Received: 13 November 2020 | Revised: 20 June 2021 | Accepted: 27 June 2021

DOI: 10.1002/mar.21550

RESEARCH ARTICLE

Psychology & Marketing WILEY

Why retail investors traded equity during the pandemic? An application of artificial neural networks to examine behavioral biases

Shalini Talwar[1] | **Manish Talwar**[2] | **Visa Tarjanne**[3] | **Amandeep Dhir**[4,5,6]

[1]K J Somaiya Institute of Management, Somaiya Vidyavihar University, Mumbai, India

[2]Alkesh Dinesh Mody Institute for Financial and Management Studies, Mumbai, India

[3]School of Business and Management, LUT University, Lappeenranta, Finland

[4]Department of Management, School of Business & Law, University of Agder, Agder, Norway

[5]Norwegian School of Hotel Management, University of Stavanger, Stavanger, Norway

[6]Optentia Research Focus Area, North-West University, Vanderbijlpark, South Africa

Correspondence

Amandeep Dhir, Department of Management, School of Business & Law, University of Agder, Norway.

Email: amandeep.dhir@uia.no

Abstract

Behavioral biases are known to influence the investment decisions of retail investors. Indeed, extant research has revealed interesting findings in this regard. However, the literature on the impact of these biases on millennials' trading activity, particularly during a health crisis like the COVID-19 pandemic, as well as the equity recommendation intentions of such investors, is limited. The present study addressed these gaps by investigating the influence of eight behavioral biases: overconfidence and self-attribution, over-optimism, hindsight, representativeness, anchoring, loss aversion, mental accounting, and herding on the trading activity and recommendation intentions of millennials during the pandemic. An artificial neural network approach was used to analyze the data collected from 351 millennial men in Finland. The results revealed that herding, hindsight, overconfidence and self-attribution, representativeness, and anchoring influence both trading activity and recommendation intentions, albeit to varying extents. Notably, loss aversion and mental accounting influence only the recommendation intentions. Furthermore, the relationship of the two endogenous variables is nonlinear with herding, representativeness, and anchoring but is linear with other biases. In addition to the quantitative study, we also conducted a post hoc qualitative study with 19 millennials to evaluate the persistence of behavioral biases among them through the pandemic.

KEYWORDS

artificial neural network (ANN), behavioral biases, behavioral finance, heuristic simplification, retail investors

1 | INTRODUCTION

Behavioral finance has emerged as a key field of study in the area of investment management. It examines the rationally inexplicable behavioral aspects of individuals and institutions transacting in financial markets. An increase in the investment activity of retail participants during the recent past has made understanding such behavioral aspects all the more critical (Seth et al., 2020). In this regard, scholars have observed that two distinct sets of factors drive retail investors' decision to invest: (a) rational factors related to traditional finance (Cuong & Jian, 2015) and (b) irrational factors that come under the domain of behavioral finance (Baltussen & Post, 2011). Traditional finance assumes that investors consider the available information and act rationally while making a decision (Szyszka, 2013). In comparison, behavioral finance examines the effect of emotions and cognitive errors in financial decision-making (Hirschey & Nofsinger, 2008).

Behavioral finance explicates investor behavior by drawing upon insights not only from finance but also from psychology, sociology, and other related areas to examine behavior in varied markets that deviate from standard assumptions (Yoong & Ferreira, 2013). Taking the debate further, the proponents of market efficiency and its assumption that markets are rational use theories of traditional finance to explain the anomalies in the market (Yalcin et al., 2016). In comparison, behavioral finance supporters explain market anomalies through behavioral biases (e.g., Sahi et al., 2013). In addition, the role of sentiment and emotions in investment decision-making is well-recognized in the literature. For instance, Piñeiro-Chousa et al. (2016) examined investors' social media activity to confirm that sentiments related to social media use impact stock markets. Similarly, scholars have noted that emotional stress associated with loss from investments may impact the quality of future investment decisions (Chu et al., 2014).

Behavioral biases have attracted researchers' attention over the past several decades (e.g., Baker et al., 2019; Tversky & Kahneman, 1986), with different biases being proposed and examined to explain retail investors' decision-making. In this regard, some of the recently examined behavioral biases are the disposition effect in the options market (Bergsma et al., 2019), overconfidence and underdog bias (Combrink & Lew, 2019), home bias tendency while trading (Gavish et al., 2020), and myopic loss aversion (Durand et al., 2019). While the accumulated knowledge is rich, the literature is deficient in terms of three aspects: First, there are limited prior studies on investor behavior in the face of an external stressor, such as a global health crisis, even though the existing scholarship has noted the impact of events, such as the Ebola virus outbreak (Ichev & Marinč, 2018) and various disasters (Kowalewski & Śpiewanowski, 2020) on stock market returns. It is important to acknowledge here that although such events wreak havoc, they provide natural experimental settings to assess investor behavior, in addition to offering opportunities for assessing the pricing and reaction of funds (Mirza et al., 2020). The COVID-19 pandemic offers another such natural setting for examining investors' behavior to address the gap in the related findings (Ortmann et al., 2020). In concurrence, some recent studies have discussed the upheaval caused by the pandemic in the financial markets and its impact on investors, thereby underscoring the need to understand investor behavior better (e.g., Al-Awadhi et al., 2020; O'Donnell et al., 2021; Okorie & Lin, 2021). In this regard, Bansal (2020) has suggested that the extreme volatility and market crash during COVID-19 should be analyzed through the lens of behavioral biases and related cognitive errors. Responding to these calls, the present study examines investors' behavioral biases and their influence on trading activity during the COVID-19 pandemic.

Second, although scholars have acknowledged the effect of demographic variables on the decisions of retail investors (Baker et al., 2019), no studies have focussed on millennials' (also called Generation Y) behavioral biases. Millennial investors are those born between the years 1981 to 1996 (Dimock, 2019). Since they can be anticipated to be active in the stock market for the foreseeable future, given their age, a deeper understanding of millennials' behavioral biases could help managers plan their future strategies (Dimock, 2019). Due to this, the present study investigates millennials' behavioral biases and their influence on trading activity during the COVID-19 pandemic.

Third, although it is known anecdotally that trading in equity markets is driven largely by peers' and professionals' recommendations, no prior study has examined the association between behavioral biases and recommendation intentions in this context. The link between investment and recommendation intentions has also been highlighted by the academic research. In this regard, scholars have observed that in addition to seeking economic gains, investors have certain social motives associated with their investment activity that may manifest as word of mouth or recommendation intentions (e.g., Ahmad et al., 2020). Given that recommendations can impact investment decisions, it would be quite useful for the concerned stakeholders to understand how various behavioral biases can influence the recommendation intent of retail investors. We propose to address the paucity of insights in this context by examining the association between the behavioral biases and recommendation intentions of millennials during the COVID-19 pandemic.

Cognisant of the gaps in the extant literature and the need to address them, the present study thus utilizes a mixed-method approach to elucidate the association between millennials' behavioral biases on the one hand and their trading activity and recommendation intentions during the pandemic on the other. Specifically, the study addresses two main research questions (RQs): RQ1. How do behavioral biases predict the equity trading activity of millennials in the face of an external stressor (i.e., COVID-19) that has both psychological and economic implications? RQ2. How do behavioral biases predict the recommendation intentions of millennials related to equity trading under the impact of a health crisis?

Scholars have examined different sets of behavioral biases in various contexts in the recent past. In addition, behavioral scientists have classified these biases into different categories for ease of understanding and evaluation. We have referred to one such classification/taxonomy, proposed by Montier (2002) and simplified from Hirshleifer (2001) and Yalcin et al. (2016), to identify the biases to be examined in the present study. Accordingly, we developed a conceptual model comprising eight biases as exogenous variables and millennials' trading activity and recommendation intentions as outcome variables. We analyzed survey data collected from 351 Finnish millennials to test the theorized associations.

Furthermore, drawing upon the past literature observing the presence of nonlinearity in behaviors, investment outcomes, and business phenomena (e.g., Layng, 2009; You, 2020), as well as the contention that biases are associated with irrational decision-making that goes against the postulates of the Theory of Expected Utility (Kahneman & Tversky, 1979), we expect the association of behavioral biases with the proposed outcome variables to be nonlinear.

Scholars have observed that in a given relationship, nonlinearity occurs when the marginal impact of an additional unit of change is not the same as that of the preceding one (Amanatiadis et al., 2014). However, the associations can be linear as well. In sum, recognizing that the relationship of biases with outcome variables may be more complex than simple linear variations, the present study analyzed the data using the artificial neural network (ANN) method, which accommodates both linear and nonlinear associations. Finally, we followed this empirical investigation with a post hoc qualitative study to evaluate if the biases that manifested at the pandemic's beginning persisted as it advanced.

The novelty of the present study comes from the following: (a) It investigates behavioral biases and investor behavior during the COVID-19 pandemic, thereby clarifying the effect of unprecedented outliers, such as global lockdown and the subsequent economic ramifications, on investment decisions, (b) it highlights millennials as strategically important generational cohorts to be focused upon in the contemporary research on investment decision-making, (c) it examines recommendation intentions, which have remained under-explored in the prior literature on biases and investment decisions despite being recognized as a key influence in equity markets, and (d) it recognizes the possibility of the existence of both linear and nonlinear associations between biases, trading activity, and recommendation intentions. To our knowledge, past studies on investors' behavioral biases have not captured this possibility. Given that retail investors may have low acumen in investment matters (Bhattacharya et al., 2012), the possibility of nonlinear associations cannot be ignored.

2 | BACKGROUND LITERATURE

2.1 | COVID-19 and the stock markets

The COVID-19 pandemic made its first appearance in 2019 in China, and soon after, it spread around the world (Chinazzi et al., 2020). Due to the scale of its impact, the World Health Organization (WHO) declared it a global pandemic in March 2020. Countries responded to the pandemic by unveiling various control measures, including complete domestic shutdown, social distancing, travel restrictions, and provisions of quarantine for those exposed to the virus (Fang et al., 2020). The massive scale of the lockdown produced severe economic challenges due to the complete stoppage in commercial activity and tourism and other consequences, such as job loss, lower growth, and damage to the supply side (Leduc & Liu, 2020), which also adversely affected the financial system. For instance, the restrictions imposed in the wake of the pandemic increased the banking sectors' systemic risk in many affected economies initially (Rizwan et al., 2020), though the pandemic is expected to have high economic costs in the future as well (Goodell, 2020). Even before the onset of the COVID-19 pandemic, scholars had raised concerns about the susceptibility and vulnerability of economies to health pandemics (Bloom et al., 2018).

Past studies have observed that, in the same way as economies, the stock market returns are also susceptible to major events (Zach, 2003). This contention was confirmed when the markets worldwide registered a substantial fall in their value, as presented in Figure 1, when the health crisis was declared a pandemic in March 2020. To elaborate, Figure 1 indicates that the stock markets worldwide showed a declining trend during the said period, losing 15%–20% of their value. Notably, scholars expressed that the financial crisis unleashed by the pandemic has been more perilous than the 2008 crisis (Georgieva, 2020), with financial markets reaching close to collapse in its wake (Adam, 2020). However, it is not entirely correct to compare the crisis caused by the COVID-19 pandemic with the 2008 crisis.

The 2008 crisis was triggered by institutional structures and practices in the financial sector (Crotty, 2009), beginning with the collapse of the subprime mortgage market in the United States (Hodson & Quaglia, 2009), thereby making it easier to contain and counteract. In comparison, the pandemic has impacted all aspects of human life, which has made it much more difficult to control. Furthermore, the 2008 crisis was largely a financial turmoil that affected the global economy, leading to a contraction in the gross domestic product (World Bank, 2009). As the 2008 crisis unfolded, central banks in various countries introduced a slew of monetary policy measures to stabilize prices and financial markets (Collingro & Frenkel, 2020). In contrast, in response to the COVID-19 pandemic, the governments focused on public health measures before initiating any economic recovery plans.

In addition to its macro influence at the national and global level, the pandemic has also produced a micro effect at the individual level. Apart from impacting the movement and livelihood of individuals, the panic created by the life-threatening element of the pandemic could have impacted the psyche and behavior of retail investors, thereby causing them to make suboptimal investment decisions. The association between panic and stock market activity has been documented in the past literature, revealing the role of sentiment and irrational thought-process in investment decisions (Aggarwal et al., 2021). For instance, scholars have observed that the panic created by terrorist attacks has caused temporary declines in stock markets in the past (Brounen & Derwall, 2010). This revelation is pertinent in the present context since scholars have compared the pandemic to terrorist attacks due to the fear, panic, and uncertainty it has incited (Goodell, 2020; Ortmann et al., 2020).

The movement of stock markets worldwide confirmed the drastic impact of the pandemic on investors. One after the other, all markets registered a steep fall in March 2020. The US market, which had hit circuit breaker only once before, in 1997, hit it four times in the space of ten days in March 2020 (D. Zhang et al., 2020). Particularly, the returns of the S&P 500 were severely impaired (Shehzad et al., 2020). The story in Europe and Asia was no different, with FTSE (UK's main index) plunging more than 10% within a day and Japan losing more than 20% of its peak reached in December 2019 (Vishnoi & Mookerjee, 2020). Such volatility not only eroded market capitalization at an aggregate level but also diminished retail investor wealth, potentially impacting their short- and long-run investment decisions and choices. Retail investors' decisions and choices can produce serious repercussions for the markets since retail trades can

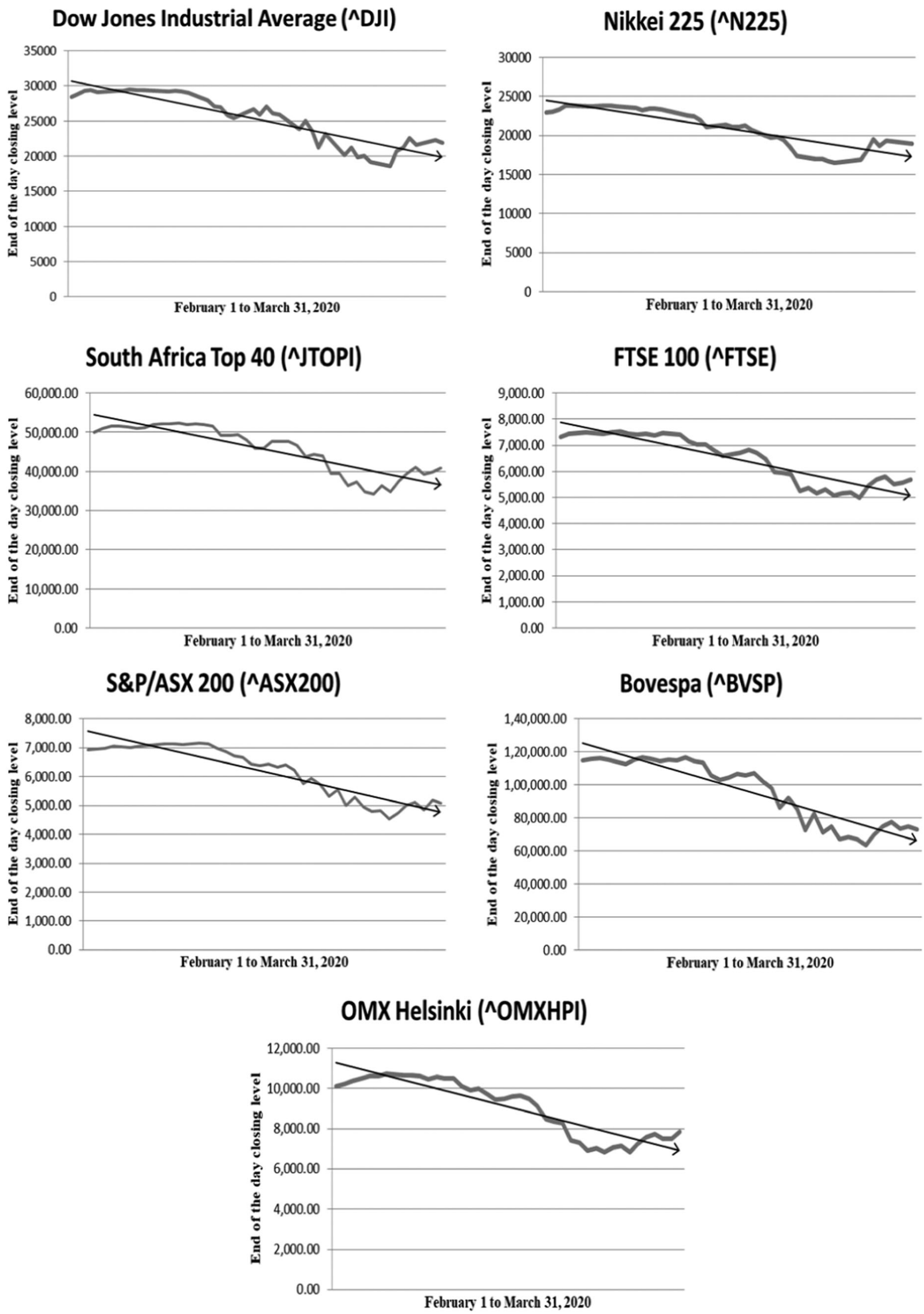

FIGURE 1 Fall in world stock markets in response to COVID-19 spread

move stock prices (Burch et al., 2016), and the short-selling activity of retail investors can predict negative stock returns in the future (Kelley & Tetlock, 2016).

Given their potential to impact the market as a whole, we contend that it is important to examine retail investors' behavior in unprecedented times, such as the COVID-19 pandemic, to better understand the aggregate market response (Ortmann et al., 2020). Moreover, since investors' preferences may be influenced by trends (Caginalp & Balenovich, 1996), the behavior of a set of retail investors causing a downtrend in prices may trigger panic in other investors. This bodes ill for broader market valuations and underscores the need to understand the drivers of investment/trading behavior. Furthermore, from the perspective of the investors themselves, they may make suboptimal investment decisions by becoming more risk-averse, lowering their growth expectations, expecting higher market risk premium, and reducing their trading activity (Aggarwal et al., 2021; Ortmann et al., 2020), as observed in post-terrorist attack periods (e.g., Wang & Young, 2020). This supposition is corroborated by the finding that there has been a general reduction in individual risk tolerance during the pandemic (Bu et al., 2020). Due to this, the present study proposes to examine the investment behavior of retail investors during the COVID-19 pandemic.

2.2 | Behavioral biases

The debate around the existence of biases in decision-making is rooted primarily in Kahneman and Tversky's (1979) Prospect Theory. Examining behavioral biases can be expected to yield a better understanding of investors' decision-making process (Sahi et al., 2013) as these biases represent errors of judgment in decision-making (Kahneman & Riepe, 1998) and suggestions regarding how investors process the available information to make decisions (Shefrin, 2000). Scholars have categorized these biases in many different ways. Shefrin (2000) classified the biases into two categories: heuristic-driven biases and frame-dependent biases. Pompian (2011) categorized them as cognitive and emotional biases. Montier (2002), meanwhile, gave a comprehensive taxonomy of biases, spanning three broad categories: self-deception, heuristic simplification, and social interaction. These three categories comprise nearly twenty biases. The self-deception bias captures overconfidence, self-attribution, and hindsight bias. Heuristic simplification includes representativeness and anchoring/salience. In comparison, the last category, which is social interaction, includes biases like herding. In the present study, we have selected a set of biases to represent each of the three categories proposed by Montier (2002).

3 | CONCEPTUAL MODEL

The present study examines how behavioral biases influence the trading activity and recommendation intentions of retail investors in the face of crises, such as the one posed by the spread of the COVID-19 virus (Figure 2). As mentioned above, the study has identified biases from Montier's taxonomy (2002). This taxonomy was preferred for two reasons: First, it is very comprehensive, since it includes nearly twenty biases that cover various cognitive errors manifested by investors, and, second, because it provides a clear

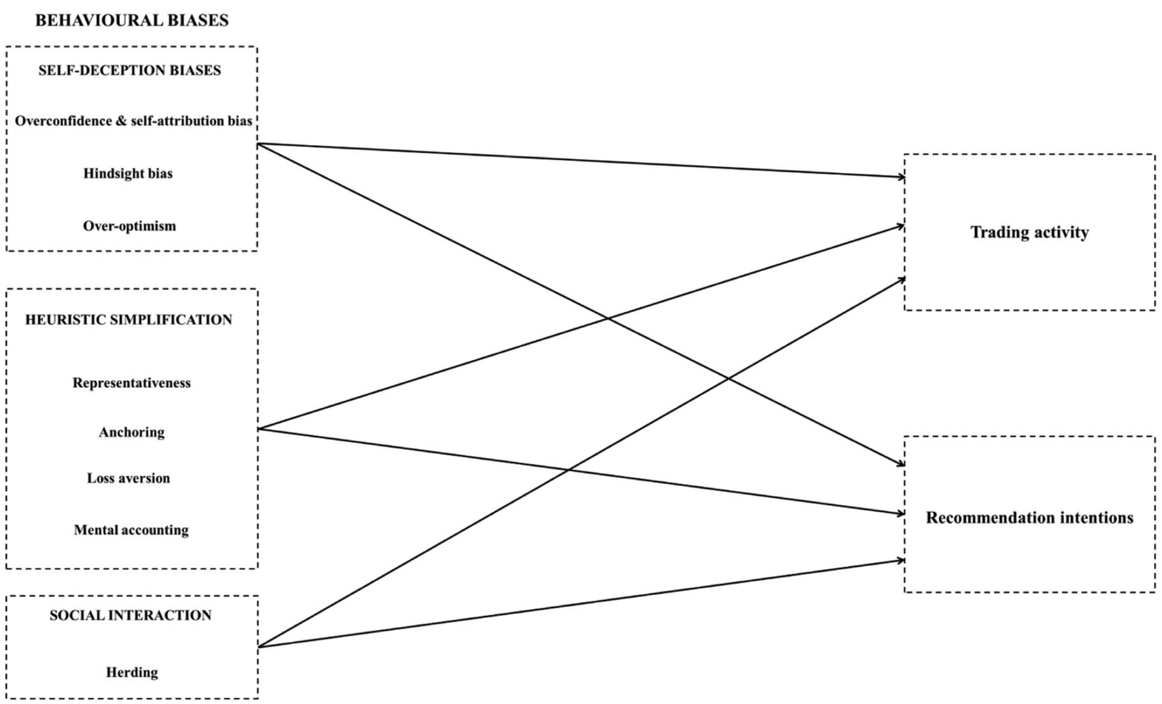

FIGURE 2 Conceptual model

delineation of biases into three categories, which makes it easy to understand why a particular bias is manifested. Furthermore, only some biases representing the three categories given by Montier were selected since it is not possible to examine all the biases in one study.

These biases were selected in consultation with a panel of three professors (specialized in Marketing and Finance) and three practitioners. The biases include overconfidence and self-attribution bias (taken together, in consonance with Baker et al., 2019), hindsight bias, over-optimism, representativeness, anchoring, loss aversion, mental accounting, and herding. Although mental accounting is not a part of Montier's classification, it was included based on the suggestion of the panel. The variables used in the study are described in Table 1.

3.1 | Self-deception biases and trading activity

Self-deception poses limits to learning that may prevent individuals from training their minds towards alternative thought processes (Montier, 2002). We have examined self-deception through overconfidence, self-attribution, hindsight, and over-optimism biases. Overconfidence causes under- or overreactions in the financial markets (Daniel et al., 1998) and may be exacerbated by an increase in experience that, in turn, results in the deterioration of returns from investment (Wulfmeyer, 2016; Xiao, 2015). Self-attribution is a manifestation of over-confidence, due to which investors attribute their success to the self and failure to others (Stracca, 2004). Prior empirical studies have revealed that overconfidence can affect investment decision-making adversely and cause losses by decreasing risk-aversion (Nosić & Weber, 2010), increasing market volatility (Daniel et al., 1998), and instigating investors to indulge in trading excessively (Barber & Odean, 2000; Meier, 2018).

Hindsight bias has been confirmed to exist in financial markets and is known to produce financial consequences (Baker et al., 2019; Moosa & Ramiah, 2017). Individuals with hindsight bias tend to believe, albeit falsely, that they had foreseen the possibility of an event, such as the volatility of a particular stock, and accurately predicted its actual outcome (Biais & Weber, 2009). Such a tendency to overestimate their ability to predict movement in stock prices may cause investors to over-react by potentially indulging in heightened trading activity (Camerer et al., 1989).

Over-optimism represents individuals' tendency to think that the likelihood of their experiencing positive outcomes is more than that of them experiencing adverse outcomes, particularly if the related event is perceived to be controllable by them (Bansal, 2020). Such optimism has also been found to exist in investment decision-making (Skala, 2008).

TABLE 1 Variable description

Bias	Operational description	Authors
Overconfidence and self-attribution	The tendency of investors to have an unrealistic estimate of their knowledge about investing, based on some past successes that may cause them to trade more	Barber and Odean (2001), Daniel et al. (1998)
Hindsight bias	The ex-post tendency of investors to accept as true that they could have predicted stock-related events that have occurred already	Biais and Weber (2009)
Over-optimism	The tendency of investors to overvalue the returns of a risky asset under consideration by focussing decision-making selectively on good news, thereby creating bubbles in the related markets	Bansal (2020)
Representativeness	The tendency of investors to extrapolate earning surprise and overreact to the next one, anticipating the outcome of an event by comparing it with a past incident, and considering past price as representative of the future price	Tversky and Kahneman (1974), A. Kumar (2009)
Anchoring	The tendency of investors to make stock-related forecasts by being too influenced by certain values and pegging the estimates to an arbitrary, initial, or prior value/quantity that might be meaningless	Tversky and Kahneman (1974), Hirshleifer (2001)
Loss aversion	The tendency of investors to experience regret on incurring losses which causes them to avoid future loss and regret. Usually, individuals are more loss averse in bull markets	Kahneman and Tversky (1979)
Mental accounting	The tendency of investors to make a mental account of investments that affects stock selection and asset prices	Barberis and Huang (2001), Thaler (1999)
Herding	The tendency of investors to infer information and make choices based on actions of others, be influenced by and act in accordance with their judgment	S. Kumar and Goyal (2016), Shantha (2019)
Trading activity	Buying and selling of equity	
Recommendation intentions	Intentions of investors to spread positive word of mouth about an equity investment in general and specific shares in particular	

Over-optimism related to investment decision-making may lead to a better-than-average effect in financial markets, which is linked with a high volume of trading (Glaser & Weber, 2007). Scholars have also linked over-optimism with overconfidence (Hilton et al., 2011), which again provides a basis for associating it with increased trading activity.

Based on the preceding discussion, we expect the over-confidence and self-attribution, hindsight, and over-optimism biases of millennial investors to influence their trading activity.

3.2 | Heuristic simplification and trading activity

Heuristic simplification represents errors in processing information, including the effect of emotions due to the limited mental capacity of humans (Montier, 2002). We have examined heuristic simplification in the present study through representativeness, anchoring, loss aversion, and mental accounting biases. Representativeness is a cognitive bias that causes investors to make forecasts based on the analogues they associate with something (C. Zhang, 2008). For instance, investors may consider the realized returns as representations of expected returns in the future and act to sell or buy accordingly (De Bondt, 1998). Prior scholars have confirmed the influence of representative bias in investment decision-making (Mokhtar, 2014; Baker et al., 2019), revealing age and gender-based differences in its manifestation (Tekçe et al., 2016). Such bias can influence the quality of investment made by individuals and adversely impact markets in the long run. For instance, during the COVID-19 pandemic, a tendency to compare the 2020 crash of the stock market with the 2008 crisis has been observed, which is a manifestation of representativeness bias (Bansal, 2020). However, experts warn that the decline in the markets due to the COVID-19 crisis may continue longer than the duration observed in 2008, similar to the prolonged recovery witnessed after the 1929 crash (McCaffrey, 2020).

Anchoring bias causes investors to begin their estimates with a certain initial value before adjusting it thereafter (Tversky & Kahneman, 1974). It can potentially influence decision-making and lead to poor investment choices based on limited and subjective information (Caputo, 2014; Costa et al., 2017). Due to this, the bias can affect the market as well. For instance, anchoring bias can lead to a 52-week high momentum, especially when the investor sentiment is high (Hao et al., 2018). Furthermore, it can influence buying and selling activity by causing investors to expect earnings to conform to past trends or shares to trade within a range. This can lead to under-reaction to changes in trends. Such bias is also present in market participants' estimates of the profitability of a firm (Cen et al., 2013).

Loss aversion represents the investors' decision to sell stock that has risen in price and keep holding stock that has fallen (Kahneman & Tversky, 1979). Emotions drive this decision and manifest less when the decision is being made for others (Andersson et al., 2016). Loss aversion influences selling decisions since investors react differently to the possibility of losses compared with assured profits (Zahera & Bansal, 2018). There are findings relating loss aversion to demographic profile as well, with investors who are unmarried exhibiting more loss aversion than married ones (Ates et al., 2016).

Mental accounting causes investors to compartmentalize their investments separately into mental categories (Thaler, 1985). To maximize returns and minimize risk, investors apply different policies in managing these categories and consider each to have a specific aim. Such cognitive error can adversely impact the portfolio selection process since it is largely driven by emotions (Zahera & Bansal, 2018). Scholars have also discussed mental accounting along with other biases as risk factors that can lead to suboptimal investment decisions at both the retail and institutional levels (Otuteye & Siddiquee, 2019). Mental accounting has also been examined in the larger context of consumer behavior to explain aspects like inaction inertia (Liu & Chou, 2018).

The above discussion confirms that heuristic simplification biases can influence investment decisions. Accordingly, we extrapolate the same outcome to the millennial investors and suggest that these biases will influence their trading activity.

3.3 | Social interaction and trading activity

Social interaction represents human beings' intrinsic social nature, which results in the horizontal transmission of information across social groups (Montier, 2002). In the present study, we have examined the impact of social interaction on millennials' investment decision-making through herding bias. The tendency to trust others' judgment, manifested as herding bias, has been cited as a key cause of bubbles, volatility, and crashes in financial markets (Shantha, 2018; Yao et al., 2014). Other studies have also confirmed that herding bias produces adverse consequences for markets and causes financial losses for investors (Shantha, 2018; 2019). Focusing on demographic factors, Lin (2011) observed that men exhibit lower herding bias than women, and younger investors exhibit this bias more than older ones. Taking these findings forward, other scholars have also examined the effect of demographic characteristics, including age, on herding bias (Baker et al., 2019; Prosad et al., 2015).

Based on the preceding discussion, we expect herding bias to influence millennials' decision to imitate others and trade more if others are doing it.

3.4 | Behavioral biases and recommendation intentions

Recommendation intentions or positive word of mouth is a well-researched form of consumer behavior and has been examined in various contexts, including online products and services, mobile wallets, hospitality, and so on (e.g., Karjaluoto et al., 2016; Kaur, Dhir, Bodhi, et al., 2020; Kaur, Dhir, Singh, et al., 2020). Although the prior studies on behavioral bias have not investigated the association between these biases and recommendation intentions, the existing literature does indicate its importance. Montier's taxonomy itself, which is the basis of the present study, has identified social interaction and transmission of information across social groups as a potential source of bias (Montier, 2002). Scholars have also argued that, in the future, the individual decision-making process might be better understood by evaluating group decision-making processes (Preda & Muradoglu, 2019). Recommendation intentions are particularly important to understand in the case of millennials as they represent generational cohorts exposed to information technology at a young age (Chen & Howard, 2020), which enables them to stay connected with others. In fact, this generation has been called digital natives as they are known to maintain a continuous online presence (Lester et al., 2005). Furthermore, millennials are more likely to consult others while making decisions (Viswanathan & Jain, 2013). In the general context of consumer decision-making, scholars have also noted the rising importance of reviews available online (Agnihotri & Bhattacharya, 2016), which underscores the importance of consumer recommendations.

Given their connectivity and dependence on others for decision-making, including investments, it is plausible to assume that millennials would be inclined to share their knowledge about investment with their social groups. Since the recommendations made may influence the investment decisions of such groups, it is important to understand how millennials' behavioral biases shape their recommendation intentions. This can help understand how contagion and panic in the stock market may cascade at the retail level through the communication of investors with each other.

4 | DATA AND METHODS

4.1 | Data collection

We used a mixed-method approach to achieve the objectives of our study. The first part comprised quantitative data collection, and the second part comprised a post hoc qualitative study.

We collected data for empirical analysis through a cross-sectional survey conducted in Finland. The respondents were recruited by specifying three screening questions: (a) They should have been born between 1981 and 1996, (b) their gender should be male, and (c) they should have experience with trading in equity. These screening criteria enabled us to recruit respondents from our target sample, which comprised Finnish millennial males active in equity markets. Finland was chosen to collect data based on recent regulatory developments. In March 2019, the Parliament in Finland accepted the law related to equity savings accounts to encourage equity investment. In this regard, millennials constitute 50% of the accounts opened so far, with the majority being males (Euroclear Finland, 2020).

The questionnaire was developed by adapting pre-validated scales from prior studies in the area of behavioral finance. The following scales were derived from Baker et al. (2019). Overconfidence and self-attribution, hindsight bias, representativeness, anchoring, mental accounting, and herding. Over-optimism was operationalized by adapting the scale from Barrafrem et al. (2020), while the loss aversion scale was adapted from Chun and Ming (2009). For trading activity, items were developed based on Milgrom and Stokey (1982) and Barber and Odean (2000), and recommendation intentions were captured through a scale adapted from Riquelme et al. (2016). Before finalizing the questionnaire, we followed the due procedure to ensure the face and content validity of the survey items, in consonance with recent studies (e.g., M. Talwar et al., 2020). To this end, we first presented the preliminary questionnaire to a panel of three professors (specialized in Marketing and Finance) and three professionals experienced in advising retail investors. Corrections suggested by them were used to modify the questionnaire, which was then pilot tested with ten respondents representing the target sample. These respondents' feedback was then used to change the language of the items further as required. This process culminated in the preparation of the final questionnaire.

The survey was conducted during May 2020 to capture the responses during the ongoing COVID-19 pandemic. Due to this, multiple touchpoints were used to solicit a response. The online survey link was shared on WhatsApp and Facebook groups and different Facebook pages related to equity investment. To control for self-response bias, we informed the participants that their anonymity would be maintained, and no personal information except basic demographic details would be collected. Furthermore, we did not disclose that the purpose of the study was to measure behavioral biases. This was done to prevent biases in response that may manifest if the respondents knew the purpose of the study (Saunders et al., 2009). No incentive was offered for responding to the survey. A total of 380 responses were received, of which 351 were taken forward for analysis after the removal of incomplete responses and outliers.

We followed the empirical analysis with a post hoc qualitative study conducted through open-ended essays. To this end, we recruited 19 male millennial investors as participants through Prolific Academic. The objective of this study was to evaluate whether the biases that manifested immediately after the onset of the pandemic persisted as it advanced. Such insight can be useful to understand how the panic and uncertainty associated with a crisis drive biases initially and how coming to terms with the unfolding situation changes them over time.

4.2 | Methods

We considered three potential methods for data analysis, covariance-based structural equation modelling (CB-SEM), variance-based structural equation modelling (VB-SEM), and ANNs, based on the nature of the data and research questions. With regard to the nature of the data, Henseler et al. (2009) suggested that the suitability of an analysis method depends on its requirements related to the size of the sample, outliers, normality, multicollinearity, linearity, and homoscedasticity.

In this context, if the research questions are grounded in a conceptual model based on a strong theoretical framework, and the collected data meets the requirements mentioned above, then CB-SEM is suitable. Similarly, if the research questions are related to theory-building, and the collected data does not conform to some of the requirements mentioned above, VB-SEM is suitable since it is lenient about sample size, outliers, and normality. In comparison, if the research questions mandate the detection of both linear as well as nonlinear relationships to uncover the predictive capacity of exogenous variables, then ANN is better suited for data analysis, as suggested by Hew et al. (2019) and M. Talwar et al. (2021). ANN method utilizes artificial intelligence to generate a solution and is lenient on the various data-related assumptions mentioned above. In the present study, we have used ANN to analyze data since our objective is to detect both types of relationships and determine the predictive power of biases in the context of millennials' trading activity and recommendation intentions. We performed the ANN analysis using sklearn and multi-layer perceptron in Python and SPSS.

ANN uses neurons distributed in multiple layers, grouped as input, output, and hidden (Höglund, 2012). The network is based on the principle of how the human brain works and learns new information. This learning occurs through a training process that involves forward iterations and backward propagation of information to fine-tune the output (Taneja & Arora, 2019). The learned information is stored in the model as synaptic weights. These weights are then adjusted using activation function (sigmoid function in this study) and through the propagation of errors in the backward direction. The key idea here is to reduce the gap between the actual and the desired output over numerous iterations to reach the level where bias is minimized (El Idrissi et al., 2019; Sharma & Sharma, 2019).

We employed a cross-validation process for analysis, wherein the data were bifurcated into two parts, training and validation, as suggested by scholars (Kuhn & Johnson, 2013). Moreover, we utilized 70% of the data as training data and the balance 30% for validation to avoid over-fitting. To assess the model's prediction accuracy, we evaluated the root mean square error (RMSE) value, as recommended by Samuel et al. (2014). The relative influence of each exogenous variable was gauged through sensitivity analysis, in which we first calculated the relative importance of each variable and then expressed it as the proportion of the highest value.

5 | RESULTS

5.1 | Validity and reliability of the instrument

The present study computed Cronbach's α and the composite reliability (CR) to confirm the reliability of the scale, in line with prior literature (J. Hair et al., 2010). Both criteria for reliability were met, in line with the recommended cut-off value of 0.70 (J. Hair et al., 2010), except in the case of over-optimism, due to which it was excluded from analysis (Table 2). Next, the instrument's validity was assessed through convergent and discriminant validity, as suggested by prior methodological literature (J. Hair et al., 2010). In this context, the average variance extracted (AVE) for all of the constructs taken forward was greater than 0.50, thereby confirming the convergent validity (Table 2). Similarly, square roots of the AVEs were generally higher than the pairwise correlations, confirming discriminant validity (Table 2).

5.2 | Data diagnostics

5.2.1 | Normality, multicollinearity, linearity, and homoscedasticity

We used the Kolmogorov–Smirnov (K–S) test to evaluate if the data under the study were normally distributed (Chakravarti et al., 1967). Since the null hypothesis of normal distribution was rejected ($p > .00$), we concluded that the data followed a non-normal distribution. This outcome provides another justification for using ANN. Next, the multicollinearity issue was examined by computing values of tolerance and variance inflation factor (VIF), as suggested by prior studies (e.g., Chong, 2013). All tolerance values were greater than

TABLE 2 Validity and reliability

	α	CR	AVE	OSCA	HB	ANCH	REP	LAV	HER	MAAC	TA	RI
OSCA	0.75	0.75	0.50	**0.71**								
HB	0.73	0.73	0.47	0.49	**0.69**							
ANCH	0.77	0.78	0.47	−0.19	−0.17	**0.68**						
REP	0.77	0.77	0.45	0.49	0.48	−0.09	**0.67**					
LAV	0.71	0.72	0.46	−0.08	0.00	0.13	−0.01	**0.68**				
HER	0.76	0.76	0.51	0.50	0.50	−0.22	0.42	0.05	**0.72**			
MAAC	0.75	0.76	0.51	0.06	0.06	0.06	0.10	0.05	0.10	**0.72**		
TA	0.76	0.76	0.52	0.68	0.70	−0.34	0.63	−0.01	0.70	0.05	**0.72**	
RI	0.82	0.83	0.63	0.57	0.58	−0.22	0.47	−0.04	0.68	0.02	0.65	**0.79**

Abbreviations: ANCH, anchoring; AVE, average variance extracted; CR, composite reliability; HB, hindsight bias; HER, herding; LAV, loss aversion; MAAC, mental accounting; OSCA, overconfidence and self-attribution; REP, representativeness; RI, recommendation intention; TA, trading activity; α, Cronbach's α.

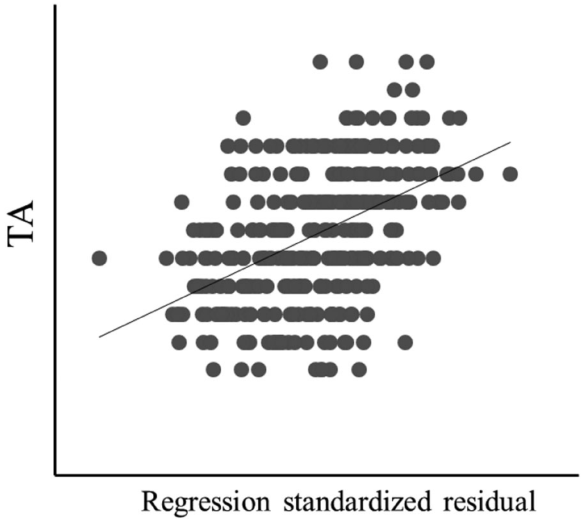

FIGURE 3 Scatter plot of standardized residuals (trading activity)

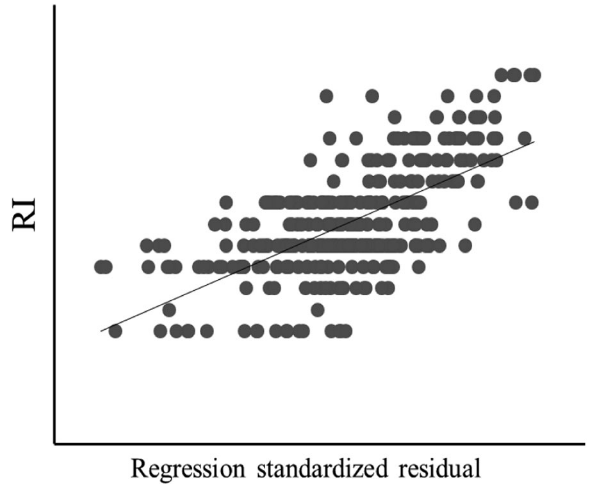

FIGURE 4 Scatter plot of standardised residuals (recommendation intentions)

0.1, and VIFs were below the threshold value of 3, which confirmed the absence of collinearity issues in the data (Hair et al., 2011). The absence of multicollinearity was also confirmed by the value of the correlations between the exogenous variables being less than 0.90 (e.g., Wong et al., 2016) (Table 2).

In consonance with Hew et al. (2019), we conducted the ANOVA test to confirm the type of relationship (linear vs. nonlinear) between the variables. The test confirmed that both trading activity and recommendation intentions have a nonlinear relationship with representativeness, anchoring, and herding biases. The existence of these relationships yields further support for the use of ANN.

We also examined the data under study to understand whether it was homoscedastic or heteroscedastic. To this end, in consonance with Hew et al. (2019), we generated a scatter plot to visually examine if the residuals were evenly distributed around the fitted line. As seen in Figures 3 and 4, the trading activity data is homoscedastic, whereas the recommendation intentions data is not. However, the heteroscedasticity of the data was not a concern in the present study since the feedforward neural network estimates are better than those of the weighted least square regression in the instance of deviation from homoscedasticity (Paliwal & Usha, 2011).

5.2.2 | Common method bias (CMB)

The issue of CMB may exist in the present study since the data for all of the variables were collected through a single instrument in one wave. Due to this, we used a two-pronged approach to control and assess the issue of CMB, as suggested by Podsakoff et al. (2003). Due attention was paid to the questionnaire design and protection of the respondents' anonymity. Next, we conducted Harman's single factor test, which revealed that one factor explained only 26.82% of the total variance. Being less than the suggested threshold of 50%, this value confirmed that CMB was not an issue in the data under study.

5.3 | Validation of ANN

Alternative ANN models were generated with seven input neurons, three hidden neurons, and two output neurons (Figure 5). Based on the RMSE values presented in Tables 3 and 4, we can conclude that these models have a high prediction accuracy. This is further confirmed by the fact that the mean values of the RMSE of the training and validation data are 0.1455 and 0.1484 for trading activity and 0.1972 and 0.2197 for recommendation intentions. We have reported RMSE values in consonance with recent studies that have applied ANN for data analysis (e.g., Hew et al., 2019; Leong et al., 2020; M. Talwar et al., 2021).

5.4 | Sensitivity analysis

The present study conducted a sensitivity analysis to assess the comparative influence of biases by computing their normalized importance. This was calculated by expressing each value as a percentage of the highest value. As presented in Table 5, in the case of trading activity, herding is the most important bias, followed by hindsight, overconfidence and self-attribution, representativeness, and anchoring. As presented in Table 6, in the case of recommendation intentions, herding is the most important bias, followed by hindsight, overconfidence and self-attribution, representativeness, anchoring, mental accounting, and loss aversion.

5.5 | Post hoc qualitative study

We followed our quantitative empirical investigation with a post hoc qualitative study to understand whether the biases that manifested during the early part of the pandemic were still playing a role in influencing millennials' trading activity and recommendation intentions. To this end, we collected and analysed data from 19 male

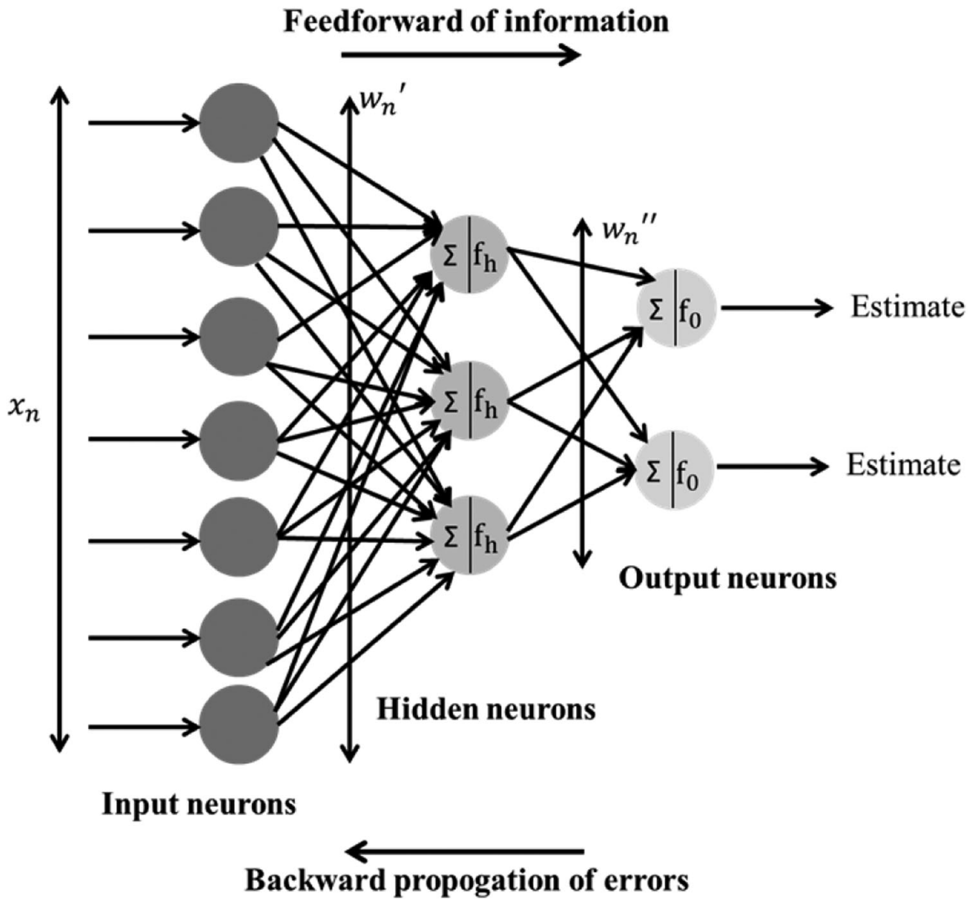

FIGURE 5 Artificial neural network model

TABLE 3 RMSE of training and validation data (70/30) for trading activity

	Training		Validation	
Neural network	*N*	RSME	*N*	RSME
ANN1	106	0.1468	106	0.1488
ANN2	106	0.1468	106	0.1488
ANN3	106	0.1462	106	0.1471
ANN4	106	0.1429	106	0.1497
ANN5	106	0.1390	106	0.1481
ANN6	106	0.1446	106	0.1488
ANN7	106	0.1446	106	0.1488
ANN8	106	0.1408	106	0.1443
ANN9	106	0.1506	106	0.1505
ANN10	106	0.1522	106	0.1494
	Mean	0.1455		0.1484
	SD	0.0037		0.0015

Abbreviations: RMSE, root mean square error; *SD*, standard deviation.

TABLE 4 RMSE of training and validation data (70/30) for recommendation intentions

	Training		Validation	
Neural network	*N*	RSME	*N*	RSME
ANN1	106	0.2002	106	0.2227
ANN2	106	0.2002	106	0.2227
ANN3	106	0.2000	106	0.2217
ANN4	106	0.1960	106	0.2210
ANN5	106	0.1781	106	0.2170
ANN6	106	0.1951	106	0.2192
ANN7	106	0.1951	106	0.2192
ANN8	106	0.1942	106	0.2184
ANN9	106	0.2068	106	0.2171
ANN10	106	0.2062	106	0.2180
	Mean	0.1972		0.2197
	SD	0.0073		0.0020

Abbreviations: RMSE, root mean square error; *SD*, standard deviation.

TABLE 5 Normalized relative importance of biases in the case of trading activity

Neural network	OSCA	HS	ANCH	REP	LAV	HER	MAAC
ANN1	0.642	0.835	0.125	0.545	0.001	1	0.009
ANN2	0.641	0.831	0.119	0.512	0.002	1	0.002
ANN3	0.67	0.875	0.136	0.537	0.001	1	0.007
ANN4	0.682	0.913	0.118	0.626	−0.003	1	0.003
ANN5	0.648	1	0.109	0.487	0.007	0.708	−0.003
ANN6	0.615	0.94	0.172	0.443	−0.004	1	−0.012
ANN7	0.618	0.99	0.185	0.46	−0.004	1	−0.06
ANN8	0.737	1	0.142	0.49	−0.003	0.817	−0.01
ANN9	0.338	0.448	0.031	0.223	0.006	1	0.012
ANN10	0.349	0.443	0.021	0.249	0.001	1	0.02
Mean	0.594	0.8275	0.1158	0.4572	0.0004	0.9525	−0.0032
Normalized	62%	87%	12%	48%	0%	100%	0%

Abbreviations: ANCH, anchoring; HB, hindsight bias; HER, herding; LAV, loss aversion; MAAC, mental accounting; OSCA, overconfidence and self-attribution; REP, representativeness.

TABLE 6 Normalized relative importance of biases in the case of recommendation intentions

Neural network	OSCA	HS	ANCH	REP	LAV	HER	MAAC
ANN1	0.091	0.122	0.001	0.062	0.015	1	0.023
ANN2	0.099	0.128	0.008	0.069	0.02	1	0.031
ANN3	0.089	0.122	0.001	0.059	0.014	1	0.021
ANN4	0.087	0.14	0.001	0.087	0.02	1	0.015
ANN5	0.255	0.617	0.01	0.265	0.06	1	0.042
ANN6	0.113	0.133	0.01	0.059	0.002	1	−0.002
ANN7	0.113	0.133	0.01	0.059	0.002	1	−0.002
ANN8	0.149	0.186	0.008	0.068	0.009	1	0.002
ANN9	0.332	0.441	0.031	0.219	0.006	1	0.012
ANN10	0.349	0.443	0.021	0.249	0.001	1	0.02
Mean	0.1677	0.2465	0.0101	0.1196	0.0149	1	0.0162
Normalized	17%	25%	1%	12%	1%	100%	2%

Abbreviations: ANCH, anchoring; HB, hindsight bias; HER, herding; LAV, loss aversion; MAAC, mental accounting; OSCA, overconfidence and self-attribution; REP, representativeness.

millennials with varying degrees of experience in equity investment. The relevant details of the participants are presented in Table 7.

We developed the questions for the open-ended essay by using key descriptors of each bias (as given in Table 1). To elaborate, we formulated eight questions, one for each bias, with two subparts. One subpart was related to the influence of the concerned bias on trading activity, and another was related to the influence of the concerned bias on recommendation intentions. The questions and sample responses are presented in Appendix A. Each author independently assessed the responses and prepared a matrix recording whether a given bias influenced the participants' trading activity and recommendation intentions. Since the responses were quite clear and distinct, there was no inter-coder disagreement. We consolidated the independent codes into a single table, using a tick mark to indicate the presence of a bias. The results are presented in Tables 8 and 9.

6 | DISCUSSION OF RESULTS AND IMPLICATIONS

Using Montier's (2002) taxonomy as a reference, we identified eight behavioral biases (i.e., overconfidence and self-attribution, hindsight bias, over-optimism, representativeness, anchoring, loss aversion,

TABLE 7 Profile of post hoc qualitative study participants

Participant number	Age	Educational qualification	Number of years of equity trading experience
P1	28	NVQ Lvl 4	2
P2	27	Masters degree	2
P3	36	Bachelors degree	11
P4	28	Masters degree	1
P5	28	Bachelors degree	3
P6	29	College A level	1
P7	32	Bachelors degree	10
P8	33	Bachelors degree	3
P9	34	Post Graduate Diploma, masters degree	4
P10	31	Bachelors degree	5
P11	26	Masters degree	5
P12	27	Masters degree	5
P13	28	Masters degree	3
P14	30	Bachelors degree	10
P15	27	High school	Less than 1 year
P16	28	Bachelors degree	3
P17	31	Engineering Masters degree	5
P18	30	Masters degree	1
P19	31	Bachelors degree	1

TABLE 8 Results of post hoc qualitative study (biases and trading activity)

Participant number	OSCA	HS	OP	REP	ANCH	LAV	MAAC	HER
P1	√	√		√	√			
P2	√		√		√	√	√	√
P3		√		√	√			√
P4		√		√	√	√	√	√
P5							√	√
P6	√			√			√	√
P7	√	√		√			√	√
P8	√			√	√			
P9		√	√	√			√	√
P10		√		√	√	√		√
P11	√	√			√			√
P12	√		√	√	√			√
P13						√		√
P14	√		√					
P15			√	√	√			√
P16	√	√			√			
P17	√	√		√	√	√	√	
P18	√					√		√
P19					√			√
	11	9	5	11	12	6	7	14

Abbreviations: ANCH, anchoring; HB, hindsight bias; HER, herding; LAV, loss aversion; MAAC, mental accounting; OSCA, overconfidence and self-attribution; REP, representativeness.

mental accounting, and herding) to examine their relative influence on millennials' trading activity and recommendation intentions during the pandemic. All biases except over-optimism were found to exist among this population. The absence of over-optimism implies that millennials do not feel that financial advisors are redundant. It also indicates that they do not live in the moment. This result is not as anticipated in light of the prior extended literature (Glaser & Weber, 2007; Hilton et al., 2011). A potential reason for the absence of over-optimism could either be due to the mental make-up of the millennials or the effect of the pandemic. However, before drawing any firm conclusion about the absence of over-optimism in millennials, further analysis with a larger sample size drawn from different geographies is required. The extent of the influence of other biases on the endogenous variables and the potential reasons are discussed below.

6.1 | Biases and trading activity

The results revealing the relative influence of the biases on trading activity are presented in Table 10. Herding is the most important bias predicting trading activity as its relative importance is 100%. The association between the two is nonlinear and positive, as observed from their correlation. The outcome indicates that a higher herding bias increases the trading activity in the face of external stressors like a pandemic. This also implies that millennials tend to consult others and are impacted by their stock market reactions. Accordingly, they are likely to buy and sell more stocks during a crisis if others are doing the same. Such heightened trading activity when markets are volatile can result in financial losses for individual investors and impact the market's volatility further, as argued by prior scholars (Shantha, 2018, 2019). This finding is in consonance with past extended literature (Shantha, 2018; Yao et al., 2014).

Hindsight is the second most influential bias for trading activity, with the value of influence equal to 87%. In addition, the relationship between the two is linear and positive, as seen from the correlation between the two. This implies that millennials with hindsight bias, believing that they had been able to predict past collapses in stock markets and even the initial crash during the COVID-19 pandemic, would indulge in heightened trading activity in the face of an

TABLE 9 Results of post hoc qualitative study (biases and recommendation intentions)

Participant number	OSCA	HS	OP	REP	ANCH	LAV	MAAC	HER
P1	√			√	√	√		√
P2	√	√		√	√	√		
P3				√	√	√		√
P4				√				
P5					√		√	√
P6	√			√			√	√
P7						√	√	√
P8								
P9								
P10	√	√			√	√		
P11	√	√				√		√
P12								
P13	√					√		√
P14								
P15			√	√	√			
P16				√		√	√	√
P17	√			√			√	
P18	√	√		√	√	√	√	√
P19								
	8	4	1	9	7	9	6	9

Abbreviations: ANCH, anchoring; HB, hindsight bias; HER, herding; LAV, loss aversion; MAAC, mental accounting; OSCA, overconfidence and self-attribution; REP, representativeness.

TABLE 10 Summary of findings for trading activity

Bias	Normalized relative importance (%)	Correlation	Linear/ nonlinear
Herding	100	0.70	Nonlinear
Hindsight	87	0.70	Linear
Overconfidence and self-attribution	62	0.68	Linear
Representativeness	48	0.63	Nonlinear
Anchoring	12	−0.34	Nonlinear

external stressor. Such a tendency can be extremely risky since it might lead to adverse financial consequences for them, as argued by the existing scholarship (Baker et al., 2019; Moosa & Ramiah, 2017). Put differently, individuals with hindsight bias tend to believe, albeit falsely, that they had foreseen the possibility of an event, such as the volatility of a particular stock, and accurately predicted its actual outcome (Biais & Weber, 2009). Such a tendency to overestimate their ability to predict is an indicator of the high level of overconfidence, which may cause them to over-react by potentially indulging in heightened trading activity (Camerer et al., 1989).

The third bias that influences trading activity is overconfidence and self-attribution, with a relative importance equal to 62%. Furthermore, the relationship between the two is linear and positive, implying that the millennials who think that their actions, knowledge, and opinions are responsible for the increase in the value of their investments and that their skills can help beat the market are likely to trade more in situations like a pandemic. The result aligns with our anticipation based on the prior findings (e.g., Barber & Odean, 2000; Meier, 2018). This bias makes the millennials vulnerable to making investment/trading decisions that may not be in their favor. In other words, overconfidence and self-attribution bias is potentially precarious since it may decrease investors' risk-aversion, as discussed in past studies (e.g., Nosić & Weber, 2010), and increase their market volatility as well (Daniel et al., 1998).

Representativeness is the fourth most influential bias for trading activity, with the value of influence equal to 48%. Moreover, the relationship between the two is nonlinear and positive. The finding confirms that millennials who estimate future prices based on current stock price and depend on past prices and earnings for decision-making are likely to trade more during a crisis. This result is in concordance with our expectations based on prior studies (Mokhtar, 2014; Baker et al., 2019). The risk, in this case, is that such cognitive errors can influence the quality of investments and impact markets negatively in the long run.

The next bias in the order of importance is anchoring, with the value of influence equal to 12%. Furthermore, its relationship with trading activity is nonlinear and negative. The influence of anchoring is relatively small in magnitude. The presence of this bias implies that the millennials who take their stock buying and selling decisions by keeping past prices and purchase price in mind and tend to hold a falling stock until it returns to its purchase price are unlikely to indulge in heightened trading activity during a crisis. Since anchoring bias causes under-reaction, especially at the time of high investor sentiment (e.g., Hao et al., 2018), the presence of this bias may cause these millennials to miss out on some good investment opportunities by under-reacting when the markets are moving, especially during a crisis.

The relative importance of the remaining two biases, loss aversion and mental accounting, is zero, indicating that they do not influence millennials' decision to trade during a crisis. This implies that the tendency of retail millennial investors to hold on to falling stocks and their nervousness about their investments in the presence of an external stressor does not predict their trading activity. Similarly, their tendency to put different investments in different mental categories and not look at their portfolio as a whole also does not influence millennials' trading activity during a crisis. These results are contrary to prior findings that revealed the impact of loss aversion and mental accounting on retail individuals' investment behavior (e.g., Otuteye & Siddiquee, 2019; Zahera & Bansal, 2018). The reason

TABLE 11 Summary of findings for recommendation intentions

Bias	Normalized relative importance (%)	Correlation	Linear/ nonlinear
Herding	100	0.68	Nonlinear
Hindsight	25	0.58	Linear
Overconfidence and self-attribution	17	0.57	Linear
Representativeness	12	0.47	Nonlinear
Mental accounting	2	0.02	Linear
Anchoring	1	−0.22	Nonlinear
Loss aversion	1	−0.04	Linear

behind this unanticipated outcome could be situational or cultural. Due to this, further studies based on diverse samples, settings, and multiple countries are required to fully understand why these two biases do not play any role in influencing millennials' trading activity during a crisis.

6.2 | Biases and recommendation intentions

The results revealing the relative influence of the biases on recommendation intentions are presented in Table 11. Herding is the most important bias predicting recommendation intentions as its relative importance is 100%. In addition, its relationship with intentions is nonlinear and positive, as seen from the correlation between the two. This outcome implies that higher herding bias increases millennials' recommendation intentions in the face of an external stressor like a pandemic. The finding confirms that the millennials, who are likely to consult others and be impacted by their reactions in the market, are more likely to recommend equity investments. This could be detrimental for the efforts to stabilize the markets since the recommendations may get translated into actual buying or selling, without much knowledge, by those who have received the recommendations, thereby increasing the market's volatility, as contended by prior studies (e.g., Shantha, 2018). We had anticipated millennials' behavior to exhibit recommendation intentions given their tendency to consult others while making decisions (Viswanathan & Jain, 2013) and be part of an online world of constant connectivity.

Hindsight is the second most influential bias for recommendation intentions, with the value of influence equal to 25%. Moreover, its relationship with intentions is linear and positive, as seen from their correlation value. This indicates that millennials with hindsight bias, having the tendency to believe that they had been able to predict past collapses in stock markets and even the initial crash during the COVID-19 pandemic, would show positive intentions to recommend equity investment during such a crisis. Such tendency can have adverse financial consequences for their peer group who might act on millennials' recommendations, as argued by prior extended literature (Baker et al., 2019; Moosa & Ramiah, 2017). In other words, recommendations given by millennials can potentially lead to imprudent investments by their social group, causing losses and panic in the market. In sum, our finding indicates that a belief in their hindsight, which makes them overconfident (Camerer et al., 1989), causes millennials to feel that they know enough to advise others.

The third bias that predicts recommendation intentions is overconfidence and self-attribution, with the value of influence equal to 17%. Moreover, its relationship with intentions is linear and positive. The result indicates that the millennials who feel that their knowledge of investing and ability is superior to that of financial analysts are more likely to recommend equity investments to others in situations such as a pandemic. Additionally, in believing that they can exceed market returns, such millennial investors would be quite keen about making equity investment-related recommendations to others. This tendency of making recommendations can be quite detrimental for others since the advice received may cause them to act in a less circumspect and less risk-averse manner, as contended by past studies (e.g., Nosić & Weber, 2010), and have a cascading effect of increasing market volatility (Daniel et al., 1998).

Representativeness is the fourth most influential bias for recommendation intentions, with the value of influence equal to 12%. In addition, its relationship with intentions is nonlinear and positive. This finding indicates that the millennials who decide to buy a stock based on its past price and firm performance and who forecast price changes based on recent prices will show a higher tendency to recommend equity investments during a crisis. Although there is no a priori basis in the literature to support this finding, a plausible reason behind such behavior could be millennials' strong belief in their decisions based on the available information. To express this differently, millennials may believe that analyzing relevant data can help in superior stock selection, making them feel more confident about recommending the same to others. However, such recommendations are quite risky since they might be based on misjudgements, as discussed by existing scholarship (e.g., McCaffrey, 2020). Such misjudgements may result from the fact that retail millennials investors may identify naive patterns in stock price changes and trade in less effective ways, as observed in the case of other individual investors (De Bondt, 1998). By sharing their misjudgements with others, these millennials might transmit cognitive errors that can potentially harm the markets and adversely impact the quality of investments of the recipients of such suggestions.

The remaining three biases: mental accounting, loss aversion, and anchoring, have a very low relative influence on the recommendation intentions of millennials, with the value of influence being 2% for mental accounting and 1% each for the other two. Furthermore, while the relationship of mental accounting with intentions is linear and positive, both loss aversion and anchoring have a negative relationship with it. However, the relationship of loss aversion is linear, whereas that of anchoring is nonlinear. Since the present study is the first empirical endeavor to examine these relationships, there is a need to examine them in various contexts and evaluate the variances in the outcomes before drawing any conclusive inferences regarding the reasons behind the weak influence of these biases on recommendation intentions of millennials during a crisis.

It can also be observed that the influence of biases is greater in the case of trading activity than recommendation intentions, indicating that trading activity is predicted to a greater extent by the biases than recommendation intentions.

Since the findings of our study are based on the analysis of data collected from millennial investors in the initial phase of the pandemic, we followed them up with a post hoc qualitative study. The purpose of this study was to evaluate if the manifestation of biases and their influence on trading activity and recommendation intentions have changed with the advancement of the pandemic or not. The results of this study, presented in Tables 8 and 9, reveal that the manifestations and the impact of biases on the two endogenous variables have changed, though not drastically, in the later phase of the pandemic.

Specifically, most participants have accepted herding to have played an important role in influencing both their trading activity (74%) and recommendation intentions (47%). Our quantitative analysis had also indicated the same outcome. This implies that consistently throughout the pandemic, millennials made their stock buying and selling decisions based on the actions and judgment of others, a dependence that also motivated them to make recommendations to their social group to some extent. A potential reason behind this could be that, like all others, millennials also depend more on their social groups in times of crisis, resulting in increased interaction during the pandemic. Another reason could be that a reliance on social media has increased with enforced social distancing norms during the pandemic, making it easier to send and receive information.

Interestingly, many participants have not considered hindsight bias to be influential, with 47% expressing its effect in the case of their trading activity and 21% in the case of recommendation intentions. This outcome contradicts the findings of our quantitative study, wherein hindsight was the most prominent after herding. This result indicates that the belief that they could have predicted the movement already occurred in some stocks during the pandemic did not play as significant a role later on in influencing millennials' trading activity and recommendation intentions, as compared to the initial phase of the pandemic. A reason behind this could be that global stock markets scaled new heights quickly after crashing extensively at the beginning of the pandemic, taking millennials, like most other investors, by complete surprise. No one could have predicted or anticipated such a recovery, with the pandemic still impacting economic activity.

In comparison, although less than herding, most participants agree that two biases, overconfidence and self-attribution and representativeness, have been influential in impacting their trading activity (nearly 58% each) and recommendation intentions (42% and 47%, respectively). The result in the case of overconfidence and self-attribution indicates that past knowledge about investing and past successes caused millennials to buy and sell more stocks as the pandemic progressed. It also made them feel more confident to make recommendations to others. The gains made after the markets' recovery could have played a major part in the increased manifestation of this bias.

Similarly, the influential role of representativeness indicates that as the pandemic progressed, the millennials felt that it was better to anticipate the movement in future prices based on the past prices of stock while undertaking trading and recommendation decisions. A potential reason behind this could be the faster recovery of stocks that were trading high before the onset of the pandemic, which may have reinforced the perception that past prices provide a reliable cue for future movement.

In the case of anchoring, 63% of participants confirmed its influence on trading activity, and 37% confirmed its influence on recommendation intentions. This finding implies that millennials tended to forecast future stock prices as the pandemic progressed by focusing more on certain information. This also encouraged many of them to make recommendations to their social group. Such behavior is quite understandable since public and media debates have been spotlighting key sectors and activities that could gain more prominence with reference to the new normal enforced by the pandemic. These discussions could have attracted the attention of millennial investors, making them focus on specific information related to certain stocks and sectors.

Our quantitative analysis had revealed that loss aversion and mental accounting do not influence trading activity at all and have a very small effect on recommendation intentions. However, the post hoc qualitative study indicated that these two biases influenced the recommendation intentions of a substantial number of participants (47% and 32%, respectively). In comparison, in the case of trading activity, 32% of participants indicated the influence of loss aversion, and 37% confirmed the influence of mental accounting. The influential role of loss aversion implies that millennials experienced regret for incurring losses in stocks during the pandemic, which caused them to consciously focus on avoiding future loss and regret. Such experience also impacted their recommendation intentions to some extent. A potential reason behind this could be that some suboptimal investments made during the initial phase of the pandemic did not turn out as anticipated, making the millennials experience regret and subsequently cause loss aversion to influence their decisions as the pandemic progressed.

In comparison, the influence of mental accounting on trading activity and recommendation intentions indicates that millennials exhibited the tendency to make separate investments for different purposes, such as education, buying a home, travelling, etc., as the pandemic progressed, and advised others to do the same. A potential reason behind this could be the personal experience of a reduction in income, the loss of a loved one, or the general environment of insecurity prevailing during the pandemic that could have made millennials seek safety and become more risk-averse.

Finally, in consonance with the results of the quantitative data analysis, the results of the qualitative data also indicated that overoptimism bias does not have much effect on trading activity and recommendation intentions, with only 26% of participants confirming its influence on trading activity and only one participant indicating its influence on his recommendation intentions. This implies that millennials do not think it is better to focus on good news only while trading or making stock recommendations during the pandemic. A potential reason behind this could be the milieu in which the millennials have grown, wherein they have been exposed to multiple aspects of any event and know better than to focus on limited factors while making any decision.

In addition, a comparison between Tables 8 and 9 indicates that the biases play a more prominent role in influencing trading activity than their influence on millennial investors' recommendation intentions. This is consistent with the findings of our quantitative analysis.

6.3 | Theoretical implications

The study makes five theoretical contributions: First, it answers the research call to empirically examine the impact of behavioral biases on retail investors' stock market behavior, thereby underscoring the importance of behavioral finance and the related asset pricing models (Sharma & Kumar, 2019). In addition, the empirical findings of our study are based on data collected through a primary survey, an approach that has seldom been used to examine biases (Shantha, 2019). Furthermore, although behavioral finance has emerged as a key part of mainstream finance to explain biases that impact investment decisions (Baker & Nofsinger, 2010), past studies have focussed more on the existence of biases and their association with financial decision-making/investment decision-making in general (e.g., Costa et al., 2017). In comparison, a specific focus on trading activity and recommendation intentions has remained under-explored, even though trading activity in the form of buying and selling can affect prices and subsequently cause market volatility (Daniel et al., 1998). At the same time, the recommendations of peers and social groups can cause retail investors to make misjudgements and make suboptimal decisions that can adversely affect their investment portfolios. Clearly, understanding the drivers of both trading activity and recommendation intentions is very critical. Notably, this is the first study to empirically examine recommendation intentions as the outcome of behavioral biases, even though recommendations and mutual consultations are quite popular in practice. Thus, by revealing the impact of biases on retail investors' trading activity and recommendation intentions, our study generates useful insights to explain irrationalities, as represented by biases, that can affect stock prices and lead to market inefficiency (Daniel et al., 2001). In sum, our findings strengthen the accumulated knowledge available for the reference of key stakeholders by exploring novel associations. More importantly, the continued persistence of most biases with the advancement of the pandemic, as revealed by our qualitative study, indicates that they were not manifested under the impact of the fear and panic incited by the pandemic alone; rather, these biases are a deeper part of investors' psyche, making them all the more critical to examine and understand.

Second, our choice of millennials as the target segment yields new theoretical findings related to biases and their effect on trading activity and recommendation intentions. The insights related to millennials are quite important since they represent a group that is likely to remain active in the market for a long time (Dimock, 2019). In addition, an enhanced understanding of their behavior can be useful for future research in the area. The focus on millennials as the target group is also in concordance with the growing trend of examining consumer behavior in the context of generational cohorts (e.g., Lissitsa & Kol, 2019). Moreover, scholars and investment consultants worldwide have noted certain aspects of the milieu in which millennials have grown that makes them and their financial decision-making a significant consideration. For instance, according to a survey from asset manager BlackRock, millennials save more than Baby Boomers in the United States and have become more interested in investing during the past few years (Chen & Howard, 2020). This makes them an important segment to examine since their decisions and biases can impact market volatility. In the specific context of this study, a report published by Deloitte in 2018 revealed that Nordic millennials, including Finns, invest more than their generational counterparts in other countries (Deloitte, 2018). Therefore, our findings explicating their behavioral biases can be of use to multiple stakeholders. Furthermore, being the digital natives that they are, millennials tend to use technology-based approaches and social media tools to make their investment decisions and remain connected. Due to this, they are in a position to influence the investment decisions of others as well.

Third, our study captures retail investor behavior during the COVID-19 pandemic, a crisis that has placed the economic and social structures worldwide under severe stress (S. Baker et al., 2020). Since the prices of stocks are considered to move in response to several anticipated, unanticipated, and unknown factors, academic research has continually examined various aspects of financial markets, including investor behavior, to evaluate the impact of a variety of events. The ongoing thought process is to have accumulated learnings based on the investigation of dynamic factors, which would help formulate strategies, design educational courses, develop risk-hedging products, and so on. The pandemic is another interesting context in this regard since it represents a crisis and an extrinsic stressor. By explicating investor behavior in the presence of such extrinsic stressors beyond the control of individuals, firms, and regulators, our study provides useful theoretical insights that can serve as the basis for predictive modelling to forecast the related outcomes in future crisis events.

Fourth, since heuristics offer a way of simplifying the decision-making process in a dynamic environment, one way to prevent the influence of biases is to develop algorithms that can be applied unemotionally and with ease, as discussed by Otuteye and Siddiquee (2015). The findings of our study can thus serve as a basis for developing such algorithms by researchers in the area.

Lastly, the study contributes to methodological advancement in the area by applying an advanced data analysis technique, ANN, which addresses the deficiencies of the popular structural path analysis methods' specific data-related requirements. At the same time, ANN is not challenging to apply since it is a part of SPSS and is a well-recognized, albeit less used, method. Moreover, ANN is acknowledged to be a suitable prognostic method to analyze data in situations where other statistical tools are not applicable (Stangierski et al., 2019). The key advantages of this method are its ability to learn through a training process, its fault tolerance, its versatility in analyzing nonlinear data, and its ability to generate optimal results through updating weights continuously (Goyal & Goyal, 2012). This intelligence, inspired by the human brain and biological neurons, makes ANN a more robust choice for analyzing nonlinear data as compared to nonlinear structural equation modelling.

6.4 | Practical implications

The study findings offer five practical inferences for regulators, millennials, and firms. First, from the regulatory perspective, the confirmation of the existence of behavioral biases among millennials indicates a need for investor education efforts directed towards this generation to reduce such biases. This is important since biases lead to irrational decisions, which can potentially cause losses in retail investors' equity portfolios. It is also important to address these biases since various stock market bubbles and depressions that have harmed the interests of individuals and economies have been attributed to investor irrationality and sentiment (Shiller, 2003). Furthermore, the findings of our study provide inputs for formulating and revising investor protection policies, in line with the past contributions in the area (e.g., Thaler & Sunstein, 2009).

Second, by uncovering the effect and relative importance of key behavioral biases influencing the trading activity and recommendation intentions of retail investors, our study provides useful information for firms offering investment advisory services to such investors. Knowing the effect of behavioral biases on investors' decisions can help these firms offer advice in line with their expectations, perceptions, and thought processes. This is particularly crucial since most countries have some guidelines for investor protection, which mandate that potential investors should be offered investment products aligned with their objectives and risk appetite, as also discussed by scholars (e.g., S. Talwar, 2016).

Third, from the perspective of the millennials themselves, the study reveals the presence of behavioral biases that can affect their trading activity and recommendation intentions irrationally, which, in turn, can adversely impact their equity returns (Sharma & Kumar, 2019). Since, more often than not, these biases manifest subconsciously, awareness about their role can guide retail investors to consciously try and overcome them and be as rational as possible in their investment-related decision making.

Fourth, the findings of our study can help firms and academics engaged in retail investor education and training to design useful and effective content, courses, and programs. In addition, information about biases that influence investment-related decision-making and the efforts of trainers to overcome such biases can enhance millennials' financial sophistication and make them appreciate the benefits of diversification, thereby helping to increase the robustness of markets. In this regard, it is important to note that the existing scholarship has contended that sophisticated investors are less likely to manifest these biases (e.g., Boolell-Gunesh et al., 2012).

Lastly, our findings with the COVID-19 pandemic as the context provide insights for policymaking, investor education, and the strengthening of the financial system in preparation for future challenges. As a result, all stakeholders can be better fortified to deal with crises in the future, which can ultimately help reduce losses for investors at an individual level and volatility in the market at an aggregate level. For instance, the finding that herding has the highest relative influence on trading activity during a crisis can be used to educate retail investors in strategies, such as asset allocation, to counter such bias. In more specific terms, the findings of the present study can be used to prepare simulation software for training, through which the retail investors can then be exposed to simulated health or other crises/disasters wherein they can practice strategies that can counter the effect of behavioral biases. Such training imparted regularly can prepare retail investors to make more informed trading decisions when faced with any crisis.

7 | CONCLUSION, LIMITATION, AND FUTURE RESEARCH AREAS

The present study investigated the influence of behavioral biases on millennials' trading activity and recommendation intentions during the COVID-19 pandemic through two research questions, which queried about the predictive capacity of the selected behavioral biases, namely, overconfidence and self-attribution, hindsight, representativeness, anchoring, mental accounting, loss aversion, and herding on trading activity and recommendation intentions of millennials during a pandemic. To address these questions, we applied the ANN approach to analyze data collected from 351 millennials in Finland. Thereafter, we conducted a post hoc qualitative study to examine if the biases that manifested at the pandemic's beginning persisted as it advanced. The findings of the empirical analysis revealed that herding, hindsight, overconfidence and self-attribution, representativeness, and anchoring influence both trading activity and recommendation intentions, but to a varying degree, with the values of influence being higher for trading activity and only anchoring having a negative influence. In comparison, loss aversion and mental accounting influence only recommendation intentions to a very small extent as well, with loss aversion having a negative influence. Furthermore, the relationship of the two endogenous variables is nonlinear with herding, representativeness, and anchoring and is linear with the rest.

The findings of the post hoc qualitative study indicate that most biases observed at the beginning of the pandemic continue to manifest with its advancement, giving us a reason to contend that they were not manifested under the influence of panic caused by the crisis alone. Rather, they are an ingrained part of the psyche of millennial investors.

7.1 | Limitations and future research areas

The contribution of our study needs to be evaluated in light of three limitations: First, our study is based on a cross-sectional data collection approach that may allow for certain respondent-related biases to manifest. Being aware of this issue, we followed the laid down processes to minimize the self-response biases, thereby increasing the robustness of the results. We also conducted a post hoc qualitative study to evaluate the implications of our findings. Second, we collected the data for analysis from only one country, which might restrict the broader generalizability of the findings. Nevertheless, our study being the first to investigate millennials in the said context contributes by laying a basis for future replication studies in various geographies to provide the regulators and firms with relevant decision-making inputs. Lastly, our study is focused on a narrow sample of male millennials that might again restrict the generalizability of the findings to a broader population. However, since gender differences have been acknowledged to impact the manifestation of biases (S. Kumar & Goyal, 2016), we consciously decided to base our analysis on an all-male sample. Future researchers can expand the findings of our study by testing the influence of gender and other demographic variables of behavioral biases of millennials, as suggested for investors, in general, by prior studies (e.g., Ates et al., 2016; Tekçe et al., 2016). Furthermore, future researchers can test biases, such as moods, cognitive dissonance, and so on, by referring to Montier's (2002), Pompian's (2011), and other classifications.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Amandeep Dhir https://orcid.org/0000-0002-6006-6058

REFERENCES

Adam, T. (2020). How coronavirus almost brought down the global financial system. Retrieved from https://www.theguardian.com/business/2020/apr/14/how-coronavirus-almost-brought-down-the-global-financial-system

Aggarwal, S., Nawn, S., & Dugar, A. (2021). What caused global stock market meltdown during the COVID pandemic—Lockdown stringency or investor panic? *Finance Research Letters*, *38*, 101827–101827. https://doi.org/10.1016/j.frl.2020.101827

Agnihotri, A., & Bhattacharya, S. (2016). Online review helpfulness: Role of qualitative factors. *Psychology & Marketing*, *33*(11), 1006–1017. https://doi.org/10.1002/mar.20934

Ahmad, F., Oriani, R., & De Angelis, M. (2020). Investor's intrinsic motives and the valence of word-of-mouth in sequential decision-making. *Journal of Behavioral Finance*, *22*(2), 170–188. https://doi.org/10.1080/15427560.2020.1751630

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., & Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, *27*, 100326. https://doi.org/10.1016/j.jbef.2020.100326

Amanatiadis, A., Mitsinis, N., & Maditinos, D. (2014). A neural network-based approach for user experience assessment. *Behaviour & Information Technology*, *34*, 304–315.

Andersson, O., Holm, H. J., Tyran, J. R. K., & Wengström, E. R. (2016). Deciding for others reduces loss aversion. *Management Science*, *62*(1), 29–36. https://doi.org/10.1287/mnsc.2014.2085

Ates, S., Coskun, A., Sahin, M. A., & Demircan, M. L. (2016). Impact of financial literacy on the behavioral biases of individual stock investors: Evidence from Borsa Istanbul. *Business and Economics Research Journal*, *7*(3), 1–19.

Baker, H. K., Kumar, S., Goyal, N., & Gaur, V. (2019). How financial literacy and demographic variables relate to behavioral biases. *Managerial Finance*, *45*(1), 124–146. https://doi.org/10.1108/mf-01-2018-0003

Baker, H. K., & Nofsinger, J. R. (2010). *Behavioral finance: Investors, corporations, and markets*. John Wiley & Sons. ISBN: 978-0-470-49911-5.

Baker, S., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *The Review of Asset Pricing Studies*, *10*(4), 834–862. https://doi.org/10.3386/w26949

Baltussen, G., & Post, G. T. (2011). Irrational diversification: An examination of individual portfolio choice. *Journal of Financial and Quantitative Analysis*, *46*(5), 1463–1491.

Bansal, T. (2020). Behavioral finance and COVID-19: Cognitive errors that determine the financial future. *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3595749

Barber, B., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, *55*(2), 773–806.

Barber, B., & Odean, T. (2001). Boys will be boys: Gender, overconfidence and common stock investment. *The Quarterly Journal of Economics*, *116*(1), 261–292. https://doi.org/10.1162/003355301556400

Barberis, N. C., & Huang, M. (2001). Mental accounting, loss aversion and individual stock returns. *The Journal of Finance*, *56*(4), 1247–1292. https://doi.org/10.1111/0022-1082.00367

Barrafrem, K., Västfjäll, D., & Tinghög, G. (2020). Financial Homo Ignorans: Measuring vulnerability to behavioral biases in household finance. *Journal of Behavioral and Experimental Finance*, *28*, 100410. https://doi.org/10.31234/osf.io/q43ca

Bergsma, K., Fodor, A., & Tedford, E. (2019). A closer look at the disposition effect in US equity option markets. *Journal of Behavioral Finance*, *21*(1), 66–77. https://doi.org/10.1080/15427560.2019.1615913

Bhattacharya, U., Hackethal, A., Kaesler, S., Loos, B., & Meyer, S. (2012). Is unbiased financial advice to retail investors sufficient? Answers from a large field study. *Review of Financial Studies*, *25*(4), 975–1032. https://doi.org/10.1093/rfs/hhr127

Biais, B., & Weber, M. (2009). Hindsight bias, risk perception, and investment performance. *Management Science*, *55*, 1018–1029.

Bloom, D. E., Cadarette, D., & Sevilla, J. P. (2018). Epidemics and economics: New and resurgent infectious diseases can have far-reaching economic repercussions. *Finance and Development*, *55*(2), 46–49.

Boolell-Gunesh, S., Broihanne, M., & Merli, M. (2012). Sophistication of individual investors and disposition effect dynamics. *Finance*, *33*(1), 9–37. https://doi.org/10.3917/fina.331.0009

Brounen, D., & Derwall, J. (2010). The impact of terrorist attacks on international stock markets. *European Financial Management*, *16*(4), 585–598. https://doi.org/10.1111/j.1468-036x.2009.00502.x

Bu, D., Hanspal, T., Liao, Y., & Liu, Y. (2020). Risk taking during a global crisis: Evidence from Wuhan. *Covid Economics*, *5*, 106–146.

Burch, T. R., Emery, D. R., & Fuerst, M. E. (2016). Who moves markets in a sudden marketwide crisis? Evidence from 9/11. *Journal of Financial and Quantitative Analysis*, *51*(2), 463–487. https://doi.org/10.1017/s0022109016000211

Caginalp, G., & Balenovich, D. (1996). Trend-based asset flow in technical analysis and securities marketing. *Psychology & Marketing*, *13*, 407–444. https://doi.org/10.1002/(SICI)1520-6793(199607)13:4%3C405::AID-MAR5%3E3.0.CO;2-E

Camerer, C., Loewenstein, G., & Weber, M. (1989). The curse of knowledge in economic settings: An experimental analysis. *Journal of Political Economy*, *97*(5), 1232–1254. https://doi.org/10.1086/261651

Caputo, A. (2014). Relevant information, personality traits and anchoring effect. *International Journal of Management and Decision Making*, *13*(1), 62–76. https://doi.org/10.1504/IJMDM.2014.058470

Cen, L., Hilary, G., & Wei, K. C. J. (2013). The role of anchoring bias in the equity market: Evidence from analysts' earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis*, *48*, 47–76.

Chakravarti, I. M., Laha, R. G., & Roy, J. (1967). *Handbook of methods of applied statistics* (Vol. I, pp. 392–394). John Wiley and Sons.

Chen, J., & Howard, E. (2020). *Millennials: Finances, investing, and retirement.* Retrieved from https://www.investopedia.com/terms/m/millennial.asp

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Pastore Y Piontti, A., Mu, K., Rossi, L., Sun, K., Viboud, C., Xiong, X., Yu, H., Halloran, M. E., Longini, I. M., Jr., & Vespignani, A. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science*, *368*(6489), 395–400. https://doi.org/10.1126/science.aba9757

Chong, A. Y. L. (2013). Mobile commerce usage activities: The roles of demographic and motivation variables. *Technological Forecasting and Social Change*, *80*, 1350–1359.

Chu, W., Im, M., & Lee, E.-J. (2014). Investor expertise as mastery over mind: Regulating loss affect for superior investment performance. *Psychology & Marketing*, *31*(5), 321–334. https://doi.org/10.1002/mar.20697

Chun, W. W., & Ming, L. M. (2009). Investor behavior and decision-making style: A Malaysian perspective. *Banker's Journal Malaysia*, *133*, 3–13.

Collingro, F., & Frenkel, M. (2020). On the financial market impact of euro area monetary policy: A comparative study before and after the global financial crisis. *Global Finance Journal*, *45*, 100480–100904. https://doi.org/10.1016/j.gfj.2019.100480

Combrink, S., & Lew, C. (2019). Potential underdog bias, overconfidence and risk propensity in investor decision-making behavior. *Journal of Behavioral Finance*, *21*(4), 337–351. https://doi.org/10.1080/15427560.2019.1692843

Costa, D. F., de Melo Carvalho, F., de Melo Moreira, B. C., & do Prado, J. W. (2017). Bibliometric analysis on the association between behavioral finance and decision making with cognitive biases such as overconfidence, anchoring effect and confirmation bias. *Scientometrics*, *111*(3), 1775–1799. https://doi.org/10.1007/s11192-017-2371-5

Crotty, J. (2009). Structural causes of the global financial crisis: A critical assessment of the 'new financial architecture. *Cambridge Journal of Economics*, *33*(4), 563–580.

Cuong, P. K., & Jian, Z. (2015). Factors influencing individual investors' behavior: An empirical study of the Vietnamese stock market. *American Journal of Business and Management*, *3*(2), 77–94.

De Bondt, W. F. (1998). A portrait of the individual investor. *European Economic Review*, *42*, 831–844.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, *53*(6), 1839–1885.

Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *The Journal of Finance*, *56*(3), 921–965. https://doi.org/10.1111/0022-1082.00350

Deloitte, A. B. (2018). Gen Y The rise of the individual Nordics Millennial study ages 18–37. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/se/Documents/technology-media-telecommunications/Deloitte-Millennial-Nordic-Report.pdf

Dimock, M. (2019). Defining generations: Where Millennials end and Generation Z begins. Retrieved from https://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/

Durand, R. B., Fung, L., & Limkriangkrai, M. (2019). Myopic loss aversion, personality, and gender. *Journal of Behavioral Finance*, *20*(3), 339–353. https://doi.org/10.1080/15427560.2018.1511562

Euroclear Finland (2020). More than 100,000 active share savings accounts in Finland with accumulated share assets of EUR 335 million. Retrieved from https://www.euroclear.com/finland/fi/news-and-insights/news/Suomessa-yli-100000-aktiivista-osakesaastotilia.html

EL Idrissi, T., Idri, A., & Bakkoury, Z. (2019). Systematic map and review of predictive techniques in diabetes self-management. *International Journal of Information Management*, *46*(June), 263–277. https://doi.org/10.1016/j.ijinfomgt.2018.09.011

Fang, Y., Nie, Y., & Penny, M. (2020). Transmission dynamics of the COVID-19 outbreak and effectiveness of government interventions: A data-driven analysis. *Journal of Medical Virology*, *92*(6), 645–659. https://doi.org/10.1002/jmv.25750

Gavish, L. R., Qadan, M., & Yagil, J. (2020). Net buyers of attention-grabbing stocks? Who exactly are they? *Journal of Behavioral Finance*, *22*(1), 26–45. https://doi.org/10.1080/15427560.2020.1716360

Georgieva, K. (2020). The great lockdown: Worst economic downturn since the great depression. Retrieved from https://www.imf.org/en/News/Articles/2020/03/23/pr2098-imf-managing-director-statement-following-a-g20-ministerial-call-on-the-coronavirus-emergency

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, *32*(1), 1–36. https://doi.org/10.1007/s10713-007-0003-3

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, *35*, 101512. https://doi.org/10.1016/j.frl.2020.101512

Goyal, S., & Goyal, G. K. (2012). Shelf-life prediction of processed cheese using artificial intelligence ANN technique. *Croatian Journal of Food Technology, Biotechnology and Nutrition*, *7*(3-4), 184–187.

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis: A global perspective*. Prentice-Hall.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hao, Y., Chou, R. K., Ko, K.-C., & Yang, N.-T. (2018). The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis*, *57*, 167–183. https://doi.org/10.1016/j.irfa.2018.01.014

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*, 177–191.

Hew, J.-J., Leong, L.-Y., Tan, G. W.-H., Ooi, K.-B., & Lee, V.-H. (2019). The age of mobile social commerce: An artificial neural network analysis on its resistances. *Technological Forecasting and Social Change*, *144*, 311–324. https://doi.org/10.1016/j.techfore.2017.10.007

Hilton, D., Regner, I., Cabantous, L., Charalambides, L., & Vautier, S. (2011). Do positive illusions predict overconfidence in judgment? A test using interval production and probability evaluation measures of miscalibration. *Journal of Behavioral Decision Making*, *24*(2), 117–139.

Hirschey, M., & Nofsinger, J. (2008). *Investments: Analysis and behaviour*. Tata McGraw Hill.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance*, *56*(4), 1533–1597.

Hodson, D., & Quaglia, L. (2009). European perspectives on the global financial crisis: Introduction. *Journal of Common Market Studies*, *47*(5), 939–953. https://doi.org/10.1111/j.1468-5965.2009.02029.x

Höglund, H. (2012). Detecting earnings management with neural networks. *Expert Systems with Applications*, *39*(10), 9564–9570.

Ichev, R., & Marinč, M. (2018). Stock prices and geographic proximity of information: Evidence from the Ebola outbreak. *International Review of Financial Analysis*, *56*, 153–166.

Kahneman, D., & Riepe, M. W. (1998). Aspects of investor psychology. *The Journal of Portfolio Management*, *24*(4), 52–65. https://doi.org/10.3905/jpm.1998.409643

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Karjaluoto, H., Munnukka, J., & Kiuru, K. (2016). Brand love and positive word of mouth: The moderating effects of experience and price. *Journal of Product & Brand Management*, *25*(6), 527–537.

Kaur, P., Dhir, A., Bodhi, R., Singh, T., & Almotairi, M. (2020a). Why do people use and recommend m-wallets? *Journal of Retailing and Consumer Services*, *56*, 102091. https://doi.org/10.1016/j.jretconser.2020.102091

Kaur, P., Dhir, A., Singh, N., Sahu, G., & Almotairi, M. (2020b). An innovation resistance theory perspective on mobile payment solutions. *Journal of Retailing and Consumer Services*, *55*, 102059. https://doi.org/10.1016/j.jretconser.2020.102059

Kelley, E. K., & Tetlock, P. C. (2016). Retail short selling and stock prices. *The Review of Financial Studies*, *30*(3), 801–834. https://doi.org/10.1093/rfs/hhw089

Kowalewski, O., & Śpiewanowski, P. (2020). Stock market response to potash mine disasters. *Journal of Commodity Markets*, *20*, 100124. https://doi.org/10.1016/j.jcomm.2020.100124

Kuhn, M., & Johnson, K. (2013). *Applied predictive modeling*. Springer Nature.

Kumar, A. (2009). Hard-to-value stocks, behavioural biases, and informed trading. *Journal of Financial and Quantitative Analysis*, *44*(6), 1375–1401. https://doi.org/10.1017/S0022109009990342

Kumar, S., & Goyal, N. (2016). Evidence on rationality and behavioural biases in investment decision making. *Qualitative Research in Financial Markets*, *8*(4), 270–287.

Layng, T. V. J. (2009). The search for an effective clinical behavior analysis: The non-linear thinking of Israel Goldiamond. *The Behavior Analyst*, *32*(1), 163–184. https://doi.org/10.1007/bf03392181

Leduc, S., & Liu, Z. (2020). The uncertainty channel of the coronavirus. *Economic Letter*, https://www.frbsf.org/economic-research/publications/economic-letter/2020/march/uncertainty-channel-of-coronavirus/

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., & Wei, J. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, *51*, 102047. https://doi.org/10.1016/j.ijinfomgt.2019.102047

Lester, D. H., Forman, A. M., & Loyd, D. (2005). Internet shopping and buying behavior of college students. *Services Marketing Quarterly*, *27*(2), 123–138. https://doi.org/10.1300/J396v27n02_08

Lin, H. W. (2011). Elucidating rational investment decisions and behavioral biases: Evidence from the Taiwanese stock market. *African Journal of Business Management*, *5*(5), 1630–1641.

Lissitsa, S., & Kol, O. (2019). Four generational cohorts and hedonic m-shopping: Association between personality traits and purchase intention. *Electronic Commerce Research*, *21*, 545–570. https://doi.org/10.1007/s10660-019-09381-4

Liu, H., & Chou, H. (2018). The effects of promotional package frames and price strategies on inaction inertia. *Psychology & Marketing*, *36*(3), 214–228. https://doi.org/10.1002/mar.21173

McCaffrey, P. (2020). Meir Statman on coronavirus, behavioral finance: The second generation, and more. Retrieved from https://blogs.cfainstitute.org/investor/2020/04/08/meir-statman-on-coronavirus-behavioral-finance-the-second-generation-and-more/

Meier, C. (2018). Aggregate investor confidence in the stock market. *Journal of Behavioral Finance*, *19*(4), 421–433. https://doi.org/10.1080/15427560.2018.1406942

Milgrom, P., & Stokey, N. (1982). Information, trade and common knowledge. *Journal of Economic Theory*, *26*(1), 17–27.

Mirza, N., Naqvi, B., Rahat, B., & Rizvi, S. K. A. (2020). Price reaction, volatility timing and funds' performance during Covid-19. *Finance Research Letters*, *36*, 101657. https://doi.org/10.1016/j.frl.2020.101657

Mokhtar, A. I. (2014). Behavioral finance, investor psychology perspective. *Journal of Finance and Investment Analysis*, *3*(2), 41–60.

Montier, J. (2002). Darwin's mind: The evolutionary foundations of heuristics and biases. Retrieved from https://doi.org/10.2139/ssrn.373321

Moosa, I. A., & Ramiah, V. (2017). Other biases in the behavioural finance literature, *The financial consequences of behavioural biases*. Palgrave Macmillan.

Nosić, A., & Weber, M. (2010). How riskily do I invest? The role of risk attitudes, risk perceptions, and overconfidence. *Decision Analysis*, *7*(3), 282–301. https://doi.org/10.1287/deca.1100.0178

O'Donnell, N., Shannon, D., & Sheehan, B. (2021). Immune or at-risk? Stock markets and the significance of the COVID-19 pandemic. *Journal of Behavioral and Experimental Finance*, *30*, 100477. https://doi.org/10.1016/j.jbef.2021.100477

Okorie, D. I., & Lin, B. (2021). Adaptive market hypothesis: The story of the stock markets and COVID-19 pandemic. *The North American Journal of Economics and Finance*, *57*, 101397. https://doi.org/10.1016/j.najef.2021.101397

Ortmann, R., Pelster, M., & Wengerek, S. T. (2020). COVID-19 and investor behavior. *Finance Research Letters*, *37*, 101717. https://doi.org/10.1016/j.frl.2020.101717

Otuteye, E., & Siddiquee, M. (2015). Overcoming cognitive biases: A heuristic for making value investing decisions. *Journal of Behavioral Finance*, *16*(2), 140–149. https://doi.org/10.1080/15427560.2015.1034859

Otuteye, E., & Siddiquee, M. (2019). Underperformance of actively managed portfolios: Some behavioral insights. *Journal of Behavioral Finance*, *21*(3), 284–300. https://doi.org/10.1080/15427560.2019.1692210

Paliwal, M., & Usha, A. K. (2011). The predictive accuracy of feed forward neural networks and multiple regression in the case of heteroscedastic data. *Applied Soft Computing*, *11*, 3859–3869.

Piñeiro-Chousa, J. R., López-Cabarcos, M. Á., & Pérez-Pico, A. M. (2016). Examining the influence of stock market variables on microblogging sentiment. *Journal of Business Research*, *69*(6), 2087–2092. https://doi.org/10.1016/j.jbusres.2015.12.013

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903.

Pompian, M. (2011). *Behavioral finance and wealth management: How to build optimal portfolios that account for investor biases* (2nd ed.). Wiley Finance Publications.

Preda, A., & Muradoglu, G. (2019). Groups, social processes and decision making in finance. *Qualitative Research in Financial Markets*, *11*(4), 429–455.

Prosad, J. M., Kapoor, S., & Sengupta, J. (2015). Behavioral biases of Indian investors: A survey of Delhi-NCR region. *Qualitative Research in Financial Markets*, *7*(3), 230–263.

Riquelme, I. P., Román, S., & Iacobucci, D. (2016). Consumers' perceptions of online and offline retailer deception: A moderated mediation analysis. *Journal of Interactive Marketing*, *35*, 16–26.

Rizwan, M. S., Ahmad, G., & Ashraf, D. (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters*, *36*, 101682. https://doi.org/10.1016/j.frl.2020.101682

Sahi, S. K., Arora, A. P., & Dhameja, N. (2013). An exploratory inquiry into the psychological biases in financial investment behavior. *Journal of Behavioral Finance*, *14*(2), 94–103. https://doi.org/10.1080/15427560.2013.790387

Samuel, S. S., Mathew, A. V., & Sreekumar, S. (2014). Comparative study between sparse representation classification and classical classifiers on cervical cancer cell images. *International Journal of Advanced Research in Computer and Communication Engineering*, *3*, 7788–7791.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson Education.

Seth, H., Talwar, S., Bhatia, A., Saxena, A., & Dhir, A. (2020). Consumer resistance and inertia of retail investors: Development of the resistance adoption inertia continuance (RAIC) framework. *Journal of Retailing and Consumer Services*, *55*, 55. https://doi.org/10.1016/j.jretconser.2020.102071

Shantha, K. V. A. (2018). Shifts in herd mentality of investors in uncertain market conditions: New evidence in the context of a frontier stock market. *Journal of Economics and Behavioral Studies*, *10*(3(J)), 203–219. https://doi.org/10.22610/jebs.v10i3.2328

Shantha, K. V. A. (2019). Individual investors' learning behavior and its impact on their herd bias: An integrated analysis in the context of stock trading. *Sustainability*, *11*(5), 1448. https://doi.org/10.3390/su11051448

Sharma, A., & Kumar, A. (2019). A review paper on behavioral finance: Study of emerging trends. *Qualitative Research in Financial Markets*, *12*(2), 137–157. https://doi.org/10.1108/qrfm-06-2017-0050

Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, *44*(February), 65–75. https://doi.org/10.1016/j.ijinfomgt.2018.09.013

Shefrin, H. (2000). *Beyond greed and fear: Understanding behavioral finance and psychology of investing*. Oxford University Press.

Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19's disasters are perilous than Global Financial Crisis: A rumor or fact? *Finance Research Letters*, *36*, 101669. https://doi.org/10.1016/j.frl.2020.101669

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *The Journal of Economic Perspectives*, *17*(1), 83–104.

Skala, D. (2008). Overconfidence in psychology and finance—An interdisciplinary literature review. *Bank i Kredyt*, *April*, *4*, 33–50.

Stangierski, J., Weiss, D., & Kaczmarek, A. (2019). Multiple regression models and artificial neural network (ANN) as prediction tools of changes in overall quality during the storage of spreadable processed gouda cheese. *European Food Research and Technology*, *245*(11), 2539–2547. https://doi.org/10.1007/s00217-019-03369-y

Stracca, L. (2004). Behavioral finance and asset prices: Where do we stand? *Journal of Economic Psychology*, *25*(3), 373–405.

Szyszka, A. (2013). Behavioral approach versus neoclassical finance, *Behavioral finance and capital markets*. Palgrave Macmillan.

Talwar, S. (2016). *Security analysis and portfolio management* (first ed.). Cengage Learning.

Talwar, M., Talwar, S., Kaur, P., Islam, A. K. M. N., & Dhir, A. (2020). Positive and negative word of mouth (WOM) are not necessarily opposites: A reappraisal using the dual factor theory. *Journal of Retailing and Consumer Services*, 102396. https://doi.org/10.1016/j.jretconser.2020.102396, in press.

Talwar, M., Talwar, S., Kaur, P., Tripathy, N., & Dhir, A. (2021). Has financial attitude impacted the trading activity of retail investors during the COVID-19 pandemic? *Journal of Retailing and Consumer Services*, *58*, 102341. https://doi.org/10.1016/j.jretconser.2020.102341

Taneja, A., & Arora, A. (2019). Modeling user preferences using neural networks and tensor factorization model. *International Journal of Information Management*, *45*, 132–148. https://doi.org/10.1016/j.ijinfomgt.2018.10.010

Tekçe, B., Yılmaz, N., & Bildik, R. (2016). What factors affect behavioral biases? Evidence from Turkish individual stock investors. *Research in International Business and Finance*, *37*, 515–526.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making*, *12*(3), 183–206.

Thaler, R. H. (1985). Mental accounting and consumer choice. *Marketing Science*, *4*(3), 199–214. https://doi.org/10.1287/mksc.4.3.199

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1986). Rational choice and the framing of decisions. *The Journal of Business*, *59*(S4), S251–S278. https://doi.org/10.1086/296365

Vishnoi, A., & Mookerjee, I. (2020). Perfect storm plunges Asia stocks into bear markets one by one. Retrieved from: https://www.bloomberg.com/news/articles/2020-03-09/perfect-storm-is-plunging-asia-stocks-to-bear-markets-one-by-one

Viswanathan, V., & Jain, V. (2013). A dual system approach to understanding "Generation Y" decision making. *Journal of Consumer Marketing*, *30*, 484–492. https://doi.org/10.1108/JCM(07(2013(0649

Wang, A. Y., & Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics*, *137*(2), 491–514. https://doi.org/10.1016/j.jfineco.2020.02.008

Wong, C. H., Tan, G. W. H., Hew, T. S., & Ooi, K. B. (2016). Can mobile TV be a new revolution in the television industry? *Computers in Human Behavior*, *55*, 764–776.

World Bank. (2009). *Global development finance charting a global recovery*. World Bank. Retrieved from https://openknowledge.worldbank.org/handle/10986/8128

Wulfmeyer, S. (2016). Irrational mutual fund managers: Explaining differences in their behavior. *Journal of Behavioral Finance*, *17*, 99–123.

Xiao, W. (2015). Does practice make perfect? Evidence from individual investors' experiences and investment returns. *Journal of Interdisciplinary Mathematics*, *18*, 811–825.

Yalcin, K. C., Tatoglu, E., & Zaim, S. (2016). Developing an instrument for measuring the effects of heuristics on investment decisions. *Kybernetes*, *45*(7), 1052–1071. https://doi.org/10.1108/k-05-2015-0130

Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics & Finance*, *29*, 12–29.

Yoong, J., & Ferreira, V. R. D. M. (2013). Improving financial education effectiveness through behavioural economics: OECD, *Key findings and way forward* (Vol. 1, pp. 1926–1982). OECD Publishing.

You, T. (2020). Behavioural biases and non-linear adjustment: Evidence from the housing market. *Applied Economics*, *52*(46), 5046–5059. https://doi.org/10.1080/00036846.2020.1752902

Zach, T. (2003). Political events and the stock market: Evidence from Israel. *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.420242

Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210–251. https://doi.org/10.1108/QRFM-04-2017-0028

Zhang, C. (2008). An important factor on bearish expectations of investors: Application of cognitive biases in market forecasts. *China Business Research of Economic Theory*, *7*, 73–74.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Talwar, S., Talwar, M., Tarjanne, V., & Dhir, A. (2021). Why retail investors traded equity during the pandemic? An application of artificial neural networks to examine behavioral biases. *Psychology & Marketing*, 1–22. https://doi.org/10.1002/mar.21550