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Association Between Behavioral Biases and Technical Analysis

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Abstract
This study explores the topic of behavioral biases. and their intricate relationship with technical analysis in stock market investment decisions. Focusing on biases like mental accounting, disposition effect, narrow framing, and availability bias, the study aims to uncover their impact on the utilization of technical analysis. Employing a correlation-based research design, data is gathered from stock investors in Pakistan's twin cities. Utilizing Likert-scale questionnaires and Structural Equation Modeling (SEM), the learning explores the interplay between these biases and technical analysis techniques. Through this investigation, the study contributes to a deeper comprehension of how cognitive biases influence investment determination and the incorporation of technical analysis in stock market strategies.

Keywords: Technical Analysis, Disposition Effect, Mental Accounting, Availability Bias

Introduction
Behavioral finance presumes that Decisions on investments are influenced by behavioral biases. Investors' irrationality is a probable reality that has been time and again pointed out by Researchers like (Statman, 2008). Moreover, the study of behavioral finance examines how psychology affects financial professionals' actions and how this affects stock markets. Given the Pakistani stock markets, where uncertainty is a typical occurrence, investor behavior plays a crucial part in investment decision-making. Behavioral finance arose as a new financial theory because previous paradigms were eventually criticized. According to Tversky and Kahneman (1974), uphold. that the presence of cognitive biases and heuristics influences people's decision-making in uncertain circumstances. Financial behavior is the study of how psychology influences personal financial conduct, according to Rai et al.

(2019). The character and extent of activity on a stock market are determined by investor behavior. Overconfidence, anchoring, and representativeness are three psychological biases that are common among retail investors in the Indian capital market when they are making investment decisions. One of the major problems facing Malaysian retail investors is a lack of financial education and awareness, which can result in poor investment decisions and potential losses. Furthermore, Decision-making in stock markets, mutual funds, and real estate is influenced by several other biases, including loss aversion, overconfidence, representativeness, disposition effect, herding effect, and more. Conventional theories of finance, including the efficient market hypothesis, make the assumptions that asset prices fairly represent all available information and that investors are logical. Behavioral finance theories, on the other hand, take into account the psychological and emotional characteristics of investors, recognizing that social factors, emotions, and cognitive biases prevent people from always making logical judgments. Both situations show that in order to make better investment decisions, individual investors should increase their proficiency with investing tools, including technical and fundamental research.

This study is concerned with examining the association between behavioral biases and technical analysis. By considering Independent variables like disposition effect, Mental accounting, availability bias, and narrow framing as well. Moreover, the dependent variable is I this study is technical analysis in the field of finance in 1960, 1970, a new concept was studied named behavioral finance by a famous psychologist named. Amos Tversky and Daniel Kahneman are regarded as the founders of behavioral finance. The focus of behavioral finance is on investors' irrational actions that affect market pricing and investment choices. While various studies have revealed that investor behavior is not always rational but occasionally consistently irrational, classic financial market theories assume that market participants are reasonable. Technical analysis claims to be able to forecast future trends with a high degree of accuracy. Regarding the behavioral background of investors, there are primarily two ideas.

The study will use prospect theory. Prospect theory was deemed by Thaler, Barberies, and Richard (2003) to be the most effective method for collecting experimental outcomes. within the framework of contemporary finance theory. A new paradigm called behavioral finance aims to recognize and anticipate the systematic impact of psychological decision-making on the financial market. The study will use various biases such as the Disposition effect, Mental Accounting, Availability Bias, and new thing Technical Analysis to examine their impact on investment decisions. Kahneman and Tversky

(1979) created the Prospect Theory, the fundamental theory of behavioral bias. According to this idea, psychological variables might influence investment decision-making and lead to irrationality. This theory also explains how risk and uncertainty are part of human judgment and decision-making. Investors are more likely to be risk-averse when they are in a winning position and more likely to be risk-seekers when they are losing. The fundamental tenet of behavioral finance is that psychological biases cause investing decisions to be illogical, national characteristics of investors, recognizing that social factors, emotions, and cognitive biases prevent people from consistently making logical judgments (Devadas & Vijayakumar, 2019). By examining real investor behavior and decision-making processes, behavioral finance focuses on how markets and investors respond in reality rather than theory (Bankole, 2020). According to behavioral finance, human emotions, biases, and cognitive mistakes have a significant impact on market results and financial decision-making. Therefore, in order to make investment decisions more efficiently, it is critical to understand the true behavior of investors. Investor behavior has a big impact on how well financial markets and the economy as a whole function. A comprehensive examination and evaluation of investment objectives, risk tolerance, expected returns, market circumstances, and other pertinent factors are also necessary when making investment decisions. It also entails adjusting and allocating the investment portfolio. The psychological and behavioral inclinations that investors have while making investment decisions that depart from realistic goals and expectations are known as behavioral biases. These biases reflect the irrational emotions and attitudes of investors. Three perceptual biases that have been thoroughly studied in the context of Pakistan and have been shown to significantly impact investment decision-making are the disposition effect, herding behavior, and overconfidence... While professional investors employ fundamental and technical research more extensively, retail investors often rely on a variety of information sources, including newspapers, the media, and market rumors, when making investment decisions. The use of technical analysis in portfolio selection for investment decisions has been the subject of several studies. Decision-making is also greatly impacted by investor behavior, which is driven by psychological aspects and market circumstances. For example, although investors' judgments are usually logical and impacted by both technical and fundamental analysis, they may display overconfidence during periods of rise and fail to take into account the underlying worth of companies. To sum up, technical analysis plays a critical role in stock market investment decision-making. Investors may obtain important insights into market patterns, price fluctuations, and ideal trading times by examining historical data and market indicators. This information will eventually impact their investing choices. Prior studies on the usefulness of technical analysis have largely concentrated on the data market. Empirical research has been done on professional forecasters, who most likely use technical analysis and other methods. Conceptual publications addressing the theoretical framework of behavioral finance, behavioral biases in investing decisions, technical analytical studies, and reviews of literature-based research were among the findings of the literature review conducted for this study.

When investors perform technical analysis, they do not consider behavioral biases. Due to this, stock selection does not incorporate such biases. Similarly, when an investor is biased about a stock, he will not rely on technical analysis. That is why studying both is beneficial. There are several studies done on fundamental analysis along with biases, but biases along with Technical analysis are less explored. Shakeel (2018) has suggested that Fundamental analysis is not enough for successful forecasting, acknowledgment between biases and fundamental analysis, which is why Technical analysis can be incorporated to examine the association between biases and technical analysis. However, different behavioral characteristics like framing, overconfidence, and confirmation, among others, were not used in the prior study. Therefore, it is advised that these aspects be used in future research and that other behavioral biases be investigated in Pakistan's various regions, as suggested by aHir (2020). To better understand investor behavior, Future studies on other behavioral components are possible. such knowledge difficulties, over- and underreaction, mental accounting, herd behavior, and demography, suggested by Aisha et el 2011. Nevertheless, a combination of technical and fundamental elements has a role in stock investing choices, with neither technique having a greater influence than the other. Technical analysis is a technique used in the stock market to anticipate future price movements and identify the best times to enter and exit trades by examining historical data, price patterns, and trading volumes. Technical analysis helps investors make well-informed decisions about whether to purchase or sell stocks by examining indications such as price patterns and moving averages. For short-term traders who must act quickly to purchase, sell, or hold stocks in order to maximize earnings, technical analysis is also helpful. Due to its capacity to examine market behavior and trends, technical analysis is regarded as an essential instrument for financial decision-making. Investors utilize it to forecast changes in the prices of stocks and other assets by utilizing historical data and technical indicators. Additionally, technical analysis supports fundamental analysis in investment strategies and helps predict changes in stock prices.

Research Objectives

The objective of this Research is to investigate the Association between Behavioral Biases and Technical Analysis.

Problem Statement

Prior Researchers have researched various biases as well as fundamental analysis, but still, there is a gap left that needs to be addressed, as suggested by Shakeel (2008) and Said (2018). He suggested that Fundamental analysis is not enough for successful forecasting, acknowledgment between biases and fundamental analysis, which is why Technical analysis can be incorporated to examine the association between biases and technical analysis. Moreover, if we talk about biases, there are many biases that have been explored by many researchers, but still, there is a gap in that there are very few researchers who examine the impact of biases with technical analysis. However, different behavioral characteristics like framing, overconfidence, and confirmation, among others, were not used in the prior study. Therefore, it is advised that these aspects be used in future research and that other behavioral biases be investigated in Pakistan's various regions, as suggested by Rasool (2020).

Review Of Literature

Hirshleifer, D. (2015) concludes that the primary topic of behavioral finance research is how psychology can be used to understand and manage financial matters. Both on an individual and organizational level, behavioral finance is crucial. Baker & Yi (2015) have described the influence of several biases and how they affect investor decision-making. Another significant behavioral bias is known as the disposition effect, where selling a successful stock is more likely for investors, and they are more likely to hang onto a losing one Kumar et al, 2015). A look back at the Journal of Behavioral Finance (JBF), one journal in the behavioral finance area, provides an overview of the field (Calma, 2019). The concept of behavioral finance originated with the work of Tversky and Kahneman (1974). The efficient market theory. and the anticipated utility theory was dominant at the time. In contrast, individuals would make only rational decisions and attempt to maximize the value of each one under financial and economic theories. The publications in the Journal of Behavioral Finance were the focus of Calma's (2019) literature review, which did not prioritize the experimental approach. The association between cognitive biases such as overconfidence and the anchoring effect was examined in the SLR by Costa et al. (2017). and anchoring bias and decision-making with behavioral finance, but they made no mention of the experimental approach.

As these assumptions were challenged throughout time, a new financial theory known as behavioral finance emerged. Using this tactic, Tversky and

Kahneman (1974) demonstrated how heuristics and cognitive biases affect people's decision-making in ambiguous circumstances, preventing them from acting rationally as previous theories had proposed. In order to understand asset pricing, behavioral finance (BeFi) theory examines the psychological effects, biases, and heuristics that affect investor behavior. The need for financial markets to be constructed with behavioral factors influencing investor choices in mind is one of the BeFi theory's most significant implications. For instance, financial markets may be made more transparent, which would enable investors to make better decisions. Overconfidence occurs when. People are extremely optimistic about trading outcomes and think they have enough knowledge to make informed financial decisions. Additionally, investors make the error of assuming that the market's impressive success is a mirror of their own, ignoring the risk that concentrating too much on their own advantages and neglecting other factors might lead to large losses in the future. Disposition effect was first stated in 1985 by Shefrin and Statman. Investors frequently sell investments in profitable stocks as soon as possible to realize profits and hold onto losing stocks for a long period to delay losses. There is a propensity to prevent losses more than the desire to gain advantages. Investors make their final decisions based on imagined rewards rather than losses. Aliya and associates (2018).

According to Tversky and Kahneman (1981), there is bias. When information is given favorably, investors avoid risk to guarantee profits; yet, when the same information is presented unfavorably, they are prepared to assume the risk to avoid losses. As a result, investors can be given the identical information in one of two ways to influence their decisions. The two methods of stock market data analysis that have historically received the greatest attention are fundamental and technical analysis. However, technical analysis looks for patterns in data information, such as historical returns and price fluctuations, which may be used to predict price movement for securities and the market at large Ahmai et al, 2017).

Technical analysis usually ranks second after fundamental research when investors are asked about their asset valuation processes. One of the most important methods for determining share values in both established and developing stock markets is technical analysis. However, not all developed stock markets consistently employ technical analysis. In fact, Pike et al. (1993) found that German analysts valued technical analysis more than their British counterparts. According to the research, emerging markets use technical analysis far more frequently than their counterparts in industrialized nations Al-Abdulqader et al., 2007). As stated by Singh and Bhattacharjee (2019), Information screening, investing education, fear psychosis, technical and basic competence, information asymmetry, familiarity bias, and market knowledge were found to be the major determinants of risk perception. Later, behavioral finance questions conventional finance and adds psychological aspects that influence judgment. Using this method, Tversky and Kahneman (1974) demonstrated how heuristics and cognitive biases affect people's decision-making when they are presented with uncertainty.

Advocates of behavioral finance contend that varying levels of rationality or satisfaction influence investors' actions. The reflection effect, which is revealed by Kahneman and Tversky, reveals a connection between the positive sphere of risk aversion and the negative domain of risk seeking. These arguments support the prospect theory, a different descriptive model for risk-averse decision-making. The prospect hypothesis asserts that instead of seeing results as ultimate wealth asserts, people typically see outcomes as gains and losses. Gains and losses, however, are specified in relation to some benchmark, which could be the level of wealth at the time. Additionally, the actual sums paid or received could be used to determine gains and losses. Agent-based models have not received much attention when it comes to behavioral biases Lepori, 2016). Selim et al. (2015), for example, examine the effects of alternating between technical and fundamental trading strategies on price distortions and market stability. Previous research has shown that the majority of traders adhere to the technical and fundamental philosophies.

The theoretical literature review concentrated on behavioral finance theories of the prospect theory, disposition effect, regret, certain-return bias, and random walk framing to explain these phenomena in the study's objectives statement. Mental Accounting or others. The study of how psychology affects financial professionals' actions and how that affects markets is known as behavioral finance. Because it clarifies how and why markets may be inefficient, behavioral finance is interesting. By concentrating on individual investors and how they get and use financial data, behavioral finance offers a paradigm change from Markowitz and Sharpe's mainstream finance theory. Numerous irrational investor actions in financial markets have been explained by behavioral economics. Economists use their knowledge of human cognition and behavior from sociology, psychology, and anthropology to apply economic concepts. The substantial impact of various biases on investing results is demonstrated by behavioral biases and investment decisions. Investors may make illogical financial decisions as a result of behavioral biases that cause them to depart from reason. It is essential to comprehend these biases as they have the potential to either favorably or negatively affect people's ability to reach their investing objectives. However, behavioral biases also have a significant impact on how both individual and institutional investors make investment decisions.

Despite the growth of the field of contemporary finance, it is challenging to provide a scientific explanation for why people act irrationally while handling money. An investigation of the impact of prior conduct or beliefs revealed that anchoring bias in attitudes on beliefs shows a contradictory outcome. It also looked into how people reconcile disagreements between their resulting beliefs. It also provided more evidence in favor of the theory that people reconcile the discrepancy between their beliefs about previous conduct and their attitudes about it by reorienting their anchoring attitudes toward beliefs rather than behavior. It also looked at how people change anchoring attitudes using belief rather than conduct to reconcile contradictions between their resulting beliefs and previous behavior.

Prospect Theory

Tversky and Kahneman's (1979) Prospect Theory illustrated how people respond to risk and uncertainty. In conclusion, the concept clarifies how individuals behave consistently while assessing danger in ambiguous circumstances. Humans are not inherently risk-averse; rather, they take chances when doing so might result in rewards rather than losses. A phenomenon known as the "certainty effect" occurs when individuals place a lot greater importance on occurrences that are perceived as more definite than just likely. Additionally, the "framing effect" influences people's choices. The way an issue is presented to the decision-maker and their "mental accounting" of it is referred to as its framing.

Disposition Effect

The disposal impact indicates that investors have a very difficult time accepting losses. Prospect theory is where the disposition effect first appeared. According to Munir (2018), the disposition effect stems from prospect theory, which holds that investors can sell off securities with rising values while holding onto those with dropping prices because they overestimate their losses in comparison to their gains. Shefrin & Statman (1985) were the first to recognize this phenomenon, which is known as the "disposition effect." Investors used to seek out risk when they had losses and avoid risk when they experienced profits. They also used to compare their gains and losses using the reference point, which was the share's starting purchase price (Parveen, Siddique, & Malik, 2016).

These two aspects of prospect theory are used to describe the disposition effect. The disposition effect is characterized as investors commonly disposing of winning shares and keeping losing ones, due to their unwillingness to recognize losing shares. And in fact, the disposition effect describes a desire for investors to realize gains by selling stocks that have appreciated, but to delay the realization of losses. Another common bias that afflicts individual investors when they sell stock from their portfolio is called the disposition effect. The disposition effect is an instance of narrowing framing.

The disposition effect is explained by these two facets of prospect theory. Due to their inability to identify failing shares, investors frequently dispose of winning shares while holding onto losing ones, a phenomenon known as the disposition effect. The disposition effect really characterizes investors' desire to postpone realizing losses while realizing profits through the sale of equities that have increased in value. The disposition effect is another prevalent bias that affects individual investors when they sell stocks from their portfolio. One such example of limiting framing is the disposition effect. The investor anticipates making money on each investment. A logical agent, on the other hand, would have a complete picture of the portfolio and sell the stock with the lowest chance of future success, regardless of whether it is a winner or a loser. The tendency of investors to forego realized losses in anticipation of realized profits is known as the disposition effect (Pelster & Hofmann, 2018). The difference between the percentage of realized gains and the fraction of realized losses is the estimated disposition impact. The disposition effect is the term used to describe investors' propensity to hang onto losses in order to prolong and sell winning investments too soon. Because failing investments often continue to underperform and winning investments typically continue to thrive, the disposition effect has a negative impact on an individual's investment portfolio. The Prospect Theory of Kahneman and Tversky (1979), which holds that people frequently evaluate gains and losses in relation to a reference point and that people behave risk-aversely for gains and risk-seekingly for losses, serves as the main explanation for the disposition effect. The field where risk aversion is common. On the other hand, selling previously bought stock that is trading below its purchase price would be viewed as a definite loss, while keeping the stock would be viewed as choosing the riskier course of action. Loss aversion, or the belief that losses are more significant than comparable gains, may further mitigate the disposition effect tendency.

Mental Accounting

De Bondt, Muradoglu, Shef.rin, and Staikouras (2008) define mental accounting as the process by which investors classify and evaluate financial results. Raza & Mohsin (2014) define mental accounting as the process of creating separate mental accounts that might not occur at the same time. By giving each set of goods a different role, people who use mental accounting will be able to act in ways that are harmful, irrational, and illogical without even realizing it. The method by which humans encode, categorize, and assess economic consequences is known as mental accounting, and it is relatively new in business literature. It involves remembering and interpreting different expenses as a means of making sense of the environment. In early research on judgment and decision-making, Kahneman, Tversky, Shefrin, and others defined mental accounting as a set of cognitive processes for monitoring one's financial actions, a way to overcome problems with self-control in spending and consuming.

The concept of mental accounting is deeply ingrained in cognitive psychology. Mental accounting requires an understanding of how human emotions affect decision-making (Liu and Chiu, 2015). The method by which humans encode, categorize, and assess economic consequences is known as mental accounting, and it is relatively new in business literature. It involves remembering and interpreting different expenses as a means of making sense of the environment. But mental accounting also explains the fundamental cognitive processes involved in regulating and preparing a particular choice. When presented with several possible results, for instance, people may choose to assess them independently, that is, separate various outcomes, or collectively, that is, combine diverse decision outcomes. People's spending choices and risk tolerance might differ substantially depending on how their income sources and spending options are viewed, classified, and labeled.

The investor views the assessment's scope in a way that spares it from having to deal with the bad feelings brought on by the losses. The rational evaluation of the entire portfolio is subordinated to this "hedonic pleasurable framing," which is ultimately nothing more than a purposefully motivated personal deceit to avoid feeling unpleasant. According to an experimental study, when consumers use gift cards to make purchases, instead of using cash or credit cards, they utilize mental accounts. Theoretically, the performance of all assets should be the primary determinant of a sensible investor's actions. Mental accounting-based irrational beliefs divert attention from these viewpoints, and it makes sense that every minor issue that arises or is encountered is too complicated and expensive to consider the potential ramifications for their entire existence. This can surely lead to too many problems. As a result, the investor must make investments within predetermined time frames during which the whole asset position will be routinely assessed.

For instance, it could take some time to become aware of all asset holdings at the end of a quarter or month. The investor has no other option, even if unpleasant feelings force you to accept your own losses. It's crucial to learn how to handle this by having a comprehensive understanding of the whole issue so that you can make smart judgments worry-free. The foundation for dividing various assets into several accounts and considering each one separately is the tendency of decision makers to keep track of each investment in a different mental account. Therefore, whether the current situation should be viewed as a gain or a loss depends on the reference point in each mental account. As a result, interactions are disregarded, and each investment is handled independently.

Availability Bias

Availability bias is the tendency of investors to utilize data and information without conducting additional analysis and to base their investment decisions on the probability of such data and information. Availability bias has a big influence on investment decisions (Chandra & Kumar, 2012). When investors make choices based just on information rather than analysis or other procedures, this issue occurs (Javed, Bagh, & Razzaq, 2017). Availability bias will have a significant positive influence on investment decisions due to inexperience, as investors would often trust the evidence that is easily accessible (Raut & Kumar, 2018). A cognitive heuristic bias known as "availability bias" occurs when investors place a high value on information that is simple to find (based on experience). When decision-makers depend on the information that is readily available, availability bias arises. This speaks to people's propensity to assess an event's probability depending on how quickly they can recall previous incidents. To put it another way, individuals are more likely to consider the information that is immediately accessible than to consider all pertinent information.

This may cause people to overestimate the chance that particular things will happen, which may result in less-than-ideal investing choices. The propensity of investors to use data and information without conducting additional analysis and to base their investment choices on the likelihood of such data and information is known as availability bias. Investment decisions are significantly impacted by availability bias. This speaks to people's propensity to assess an event's probability depending on how quickly they can recall previous incidents. To put it another way, individuals are more likely to consider the information that is immediately accessible than to consider all pertinent information. This may cause people to overestimate the chance that particular things will happen, which may result in less-than-ideal investing choices. For instance, a recent news article or social media post on a stock may influence an investor without taking into account other elements that might influence the stock's performance.

Research Methodology

The suggested research design, demographic and sample size, sampling methodologies, instruments and measures, data analysis techniques, and primary and secondary data collection methods are all covered. The research plan is the overall strategy for doing research that specifies data collection and analysis. The study will use a quantitative research technique, concentrating on the gathering of quantitative information and statistical evaluation to ascertain the impact of behavioral biases on the collection of numerical data and statistical analysis to determine the influence of behavioral biases on technical analysis. Research philosophy is a collection of beliefs and assumptions that directs the creation of knowledge (Saunders et al., 2015). In order to find a solution to the research challenge, the researcher must first decide on a research philosophy that will guide the research process. Numerous writers have defined and examined four primary research philosophy tendencies in their works: Positivist research philosophy, Interpretivist research philosophy, Pragmatist research philosophy, and Realistic research philosophy. Positivist research philosophy uses a reasoning methodology, has an objective, and pursues the “quantitative research methodology There are different research strategies used, like survey research strategy and experimental research strategy; researchers use a strategy based on the study situation. This study deals with the survey method by using a probability technique.

Sample And Data

Primary Data was collected from various investors. There are different research strategies used, like survey research strategy and experimental research strategy; researchers use a strategy based on the study situation. This study deals with the survey method by using a probability technique. The population of research refers to the whole group for which the data will be gathered. This study’s demography will cover Islamabad and Rawalpindi. To conduct research, sampling methodologies must choose a subset from a larger population. Stratified random sampling will be used in this study to ensure that all financial (investors) strata are appropriately represented. To establish the link between behavioral biases and technical analysis, descriptive statistics, correlation analysis, and regression analysis will all be employed in the data analysis. The usefulness of these approaches will be decided by the kind of data and research goals. The questionnaires will be sent to the chosen financial investors, and data will be gathered after they are completed.

Analysis And Discussion

Demographic Information

Table 1 shows the age distribution data, which demonstrates that the majority of respondents fall within the younger age groups. Specifically, 38% of valid responses came from individuals aged 18–24, making it the most represented

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age group. The next in line after this is the 25–31 age group, which accounts for 34% of valid responses. When combined, these two groups make up 72% of the total valid responses, indicating that the sample is largely composed of younger adults. The 32–38 age group represents 17.5% of the valid responses, while older age groups, such as 39–45 and above 45, are much less represented, accounting for only 4% and 6.5% respectively. Additionally, there were 9 respondents (4.3% of the total sample) who did not provide their age. Overall, the data suggest a strong skew toward younger individuals in the sample, which could influence the generalizability of findings to older age groups.

Table 1: ***Age Of Respondents***

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 18-24	76	36.4	38.0	38.0
25-31	68	32.5	34.0	72.0
32-38	35	16.7	17.5	89.5
39-45	8	3.8	4.0	93.5
above 45	13	6.2	6.5	100.0
Total	200	95.7	100.0	
Missing System	9	4.3		
Total	209	100.0		

Gender Of Respondents

The table displays a sample's gender distribution made up of 209 people. Among these, 200 provided valid responses regarding their gender, while 9 cases (4.3%) were missing and categorized as system-missing data. Among the valid responses, 141 those who are classified as masculine, representing 70.5% of this valid sample, while 59 people were recognized as female, accounting for the remaining 29.5%. When considering the entire sample, including the missing data, males made up 67.5% and females 28.2%. The cumulative percentage shows that all valid responses are accounted for by the time female responses are included, reaching 100%. This distribution indicates a higher representation of males in the dataset, and the small proportion of missing responses is unlikely to significantly affect the overall interpretation, though this depends on the study's context and sensitivity to missing data.

Table 2: ***Gender Of Respondents***

		Frequenc	Percent	Valid Percent	Cumulative Percent
Valid	male	141	67.5	70.5	70.5
	female	59	28.2	29.5	100.0
	Total	200	95.7	100.0	
Missing	System	9	4.3		
Total		209	100.0		

Industry Of Respondents

The table displays the allocation of respondents based on the type of institution—public or private—in a sample of 209 individuals. Out of the total sample, 200 participants provided valid responses, while 9 (4.3%) were missing and labeled as system-missing data. Among those who responded, 89 individuals (44.5%) reported being affiliated with public institutions, and 111 individuals (55.5%) with private institutions. These valid percentages are based only on the 200 responses received. When considering the full sample, public institution respondents make up 42.6%, and private institution respondents 53.1%. The cumulative percentage indicates that after accounting for all private institution responses, 100% of the valid data is represented. Overall, the data shows a slightly higher representation of individuals from private institutions compared to public ones, and the missing data makes up a small portion of the overall sample.

Table 3: ***Industry Of Respondents***

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	public	89	42.6	44.5	44.5
	private	111	53.1	55.5	100.0
	Total	200	95.7	100.0	
Missing	System	9	4.3		
Total		209	100.0		

Experience Of Respondents

The table outlines the allocation of participants according to their years of expertise, drawn from a total sample of 209 individuals. Of these, 200 respondents provided valid data, while 9 responses (4.3%) were system-missing. Among the valid responses, the largest group (36.5%) reported having between 5 and 10 years of expertise, after which by 27.5% with 0 to 5 years of experience. Individuals with 10 to 15 years made up 21.5% of the valid sample, while smaller proportions reported 15 to 20 years (9.0%) and 20 to 25 years (5.5%) of experience. The cumulative percentage shows that 85.5% of respondents possessed less than 15 years of experience, suggesting a workforce that is relatively early to mid-career. The small percentage of missing data (4.3%) does not appear to significantly impact the interpretation of the overall experience distribution.

Table 4: ***Experience Of Respondents***

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid 0-5 years	55	26.3	27.5	27.5
5-10 years	73	34.9	36.5	64.0
10-15 years	43	20.6	21.5	85.5
15-20 years	18	8.6	9.0	94.5
20-25 years	11	5.3	5.5	100.0
Total	200	95.7	100.0	
Missing System	9	4.3		
Total	209	100.0		

Measurement Model

The diagram presents A structural equation model that shows how three latent variables relate to one another —MA (Mental accounting "), DE (likely Disposition effect "), and AB (Availability Bias ")—and their effect on TA. Each of these latent constructs is measured by three observable indicators. For MA, the indicators MA1, MA2, and MA3 load strongly onto the latent construct, with standardized loadings of 0.797, 0.821, and 0.798, respectively, indicating good reliability. Similarly, DE is measured by DE1, DE2, and DE3 with very high loadings of 0.878, 0.889, and 0.895, reflecting excellent internal consistency. AB is also measured robustly by AB1 (0.872), AB2 (0.906), and AB3 (0.824).

The dependent latent variable TA is influenced by MA, DE, and AB. The model shows that DE has the strongest direct effect on TA, with a path coefficient of 0.380, followed by MA (0.368), while AB has a smaller influence (0.157). This suggests that both DE and MA play nearly equal and significant roles in explaining TA, while AB contributes less. TA itself is measured by seven items (T1 through T7), all of which show moderate to strong loadings spanning from 0.669 to 0.763, verifying the construct's reliability. The R-squared value of 0.592 for TA shows that roughly 59.2% of the variance in TA is elucidated by the three predictor variables, showcasing a moderately strong explanatory power of the model.

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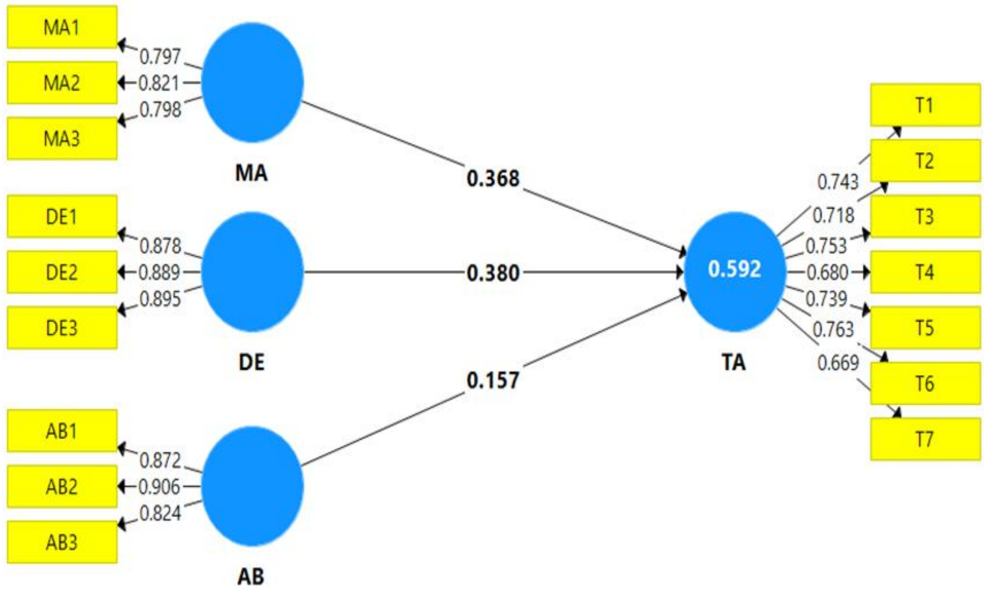

Figure 1: Measurement Model

Factor Analysis

The factor loading table provides insights into the power of the relationships between the observed indicators or their corresponding latent variables. All three indicators for Availability Bias (AB)—AB1 (0.872), AB2 (0.906), and AB3 (0.824)—demonstrate strong factor loadings, indicating that these items reliably represent the Availability Bias construct. Notably, AB2 shows the maximum burden, indicating that it is the most influential indication within this group. Similarly, the Disposition Effect (DE) is also well-represented by its three indicators—DE1 (0.878), DE2 (0.889), and DE3 (0.895)—each exhibiting high loadings that reflect excellent internal consistency and construct reliability.

For Mental Accounting (MA), the indicators MA1 (0.797), MA2 (0.821), and MA3 (0.798) all have strong loadings, confirming they are valid measures of the construct, although slightly lower than those of AB and DE. Lastly, four indicators are presented for Technical Analysis (TA): T1 (0.743), T2 (0.718), T3 (0.753), and T4 (0.680). While all four loadings are acceptable, T4 has the lowest value among them, indicating it may be a slightly weaker indicator compared to the others. Overall, the factor loadings across all constructs are strong and support the reliability and validity of the measurement model.

Table 5: ***Factor Loading***

Variable	Table: Factor Loading Variable	Factor Loading
Availability Bias	AB1	0.872
	AB2	0.906

	AB3	0.824
Disposition Effect	DE1	0.878
	DE2	0.889
	DE3	0.895
Mental Accounting	MA1	0.797
	MA2	0.821
	MA3	0.798
Technical Analysis	T1	0.743
	T2	0.718
	T3	0.753
	T4	0.68
	T5	0.739
	T6	0.763
	T7	0.669

Reliability and Validity

The reliability and validity statistics indicate that all four constructs—Availability Bias (AB), Disposition Effect (DE), Mental Accounting (MA), and Technical Analysis (TA)—are measured with acceptable to strong consistency and validity. Availability Bias shows good internal consistency with a Cronbach's Alpha of 0.836 and a high Composite Reliability (CR) of 0.901. Its Average Variance Extracted (AVE) is 0.753, well above the acceptable threshold of 0.50, indicating that the majority of variance is captured by the construction rather than error.

Disposition Effect demonstrates the strongest reliability and validity among all constructs, with a Cronbach's Alpha of 0.865, CR of 0.918, and an AVE of 0.788. The mentioned values reflect excellent internal consistency and convergent validity. Mental Accounting has a slightly lower Cronbach's Alpha of 0.729, which still falls within the acceptable range, supported by a CR of 0.847 and AVE of 0.648. These values confirm that this construct is measured reliably and that its indicators sufficiently explain the underlying variance.

Lastly, Technical Analysis exhibits good reliability with Cronbach's Alpha of 0.849 and CR of 0.885. However, its AVE is 0.525, which, while still above the minimum threshold, suggests that the indicators capture a slightly lower proportion of variance from the construction compared to the others. Overall, the statistics confirm that all constructs possess adequate reliability and convergent validity, supporting the soundness of the measurement model.

Table 6: ***Reliability and Validity***

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AB	0.836	0.901	0.753
DE	0.865	0.918	0.788
MA	0.729	0.847	0.648
TA	0.849	0.885	0.525

Discriminant Validity (Fornel Lorcker)

The Fornell-Larcker criterion results confirm that all four constructs—Availability Bias (AB), Disposition Effect (DE), Mental Accounting (MA), and Technical Analysis (TA)—demonstrate adequate discriminant validity. This means that every construct is statistically different from the other models. The square roots of the Average Variance Extracted (AVE), which appear across the diagonal of the table, are all superior to the corresponding inter-construct correlations shown in the off-diagonal cells. For Availability Bias (AB), the square root of its AVE is 0.868, which is greater than its correlations with DE (0.518), MA (0.646), and TA (0.592), indicating that AB is a distinct construct. Disposition Effect (DE) has an even higher square root of AVE at 0.887, which exceeds its correlations with all other constructs, including TA (0.660), confirming its discriminant validity. Similarly, Mental Accounting (MA) has a square root of AVE of 0.805, which surpasses its maximum correlation with TA (0.674), further supporting its uniqueness. Finally, Technical Analysis (TA) shows the lowest square root of AVE at 0.724, but it still surpasses its highest correlation, which is with MA (0.674), demonstrating that it is also empirically distinct. Overall, the results validate that the constructs used in the model are logically sound as well as internally dependable. and statistically distinct from one another, thereby supporting the structural integrity of this measurement model.

Table 7: ***Discriminant Validity (Fornell Loracker)***

	AB	DE	MA	TA
AB	0.868			
DE	0.518	0.887		
MA	0.646	0.537	0.805	
TA	0.592	0.66	0.674	0.724

Discriminant Validity (HTMT Ratio)

The correlation values among the latent constructs indicate generally strong associations, with some relationships approaching levels that may raise concerns regarding discriminant validity. The highest correlation is observed between Mental Accounting (MA) and Technical Analysis (TA) at 0.852, suggesting a very strong relationship that may imply some conceptual overlap between the two constructs. Similarly, the correlation between Availability Bias (AB) and Mental Accounting (MA) is also high at 0.826, indicating that respondents may perceive these constructs as closely related. While these values are still within acceptable thresholds, they are near the upper limit, especially if evaluated against stricter criteria for discriminant validity. In contrast, the correlations between other constructs are comparatively lower. The relationship between Disposition Effect (DE) and Technical Analysis (TA) is 0.769, between Availability Bias (AB) and Technical Analysis (TA) is 0.691, and between Availability Bias (AB) and Disposition Effect (DE) is 0.609. These values suggest moderate to strong but more distinct relationships, supporting clearer conceptual separation among these pairs. Overall, the results imply that while the constructs are all related, particularly MA and TA, as well as MA and AB, further investigation may be needed to ensure that these constructs are sufficiently distinct. This could involve refining measurement items or conducting additional validity checks to confirm that the constructs represent unique aspects of investor behavior.

Table 8: ***Discriminant validity (HTMT Ratio)***

	AB	DE	MA	TA
AB				
DE	0.609			
MA	0.826	0.677		
TA	0.691	0.769	0.852	

Structural Model (Hypotheses Testing)

The structural equation model reveals that all three cognitive biases—Mental Accounting (MA), Disposition Effect (DE), and Availability Bias (AB)—have significant positive effects on Technical Analysis (TA). Disposition Effect exerts the strongest influence on TA, using a path coefficient of 0.380 and a highly significant t-value ($p < 0.001$), showing a robust relationship. Mental Accounting also shows a similarly strong impact on TA, with a coefficient of 0.368 and a significant t-value, confirming its importance in predicting technical analysis behavior. Availability Bias, while having a smaller effect with a coefficient of 0.157, remains statistically significant ($p = 0.016$), suggesting it still plays a meaningful role. Additionally, the high t-values for all measurement indicators across constructs demonstrate that what was seen variables accurately gauge the corresponding latent variables. Overall, results support the conclusion that these psychological biases significantly contribute to investors' use of technical analysis, with Disposition Effect and Mental Accounting being the most influential factors.

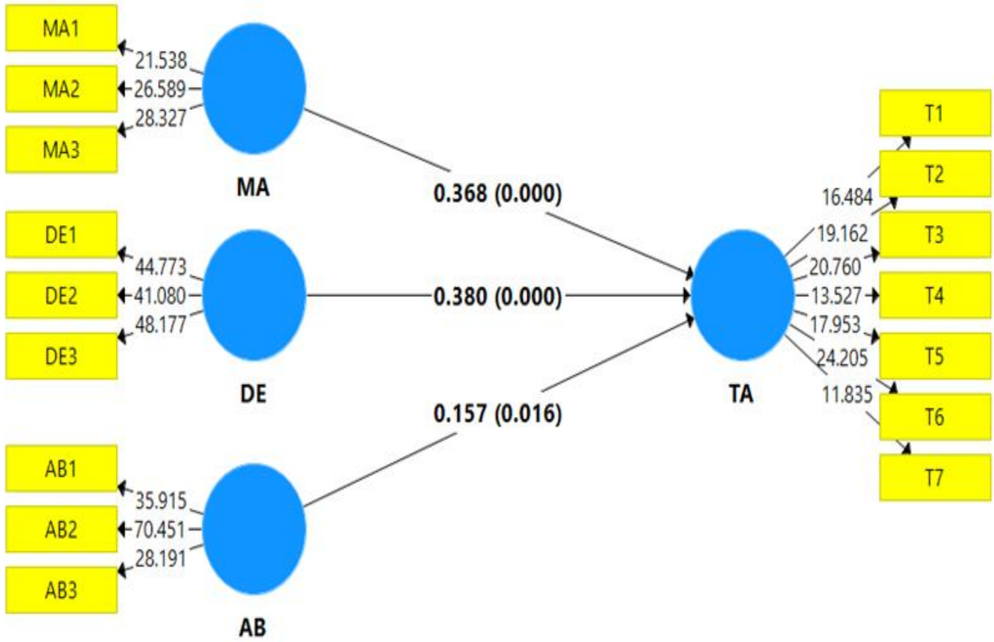

Figure 2: Structural model (Hypotheses Testing)

R Square

The value of R Square for Technical Analysis (TA) is 0.592, and the adjusted R Square is 0.586. This means that approximately 59.2% of the variance in Technical Analysis behavior can be clarified by the three predictor variables: Mental Accounting (MA), Disposition Effect (DE), and Availability Bias (AB). The number of predictors in the model is taken into consideration by the modified R Square, which is very close at 58.6%, indicating a good model fit without overfitting. Overall, these values imply that the model has a high capacity for explanation. In understanding the factors influencing investors' use of technical analysis.

Table 9: ***R-squared***

	R Square	R Square Adjusted
TA	0.592	0.586

Collinearity Analysis

The values of the Variance Inflation Factor (VIF) for Availability Bias (AB) and Disposition Effect (DE) are 1.845 and 1.513, respectively. These VIF values fall well short of the typical cutoff point of 5, and even the more cautious 3-point cutoff, demonstrating that there is no substantial multicollinearity issue between the model predictor variables. This means that AB and DE separately contribute to the variance explanation. in Technical Analysis (TA) without overlapping excessively in their effects.

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Table 10: ***Multicollinearity***

Variable	VIF
AB	1.845
DE	1.513
MA	1.898

SEM Model (Hypotheses Testing)

The analysis reveals that Availability Bias, Disposition Effect, and Mental Accounting all have statistically significant positive effects on Technical Analysis. Availability Bias shows a modest but meaningful influence on Technical Analysis, using a path coefficient of 0.157 and a p-value of 0.016, showing confidence that this relationship is not due to chance. Disposition Effect and Mental Accounting both demonstrate stronger impacts, with coefficients of 0.380 and 0.368, respectively, and highly significant p-values of fewer than 0.001. The confidence intervals for all three relationships do not cross zero, reinforcing the reliability of these findings. Overall, while Disposition Effect and Mental Accounting are the most influential predictors of Technical Analysis behavior, Availability Bias also plays a significant, albeit smaller, role.

Table 11: ***SEM model (Hypotheses Testing)***

	Original Sample (O	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	2.50%	97.50%
AB -> TA	0.157	0.065	2.408	0.016	0.027	0.282
DE -> TA	0.380	0.063	6.028	0.000	0.258	0.488
MA -> TA	0.368	0.076	4.836	0.000	0.196	0.516

Conclusion

The study concludes that behavioral biases and their link to technical analysis within financial markets. The findings demonstrate that investor psychology—manifested through emotional biases, for example, overconfidence, herd behavior, anchoring, and loss aversion—plays a vital role in shaping the market dynamics. These recurring behavioral patterns often result in non-random price movements, which technical analysis seeks to interpret and capitalize upon.

Technical analysis, traditionally viewed as a tool based on historical price and volume data, might be better understood via the prism of behavioral finance. The emergence of identifiable chart patterns, trends, and support/resistance levels reflects collective investor sentiment and behavioral tendencies rather than purely rational decision-making. This behavioral foundation offers a compelling justification for why technical analysis can be effective, despite its criticism from proponents of efficient market theory.

Ultimately, combining behavioral finance ideas with technical analysis offers a more thorough foundation for comprehending the market. behavior. Recognizing the psychological drivers behind price movements enables investors and analysts to apply technical tools more effectively and with greater awareness of the risks associated with cognitive biases. This synthesis not only deepens academic understanding of market anomalies but also has realistic consequences for improving investment strategies and making decisions in real-world trading environments.

Limitations and Future Recommendations

While the relationship between behavioral biases and technical analysis offers valuable insights into market behavior, this study is not without limitations. One of the primary constraints is the inherent subjectivity in both behavioral finance and technical analysis. Interpreting chart patterns and technical indicators often depends on individual judgment, which can vary widely among analysts and traders. Additionally, behavioral biases are difficult to quantify precisely, as much of the existing research relies on self-reported data or indirect behavioral observations, which may not fully capture the complexity of investor psychology. The reliance on historical price data in technical analysis also presents limitations, as past performance does not always guarantee future outcomes, especially in increasingly volatile and complex financial markets. Another limitation stems from the challenge posed by the Efficient Market Hypothesis (EMH), especially in its semi-strong and powerful forms, which argue that market prices already take into account all of the information that is accessible. This implies that both behavioral biases and technical patterns should be arbitraged away quickly, potentially reducing their long-term predictive value. Furthermore, findings derived from specific markets or timeframes may not be easily generalized across different regions, asset classes, or economic conditions. Behavioral biases can also vary across cultures and demographic groups, affecting how investors react and how technical patterns form. Finally, the financial markets are ever-changing and dynamic. Due to technological advances, regulatory changes, and shifts in investor behavior, which means that strategies based on historical analysis may lose effectiveness over time.

To address these limitations, future research should consider incorporating interdisciplinary approaches such as neurofinance and experimental psychology to gain a deeper and more objective understanding of cognitive and emotional biases. Advances in machine learning and artificial intelligence also offer promising tools to detect subtle behavioral patterns in large datasets, potentially reducing subjective interpretation in technical analysis. Additionally, cross-cultural studies could reveal how behavioral tendencies differ globally and how these differences impact the reliability of technical analysis. The development of hybrid investment models that combine technical, behavioral, and fundamental elements may also enhance predictive accuracy and adaptability. Educating investors about common biases through behavioral training can foster more rational decision-making, while long-term, longitudinal studies can provide more robust evidence about the persistence and evolution of behavioral influences on technical indicators. Together, these recommendations aim to strengthen the integration of behavioral insights with technical analysis, clearing the path for further effective and psychological.

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