less predictive power. This indicates that negative sentiment weighs more heavily in shaping market perceptions and investor behavior.

Based on my understanding of social media and exposure and the aforementioned definitions, within the context of this study, I propose the following definition of social media exposure.

Social media exposure refers to the frequency with which individuals engage with financial-related content like information about finance, investments, and market trends on social media platforms. It indicates how users, who both create and consume financial content, interact with information relevant to their investment choices on social media.

2.3 Dependent variable

2.3.1 Investments decisions

The study of investment decisions is an ongoing and diverse global subject, characterised by continuous exploration of various influencing variables. Investment decisions are a crucial aspect of financial markets, where individuals allocate their resources to various assets and securities in pursuit of optimal returns. Two prominent theories, as discussed in the schools of thought section are the traditional finance theory and behavioral finance theory and offer different perspectives on how investors make decisions in the world of finance. While traditional finance theory is based on that investors operate in a rational manner, driven by the objective of maximizing profits and usually exhibit risk aversion (Kamoune & Ibenrissoul, 2022), behavioral finance incorporates principles from both economics and psychology and plays a crucial role in understanding the irrational and emotional dimensions of investing decisions (Belsky & Gilovich, 2000; Prosad et al., 2015).

The behavioral traits identified in this context extend to various aspects of financial decision-making, including investment choices, portfolio composition and the precise timing of securities transactions (Barberis & Thaler, 2003; Statman, 2014; Thaler & Ganser, 2015). In the field of investment decisions, the principles of behavioral finance are becoming increasingly relevant. Behavioral principles of finance discuss the approaches in which individuals deviate from rational decision-making in finance due to psychological and emotional factors and the influence of biases. These biases include overconfidence, loss aversion, and herd mentality, among others.

As explained investment decisions are closely linked to both traditional finance and behavioral finance. However, the recent literature reveals a variety of definitions for investment decisions. Researchers, such as Bakar & Yi (2016), Hamzaçebi & Pekkaya (2011) and Lin (2011), present investment decisions as a rational process in line with traditional financial principles. An alternative perspective is presented by Masini & Menichetti (2012) , they associate investment decisions with the amount of resources invested and see it as a process where individuals make choices about the allocation of their financial resources across different assets or securities. Kumar & Kishori (2016) argue that investment decisions are made strategically to achieve superior returns, with immediate benefits being deliberately weighed. Their perspective emphasizes that the essence of investment decisions lies in pursuing future gains, even if this requires sacrificing immediate gains in the present.

Based on my understanding of investment decisions and the aforementioned definitions, within the context of this study, I propose the following definition of investment decisions.

> *"Investment decisions refer to the choices individuals make about their investments. These decisions are influenced by a range of factors, including investment propensity and resource allocation. This intricate process involves a mix of rational considerations, emotional influences, and various biases, which collectively influence the decision-making process."*

2.4 Moderator variables

2.4.1 Tie strength

Not all social relationships are equally strong. Individuals distinguish between friends and best friends, and between close friends and casual acquaintances. Researchers have recognized this aspect of social relationships and use the term "tie strength" to describe this concept (Granovetter, 1973; Marsden & Campbell, 1984).

Granovetter's (1973) original framework outlined four dimensions that determine the strength of ties. The time dimension examines the time aspects of a connection, considering the time of the first and last interaction and the frequency of interactions. Intimacy examines factors such as emotional closeness, and relationship status (e.g. marriage, close friendship, circle of acquaintances), offering insight into the depth of relationships. The intensity dimension quantifies the frequency and volume of interactions, including messages, posts, and comments. Finally, reciprocal services measure the shared applications and links exchanged between individuals, shedding light on the mutual services they interact with (Gilbert & Karahalios, 2009; Perikos & Michael, 2022). Further research has expanded the range of factors influencing the strength of ties. For example, a study by Wellman and Wortley (1990) finds that providing emotional support, such as counselling within family issues, produces a stronger tie. Research by Lin et al., (1981) shows that social distance, which includes factors such as, education level, political affiliation, ethnicity and gender, plays a crucial role in influencing tie strength.

In the literature other definitions, yet related, of tie strength are given. Money et al., (1998, p. 79) explain tie strength as "a multidimensional construct that represents the strength of the dyadic interpersonal relationships in the context of social networks". Gilbert (2012) refer to tie strength as a general feeling of intimacy of closeness between individuals.

However, the existing literature most frequently distinguishes between two types of ties: weak and strong ties. Weak ties include connections between individuals without close relationship or frequent interaction, often exemplified by relationships with acquaintances or colleagues with infrequent involvement. Strong ties, on the other hand, indicate strong social connections usually found among close friends or family members who have regular interactions (Bapna et al., 2017; Brown & Reingen, 1987). When observing friendships in an offline social network, Granovetter (1973) identified that weak ties could serve as sources of information through their connections in separate social circles, allowing for better dissemination of new information. When Granovetter (1983) revisited this topic a decade later, he identified that individuals with strong ties were more likely to be called on and willing to help, even though they might be limited in the amount of new information they could provide.

A study by Samuel-Azran & Hayat (2019) found that the strength of the tie between the person sharing the item and its recipient plays a mediating role in the impact of the credibility perception toward the news source, the perceived credibility of the item and the propensity to seek more information about the presented content. In simple terms, participants with a stronger tie with the person believed to have shared the content, tended to rate the credibility of the shared content more positively. Although the strength of the ties between the participants and the content sharer has nothing to do with the actual credibility of the content, the findings show that the strength of the tie biases the participants perception regarding the shared content. Putnam (2000) emphasizes, each type of tie involves different forms of information. Weak ties serve as valuable channels for exposure to new information and play a crucial role in broadening individuals' horizons. On the other hand, strong ties contribute to emotional and social support, underlining the importance of information coming from weak ties.

In the field of social media exposure and its impact on investment decisions, the strength of a tie could play a crucial role, also in determining the credibility of the investment-related information shared within digital platforms. It is essential to examine the influence of tie strength and its potential impact on the relationship between social media exposure and investment decisions. Based on my understanding of tie strength and the aforementioned definitions, within the context of this study, I propose the following definition of tie strength.

"Tie strength indicates the degree of connection between individuals specifically within social media platforms, excluding close offline relationships such as family members and friends who frequently meet in person. Within this social platform environment, tie strength influences how individuals perceive and trust investment-related information shared by their connections. A distinction is made between weak ties, representing less intimate and irregular online relationships, and strong ties, which signify deeper social ties and regular engagement on the platform."

2.4.2 Financial influencers

In the area of investment decisions, individuals use various social media platforms to share and get insights and opinions on various financial assets and securities. This practice extends to financial influencers who, unlike traditional financial advisers, play a crucial role in providing advice on spectrum of topics, such as leaving information on specific investment assets (Chikhi, 2012). The concept financial influencers, also called 'finfluencers', is a relatively underresearched area of research. Research by van Reijmersdal and Hudders (2023) defines finfluencers as individuals who provide financial advice online to their followers. These finfluencers position themselves as experts on finance and regularly share advice on platforms such as Twitter/X, reaching a significant number of followers (van Reijmersdal & Hudders, 2023). In doing so, finfluencers gain credibility in the financial field, spreading current trends and developments to their followers. Their influence appears to have a significant impact on their followers' decision-making process. This influence extends to investment decisions, as investors can look to the opinions of finfluencers for advice and insights regarding where and how much to invest. With their ability to influence opinions and potentially create trends, influencers can potentially get investors to allocate more money to specific financial assets or investment strategists that they promote.

While the study of finfluencers remains relatively unexplored, the concept is closely associated with social media influencers. More extensive research has been conducted on social media influencers, and for the purpose of this study, we will draw insights specifically from research that pertains to social media influencers in the context of investment decisions and the financial information they share.

It has been argued by numerous researchers that social media influencers have significant persuasive power, shape opinions and influence consumers' decision-making processes (Glucksman, 2017). With some influencers having millions of followers, their actions can influence a significant proportion of public opinion and trigger shifts in behavior, attitudes and even aspects of personal identity (Alves de Castro et al., 2021). Freberg et al., (2011) characterize social media influencers as a new category of independent third parties who shape public opinion through blogs, tweets and various social media platforms. Lou and Yuan (2018) define social media influencers as expert content generators, recognized for their expertise in specific domains, with a significant amount of followers cultivated by regularly creating valuable content on social media platforms. It's important to note that while influencers may operate in diverse sectors beyond finance and investment, this study focuses solely on these domains. They are individuals who have built considerable credibility within a specific sector, the financial and investment sector in this instance (Arora et al., 2019).

A study conducted by Ante (2021) examined the impact of Elon Musk's tweets regarding cryptocurrency on both pricing and trading volume. The results show a significant effect of Musk's tweets on cryptocurrency, evidenced by changes in both pricing dynamics and trading volume. This can be attributed to Elon Musk's status as a well-known and successful entrepreneur who consistently communicates with a substantial follower base on Twitter/X. Followers tend to associate the cryptocurrencies mentioned in his tweets with similar success in terms of financial returns. Musk's tweets and investments in cryptocurrencies, such as Bitcoin, automatically generate trust among his followers, which then influences their perception of this currency (Ante, 2021; Gupta et al., 2022; Shahzad et al., 2022). A study by Liljander et al., (2015) found that people see recommendations from social media influencers in the same way as those from friends and family and find them equally reliable and credible.

Studies by Brans and Scholtens (2020) and Ge et al., (2019) have both investigated the impact of individual tweets on financial market return. Ge et al., (2019) found that tweets from Donald Trump have the power to influence stock prices, leading to increased trading volume, volatility and attention from investors. Brans and Scholtens (2020) found that tweets, especially tweets expressing strong negative sentiment, trigger a significant economically negative reaction from the investors. Although Elon Musk and Donald Trump are extreme examples of individuals with high influence on social media, countless less influential individuals, groups and companies also express their opinions on currency through social media, influencing investment decisions (Ante, 2021).

In terms of social media exposure and its impact on investment decisions, financial influencers could play a crucial role in shaping individuals' perceptions and choices regarding investment decisions. Within the context of this study, I propose the following definition for financial influencers.

> *"Financial influencers are content generators with a substantial follower amount specialized in the financial field, who use their digital platforms to shape their followers' attitudes and decision-making processes regarding financial investments."*

2.5 The link between traditional/behavioral finance, social media exposure and investment decisions

In recent years, social media has had a major impact on various aspects of society, including finance. To understand this impact, it is essential to examine the fundamental theories of traditional finance and behavioral finance. Traditional finance assumes that investors are rational individuals who make decisions based on objective assessments of risk and return. This framework emphasizes principles such as market efficiency, where asset prices reflect all available information, and portfolio diversification, which aims to minimize risk by spreading investments across different assets (Chen et al., 2013; Kamoune & Ibenrissoul, 2022).

In contrast, behavioral finance challenges investors' notion of rationality by including psychological factors in the analysis of financial decision-making. It recognizes that cognitive biases and emotional reactions can lead to deviations from optimal investment strategies. Behavioral finance identifies several biases, such as herd behavior, overconfidence and confirmation bias that can significantly influence investors' actions and market outcomes (Almansour et al., 2023; Byrne & Brooks, 2008). Social media has emerged as a powerful tool shaping both traditional and behavioral finance through its role in information dissemination and interaction with investors. Platforms such as Twitter and LinkedIn provide a continuous flow of real-time data, opinions, and market trends, allowing investors to make timely decisions (Agarwal et al., 2021). However, the influence of social media goes beyond just providing information; it also influences investor sentiment and behaviour in multiple ways (Ausat, 2023).

One of the primary biases influenced by social media is herd behavior. Social media reinforces this behavior by spreading trends and opinions quickly, making it easy for investors to see what others are doing and feel compelled to do the same. For example, if a particular stock becomes popular on Twitter, many investors may rush to buy it, causing the stock price to skyrocket. This collective movement can inflate asset prices and create market bubbles (Sharma & Bikhchandani, 2000). One example is the rise in GameStop's share price in early 2021, when buying efforts fueled by social media platforms such as Reddit led to an unsustainable rise in the share price, ultimately resulting in a significant correction and financial losses for many latecomers (Zhu et al., 2022).

Confirmation bias is another key factor driven by social media. Investors often use these platforms to seek information that supports their existing beliefs, while ignoring contradictory evidence. This selective exposure reinforces their biases and can lead to poor investment decisions. For example, an investor who is optimistic about the future of stocks might only follow accounts that share positive news about it, ignoring negative developments or warnings. This behavior can lead to a skewed perception of the market and sub-optimal investment choices (Park et al., 2010).

The fear of missing out (FOMO) is reinforced by social media, where success stories of profitable investments are often showcased. This can lead investors to make impulsive decisions to join perceived lucrative trends without doing proper research. For example, seeing reports of individuals making significant profits from a new cryptocurrency can prompt other investors to rush into it, often without understanding the underlying risks. This behaviour can lead to investments in over-hyped assets that may not be fundamentally sound (Güngör et al., 2022). The rise in popularity of certain meme coins and their subsequent crash illustrate how FOMO driven by social media can lead to significant financial losses for uninformed investors (Friederich et al., 2023).

Overconfidence is also common in social media environments, with social media creating echo chambers that reinforce investors' belief in their knowledge and decision-making abilities. Constant validation from social media groups, for example, can lead investors to overestimate their understanding of market dynamics, leading them to make riskier investments without adequate risk assessment. This overconfidence can lead investors to overlook the need for thorough research and proper risk management, which can lead to significant financial losses (Ausat, 2023).

Understanding these behavioral trends is essential for identifying and mitigating biases, thereby improving investment decision-making. By recognizing the key biases that shape investment behavior in the context of social media interaction, investors can make more rational and informed decisions. By being aware of these biases, investors can implement strategies to counter them, such as seeking different opinions, conducting thorough research and maintaining a long-term perspective.

2.6 Research hypothesis

The theoretical framework presented above explained the concepts of social media exposure, investment decisions, tie strength and financial influencers. The framework suggests that social media exposure may influence individuals' investment decisions in financial markets. Besides that, it is possible that the relationship between social media exposure and investment decisions is impacted by the variables of tie strength and financial influencers. Therefore, the primary objective of this study is to examine the influence of social media exposure on investment decisions and whether tie strength and financial influencers are moderators in this relationship.

Based on this assumption, the following hypotheses are formulated:

H0a: Social media exposure has no perceived impact on investors own investors' decisions.
H1a: Social media exposure has a significant positive perceived impact on investors own investors' decisions.
H0b: Social media exposure has no perceived impact on others investors investment decisions.
H1b: Social media exposure has a significant positive perceived impact on others investors investment decisions

H0a: The perceived impact between social media exposure and investors own investor's decisions is not moderated by tie strength
H2a: The perceived impact between social media exposure and investors own investor's decisions is moderated by tie strength
H0b: The perceived impact between social media exposure and others investors investment decisions is not moderated by tie strength
H2b: The perceived impact between social media exposure and others investors investment decisions is moderated by tie strength

H0a: The perceived impact between social media exposure and investors own investor's decisions is not moderated by financial influencers
H3a: The perceived impact between social media exposure and investors own investor's decisions is moderated by financial influencers
H0b: The perceived impact between social media exposure and others investors investment decisions is not moderated by financial influencers

H3b: The perceived impact between social media exposure and others investors investment decisions is moderated by financial influencers

These hypotheses are intended to guide empirical research into the connection between social media and investor decisions.

2.7 Conceptual framework

Considering the independent, dependent, and moderating variables, as well as the hypotheses formulated to investigate the impact of social media exposure on investment decisions, the following conceptual framework has been developed:

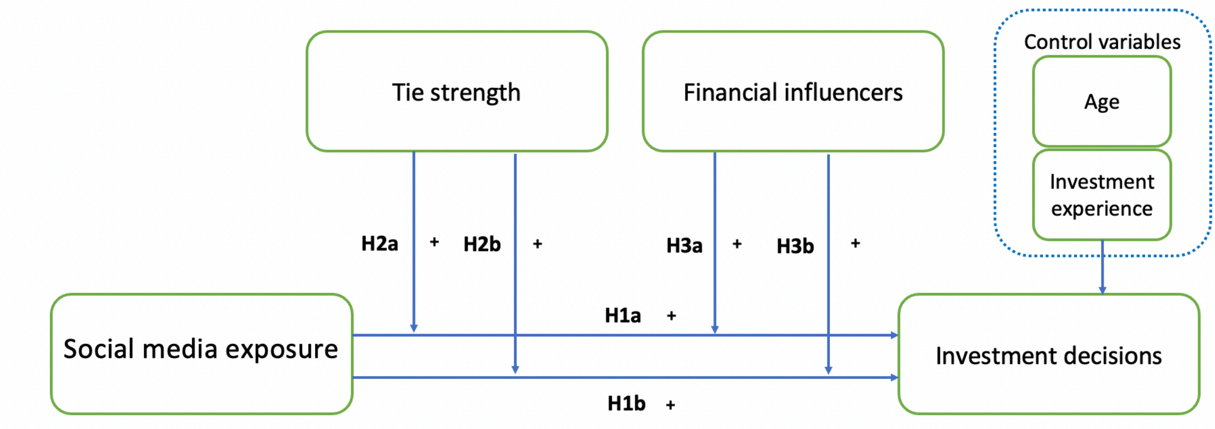

Table 1 Conceptual framework

2.8 Literature search

The search for theoretical support in our research included an extensive literature review, aiming to find relevant articles to our research topic. This extensive research included several important studies that contribute different perspectives to the study. Barberis and Thaler (2003), Statman (2014) and Thaler and Ganser (2015) made important contributions to the behavioral aspects of investment decisions. These researchers delved into the behavioral traits that may influence investment decisions. In parallel, an important contribution was made by a study conducted in Malaysia by Ismail et al (2018), which specifically examined the impact of social media on investment decisions. In addition to these studies, the literature review included a range of other relevant sources, including academic articles and books. This ensured that a comprehensive theorical framework was formed by different perspectives.

Using databases, including Scopus and ResearchGate, eased the search for relevant articles within the scope of the study. Some key concepts of the topic were defined and searched for. These concepts covered a wide range, including but not limited to "investment decision", "social media" AND "exposure", "social media sentiment", "behavioral finance", "tie strength" and "social media influencer". After finding relevant articles while searching for key concepts, an additional strategy for seeking worthy information was to search for different citations within the paper found. This method, known as citation search, starts by identifying an original article, followed by a search for newer articles that were cited by the original article (Linder et al., 2015). Papaioannou et al., (2010) found citation searches to be an effective addition to traditional subject search to provide additional high-quality references.

The influence of social media on investment decisions, as shown in articles from various databases, provides a solid foundation for understanding the concepts explored in this study. Moreover, it sheds light on the decisions investors make about their investments. This research examines the ways in which information through social media platforms affects investors' financial investment choices.

3. Research methodology

In this paragraph, we begin with an explanation of the research methodology that has been carefully designed and used in this study. The paragraph outlines key aspects of our research methodology. We will discuss sample selection, emphasizing its size. Subsequently, the chosen research design will be explained, followed by insights into data collection, literature search, survey design and measurements, and data processing. Finally, ethical considerations of the survey and study will be addressed.

3.1 Sample selection

The sample selection involves a carefully considered process to ensure that the representation of participants matches the research objectives. In research, a sample refers to a subset of individuals or elements selected from a larger population. Sampling is a crucial methodological step that allows researchers to study a smaller group that is representative of the entire population, drawing conclusions about the population based on the characteristics of the sample (Cohen et al., 2017). The chosen sample includes all individuals who are involved in social media platforms. A diverse field of participants in searched for to capture different perspectives and behavior, which evidently will contribute to a better understanding of the impact of social media exposure on investment decisions.

3.1.1 Sample size

During the sample selection process, it is necessary to ensure that the sample size is sufficiently large to successfully fulfil the primary purpose of the study, which is to answer the research question (Rahman, 2023). Sample size essentially refers to the subset of a population needed to ensure that a substantial amount of information is available to draw meaningful conclusions (Sekaran & Bougie, 2010). Researchers often struggle with the question of what the right size for their research samples is. However, there is no single answer, as the ideal sample size depends on the specific objectives of the study and the characteristics of the population being studied (Cohen et al., 2017). A larger sample size, all other things being equal, contributes to reduced error and higher reliability or precision of survey results. This link with statistical power is inherently clear: with more accurate sample results, the probability of identifying significancy increases. Conversely, if the sample size is insufficiently small, the probability of achieving statistical significance decreases (Cohen, 1988). Various methods exist for determining sample size. According to Hair et al., (2019) a sample size of at least 50 is recommended for regression analysis, with a preference for 100 or more. Another approach, utilized in a study by Suhr (2006), involves the sample-to-item ratio, commonly used for factor analysis but other analytical methods as well, including regression analysis. This ratio suggests a minimum of 5 respondents per question or statement posed. While some studies advocate for a slightly higher ratio, for this study, with 24 questions/statements, a minimum of 120 respondents would be required. Considering the recommendation for a sample size exceeding 100, this study targets 150 respondents, to ensure an adequate amount of data for statistical testing. The target population for this study consists of Dutch individuals who have some level of interest in financial markets and could be exposed to financial content on social media platforms. This group includes experienced investors, traders, financial analysts, potential investors, students, and others interested in exploring financial opportunities. It is not necessary for participants to have prior investment experience, as the study aims to capture a broad range of perspectives. Participants are approached via LinkedIn, where the questionnaire has been distributed to gather responses.

3.1.2 Method

As said sampling is the process of selecting a sample from a population. The two main types of sampling methods are probability sampling and non-probability sampling (Elfil & Negida, 2017; Shorten & Moorley, 2014). In probability sampling, each sample has an equal chance of being selected, ensuring fair representation. Conversely, non-probability sampling methods use non-randomized approaches to collect samples, where participants are chosen based on accessibility rather than random selection. This study chooses non-probability sampling, using convenience sampling and snowball sampling. Convenience sampling involves selecting participants based on accessibility, with researchers choosing individuals who are readily available. In this method, those closest to them are often selected as respondents (Showkat & Parveen, 2017). In the snowball sampling method, participants who are already involved in the study actively refer/share the survey to other individuals within their social circles or acquaintances. This approach relies on the network created by the initial participants, expanding the sample size as the study progresses (Naderifar et al., 2017).

3.2 Research design

In this study, the methodology chosen takes the form of a survey. Survey research is the collection of information from a sample of individuals by seeking their answers to a series of questions (Check & Schutt, 2012, p. 160). Historically, survey research has involved large-scale, population-based data collection. The primary goal was to quickly obtain information about the characteristics of a substantial sample of interesting individuals (Ponto, 2015).

Survey research allows researchers to study variables scientifically in real-life situations. Because surveys often involve people, they help researchers connect with and understand relationships between individuals. Put more simply, it allows researchers to examine and learn about human behavior in different situations (Akpan & Senam, 2014). Survey research offers flexibility in participant recruitment, and data collection (Ponto, 2015). Surveys are not limited by geographical boundaries and are cost-effective, making them ideal for in-depth studies with minimal resources (Akpan & Senam, 2014).

When conducting a survey both open-ended as closed-ended can be asked to respondents. Open-ended questions allow free expression and offer insights beyond predetermined answers They are useful in unfamiliar topics, but require more time and effort, making analysis and decision-making more difficult (Salant & Dillman, 1994, pp. 79-81). In contrast, closed-ended questions restrict respondents to predetermined answers, with the questions forming sequential responses (Reja et al., 2003). In this study, survey research was applied, using mainly closed questions structured on a Likert scale. Respondents had to indicate the extent to which they agreed (from strongly disagree to strongly agree) with a number of statements related to the hypotheses (Joshi et al., 2015).

This study investigates the influence of social media exposure on investors' decision-making process, examining the moderating role of strong ties and financial influencers in this relationship. Social media exposure is considered as an independent variable, while investment decisions serve as the dependent variable. The dependent variable is measured using two different parameters. First, it investigates whether exposure to social media affects the investment propensity to invest in specific assets or securities. Second, it examines the influence of exposure to social media on the amount of resources invested. Some examples of the statements; “I believe, other people can be influenced by the financial information they encounter on social media when deciding to invest or not.” or “I am likely to make a decision on whether to invest or not based on a recommendation on social media.”.

3.3 Data collection

In survey research, questionnaires and interviews are the most used data collection methods (Ponto, 2015). This study will use a self-completed questionnaire, which has both advantages and disadvantages. Self-completed questionnaires offer broad coverage within the target population, are suitable for sensitive topics and are cost-effective compared to interviews (Bowling, 2005; Gwaltney et al., 2008). However, they face quality problems due to lack of seriousness or attentiveness among respondents, leading to biased results (Aust et al., 2013; Barnette, 1999; Fleischer et al., 2015). Survey fatigue, where respondents lose interest or motivation, can further compromise survey accuracy and quality (Brown et al., 2024).

In addition, the challenges associated with non-response add to the general survey quality considerations. Non-response, in which respondents choose not to answer specific questions or statements, for whatever reason, hinders obtaining comprehensive data (Kwak & Radler, 2002). Surveys with a high degree of item completeness, indicating that respondents answer most, if not all, of the questions, are generally considered of higher quality (Schaefer & Dillman, 1998).

For this study, the self-administered questionnaire was generated using Qualtrics. The questionnaire was distributed across various social media platforms, including LinkedIn and Instagram, as well as to other individuals within the network. People sharing the questionnaire ensured a greater reach among the participants. Upon reaching enough respondents, the questionnaire was closed, and the collected data were analyzed using RStudio.

3.4 Design of the survey and measurements

As mentioned earlier, this study chose to collect data using a self-administered questionnaire. This choice was made to gather valuable insights directly from the participants, allowing them to respond independently to a series of statements and questions. The design of the questionnaire involved statements and questions borrowed of studies by Luong & Ha (2011) and Sarva (2014).

The questionnaire is structured into four different sections. Firstly, the personal information section includes demographic questions aimed at collecting background data of participants. Participants are asked about factors such as gender, age, and education level to explore whether these variables might influence the relationship between social media exposure and investment decisions. In the second section, the focus shifts to examining the influence social media exposure in relation to the dependent variable, investment decisions. Here, first, the concept of exposure to social media, as formed in the literature review, is explained. Respondents are then presented with a series of questions and statements that examine the relationship of this concept with investment decisions. The third section focuses on exploring the possible influence of tie strength on this relationship. A detailed explanation of the concept of tie strength is introduced before a series of questions and statements examining the relationship with social media exposure and investment decisions. The last section follows a similar approach, focusing on the examination of another potential moderator variable: financial influencers. A structure of the questionnaire is displayed below.

Area of focus	Questions
Personal information	
Questions related to demographics and investments	Questions 1-8
Social media exposure - Investment decisions	
Questions on social media influencing investment decisions	Questions 9-15
Tie strength	
Questions on social media ties' impact on investment decisions.	Questions 16-20
Financial influencers	
Questions on financial influencers impact on social media on investment decisions	Questions 21-24

Table 2 Questionnaire information

The statements in this questionnaire are measured using Likert Scaling, a commonly employed psychometric scale in surveys and one of the most prevalent measurement tools in research studies. When responding to Likert questionnaire items, participants indicate their level of agreement with specific statements (Pimentel, 2010). There was uncertainty about whether to use a 5-point Likert Scale with a midpoint or a 6-point Likert Scale without a midpoint. Questionnaires with a midpoint allow respondents to express a truly neutral opinion. This allows people to neither agree nor disagree if they feel uncertain or unsure about the topic. Conversely, questionnaires without a midpoint prevent respondents from abusing this option. However, if there is no midpoint, respondents are denied the opportunity to take a neutral point of view. As a result, they may feel forced to choose a side, which may introduce bias into the data collected (Chyung et al., 2017). In this questionnaire specifically, the statements were measured with a 5-point Likert Scale. This was chosen because it provides enough response options to capture variation in attitudes or opinions, while still allowing respondents to express neutrality when unsure about a statement. Table 3 gives an overview of the defnition of the variables.

Variable	Measured by question	Scale	Source	Own definition
Social media exposure (IV)	10	1-5 likert scale	(Dellaracas et al., 2010; Bechmann & Lomborg, 2013; Park et al., 2018).	*"Social media exposure refers to the frequency with which individuals engage with financial-related content like information about finance, investments, and market trends on social media platforms."*
Investment decisions (DV)	12-13-14-15	1-5 likert scale	(Lin ,2011; Masini & Menichetti, 2012; Bakar & Yi, 2016)	*"Investment decisions involve allocating financial resources among various assets and securities. This intricate process involves a mix of rational considerations, emotional influences, and various biases, which collectively influence the decision-making process."*
Tie strength (Moderator)	17-18-19-20	1-5 likert scale	(Granovetter, 1973; Marsden & Campbell, 1984; Gilbert, 2012)	*"Tie strength indicates the degree of connection between individuals specifically within social media platforms, excluding close offline relationships such as family members and friends who frequently meet in person. Within this social platform environment, tie strength influences how individuals perceive and trust investment-related information shared by their connections.*
Financial influencers (Moderator)	23-24	1-5 likert scale	(Reijmersdal and Hudders, 2023)	*"Financial influencers are content generators with a substantial follower amount specialized in the financial field, who use their digital platforms to shape their followers' attitudes and decision-making processes regarding financial investments."*
Age (CV)	2	Sociodemographic data	-	*"Age of respondents"*
Investment experience (CV)	6	Sociodemographic data	-	"Experience with investing in stocks, bonds etc."

Table 3 Variable definition

3.5 Data analysis

The data analysis will be done using RStudio. Initially, the data collected from Qualtrics will be imported into RStudio for analysis. After importing the data, a search is performed to identify missing values. The values are removed from the dataset to ensure data accuracy. After cleaning the data, analysis is performed in two stages. In the first stage, descriptive statistics are used to provide an overview of the data. The second stage of analysis uses inferential statistics to examine relationships and conclusions about the data.

3.5.1 Descriptive statistics

Descriptive statistics are used in summarizing data in a structured manner and can provide first-ever insights into the relationships between variables within a sample or population. This first step in research is important because it lays the foundation for the next step, inferential statistics (Yellapu, 2018). In this study, descriptive statistics are used to summarize respondents' personal information. This includes, for example, the measurement of frequency, mode, mean of factors such as gender and education level.

3.5.2 Inferential statistics

Inferential statistics go beyond merely summarizing data, which is the case with descriptive statistics. Inferential statistics is concerned with making inferences about entire populations based on observations from a small sample. Inferential statistics uses different methodologies to assess hypotheses and draw conclusions applicable to a larger population (Gillian, 2007).

This study uses regression analysis, more specifically, moderated regression analysis in the sense of an ordinary least squares (OLS) analysis. This technique is employed to investigate whether one or more variables (the independent variable or X) can predict or account for the variability in another variable (the dependent variable or Y) (Wooditch et al., 2021). In this study, the moderator variables studied are tie strength and financial influencers, which can interact with the independent variable to affect the dependent variable.

3.5.3 Cronbach's alpha

In the data analysis process, Cronbach's alpha is used to assess reliability. This metric serves as a valuable tool for evaluating the consistency of the questionnaire used in data collection. Calculating Cronbach's alpha allows evaluating the reliability of the measurements obtained through the questionnaire and ensures that the data accurately represent the constructs being studied (Christmann & Van Aelst, 2006). Cronbach's alpha ranges from zero to one, with higher values indicating that response values for each participant across a set of questions are consistent (Bujang et al., 2018). A general rule of thumb is that Cronbach's alpha values of 0.7 or higher indicate acceptable internal consistency (Taber, 2018). Some researchers argue that a Cronbach's alpha exceeding 0.6 can be considered acceptable (Shelby, 2011). In this study, our goal is to achieve a Cronbach's alpha value that is as high as possible, ideally surpassing the 0.7 but certainly not falling below 0.6, considering questions that measure the same variable.

3.6 Ethics

Ethical considerations are fundamental in any research, even if it involves collecting data through questionnaires. Questionnaires are valuable tools for collecting information, but they also pose ethical issues that researchers must deal with carefully. A study by Roberts and Allen (2015) and Ng (2006) listed some ethical issues that arise within the use of online questionnaires.

3.6.1 Informed voluntary consent

Informed consent is a crucial part of ethical and legal requirements for research involving human participants. It involves providing participants with information about the study so that they can make an informed decision about their involvement. After reviewing all relevant details of the study, participants voluntarily indicate their willingness to participate (Nijhawan et al., 2013). In this study, the ethical issue of informed consent is addressed by giving participants information about the study before they start the questionnaire. In addition, emphasis is placed on the voluntary nature of participation, allowing individuals to freely decide whether to participate or not.

3.6.2 Privacy, anonymity, and confidentiality

Privacy, anonymity, and confidentiality are essential ethical issues in online survey research. It is essential to limit any invasion of participants' privacy, anonymity and confidentiality at all stages of the survey (Roberts & Allen, 2015). Insufficient measures to ensure privacy, anonymity, and confidentiality by a researcher may not only cause harm to participants, but also affect the overall credibility of research findings (Kang & Hwang, 2023). This study addresses the ethical issues of privacy, anonymity, and confidentiality by taking measures to protect participants' personal information. These measures include maintaining strict confidentiality and anonymizing all data collected. Identifying details (names) are not required, ensuring participants' privacy throughout the study.

3.6.3 Conflicts of interest

A conflict of interest occurs when researchers have undisclosed interests that could influence their publication decisions. These conflicts include personal, commercial, political, academic, or financial interests. Financial interests in this case, may involve employment, or research funding (Ng, 2006). This study is being conducted as part of the master's program in Business Administration. There are no financial gains or conflicts of interest associated with academic pursuits or any other form of conflict in this study. Consequently, there is no internal or external influence on the analysis of the results.

4. Empirical findings

In this paragraph, the empirical findings of the study are presented. In the first part of the results, descriptive statistics are presented to give a general summary of the data. The second part consists of inferential statistics to examine relationships and draw conclusions from the data. The questionnaire results are primarily displayed in tables and charts, while statistical tests determine whether research hypotheses are rejected or accepted.

4.1 Descriptive statistics

Initially, there were 175 respondents for the questionnaire. After filtering out those who did not fully agree to the terms of the survey (1 individual) and those who did not complete the survey (32 individuals), we were left with a sample of 142 respondents. The largest age group consisted of those aged between 18 and 25 years, a total of 44 respondents. The second largest age group consisted of persons between 26 and 35 years, with 31 respondents. This was followed by 28 respondents in the 46-55 age group, making it the third-largest group. The fourth-largest group consisted of people over 55, with 23 responses. The smallest groups consisted of persons aged 36-45, with 16 responses. Among the 142 respondents, 87 identified as male, 52 identified as female, 2 chose not to disclose their gender, and 1 identified as a third gender. All of which can be seen in the graphs of table 2.

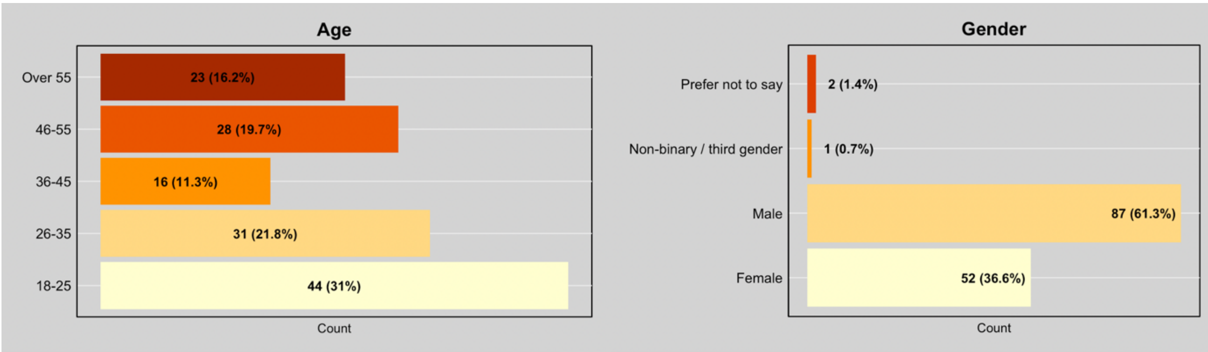

Table 4 Age + Gender

Among all respondents, 9 reported being unemployed, while 43 were employed part-time and 90 were employed full-time. In terms of their highest education levels: 7 respondents held a Ph.D. or higher degree, 33 respondents completed a master's degree, 74 respondents had a bachelor's degree as their highest educational attainment, 18 respondents had a high school diploma or lower as their highest form of education, and 10 respondents indicated something else as their highest level of education. These details are visible in table 3.

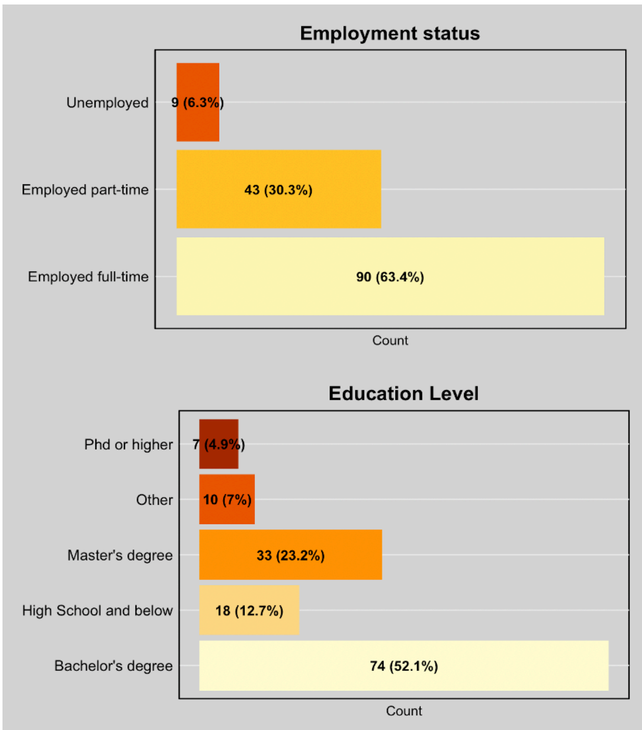

Table 5 Employment status + Education level

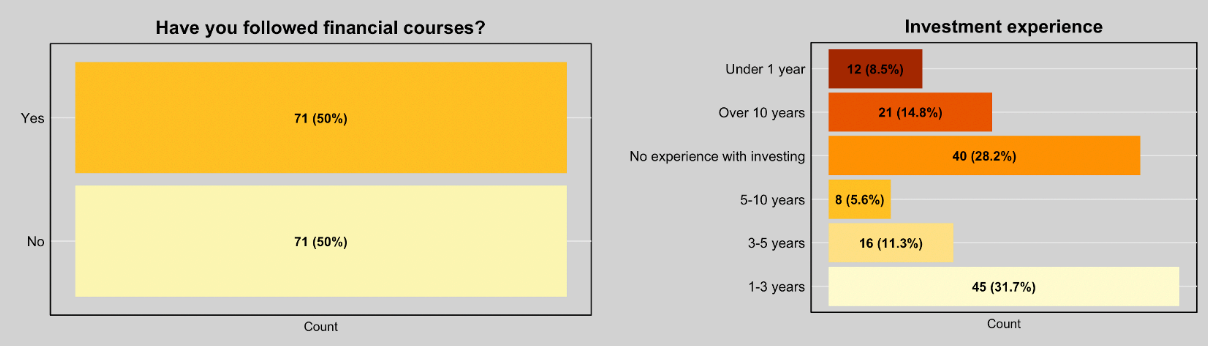

Table 6 Financial courses + Investment experience

Out of all respondents, exactly half of them, or 71 individuals, took financial courses either during school or for work, while the remaining 71 did not. It's important to note that lack of financial course-taking doesn't necessarily imply a lack of investment experience. Among the respondents, 40 had no investment experience, 12 had less than 1 year of experience, 45 had 1-3 years of experience, 16 had 3-5 years of experience, and 21 had over 10 years of experience. The above information is visible in table 4.

The above text mentioned that of the 142 respondents surveyed, 40 indicated that they had no experience in investing, leaving 102 respondents who already had some experience in investing. As indicated in the table above, the investment preferences of the respondents vary. Most respondents, a total of 73, invest in stocks. In addition, 45 respondents invest in cryptocurrencies, 35 in index funds, 19 in mutual funds, 15 in exchange-traded funds and 12 in bonds. In addition to the predefined choices, respondents had the option to specify other investment options. 3 respondents mentioned investing in real estate, 1 in crowdfunding and 1 in an investment management funds. It is important to note that respondents had the flexibility to select multiple investment options.

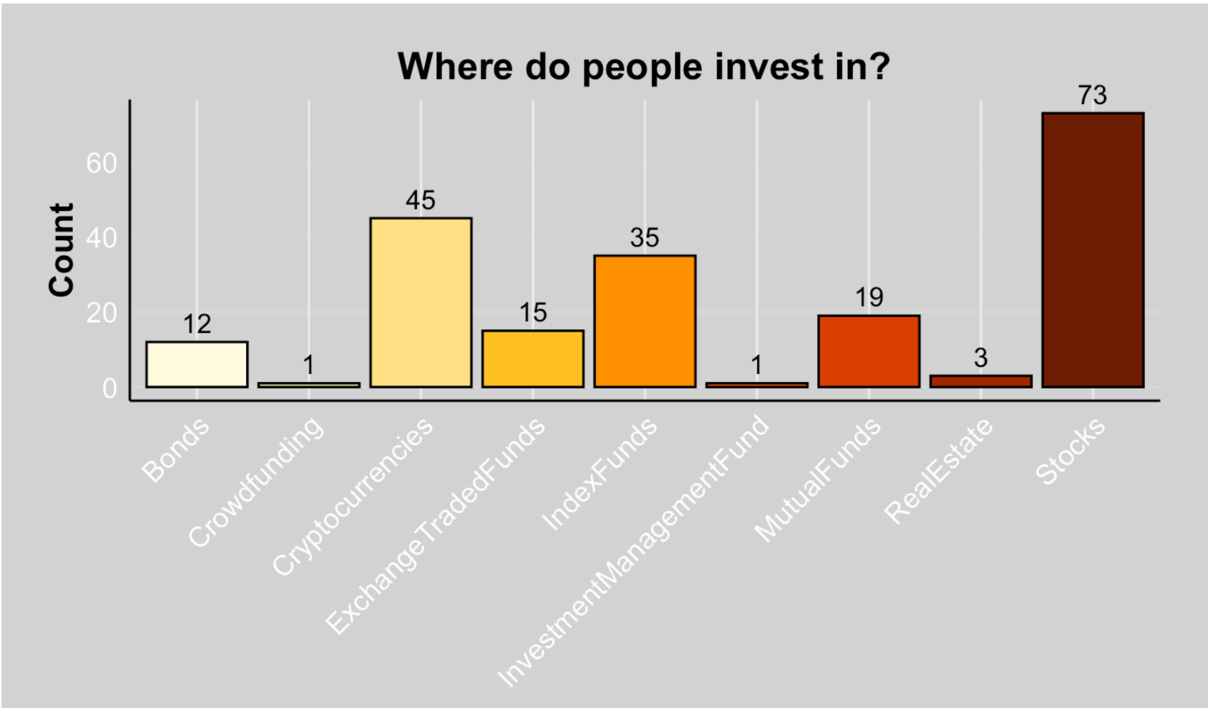

Table 7 Where do people invest in?

The questionnaire asked for insights into respondents' exposure to financial information through various social media platforms. Out of all social media platforms, LinkedIn emerged as the platform where respondents came across financial information the most. Twitter/X emerged as the second most influential platform, with 46 respondents being exposed to financial information on here.

Instagram, Facebook, TikTok, Reddit, YouTube, financial forums, and Telegram where the other social media platforms where respondents encountered financial information. More specifically, 28 respondents reported being exposed to financial information on Instagram, with this being the case for 26 respondents on Facebook. TikTok, although less featured in this context, was the platform where 6 respondents encountered financial information. Reddit and YouTube were also mentioned by 5 and 4 respondents respectively as platforms where they came across financial information. This was the case for financial-related forums for 2 respondents and Telegram was the social media platform for 1 respondent.

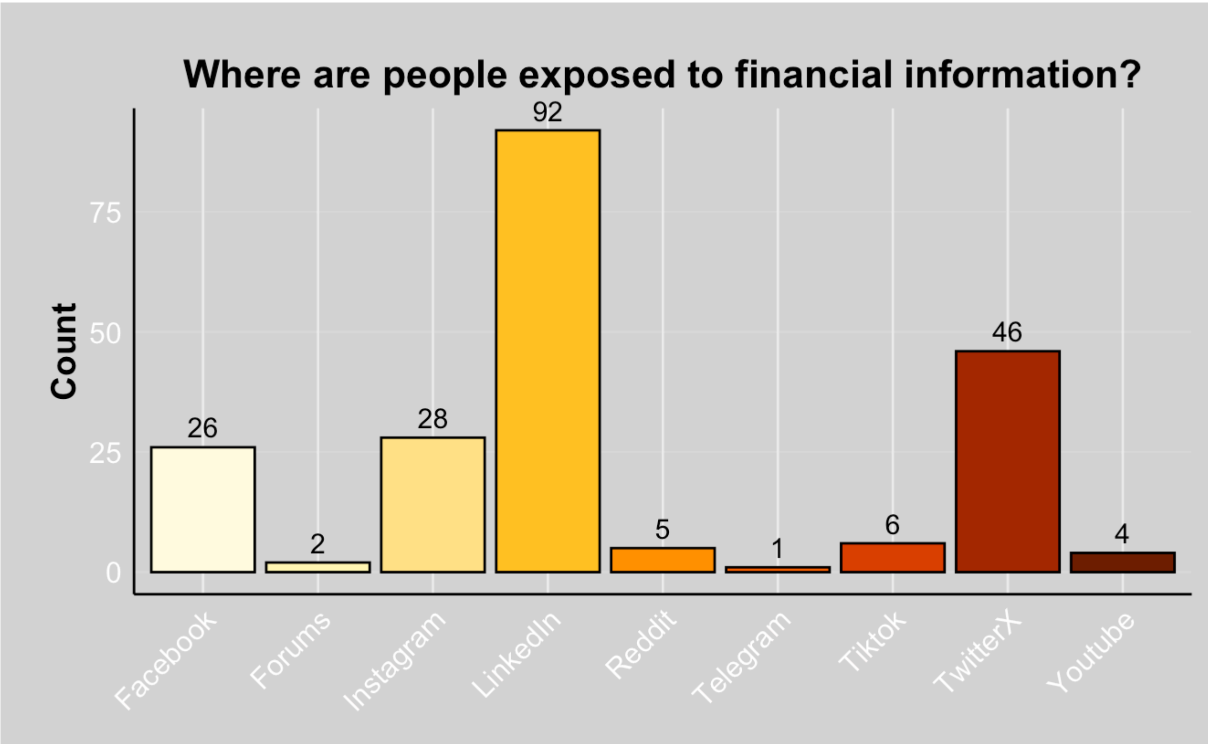

Table 8 Where are people exposed to financial information

Variable	NAME	Mean	Median	Standard deviation	Min	Max
IV	Exposure_financial_information_numeric	3,049	3	1,074	1	5
DV	SM_P_Propensity_numeric	2,908	4	1,142	1	5
DV	SM_O_Propensity_numeric	4,254	3	0,837	1	5
DV	SM_P_Resources_numeric	2,655	4	1,161	1	5
DV	SM_O_Resources_numeric	4,028	3	0,798	2	5

Table 9 Descriptive statistics IV and DVs

The table above shows the mean, median, standard deviation, minimum and maximum for the independent and dependent variables. All values were measured on a 5-point Likert scale, with 1 being the lowest and 5 the highest. The mean exposure to financial information is 3.049, indicating that people on average occasionally encounter financial information on social media. The propensity variables have averages of 2.908 and 4.254, suggesting that people generally neither agree nor disagree that they are personally influenced by financial information on social media, but do believe that others are. This pattern is similar for the resource variables. The standard deviations are about 1, indicating that values tend to be about 1 point above or below the mean. The minimum value is 1 for all variables except SM_O_Resources_numeric, which has a minimum of 2. This means that no respondent strongly disagrees that others have more incentive to invest resources when exposed to financial information on social media. The maximum value for all variables is 5, indicating that they strongly agree with the statements.

4.1 Inferential statistics

In the inferential statistics paragraph, ordinary least squares (OLS) regression analysis is conducted. This analysis first examines the relationship between exposure to financial information on social media and its influence on investment decisions, particularly investment propensity and allocation of more resources to assets. This initial relationship is controlled for age and investment experience. Next, the analysis examines the possible moderating effect of tie strength on this relationship. Finally, it examines the possible moderating effect of financial influencers. The analysis can be split into four parts for each relationship being tested.

At the beginning, it is tested is whether being exposed to financial information on social media affects whether people are more incentivized to buy a certain asset or not personally. Afterwards, it examines whether individuals believe that others' willingness to invest is influenced by exposure to financial information on social media. Then, the analysis examines whether individuals personally allocate more resources to certain assets when being more exposed to financial information on social media. Finally, it examines whether individuals think others allocate more resources to certain assets when being more exposed to financial information on social media.

This analysis is based on respondents answers to specific statements in the questionnaire. The independent variable, the frequency of exposure to financial information on social media, was measured on a scale of 1 (never) to 5 (very frequently). For the dependent variables, respondents answered four different statements designed to assess different aspects of investment behaviour.

The first analysis examines whether financial information on social media platforms affects respondents willingness to invest. Respondents were asked to rate the extent to which their personal investment propensity depends on financial information from social media, ranging from 1 (strongly disagree) to 5 (strongly agree). A similar approach was used to measure regarding the amount of resources they are willing to invest and whether this is influenced by the financial content they are exposed to online. Respondents were also asked whether they think others are influenced by financial information on social media and whether this perception affects their investment propensity and the amount they are willing to invest, rated on the same scale from 1 to 5.

For the moderator variable tie strength, respondents indicated whether their willingness to invest or invest more resources is influenced by their level of connection with a person posting financial-related content on social media, with the same scale from 1 to 5. Respondents indicated whether they were willing to invest more resources by their tie strength with a person posting financially related content on social media. Finally, for the moderator variable related to financial influencers, respondents were asked whether their willingness to invest or invest more depends on financial information shared on social media by a financial influencer, such as Elon Musk, again rated on a scale of 1 (strongly disagree) to 5 (strongly agree).

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	2.04218	0.48534	<0.001***
Financial information on SM	0.24724	0.09284	0.00866**
Age (CV)	-0.17256	0.07105	0.01643*
Investment experience (CV)	0.11379	0.05528	0.04142*

Table 10 Financial information on SM - Investment propensity (Personally)

The table on the left shows a regression analysis examining the influence of exposure to financial information on social media on individuals own investment decisions (propensity). The intercept, which represents the value of the dependent variable when all independent variables are zero, is 2.04218 and highly significant with a p-value of less than 0.001. The coefficient for financial information on social media reflects the change peoples willingness to invest when individuals are more exposed to financial information on social media, estimated at 0.24724. Meaning that for every unit increase people's willingness to invest increases by 0.24724 This coefficient is highly significant with a p-value of 0.008, indicating a significant impact on investment propensity. The variable age is included in the analysis as a control variable, with a coefficient estimated at -0.17256. This suggests that for every one-unit increase in age, there is a decrease of 0.17256, meaning that whenever people get older there willingness to invest declines when exposed to social media.. Age is also significant with a p-value of 0.01643, indicating its influence on investment propensity. Investment experience, another controlled variable, has a coefficient of 0.11379, meaning that people with more investment experience are more tented to invest. With a p-value of 0.04142, this control variable is significant, suggesting that investment experience may have a significant influence on investment propensity in this analysis.

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	3.70123	0.28650	<0.001***
Financial information on SM	0.20555	0.07072	0.00426**
Age (CV)	-0.04189	0.05241	0.42552
Investment experience (CV)	0.01254	0.04379	0.77510

Table 11 Financial information on SM - Investment propensity (Other)

The table to the right illustrates a regression analysis that examines whether individuals perceive that exposure to financial information affects others investors investment decisions (propensity). The intercept coefficient in this analysis is 3.701232, which is higher than what was observed in the person-level analysis and is highly significant. This indicates that when all independent variables are zero, the value of this dependent variable is almost twice as large as in the previous analysis. Thus, respondents believe that exposure to financial information has a greater perceived impact on others' willingness to invest than their own. The coefficient for financial information on social media in this context is 0.20555, slightly lower than the coefficient at the person level, but still significant with a p-value of 0.00426. The slight decrease in coefficient suggests that the perceived impact of financial information on others' investment decisions is slightly smaller than the perceived impact on their own investment decisions. The coefficients for the control variables, age, and investment experience, are -0.04189 and 0.01254, respectively. With p-values of 0.42552 and 0.77510, neither control variable has a significant effect on investment propensity in this analysis. Overall, these findings imply that individuals perceive others as more influenced by financial information on social media than they perceive themselves to be in terms of propensity.

Variables	Coefficient	SE	Significance
Investment resources (intercept)	1.441988	0.519335	0.00626**
Financial information on SM	0.279118	0.099343	0.00568**
Age (CV)	-0.003363	0.076021	0.96478
Investment experience (CV)	0.036219	0.059151	0.54133

Table 12 Financial information on SM - Investment resources (Personally)

In the table on the left, the regression analysis examines whether exposure to financial information on social media affects individuals' own investment decisions (specifically, the amount of resources they invest). The intercept of the dependent variable is estimated at 1.441988 and found to be significant with a p-value of 0.00626. The coefficient for the independent variable, exposure to financial information on social media, is 0.279118. This means that each unit increase in financial information on social media corresponds to a change of 0.279118 in people's own willingness to invest more resources. Moreover, the independent variable is also significant with a p-value of 0.00568. In this regression analysis, the control variables, age, and investment experience, have coefficients of -0.003363 and 0.036219, respectively. Their respective p-values of 0.96478 and 0.54133 indicate that neither control variable in this analysis has a significant effect on investing more resources.

Variables	Coefficient	SE	Significance
Investment resources (intercept)	3.66685	0.36269	<0.001***
Financial information on SM	0.05497	0.06938	0.4295
Age (CV)	-0.04440	0.05309	0.4044
Investment experience (CV)	0.08650	0.04131	0.0381*

Table 13 Financial information on SM - Investment resources (Other)

The table to the right shows a regression analysis that examines whether individuals perceive that exposure to financial information influences others investors investment decisions (specifically, the amount of resources people invest). The intercept of the dependent variable is estimated at 3.66685 and found to be highly significant with a p-value of less than 0.001.
However, the coefficient for the independent variable, financial information on social media, is estimated at 0.05497 with a p-value of 0.4295, indicating that it is not significant. This suggests that individuals do not believe that exposure to financial information on social media significantly influences the investment decisions of others, in terms of the amount of resources they invest. The estimated coefficients of the control variables age and investment experience are -0.04440 and 0.08650, respectively. While the control variable age is not significant with a p-value of 0.4044, the control variable investment experience is significant with a p-value of 0.0381. This indicates that investment experience has a significant effect on individuals investing more resources. In general, individuals recognize the influence of financial information on social media on their own investment decisions, but do not believe it has a significant influence on the decisions of others. Moreover, investment experience does not affect the size of investors' own investments, but it does affect the size of other investors' investments.

A separate moderated regression analysis was conducted for the potential moderator's tie strength and financial influencers. The results of this regression analysis are shown in the table to the right. The relationship tested was the original relationship between exposure to financial information on social media and its influence on investors own investment decisions (propensity), moderated by tie strength. The intercept of the dependent variable was measured at 1.56395 and is significant with a p-value of 0.0297. The coefficients for both financial information on social media and tie strength are 0.12428 and 0.30996, respectively, but neither is statistically significant. The control variable age is significant with a p-value of 0.0130, indicating a negative effect on the dependent variable. The control variable investment experience is not significant, with a p-value of 0.0970. The moderated relationship in this analysis, indicated by the interaction term, is not significant with a p-value of 0.8214, suggesting no significant effect on the relationship between financial information on social media and investment propensity.

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	1.56395	0.71195	0.0297*
Financial information on SM	0.12428	0.20890	0.5529
Tie strength	0.30996	0.18573	0.0974
Age (CV)	-0.16514	0.06558	0.0130*
Investment experience (CV)	0.09105	0.05448	0.0970
Financial * TS	0.01356	0.05995	0.8214

Table 14 Financial information on SM - Investment propensity moderated by tie strength (Personally)

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	4.48093	0.64938	<0.001***
Financial information on SM	-0.10614	0.16130	0.5116
Tie strength	-0.32678	0.20194	0.1079
Age (CV)	-0.05147	0.05471	0.3485
Investment experience (CV)	0.04745	0.04293	0.2710
Financial * TS	0.09379	0.05020	0.0639

Table 15 Financial information on SM - Investment propensity moderated by tie strength (Other)

As we saw in all previous analyses, a distinction was made between the effect on investors own investment decisions and the perception that individuals have it can influence the investment decisions of others. The same approach is applied in the table on the left, where a regression analysis is conducted from the perspective that individuals have it can influence others. In this analysis, the intercept is highly significant with a p-value of less than 0.001 and has a coefficient of 4.48093. Neither financial information on social media nor tie strength show significance as both p-values are higher than 0.05. The same is true for the control variables. The moderated relationship in this analysis is not significant, with a p-value of 0.0639, suggesting that it has no significant effect on the relationship between financial information on social media and willingness to invest. Interestingly, the p-value for this analysis is much lower than that of the previous analysis (0.0639 vs. 0.8212), suggesting that significance is getting closer in this context, although the threshold of 0.05 is still not reached.

Variables	Coefficient	SE	Significance
Investment resources (intercept)	1.59611	0.65222	0.0157*
Financial information on SM	-0.01511	0.19445	0.9382
Tie strength	0.28282	0.19489	0.1490
Age (CV)	-0.04832	0.07050	0.4943
Investment experience (CV)	0.04707	0.05878	0.4247
Financial * TS	0.02524	0.06317	0.6901

Table 17 Financial information on SM - Investment resources moderated by tie strength (Personally)

The moderated analysis conducted for investment propensity was similarly applied to investment decisions, examining the amount of resources investors are willing to invest themselves, as shown in the table at left. In this analysis, the intercept has a coefficient of 1.59611 and a p-value of 0.0157, indicating statistical significance. However, for all other variables, including the control variables and the interaction term, no significance was found. This suggests that none of the other variables has a significant effect on the dependent variable.

Variables	Coefficient	SE	Significance
Investment resources (intercept)	4.82340	0.54410	<0.001***
Financial information on SM	-0.34886	0.13705	0.01203*
Tie strength	-0.45592	0.19491	0.02078*
Age (CV)	-0.05221	0.05137	0.31134
Investment experience (CV)	0.11083	0.04042	0.00693**
Financial * TS	0.14106	0.04695	0.00317**

Table 16 Financial information on SM - Investment resources moderated by tie strength (Other)

As done previously, the same analysis was conducted for the relationship between exposure to financial information on social media and the amount of resources people think others are willing to invest, moderated by tie strength. Interestingly, the results of this analysis showed that many variables were significant, unlike in the previous analysis where only the intercept was significant. Consistent with all other analyses conducted, the coefficient for the intercept is much higher in this case, indicating the belief that individuals believe others are more likely to invest more resources or are more willing to invest than themselves. The intercept coefficient here is 4.82340 and is highly significant with a p-value of less than 0.001. Both financial information on social media and tie strength separately has a negative effect on the dependent variable. The p-values for these variables are 0.01203 and 0.02078, respectively, indicating that both have a significant negative effect on the dependent variable. The control variable age is not significant, indicating that it has no significant effect on the dependent variable. The control variable investment experience is significant, however, with a p-value of 0.00693, indicating that it has a positive effect of 0.11083 on the dependent variable. While the interaction term was not significant in previous analyses, it is significant in this analysis, with a p-value of 0.00317. This indicates that tie strength moderates the relationship between exposure to social media and the dependent variable, suggesting that the negative effect of exposure to financial information on social media is weaker when tie strength is higher.

The table on the right tested the relationship between exposure to financial information on social media and its influence on investors own investment decisions (propensity) moderated by financial influencers. The intercept is significant with a p-value of 0.0139 and has a coefficient of 1.49432. The coefficient for financial information on social media is 0.21129; however, the p-value of 0.2245 indicates that it has no significant influence on the dependent variable. In contrast, financial influencers have a significant positive effect on the dependent variable, with a coefficient of 0.58270 and a p-value of 0.01. Both control variables are also significant: age has a negative effect on the dependent variable with a coefficient of -0.15663 and a p-value of 0.0181, while investment experience has a positive influence with a coefficient of 0.12034 and a p-value of 0.0269. The interaction term between exposure to financial information and financial influencers is not significant, with a p-value of 0.3033, indicating that it has no significant influence on the relationship between exposure to financial information and personal investment propensity.

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	1.49432	0.59967	0.0139*
Financial information on SM	0.21129	0.17316	0.2245
Financial influencers	0.58270	0.22315	0.0100*
Age (CV)	-0.15663	0.06544	0.0181*
Investment experience (CV)	0.12034	0.05380	0.0269*
Financial * TS	-0.06838	0.06618	0.3033

Table 18 Financial information on SM - Investment propensity moderated by financial influencers (Personally)

The table on the left retests the same relationship, but with investors perceptions that they can influence others rather than themselves. The coefficient of the intercept is 3.659323, which is again higher than the intercept at the personal level. The p-value of the intercept is also highly significant with a value less than 0.001, indicating that when all other variables remain constant, this represents the value of the dependent variable. For all other variables, including the independent variables, the control variables, and the interaction term, the p-value has a value above 0.05, indicating that they have no significant effect on the dependent variable.

Variables	Coefficient	SE	Significance
Investment propensity (intercept)	3.659323	0.561320	<0.001***
Financial information on SM	0.160645	0.130798	0.221
Financial influencers	-0.051822	0.245169	0.833
Age (CV)	-0.042702	0.056751	0.453
Investment experience (CV)	0.034777	0.042936	0.419
Financial * TS	0.008593	0.057227	0.881

Table 19 Financial information on SM - Investment propensity moderated by financial influencers (Other)

The last relationship tested is that between exposure to financial information on social media and the amount of resources investors themselves are willing to invest, moderated by financial influencer. In this analysis, the intercept is significant, with a p-value of 0.0306 and a coefficient of 1.451495. No significance was found for all other variables, including the interaction term. This means that exposure to financial information on social media and the moderation effect of financial influencers do not significantly affect the amount of resources people are willing to invest personally.

Variables	Coefficient	SE	Significance
Investment resources (intercept)	1.451495	0.664322	0.0306*
Financial information on SM	0.044570	0.192289	0.8171
Financial influencers	0.474240	0.256969	0.0671
Age (CV)	-0.008899	0.070944	0.9004
Investment experience (CV)	0.052874	0.058115	0.3645
Financial * TS	-0.01267	0.078258	0.8747

Table 20 Financial information on SM - Investment resources moderated by financial influencers (Personally)

Variables	Coefficient	SE	Significance
Investment resources (intercept)	4.30283	0.54459	<0.001***
Financial information on SM	-0.12115	0.12509	0.3345
Financial influencers	-0.38805	0.24462	0.1150
Age (CV)	-0.03100	0.05424	0.5686
Investment experience (CV)	0.08619	0.04118	0.0382*
Financial * TS	0.09759	0.05799	0.0947

Table 21 Financial information on SM - Investment resources moderated by financial influencers (Other)

The results in the table on the left represent individuals' perspectives on how exposure to financial information on social media platforms might influence the amount of resources others are willing to invest, moderated by financial influencers. Again, the dependent variable represented by the intercept shows a remarkably high coefficient of 4.30283 compared to the previous analysis. Moreover, the intercept is highly significant, as evidenced by the p-value being less than 0.001. For all other variables except the control variable investment experience, no significance was found, indicating no significant effect on the dependent variable. However, the control variable investment experience was significant, with a p-value of 0.0382, suggesting that each one unit increase in investment experience results in a 0.08619 increase in the dependent variable. Interestingly, as noted earlier, the p-values of this analysis are significantly different from the previous one (0.0947 vs. 0.8747).

When using the ordinary least squares (OLS) regression method, several assumptions must be satisfied for the results to be valid. These assumptions include linearity, multivariate normality, sample size, and no multicollinearity. The assumption of linearity requires the model to have a linear relationship between the independent variables and the dependent variable. If this assumption is violated, the model is incorrectly specified. In this study, we confirmed that the relationships in the model satisfy the linearity assumption. This can be visualized in the scatterplot, which explains the relationship between exposure to financial information and individuals' willingness to invest. Interestingly, only four values have no residuals in the scatterplot (Burton, 2021).

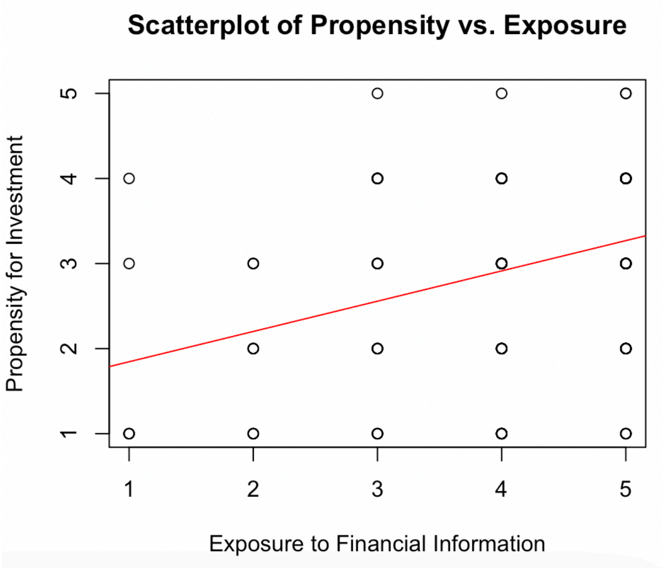

Table 22 Scatterplot - Exposure financial information - Investment propensity

Multivariate normality is another crucial assumption, which states that the residuals (differences between observed and predicted values) must be normally distributed. This is often visualized using a Q-Q plot, where normally distributed data points fall along a 45-degree reference line. For all relationships tested, including the effect of exposure to financial information on individuals' willingness to invest, there was univariate normality of the data (Burton, 2021). Also a sufficiently large sample size is needed to ensure reliable estimates and valid results.

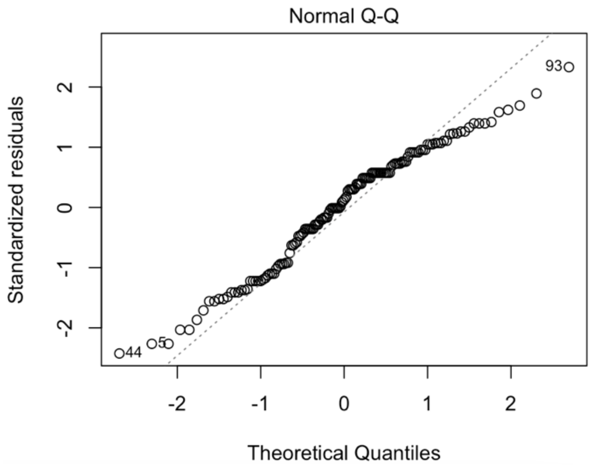

Table 23 Q-Q plot - Exposure financial information - Investment propensity

Our study provides a sample size large enough to meet this requirement.

No multicollinearity means that the independent variables should not be too highly correlated. This is assessed using Variance Inflation Factors (VIF), where values below 5 indicate no multicollinearity problems. This study uses only one independent variable (exposure to financial information), we also have two control variables (age and investment experience). Testing the VIF for these control variables is relevant because high mutual multicollinearity can still affect the stability and interpretability of the regression coefficients. In this study, the VIF values are slightly above 1, indicating that multicollinearity is not an issue (Burton, 2021).

```
> print(vif_values)
Exposure_financial_information_numeric                   Age_numeric      Investment_experience_numeric
                              1.248172                      1.317943                           1.203232
```

Table 24 VIF values

5. Analysis and discussion

This paragraph aims to discuss and analyze the empirical findings of the study on social media exposure on investment decisions presented in the text previous paragraph. There will be shed light on whether the hypotheses are supported or rejected. Afterwards practical and theorical implications are made based on the findings and resulting in answering the research question of this paper, namely, how does exposure to social media influence individuals' investment decisions?

5.1 General discussion

The main aim of this study is to establish whether there is a relationship between social media exposure and investment decisions in the sense of investment propensity and whether they invest more resources to certain assets. In addition to that, this study tests whether tie strength and financial influencers are moderators on this relationship. This study also aims to investigate whether there is a difference between the perspective social media exposure has on their own investment decisions and it has on others investment decisions. In the main relationship the hypotheses were tested whether the was a relation between the exposure of financial information on social media platforms and investment propensity and the allocation of resources on yourself and on others.

In all analysis, a clear tendency was seen. Namely, investors believe others are more influenced by financial information posted on social media than themselves. As a result they perceive others as more inclined to invest and allocate greater resources into assets than they would personally.. This is known as the phenomenon “third person effect” (Tsay-Vogel, 2020). The results of this study in this context align with other studies. For instance with the study of Laskin (2018), where he found that respondents believed that respondents social media articles had a much stronger influence on others than on themselves (Laskin, 2018).

The first hypothesis (H1a), a higher level of exposure to social media positively influences personal investment decisions, suggests that a higher level of exposure to social media influences whether you as a person are willing to invest in an asset or not and whether you are willing to invest more resources into certain assets because of being exposed more. The results of the linear regression analysis showed a positive significant relation between social media exposure and investment propensity (C = 0.24724, P = 0.008**) and investment resources (C = 0.27912, P = 0.005**). These results align with other research, such as the findings of Khadka and Chapagain (2023), who also demonstrated that social media exposure positively impacts investment decisions in the Nepali stock market. Also, the findings are consistent with Ismail et al. (2018), where a study of 100 Malaysian investors revealed significant positive relationships between social media exposure and individual investment decisions.

The second hypothesis (H1b) tests the same relationship, but then not if you as a person yourself are prone to being more exposed, but whether you think if other people are prone to more social media exposure and so they are more likely to invest or to invest more resources. The results of this linear regression analysis showed a positive significant relationship between social media exposure and investment propensity (C = 0.20555, P = 0.004**), but didn’t show a significant relationship on investment resources (C = 0.05497, P = 0,430). These results align with research of Khatik et al., (2021), who observed a significant relationship between social media exposure and investment decisions. They noted that as the volume of investment-related information on social media increases, there is an increased likelihood of making investments on the financial market.

The study examined whether tie strength moderates the impact of social media on investment decisions. The third hypothesis (H2a), being this test on a personal level, suggests that a person who you know closely posting something on social media in terms of financial information affects your personal investment propensity and investment resources. Results indicated a positive but insignificant moderation effect on both investment propensity (C = 0.01356, P = 0.821) and resources (C = 0.0254, P = 0.690). The fourth hypothesis (H2b), tests whether tie strength moderates the relationship between social media exposure and investment decisions of others. showing a positive but insignificant moderation effect on investment propensity (C = 0.09379, P = 0.064), yet a significant effect on investment resources (C = 0.14106, P = 0.003**). The study found no significant evidence supporting tie strength moderating the influence of social media on investors own investment decisions. This contrasts with Samuel-Azran & Hayat (2019), who found that tie strength mediates perceptions of credibility and the likelihood of seeking more information in the context of sharing news. While their study found that stronger ties increased perceived credibility, the results in this study suggest that in investment decisions, tie strength does not significantly influence the impact of social media exposure.
However, the findings of this study partially support the idea that investors believe other investors may increase their investments when influenced by well-known individuals posting investment-related content on social media. As no previous research has specifically examined this context, this study offers new insights into how social media influences financial decision-making. Future research could further explore and validate these findings for different demographic groups.

The study tested if financial influencers moderate the relationship between social media exposure and investment decisions. The fifth hypothesis (H3a), testing this effect on personal level, suggests that financial influencers posting something on social media affect your own investment propensity and investment resources. Results indicated a negative but insignificant moderation effect on both propensity (C = -0.06838, P = 0.303) and resources (C = -0.01267, P = 0.8747). The sixth hypothesis (H3b), tests whether financial influencers moderate the relationship between social media exposure and investment decisions of others showing a positive but insignificant moderation effect on propensity (C = 0.00859, P = 0.881) and a insignificant effect on resources (C = 0.09759, P = 0.094). Overall, no support was found for hypotheses 3a and 3b, suggesting financial influencers do not moderate the relationship between social media exposure and personal investment decisions, nor do they significantly influence other investors' decisions to invest or increase investment amounts. Lenart Ante (2018) demonstrated that financial influencers, such as Elon Musk, significantly influence investment decisions through their social media presence. Specifically, Ante found that individual’s willingness to invest increased significantly following Musk's tweets, suggesting that financial influencers significantly influence the relationship between social media and investment decisions. This contrasts with the findings of the present study. Another contradiction arises in Baviskar's (2024) study, which underscores the significant influence financial influencers on social media have on investment decisions. In his study, Baviskar (2024) emphasizes that finfluencers significantly influence investment decisions. However, respondents attributed varying levels of credibility to the advice of finfluencers on social media and still followed their advice on these platforms. This suggests that, while credibility is important, other factors such as relatability and persuasiveness also play a role in shaping individuals' decisions.

5.2 Practical implications

Results show that exposure to financial information on social media significantly influences individuals' investment decisions. This relates both to the individual's choice whether to invest in an asset, but also the amount of its allocation. This ensures that continued attention should be paid to investor education initiatives aimed at providing investors with knowledge and tools to ensure the reliability and credibility of financial information on social media platforms. These initiatives could ensure that investors are able to make better-informed decisions and mitigate risks associated with misinformation and biased content found on social media platforms. These initiatives could, for instance, take the form of educational campaigns aimed at raising awareness of potential dangers of blindly following financial advice on social media platforms. Also, the recognition that increased exposure can correlate with increased investment propensity and resource allocation underlines the importance of enabling individuals to make informed investment choices based on a well-informed source.

Given the limited significant moderation effects observed among both variable tie strength and financial influencers in the relationship between exposure to financial information on social media and investment decisions, investors should be cautious and skeptical. Instead of relying solely on the approval of financial influencers and well-known individuals, investors should conduct thorough research, assess credibility, and seek different opinions before making decisions based on information perceived to be true. This more cautious approach can mitigate the risks associated with blindly following recommendations from these individuals and ensure alignment with investors' best interests and financial objectives.

5.3 Theoretical implications

The results of this research show that the financial information people are exposed to on social media platforms affects investors' investment decisions. The findings of this research shed light on traditional financial theories, and behavioral finance theories combined with social media exposure and investment decisions. Fama (1970) argues that in principle it is assumed that investors in the market are rational, and that they make decisions on the information reflected in asset prices. However, the observed influence of exposure to financial information on social media platforms in results could suggest that investors do not always behave rationally or process available information efficiently. This trading behavior would be rational if the news on social media platforms is new and factual; otherwise, it would indicate irrational behavior. As individuals are exposed to a greater volume of financial information, they are more prone to encountering misleading or unverified content. Individuals may rely on rumors or unreported information shared on social media platforms without proper due diligence, which can lead to irrational decisions.

The findings overlap with insights from the behavioral finance perspective, where psychological and cognitive factors make investor behavior presentable. Building on the work of Kahneman and Tversky (1979), who did research in behavioral finance, this study demonstrates how social media exposure can trigger cognitive biases and influence investor behavior. Behavioral biases such as overconfidence and herd behavior can lead individuals to rely on information from social media platform, even if it contradicts rational thinking (Thaler & Shefrin, 1988). For example, investors who are more exposed to financial content on social media could be more likely to follow recommendations without critically evaluating the information due to the large amount of data they have to process. This can lead to herd behavior, where individuals replicate the actions of others instead of making independent, rational decisions. This research highlights the importance of understanding how exposure to social media can worsen these biases and influence investment decisions.

The results also show that respondents believe other people are more influenced by the financial information they encounter on social media platforms rather than themselves. The results specifically show that respondents believe other people are more tempted to invest earlier because of the financial information they encounter on social media platforms. Also the results show that they believe other investors are willing to invest more resources into certain assets. This phenomenon, known as the third-person effect, suggests that individuals believe that other individuals are more affected by social media content rather than themselves (Tsay-Vogel, 2020). The findings align with the study of Laskin (2018). This study researches whether respondents estimate that others are more strongly influenced by the media messages than they are themselves. The study finds that respondents believed that the influence of social media messages they were exposed to is much stronger on other people than on themselves (Laskin, 2018).

6. Conclusion

This paragraph presents the overall conclusions of the study. It recaps the main findings regarding the influence of social media on investors' decisions, the results of the moderation effects and provides answers to the main- and sub research questions.

6.1 General conclusion

The primary objective of this study was to discover whether exposure to financial information on social media platforms affects investors' investment decisions. To be even more specific, the aim was to find out whether increased exposure to financial information causes individuals to be more likely to buy certain assets or invest more resources in that asset, and whether they perceive others to be similarly influenced. In addition, the study examined whether tie strength and financial influencers moderated this relationship. To investigate these relationships, a questionnaire was created using Qualtrics and distributed through various platforms such as LinkedIn and Facebook. The data collected were analyzed using RStudio, using both descriptive and inferential statistics. The analysis generated results that supported or rejected the research hypotheses.

The first chapter introduced several research questions, starting with the main research question: ‘How does exposure to social media influence individuals’ investment decisions?’ To answer this question, hypotheses H1a and H1b were tested. Hypothesis H1a was fully supported, indicating that individuals who are more exposed to financial information on social media are more likely to invest in certain assets and allocate more resources to these investments. Hypothesis H1b was partially supported, indicating that although individuals believe others are more inclined to invest in certain assets because of increased exposure, they do not think others are willing to invest more resources because of the same exposure.

Next, the sub-question, ‘Does tie strength affect the relationship between exposure to social media and investment decision-making?’ was answered by testing hypotheses H2a and H2b. Hypothesis H2a was not supported and H2b was partially supported. This means that individuals do not feel more tempted to buy an asset or invest more resources when a well-known person posts financial information on social media. However, they do believe that others are willing to invest more resources when a well-known person shares financial information, indicating that tie strength affects the relationship between social media exposure and investment decisions in this context.

The final sub-question, ‘Do financial influencers influence the relationship between exposure to social media and investment decision-making?’ was tested using hypotheses H3a and H3b. Both hypotheses were not supported, indicating that financial influencers posting information on social media do not influence individuals‘ or others’ propensity to invest or willingness to allocate more resources to an asset. Finally, it was interesting to see that all intercepts (all significant), representing the value of the dependent variable when all other variables are zero, differed between individuals' perceptions of themselves and their perceptions of others. In all cases, the intercept value for individuals' perception of others was significantly higher. This indicates that respondents believe that other people are more likely to buy certain assets or invest more resources in those assets than themselves.

7. Quality criteria

This chapter discusses which quality criteria were taken into account when writing this thesis. This is done to ensure the credibility of this research.

7.1 Reliability, validity, and replicability

Reliability, validity, and replicability are three crucial aspects of research (Alvarez et al., 2018; Sürücü & Maslakci, 2020). Cronbach's alpha assesses reliability in data analysis, ensuring questionnaire consistency. It evaluates measurement reliability, ensuring accurate representation of studied constructs (Christmann & Van Aelst, 2006).

Variables	Cronbach's alpha
Investment decisions	0.63
Tie strength	0.83
Financial influencers	0.91

Table 25 Cronbach's alpha

In the table to the right Cronbach's alpha is measured. In chapter three the goal was set to achieve a Cronbach's alpha value that is as high as possible, ideally surpassing the 0.7 but certainly not falling below 0.6. In all the cases it is not falling below 0.6 and in two of the three instances Cronbach's alpha is measured to be at 0.83 and 0.91 which indicate that response values for each participant across a set of questions are consistent. For investment decisions, four statements were used to measure this variable. For tie strength, which is treated as a fluent characteristic based on the 5-point Likert scale, two different statements were used. Similarly, two different statements were used to measure the influence of financial influencers. This detailed approach ensures each variable accurately captures its intended construct, thereby producing reliable and valid results.

Validity refers to whether the measurement instrument effectively captures the intended behavior or quality, and demonstrates its ability to accurately meet its purpose (Sürücü & Maslakci, 2020). This study builds on relevant theories and draws inspiration from existing research in selecting data collection methods and variables examined. By aligning with established frameworks and seeking information from related fields, the study aims to increase the robustness and validity of the findings.

Lastly, replicability refers to the ability of a study's procedures and findings to be replicated by other researchers using the same or similar methods and data (Alvarez et al., 2018). To ensure the replicability of this study, the methodology as well as all other aspects of the study have been thoroughly described. This includes a detailed description of the methodology and specifying the constructs used to obtain the data. This allows other researchers to replicate this study, including the questionnaire, for their own research.

Bibliography

Agarwal, S., Kumar, S., & Goel, U. (2021). Social media and the stock markets: An emerging market perspective [Article]. *Journal of Business Economics and Management*, *22*(6), 1614-1632. https://doi.org/10.3846/jbem.2021.15619

Akpan, U., & Senam, N. (2014). The Survey Communication Research. *2*, 461 – 478.

Alam, S. M. I. (2022). *Prospect Theory: Logic and Fallacy*.

Alexander, R., & Gentry, J. (2013). Using social media to report financial results. *Business Horizons*, *57*. https://doi.org/10.1016/j.bushor.2013.10.009

Allen, D. E., McAleer, M., & Singh, A. K. (2019). Daily market news sentiment and stock prices [Article]. *Applied Economics*, *51*(30), 3212-3235. https://doi.org/10.1080/00036846.2018.1564115

Almansour, B., Elkrghli, S., & Almansour, A. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, *11*. https://doi.org/10.1080/23322039.2023.2239032

Alvarez, R., Key, E., & Núñez, L. (2018). Research Replication: Practical Considerations. *PS: Political Science & Politics*, *51*, 422-426. https://doi.org/10.1017/S1049096517002566

Alves de Castro, C., O'Reilly, I., & Carthy, A. (2021). Social Media Influencers (SMIs) in Context: A Literature Review. *Journal of Marketing Management*, *9*, 59-71. https://doi.org/10.15640/jmm.v9n2a9

Ante, L. (2021). How Elon Musk's Twitter Activity Moves Cryptocurrency Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3778844

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. *Journal of the Academy of Marketing Science*, *48*(1), 79-95. https://doi.org/10.1007/s11747-019-00695-1

Arora, A., Bansal, S., Kandpal, C., Aswani, R., & Dwivedi, Y. (2019). Measuring social media influencer index- insights from facebook, Twitter and Instagram. *Journal of Retailing and Consumer Services*, *49*, 86-101. https://doi.org/https://doi.org/10.1016/j.jretconser.2019.03.012

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

Aust, F., Diedenhofen, B., Waßenberg, S., & Musch, J. (2013). Seriousness checks are useful to improve data validity in online research. *Behavior research methods*, *45*, 527–535. https://doi.org/10.3758/s13428-012-0265-2

Bakar, S., & Yi, A. N. C. (2016). The Impact of Psychological Factors on Investors' Decision Making in Malaysian Stock Market: A Case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*, 319-328. https://doi.org/https://doi.org/10.1016/S2212-5671(16)00040-X

Baklaci, H., Olgun, O., & Can, E. (2011). Noise traders: A new approach to understand the phantom of stock markets. *Applied Economics Letters*, *18*, 1035-1041. https://doi.org/10.1080/13504851.2010.522513

Bakshi, S. (2020). Financial Markets Transition from Traditional Finance to

Behavioural Finance. XXI Annual International Conference,

Bapna, R., Gupta, A., Rice, S., & Sundararajan, A. (2017). Trust and the Strength of Ties in Online Social Networks: An Exploratory Field Experiment. *MIS Quarterly*, *41*, 115-130. https://doi.org/10.25300/MISQ/2017/41.1.06

Barberis, N., & Thaler, R. (2003). Chapter 18 A survey of behavioral finance. In *Handbook of the Economics of Finance* (Vol. 1, pp. 1053-1128). Elsevier. https://doi.org/https://doi.org/10.1016/S1574-0102(03)01027-6

Barnette, J. (1999). Nonattending Respondent Effects on Internal Consistency of Self-Administered Surveys: A Monte Carlo Simulation Study. *Educational and Psychological Measurement - EDUC PSYCHOL MEAS*, *59*, 38-46. https://doi.org/10.1177/0013164499591003

Baviskar, S. (2024). Unveiling the Influence of Finfluencers on India's Investment Climate: A Comprehensive Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4778162

Bechmann, A., & Lomborg, S. (2013). Mapping actor roles in social media: Different perspectives on value creation in theories of user participation. *New Media & Society*, *15*(5), 765-781. https://doi.org/10.1177/1461444812462853

Belsky, G., & Gilovich, T. (2000). *Why Smart People Make Big Money Mistakes and How to Correct Them*. SIMON & SCHUSTER PAPERBACKS.

Bikas, E., Jureviciene, D., Dubinskas, P., & Novickytė, L. (2013). Behavioural Finance: The Emergence and Development Trends. *Procedia - Social and Behavioral Sciences*, *82*, 870-876. https://doi.org/10.1016/j.sbspro.2013.06.363

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1-8. https://doi.org/https://doi.org/10.1016/j.jocs.2010.12.007

Bowling, A. (2005). Mode of Questionnaire Administration Can Have Serious Effects on Data Quality. *Journal of public health (Oxford, England)*, *27*, 281-291. https://doi.org/10.1093/pubmed/fdi031

Brans, H., & Scholtens, B. (2020). Under his thumb the effect of president Donald Trump's Twitter messages on the US stock market. *PLOS ONE*, *15*, e0229931. https://doi.org/10.1371/journal.pone.0229931

Brown, J. J., & Reingen, P. H. (1987). Social Ties and Word-of-Mouth Referral Behavior*. *Journal of Consumer Research*, *14*(3), 350-362. https://doi.org/10.1086/209118

Brown, R. F., St. John, A., Hu, Y., & Sandhu, G. (2024). Differential Electronic Survey Response: Does Survey Fatigue Affect Everyone Equally? *Journal of Surgical Research*, *294*, 191-197. https://doi.org/https://doi.org/10.1016/j.jss.2023.09.072

Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for cronbach's alpha test: A simple guide for researchers [Article]. *Malaysian Journal of Medical Sciences*, *25*(6), 85-99. https://doi.org/10.21315/mjms2018.25.6.9

Bukovina, J. (2016). Social media big data and capital markets—An overview. *Journal of Behavioral and Experimental Finance*, *11*. https://doi.org/10.1016/j.jbef.2016.06.002

Bulut, Z. A., & Karabulut, A. N. (2018). Examining the role of two aspects of eWOM in online repurchase intention: An integrated trust–loyalty perspective. *Journal of Consumer Behaviour*, *17*(4), 407-417. https://doi.org/https://doi.org/10.1002/cb.1721

Burton, A. (2021). OLS (Linear) Regression. In (pp. 509-514). https://doi.org/10.1002/9781119111931.ch104

Byrne, A., & Brooks, M. (2008). Behavioral Finance: Theories and Evidence.

Check, J., & Schutt, R. K. (2012). *Research methods in education*. SAGE Publications. https://doi.org/https://doi.org/10.4135/9781544307725

Chen, H., De, P., Hu, Y., & Hwang, B.-H. (2013). Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *Review of Financial Studies*. https://doi.org/10.2139/ssrn.1807265

Chikhi, I. (2012). "Financial Influencers and Social Media: The Role of Valuable and Trusted Content in Creating a New Form of Authenticity". *CUNY Academic Works*. https://academicworks.cuny.edu/bb_etds/113

Christmann, A., & Van Aelst, S. (2006). Robust estimation of Cronbach's alpha. *Journal of Multivariate Analysis*, *97*(7), 1660-1674. https://doi.org/https://doi.org/10.1016/j.jmva.2005.05.012

Chyung, S. Y., Roberts, K., Swanson, I., & Hankinson, A. (2017). Evidence-Based Survey Design: The Use of a Midpoint on the Likert Scale. *Performance Improvement*, *56*(10), 15-23. https://doi.org/https://doi.org/10.1002/pfi.21727

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). https://doi.org/https://doi.org/10.4324/9780203771587

Cohen, L., Manion, L., & Morrison, K. (2017). *Research Methods in Education* (8th ed.). https://doi.org/https://doi.org/10.4324/9781315456539

Dellarocas, C., Gao, G., & Narayan, R. (2010). Are Consumers More Likely to Contribute Online Reviews for Hit or Niche Products? *J. of Management Information Systems*, *27*, 127-158. https://doi.org/10.2753/MIS0742-1222270204

Eisenbeiss, M., Hartmann, S. A., & Hornuf, L. (2023). Social media marketing for equity crowdfunding: Which posts trigger investment decisions? [Article]. *Finance Research Letters*, *52*, Article 103370. https://doi.org/10.1016/j.frl.2022.103370

Elfil, M., & Negida, A. (2017). Sampling methods in Clinical Research; an Educational Review. *Emerg (Tehran)*, *5*(1), e52.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383-417. https://doi.org/10.2307/2325486

Fleischer, A., Mead, A., & Huang, J. (2015). Inattentive Responding in MTurk and Other Online Samples. *Industrial and Organizational Psychology*, *8*, 196-202. https://doi.org/10.1017/iop.2015.25

Freberg, K., Graham, K., McGaughey, K., & Freberg, L. (2011). Who are the social media influencers? A study of public perceptions of personality. *Fuel and Energy Abstracts*, *37*, 90-92. https://doi.org/10.1016/j.pubrev.2010.11.001

Friederich, F., Meyer, J.-H., Matute, J., & Palau-Saumell, R. (2023). CRYPTO-MANIA: How fear-of-missing-out drives consumers' (risky) investment decisions. *Psychology & Marketing*, *41*, n/a-n/a. https://doi.org/10.1002/mar.21906

Ge, Q., Kurov, A., & Wolfe, M. (2019). Do Investors Care about Presidential Company-Specific Tweets? *Journal of Financial Research*, *42*. https://doi.org/10.1111/jfir.12177

Geenen, S. (2023). *The Impact of Financial Influencers on Social Media on the Financial Literacy of Young Adults* Tilburg University].

Gilbert, E. (2012). *Predicting tie strength in a new medium* Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work, <conf-loc>, <city>Seattle</city>, <state>Washington</state>, <country>USA</country>, </conf-loc>. https://doi.org/10.1145/2145204.2145360

Gilbert, E., & Karahalios, K. (2009). *Predicting Tie Strength With Social Media* (Vol. 9). https://doi.org/10.1145/1518701.1518736

Gillian, B. (2007). A Statistical Primer: Understanding Descriptive and Inferential Statistics. *Evidence Based Library and Information Practice*, *2*. https://doi.org/10.18438/B8FW2H

Glucksman, M. (2017). The Rise of Social Media Influencer Marketing on Lifestyle Branding: A Case Study of Lucie Fink., *8*(2).

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*, *1*, 201-233. https://doi.org/10.2307/202051

Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, *78*(6), 1360-1380. http://www.jstor.org/stable/2776392

Grover, P., Kar, A. K., & Dwivedi, Y. (2022). The evolution of social media influence - A literature review and research agenda. *International Journal of Information Management Data Insights*, *2*(2), 100116. https://doi.org/https://doi.org/10.1016/j.jjimei.2022.100116

Gu, C., & Kurov, A. (2020). Informational role of social media: Evidence from Twitter sentiment. *Journal of Banking & Finance*, *121*, 105969. https://doi.org/https://doi.org/10.1016/j.jbankfin.2020.105969

Guijarro, F., Moya-Clemente, I., & Saleemi, J. (2019). Liquidity Risk and Investors' Mood: Linking the Financial Market Liquidity to Sentiment Analysis through Twitter in the S&P500 Index [Article]. *Sustainability (Switzerland)*, *11*(24), Article 7048. https://doi.org/10.3390/su11247048

Güngör, S., Tomris Küçün, N., & Erol, K. (2022). Fear of Missing Out Reality in Financial Investments. *International Journal of Business & Management Studies*, *03*, 53-59. https://doi.org/10.56734/ijbms.v3n10a4

Gupta, R. R., Arya, R. K., Kumar, J., Gururani, A., Dugh, R., & Dugh, A. (2022, 2022//). The Impact of Elon Musk Tweets on Bitcoin Price. Topical Drifts in Intelligent Computing, Singapore.

Gwaltney, C. J., Shields, A. L., & Shiffman, S. (2008). Equivalence of Electronic and Paper-and-Pencil Administration of Patient-Reported Outcome Measures: A Meta-Analytic Review. *Value in Health*, *11*(2), 322-333. https://doi.org/https://doi.org/10.1111/j.1524-4733.2007.00231.x

Hair, J. F., Babin, B. J., Black, W. C., & Anderson, R. E. (2019). *Multivariate Data Analysis*. Cengage. https://books.google.nl/books?id=0R9ZswEACAAJ

Hamzaçebi, C., & Pekkaya, M. (2011). Determining of stock investments with grey relational analysis. *Expert Systems with Applications*, *38*(8), 9186-9195. https://doi.org/https://doi.org/10.1016/j.eswa.2011.01.070
Hasselgren, B., Chrysoulas, C., Pitropakis, N., & Buchanan, W. J. (2023). Using Social Media & Sentiment Analysis to Make Investment Decisions. *Future Internet*, *15*(1).
He, W., Guo, L., Shen, J., & Akula, V. (2016). Social Media-Based Forecasting: A Case Study of Tweets and Stock Prices in the Financial Services Industry. *Journal of Organizational and End User Computing*, *28*, 74-91.
Ismail, S., Nair, R., Sham, R., & Wahab, S. (2018). Impacts of online social media on investment decision in Malaysia. *Indian Journal of Public Health Research and Development*, *9*, 1241. https://doi.org/10.5958/0976-5506.2018.01627.3
Jiao, P., Veiga, A., & Walther, A. (2020). Social media, news media and the stock market [Article]. *Journal of Economic Behavior and Organization*, *176*, 63-90. https://doi.org/10.1016/j.jebo.2020.03.002
Joshi, A., Kale, S., Chandel, S., & Pal, D. (2015). Likert Scale: Explored and Explained. *British Journal of Applied Science & Technology*, *7*, 396-403. https://doi.org/10.9734/BJAST/2015/14975
Joshi, Y., Lim, W. M., Jagani, K., & Kumar, S. (2023). Social media influencer marketing: foundations, trends, and ways forward. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-023-09719-z
Kahneman, D., & Tversky, A. (1979). On the interpretation of intuitive probability: A reply to Jonathan Cohen. *Cognition*, *7*(4), 409-411. https://doi.org/https://doi.org/10.1016/0010-0277(79)90024-6
Kahneman, D., & Tversky, A. (1988). *Prospect theory: An analysis of decision under risk* [doi:10.1017/CBO9780511609220.014]. Cambridge University Press. https://doi.org/10.1017/CBO9780511609220.014
Kamoune, A., & Ibenrissoul, N. (2022). Traditional versus Behavioral Finance Theory.
Kang, E., & Hwang, H.-J. (2023). The Importance of Anonymity and Confidentiality for Conducting Survey Research. *4*, 1-7. https://doi.org/10.15722/jrpe.4.1.202303.1
Kaplan, A., & Haenlein, M. (2010). Users of the World, Unite! The Challenges and Opportunities of Social Media. *Business Horizons*, *53*, 59-68. https://doi.org/10.1016/j.bushor.2009.09.003
Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in Social Media Research: Past, Present and Future. *Information Systems Frontiers*, *20*(3), 531-558. https://doi.org/10.1007/s10796-017-9810-y
Khadka, S., & Chapagain, B. (2023). Relationship between Social Media and Investment Decisions in the Nepali Stock Market. *The Spectrum*, *1*, 96-114. https://doi.org/10.3126/spectrum.v1i1.54943
Khalil, S., & Nilsson, F. (2021). *Impact of Social Media on Investment Decision* Umeå University]. https://umu.diva-portal.org/smash/get/diva2:1566008/FULLTEXT01.pdf
Khatik, S., Joshi, R., & Adwani, V. (2021). INFERRING THE ROLE OF SOCIAL MEDIA ON GEN Z'S INVESTMENTS DECISIONS. *JOURNAL OF CONTENT COMMUNITY AND COMMUNICATION*, *14*, 309-317. https://doi.org/10.31620/JCCC.12.21/24
Kumar, D. P., & Kishori, B. (2016). Study on Factors Influencing the Investors' Decision Making in the Stock Market with Special Reference to the Indian Stock Market. . *International Journal of Management and Commerce Innovations*.
Kwak, N., & Radler, B. (2002). A Comparison between Mail and Web Surveys: Response Pattern, Respondent Profile, and Data Quality. *Journal of Of®cial Statistics*, *18*, 257-273.
Lal, S., Sulemana, A.-S., Nguyen, T. X., Khan, M. S., & Kadoya, Y. (2023). Information Sources for Investment Decisions: Evidence from Japanese Investors. *International Journal of Financial Studies*, *11*(4).
Laskin, A. (2018). The third-person effects in the investment decision making: a case of corporate social responsibility. *Corporate Communications: An International Journal*, *23*. https://doi.org/10.1108/CCIJ-10-2017-0099
Li, Q., Chen, Y., Wang, J., Chen, Y., & Chen, H. (2018). Web Media and Stock Markets : A Survey and Future Directions from a Big Data Perspective. *IEEE Transactions on Knowledge and Data Engineering*, *30*(2), 381-399. https://doi.org/10.1109/TKDE.2017.2763144
Liljander, V., Gummerus, J., & Söderlund, M. (2015). Young consumers' responses to suspected covert and overt blog marketing. *Internet Research: Electronic Networking Applications and Policy*, *25*. https://doi.org/10.1108/IntR-02-2014-0041
Lin, H.-W. (2011). Elucidating rational investment decisions and behavioral biases: Evidence from the Taiwanese stock market. *African journal of business management*, *5*, 1630-1641.
Lin, N., Ensel, W. M., & Vaughn, J. C. (1981). Social Resources and Strength of Ties: Structural Factors in Occupational Status Attainment. *American Sociological Review*, *46*(4), 393-405. https://doi.org/10.2307/2095260
Linder, S. K., Kamath, G. R., Pratt, G. F., Saraykar, S. S., & Volk, R. J. (2015). Citation searches are more sensitive than keyword searches to identify studies using specific measurement instruments [Article]. *Journal of Clinical Epidemiology*, *68*(4), 412-417, Article 8737. https://doi.org/10.1016/j.jclinepi.2014.10.008
Lou, C., & Yuan, S. (2018). Influencer Marketing: How Message Value and Credibility Affect Consumer Trust of Branded Content on Social Media. *Journal of Interactive Advertising*, *19*, 1-45. https://doi.org/10.1080/15252019.2018.1533501
Luong, L., & Ha, D. T. T. (2011). Behavioral factors influencing individual investors′ decision-making and performance. : A survey at the Ho Chi Minh Stock Exchange.
Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, *17*(1), 59-82. https://doi.org/10.1257/089533003321164958
Mangold, W., & Faulds, D. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, *52*, 357-365. https://doi.org/10.1016/j.bushor.2009.03.002
Marsden, P. V., & Campbell, K. E. (1984). Measuring Tie Strength. *Social Forces*, *63*(2), 482-501. https://doi.org/10.2307/2579058

Masini, A., & Menichetti, E. (2012). The impact of behavioural factors in the renewable energy investment decision making process: Conceptual framework and empirical findings. *Energy Policy*, *40*, 28-38. https://doi.org/https://doi.org/10.1016/j.enpol.2010.06.062

Matthes, J., Nanz, A., Stubenvoll, M., & Heiss, R. (2020). Processing news on social media. The political incidental news exposure model (PINE). *Journalism*, *21*(8), 1031-1048. https://doi.org/10.1177/1464884920915371

Mello, B. A., Souza, V. M. C. S., Cajueiro, D. O., & Andrade, R. F. S. (2010). Network evolution based on minority game with herding behavior. *The European Physical Journal B*, *76*(1), 147-156. https://doi.org/10.1140/epjb/e2010-00179-1

Money, R., Gilly, M., & Graham, J. (1998). Explorations of National Culture and Word-of Mouth Referral Behavior in the Purchase of Industrial Services in the United States and Japan. *The Journal of Marketing*, *62*, 76-87. https://doi.org/10.2307/1252288

Naderifar, M., Goli, H., & Ghaljaei, F. (2017). Snowball Sampling: A Purposeful Method of Sampling in Qualitative Research. *Strides in Development of Medical Education*, *In Press*. https://doi.org/10.5812/sdme.67670

Nanz, A., Heiss, R., & Matthes, J. (2022). Antecedents of intentional and incidental exposure modes on social media and consequences for political participation: a panel study. *Acta Politica*, *57*(2), 235-253. https://doi.org/10.1057/s41269-020-00182-4

Naveed, M., Ali, S., Iqbal, K., & Sohail, M. (2020). Role of financial and non-financial information in determining individual investor investment decision: a signaling perspective. *South Asian Journal of Business Studies*, *ahead-of-print*. https://doi.org/10.1108/SAJBS-09-2019-0168

Ng, C. J. (2006). Common Ethical Issues In Research And Publication. *Malaysian Family Physician*, *1*.

Nghiem, H., Muric, G., Morstatter, F., & Ferrara, E. (2021). Detecting cryptocurrency pump-and-dump frauds using market and social signals [Article]. *Expert Systems with Applications*, *182*, Article 115284. https://doi.org/10.1016/j.eswa.2021.115284

Niehaus, G., & Shrider, D. (2014). Framing and the disposition effect: Evidence from mutual fund investor redemption behaviour. *Quantitative Finance*, *14*. https://doi.org/10.1080/14697688.2013.819114

Nijhawan, L., Janodia, M., Krishna, M., Bhat, K., Bairy, L., Udupa, N., & Musmade, P. (2013). Informed Consent: Issues and Challenges. *Journal of Advanced Pharmaceutical Technology & Research*, *4*, 134-140. https://doi.org/10.4103/2231-4040.116779

Pallavi, P., & Kusum, T. (2024). Literature Review on the Role of Financial Advisors in Shaping Investment Decisions. *11*, 152-167. https://doi.org/10.5281/zenodo.10475591

Pang, B., & Lee, L. (2004). *A sentimental education: sentiment analysis using subjectivity summarization based on minimum cuts* Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics, Barcelona, Spain. https://doi.org/10.3115/1218955.1218990

Papaioannou, D., Sutton, A., Carroll, C., Booth, A., & Wong, R. (2010). Literature searching for social science systematic reviews: Consideration of a range of search techniques. *Health information and libraries journal*, *27*, 114-122. https://doi.org/10.1111/j.1471-1842.2009.00863.x

Park, E., Rishika, R., Janakiraman, R., Houston, M. B., & Yoo, B. (2018). Social Dollars in Online Communities: The Effect of Product, User, and Network Characteristics. *Journal of Marketing*, *82*(1), 93-114. https://doi.org/10.1509/jm.16.0271

Park, J., Konana, P., Gu, B., Kumar, A., & Raghunathan, R. (2010). Confirmation Bias, Overconfidence, and Investment Performance: Evidence from Stock Message Boards. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1639470

Perikos, I., & Michael, L. (2022). *A Survey on Tie Strength Estimation Methods in Online Social Networks*. https://doi.org/10.5220/0010845100003116

Pimentel, J. (2010). A note on the usage of Likert Scaling for research data analysis. *18*, 109-112.

Ponto, J. (2015). Understanding and Evaluating Survey Research. *Journal of the advanced practitioner in oncology*, *6*, 168-171.

Prosad, J., Kapoor, S., & Sengupta, J. (2015). Theory of Behavioral Finance. In (pp. 1-24). https://doi.org/10.4018/978-1-4666-7484-4.ch001

Prosad, J. M., Kapoor, S., Sengupta, J., & Roychoudhary, S. (2018). Overconfidence and Disposition Effect in Indian Equity Market: An Empirical Evidence. *Global Business Review*, *19*(5), 1303-1321. https://doi.org/10.1177/0972150917726660

Putnam, R. D. (2000). Bowling Alone: America's Declining Social Capital. In L. Crothers & C. Lockhart (Eds.), *Culture and Politics: A Reader* (pp. 223-234). Palgrave Macmillan US. https://doi.org/10.1007/978-1-349-62965-7_12

Rahman, M. (2023). Sample Size Determination for Survey Research and Non-Probability Sampling Techniques: A Review and Set of Recommendations. *11*, 42-62.

Reja, U., Manfreda, K., Hlebec, V., & Vehovar, V. (2003). Open-ended vs. Close-ended Questions in Web Questionnaires. *Adv Methodol Stats*, *19*.

Roberts, L., & Allen, P. (2015). Exploring ethical issues associated with using online surveys in educational research. *Educational Research and Evaluation*, *21*. https://doi.org/10.1080/13803611.2015.1024421

Sadovykh, V., Sundaram, D., & Piramuthu, S. (2015). Do decision-making structure and sequence exist in health online social networks? *Decision Support Systems*, *74*, 102-120. https://doi.org/https://doi.org/10.1016/j.dss.2015.03.007

Salant, P., & Dillman, D. A. (1994). How to conduct your own survey.

Samuel-Azran, T., & Hayat, T. (2019). Online news recommendations credibility: The tie is mightier than the source. *Comunicar*, *27*. https://doi.org/10.3916/C60-2019-07

Sarva, M. (2014). Social Impact On Investor's Decision Making. *Researchjournali*, *2*, 1-7.

Schaefer, D. R., & Dillman, D. A. (1998). Development of a Standard E-Mail Methodology: Results of an Experiment. *The Public Opinion Quarterly*, *62*(3), 378-397. http://www.jstor.org/stable/2749665

Sekaran, U., & Bougie, J. R. G. (2010). *Research methods for business: A skill-building approach* (5th ed.). Wiley Publishers

.
Shahzad, S. J. H., Anas, M., & Bouri, E. (2022). Price explosiveness in cryptocurrencies and Elon Musk's tweets. *Finance Research Letters*, *47*, 102695. https://doi.org/https://doi.org/10.1016/j.frl.2022.102695
Sharma, S., & Bikhchandani, S. (2000). Herd Behavior in Financial Markets: A Review. *IMF Working Papers*, *00*, 1. https://doi.org/10.5089/9781451846737.001
Shelby, L. (2011). Beyond Cronbach's Alpha: Considering Confirmatory Factor Analysis and Segmentation. *Human Dimensions of Wildlife*, *16*, 142-148. https://doi.org/10.1080/10871209.2011.537302
Shin, H., & Park, S. (2018). Do foreign investors mitigate anchoring bias in stock market? Evidence based on post-earnings announcement drift. *Pacific-Basin Finance Journal*, *48*. https://doi.org/10.1016/j.pacfin.2018.02.008
Shleifer, A. (2000). *Inefficient Markets: An Introduction to Behavioral Finance*. Oxford University Press. https://doi.org/10.1093/0198292279.001.0001
Shleifer, A., & Summers, L. H. (1990). The Noise Trader Approach to Finance. *Journal of Economic Perspectives*, *4*(2), 19-33. https://doi.org/10.1257/jep.4.2.19
Shorten, A., & Moorley, C. (2014). Selecting the sample. *Evidence-based nursing*, *17*. https://doi.org/10.1136/eb-2014-101747
Showkat, N., & Parveen, H. (2017). Non-Probability and Probability Sampling. In (pp. 1-9).
Simon, H. A. (1997). *Models of Bounded Rationality: Empirically Grounded Economic Reason*. The MIT Press. https://doi.org/10.7551/mitpress/4711.001.0001
Singh, S., & Nag, A. (2016). The role of behavioral finance in modern age investment. *Journal of Management and Science*, *1*, 135-149. https://doi.org/10.26524/jms.2016.12
Slater, M. (2004). Operationalizing and Analyzing Exposure: The Foundation of Media Effects Research. *Journalism & Mass Communication Quarterly*, *81*, 168-183. https://doi.org/10.1177/107769900408100112
Statman, M. (1999). Behaviorial Finance: Past Battles and Future Engagements. *Financial Analysts Journal - FINANC ANAL J*, *55*, 18-27. https://doi.org/10.2469/faj.v55.n6.2311
Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65-73. https://doi.org/https://doi.org/10.1016/j.bir.2014.03.001
Suhr, D. (2006). *Exploratory or Confirmatory Factor Analysis*.
Sul, H., Dennis, A., & Yuan, L. (2016). Trading on Twitter: Using Social Media Sentiment to Predict Stock Returns: Trading on Twitter. *Decision Sciences*, *48*. https://doi.org/10.1111/deci.12229
Sun, L., Wang, T., & Guan, F. (2021). How the strength of social ties influences users' information sharing and purchase intentions. *Current Psychology*, *42*, 1-15. https://doi.org/10.1007/s12144-021-02102-x
Sürücü, L., & Maslakci, A. (2020). Validity and Reliability in Quantitative Research. *8*, 2694-2726. https://doi.org/10.15295/bmij.v8i3.1540
Syed, Z., & Bansal, R. (2019). A study of prominence for disposition effect: a systematic review. *Qualitative Research in Financial Markets*, *11*. https://doi.org/10.1108/QRFM-07-2018-0081
Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education*, *48*(6), 1273-1296. https://doi.org/10.1007/s11165-016-9602-2
Tan, W.-K., & Tan, Y.-J. (2012). An exploratory investigation of the investment information search behavior of individual domestic investors. *Telematics and Informatics*, *29*(2), 187-203. https://doi.org/https://doi.org/10.1016/j.tele.2011.09.002
Thaler, R., & Shefrin, H. (1988). The Behavioral Life-Cycle Hypothesis. *Economic Inquiry*, *26*, 609-643. https://doi.org/10.1111/j.1465-7295.1988.tb01520.x
Thaler, R. H., & Ganser, L. J. (2015). *Misbehaving: The Making of Behavioral Economics*.
Tsay-Vogel, M. (2020). Third-Person Effect. 1-8. https://doi.org/10.1002/9781119011071.iemp0130
Tseng, K. C. (2006). Behavioral Finance, Bounded Rationality, Neuro-Finance, and Traditional Finance. *Investment Management and Financial Innovations*, *3*.
Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., & Sandoval-Almazán, R. (2022). Does Twitter Affect Stock Market Decisions? Financial Sentiment Analysis During Pandemics: A Comparative Study of the H1N1 and the COVID-19 Periods. *Cognitive Computation*, *14*(1), 372-387. https://doi.org/10.1007/s12559-021-09819-8
Vamossy, D. F. (2024). *Social Media Emotions and Market Behavior* Cornell University].
van Dijck, J., & Poell, T. (2013). Understanding social media logic [Article]. *Media and Communication*, *1*(1), 2-14. https://doi.org/10.12924/mac2013.01010002
van Reijmersdal, E. A., & Hudders, L. (2023). How to become a millionaire in three steps? An experimental study on the persuasive power of financial advice by finfluencers [Article]. *Tijdschrift voor Communicatiewetenschap*, *51*(3), 284-302. https://doi.org/10.5117/TCW2023.3.004.REIJ
Wellman, B., & Wortley, S. (1990). Different Strokes From Different Folks: Community Ties and Social Support. *American Journal of Sociology - AMER J SOCIOL*, *96*. https://doi.org/10.1086/229572
Wooditch, A., Johnson, N., Solymosi, R., Ariza, J., & Langton, S. (2021). Ordinary Least Squares Regression. In (pp. 245-268). https://doi.org/10.1007/978-3-030-50625-4_15
Yang, Y., Ren, H., & Zhang, H. (2022). Understanding Consumer Panic Buying Behaviors during the Strict Lockdown on Omicron Variant: A Risk Perception View [Article]. *Sustainability (Switzerland)*, *14*(24), Article 17019. https://doi.org/10.3390/su142417019
Yellapu, V. (2018). Descriptive statistics. *International Journal of Academic Medicine*, *4*, 60. https://doi.org/10.4103/IJAM.IJAM_7_18
Zhu, Y., Cheng, Z., Liu, S., & Yao, Z. (2022). *Has GameStop Phenomenon Violated the Efficient Market Hypothesis? Verified with T-Test*. https://doi.org/10.2991/aebmr.k.220307.320

Appendices

Appendix 1. Questionnaire

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

Table 26 Question 1

What is your age?

- 18-25
- 26-35
- 36-45
- 46-55
- Over 55

Table 27 Question 2

What is your nationality?

- Dutch
- German
- English
- Spanish
- Other, namely:

Table 28 Question 3

What is your highest education level?

- High School and below
- Bachelor's degree
- Master's degree
- Phd or higher
- Other

Table 29 Question 4

What is your employment status?

- Unemployed
- Employed part-time
- Employed full-time

Table 30 Question 5

How long have you been investing?

- No experience with investing
- Under 1 year
- 1-3 years
- 3-5 years
- 5-10 years
- Over 10 years

Table 31 Question 6

What do you invest in?

- ☐ Stocks
- ☐ Bonds
- ☐ Mutual funds
- ☐ Index funds
- ☐ Exchange-traded funds
- ☐ Cryptocurrencies
- ☐ Other, namely:

Table 32 Question 7

Have you completed any finance-related courses or modules as part of your studies?

- ○ Yes
- ○ No

Table 33 Question 8

On average, how often do you typically engage with social media platforms on a weekly basis?

- ○ Never
- ○ Rarely
- ○ Occasionally
- ○ Frequently
- ○ Very frequently

Table 34 Question 9

On average, how often are you exposed to financial information on social media on a weekly basis?

- ○ Never
- ○ Rarely
- ○ Occasionally
- ○ Frequently
- ○ Very frequently

Table 35 Question 10

On what social media platform are you exposed to financial information?

- ☐ Twitter/X
- ☐ LinkedIn
- ☐ Facebook
- ☐ Other, namely:

Table 36 Question 11

Me personally, whether or not I invest in something can be influenced by the financial information I encounter on social media.

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree

Table 37 Question 12

I believe, other people can be influenced by the financial information they encounter on social media when deciding to invest or not.

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree

Table 38 Question 13

Me personally, the amount of resources I invest can be influenced by financial information I encounter on social media.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 39 Question 14

I believe, the amount of resources other people invest can be influenced by financial information they encounter on social media.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 40 Question 15

Have you ever followed financial advice from a close friend or well-known person?

- Yes
- No

Table 41 Question 16

I am likely to consider investing based on a recommendation from social media, whether it's from someone I feel strongly connected to or not.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 42 Question 17

I am likely to make a decision on whether to invest or not based on a recommendation from a close friend or individual I know well on social media.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 43 Question 18

I am likely to invest more resources based on a recommendation on social media, whether it's from someone I feel strongly connected to or not.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 44 Question 19

I am likely to invest more resources based on a recommendation from a close friends or individual I know well on social media.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Table 45 Question 20

Have you ever followed financial advice from a financial influencer?

○ Yes
○ No

Table 46 Question 21

How much do you trust the opinion of financial influencers on social media?

○ Strongly distrust
○ Somewhat distrust
○ Neither trust nor distrust
○ Somewhat trust
○ Strongly trust

Table 47 Question 22

I am likely to make a decision of whether to invest or not based on a recommendation from a financial influencer on social media.

○ Strongly disagree
○ Somewhat disagree
○ Neither agree nor disagree
○ Somewhat agree
○ Strongly agree

Table 48 Question 23

I am likely to invest more resources based on a recommendation from a financial influencers on social media.

○ Strongly disagree
○ Somewhat disagree
○ Neither agree nor disagree
○ Somewhat agree
○ Strongly agree

Table 49 Question 24

Appendix 2. Regression analysis Rstudio results

```
Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                           2.04218    0.48534   4.208 4.62e-05 ***
Exposure_financial_information_numeric  0.24724    0.09284   2.663  0.00866 ** 
Age_numeric                          -0.17256    0.07105  -2.429  0.01643 *  
Investment_experience_numeric         0.11379    0.05528   2.059  0.04142 *  
---
```

Table 50 Regression analysis #1

```
Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                           3.70123    0.28650  12.919  < 2e-16 ***
Exposure_financial_information_numeric  0.20555    0.07072   2.907  0.00426 ** 
Age_numeric                          -0.04189    0.05241  -0.799  0.42552    
Investment_experience_numeric         0.01254    0.04379   0.286  0.77510    
---
```

Table 51 Regression analysis #2

```
Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)   
(Intercept)                           1.441988   0.519335   2.777  0.00626 **
Exposure_financial_information_numeric  0.279118   0.099343   2.810  0.00568 **
Age_numeric                          -0.003363   0.076021  -0.044  0.96478   
Investment_experience_numeric         0.036219   0.059151   0.612  0.54133   
---
```

Table 52 Regression analysis #3

```
Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                           3.66685    0.36269  10.110   <2e-16 ***
Exposure_financial_information_numeric  0.05497    0.06938   0.792   0.4295    
Age_numeric                          -0.04440    0.05309  -0.836   0.4044    
Investment_experience_numeric         0.08650    0.04131   2.094   0.0381 *  
---
```

Table 53 Regression analysis #4

```
Coefficients:
                                                             Estimate Std. Error t value Pr(>|t|)  
(Intercept)                                                   1.56395    0.71195   2.197   0.0297 *
Exposure_financial_information_numeric                        0.12428    0.20890   0.595   0.5529  
TS_Y_Propensity_numeric                                       0.30996    0.18573   1.669   0.0974 .
Age_numeric                                                  -0.16514    0.06558  -2.518   0.0130 *
Investment_experience_numeric                                 0.09105    0.05448   1.671   0.0970 .
Exposure_financial_information_numeric:TS_Y_Propensity_numeric  0.01356    0.05995   0.226   0.8214  
---
```

Table 54 Regression analysis #5

```
Coefficients:
                                                              Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                                    4.48093    0.64938   6.900 1.79e-10 ***
Exposure_financial_information_numeric                        -0.10614    0.16130  -0.658   0.5116    
TS_Y_Propensity_numeric                                       -0.32678    0.20194  -1.618   0.1079    
Age_numeric                                                   -0.05147    0.05471  -0.941   0.3485    
Investment_experience_numeric                                  0.04745    0.04293   1.105   0.2710    
Exposure_financial_information_numeric:TS_Y_Propensity_numeric  0.09379    0.05020   1.868   0.0639 .  
---
```

Table 55 Regression analysis #6

```
Coefficients:
                                                              Estimate Std. Error t value Pr(>|t|)  
(Intercept)                                                    1.59611    0.65222   2.447   0.0157 *
Exposure_financial_information_numeric                        -0.01511    0.19445  -0.078   0.9382  
TS_Y_Resources_numeric                                         0.28282    0.19489   1.451   0.1490  
Age_numeric                                                   -0.04832    0.07050  -0.685   0.4943  
Investment_experience_numeric                                  0.04707    0.05878   0.801   0.4247  
Exposure_financial_information_numeric:TS_Y_Resources_numeric  0.02524    0.06317   0.400   0.6901  
---
```

Table 56 Regression analysis #7

```
Coefficients:
                                                              Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                                    4.82340    0.54410   8.865 3.79e-15 ***
Exposure_financial_information_numeric                        -0.34886    0.13705  -2.545  0.01203 *  
TS_Y_Resources_numeric                                        -0.45592    0.19491  -2.339  0.02078 *  
Age_numeric                                                   -0.05221    0.05137  -1.016  0.31134    
Investment_experience_numeric                                  0.11083    0.04042   2.742  0.00693 ** 
Exposure_financial_information_numeric:TS_Y_Resources_numeric  0.14106    0.04695   3.005  0.00317 ** 
---
```

Table 57 Regression analysis #8

```
Coefficients:
                                                             Estimate Std. Error t value Pr(>|t|)  
(Intercept)                                                   1.49432    0.59967   2.492   0.0139 *
Exposure_financial_information_numeric                        0.21129    0.17316   1.220   0.2245  
FI_Propensity_numeric                                         0.58270    0.22315   2.611   0.0100 *
Age_numeric                                                  -0.15663    0.06544  -2.393   0.0181 *
Investment_experience_numeric                                 0.12034    0.05380   2.237   0.0269 *
Exposure_financial_information_numeric:FI_Propensity_numeric -0.06838    0.06618  -1.033   0.3033  
---
```

Table 58 Regression analysis #9

```
Coefficients:
                                                              Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                                   3.659323   0.561320   6.519 1.28e-09 ***
Exposure_financial_information_numeric                        0.160645   0.130798   1.228    0.221    
FI_Propensity_numeric                                        -0.051822   0.245169  -0.211    0.833    
Age_numeric                                                  -0.042702   0.056751  -0.752    0.453    
Investment_experience_numeric                                 0.034777   0.042936   0.810    0.419    
Exposure_financial_information_numeric:FI_Propensity_numeric  0.008593   0.057227   0.150    0.881    
---
```

Table 59 Regression analysis #10

```
Coefficients:
                                                           Estimate Std. Error t value Pr(>|t|)  
(Intercept)                                                1.451495   0.664322   2.185   0.0306 *
Exposure_financial_information_numeric                     0.044570   0.192289   0.232   0.8171  
FI_Resources_numeric                                       0.474240   0.256969   1.846   0.0671 .
Age_numeric                                               -0.008899   0.070944  -0.125   0.9004  
Investment_experience_numeric                              0.052874   0.058115   0.910   0.3645  
Exposure_financial_information_numeric:FI_Resources_numeric -0.012367   0.078258  -0.158   0.8747  
---
```

Table 60 Regression analysis #11

```
Coefficients:
                                                           Estimate Std. Error t value Pr(>|t|)    
(Intercept)                                                 4.30283    0.54459   7.901 8.37e-13 ***
Exposure_financial_information_numeric                     -0.12115    0.12509  -0.969   0.3345    
FI_Resources_numeric                                       -0.38805    0.24462  -1.586   0.1150    
Age_numeric                                                -0.03100    0.05424  -0.572   0.5686    
Investment_experience_numeric                               0.08619    0.04118   2.093   0.0382 *  
Exposure_financial_information_numeric:FI_Resources_numeric  0.09759    0.05799   1.683   0.0947 .  
---
```

Table 61 Regression analysis #12

```
Reliability analysis
Call: alpha(x = data[c("Exposure_financial_information_numeric", "SM_O_Propensity_numeric", 
    "SM_P_Propensity_numeric", "SM_O_Resources_numeric", "SM_P_Resources_numeric")])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
      0.63      0.64    0.67      0.26 1.8 0.049  3.4 0.64      0.2
```

Table 62 Cronbach's alpha #1

```
Reliability analysis
Call: alpha(x = data[c("TS_Y_Propensity_numeric", "TS_N_Propensity_numeric", 
    "TS_Y_Resources_numeric", "TS_N_Resources_numeric")])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
      0.83      0.83    0.81      0.55 4.9 0.023  2.8 0.95     0.53
```

Table 63 Cronbach's alpha #2

```
Reliability analysis
Call: alpha(x = data[c("FI_Propensity_numeric", "FI_Resources_numeric")])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean  sd median_r
      0.91      0.92    0.85      0.85  11 0.014  2.2 1.1     0.85
```

Table 64 Cronbach's alpha #3