TECHNICAL ANALYSIS AND INVESTMENT DECISION MAKING IN NEPALI STOCK MARKET

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By

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CERTIFICATION OF AUTHORSHIP

I hereby corroborate that I have researched and submitted the final draft of dissertation entitled "**Technical Analysis and Investment Decision Making in Nepali Stock Market**". The work of this dissertation has not been submitted previously for the purpose of conferral of any degrees nor it has been proposed and presented as part of requirements for any other academic purposes.

The assistance and cooperation that I have received during this research work has been acknowledged. In addition, I declare that all information sources and literature used are cited in the reference section of the dissertation.

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REPORT OF RESEARCH COMMITTEE

Mr. Asbin Dahal has defended research proposal entitled **" Technical Analysis and Investment Decision Making in Nepali Stock Market"** successfully. The research committee has registered the dissertation for further progress. It is recommended to carry out the work as per suggestions and guidance of supervisor Mr. Rishi Ram Pantha and submit the thesis for evaluation and viva voce examination.

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ABBREVIATIONS

ANOVA	:	Analysis of Variances
E	:	Error Term
N	:	Number of Responses
S.D.	:	Standard Deviation
SEM	:	Structural Equation Modeling
VIF	:	Variance Inflation Factor
IND	:	Investment Decision Making
EDU	:	Education
EXP	:	Experience
TIM	:	Time Horizon
FRE	:	Trading Frequency
AOI	:	Accessibility of Information
POI	:	Perception of Investor

ABSTRACT

This study explores the technical analysis in investment decision-making among Nepali investors, addressing the effectiveness and applicability of technical analysis in the Nepali Stock Market. It identifies key challenges such as the contradiction with the Efficient Market Hypothesis (EMH), cognitive biases, and issues with data availability. The primary objective is to investigate how technical analysis influences investment decisions and its practical relevance in the Nepali context.

The research employs a quantitative approach with a causal effect design. Data were collected from a sample of 400 individual investors in the Kathmandu Valley, selected through convenience sampling. A structured questionnaire using a five-point Likert scale served as the primary instrument for gathering data, focusing on investors' behaviors and perceptions regarding technical analysis.

Statistical analysis was conducted using Microsoft Excel and SPSS, with tools including descriptive statistics, correlation analysis, and multivariate regression models. The research framework examines key independent variables—education, experience, time horizon, trading frequency, accessibility of information, and perception of investor—against the dependent variable of investment decision-making.

The findings reveal that experience, perception of investor, and accessibility of information significantly impact investment decision-making, with experience and perception being particularly influential. Education, time horizon, and trading frequency show weaker and less significant effects. These results highlight the crucial investor expertise, favorable perceptions, and access to information in enhancing decision-making.

The study underscores the practical value of technical analysis for investors, recommending an increased focus on education, better access to market data, and the need for further research on additional variables. Insights suggest that while experience and perception are pivotal, education and trading frequency play a lesser role.

Keywords: *Technical analysis, Investment decision-making, Nepali Stock Market, Investor perception, Experience.*

CHAPTER I
INTRODUCTION

1.1 Background of the Study

Technical analysis is a comprehensive approach utilized by traders in international stock markets to forecast future price movements based on historical data (Magui et al., 2023). This methodology relies on the premise that past stock prices hold predictive value for future trends. However, it challenges the random walk hypothesis, which posits that stock prices change independently of historical patterns. Despite this contradiction, technical analysts assert that studying market behavior over time provides insights beyond traditional accounting methods, tapping into the psychology and sentiment of market participants. This synthesis of financial and psychological factors underscores the importance of combining both disciplines to comprehend investor behavior accurately (Pan, 2003).

Even with complete information about asset pricing, market dynamics, and government regulations, investors remain susceptible to irrational decision-making. This paradox arises from the influence of emotional and cognitive biases on investment choices. Gorgulho and Neves (2011) argue that investors' actions are influenced not only by fundamental factors but also by perceptions shaped by peers, friends, and competitors. Integrating principles of behavioral finance into investment strategies can mitigate irrational behavior and enhance profitability. By leveraging technical analysis indicators, rational investors can identify profitable opportunities overlooked by their irrational counterparts, thereby maximizing returns and minimizing losses.

Behavioral finance offers a lens through which to understand the varying behavior of investors in response to market conditions. This interdisciplinary field examines how psychological biases impact financial decisions, shedding light on why investors may act irrationally in certain situations. The integration of psychology and finance reveals insights into market sentiment and investor behavior, guiding investment strategies (Magui et al., 2023). By acknowledging the influence of emotions, social dynamics, and cognitive biases, investors can make informed decisions aligned with their financial goals and risk tolerance.

Technical analysis equips traders with tools to anticipate shifts in security prices, identifying emerging trends or reversals in market direction. For instance, if a security has been rallying and reaching new highs, a trader can utilize technical indicators to identify potential overbought conditions. This insight enables the trader to exit positions, protect

profits, and optimize returns. Bansal (2018) emphasizes the proactive nature of technical analysis, empowering traders to capitalize on market inefficiencies and make timely investment decisions.

The adoption of technical analysis facilitates the identification of profitable opportunities and the avoidance of loss-making securities. Petrusheva (2016) highlights how rational investors leverage technical indicators to capitalize on market inefficiencies overlooked by irrational counterparts. By adhering to technical analysis principles, investors can navigate market fluctuations, optimize portfolio performance, and achieve superior returns. This proactive approach aligns with the core tenets of technical analysis, emphasizing the importance of leveraging historical price data to inform future investment decisions.

This study focusses the investment decisions of Nepali investors within the context of the Nepali Stock Market, emphasizing the technical analysis. By examining the behavior and decision-making processes of investors in this specific market, the research sheds light on the effectiveness and applicability of technical analysis in a unique financial environment. Through a comprehensive analysis of historical stock prices and market trends, the study aims to elucidate how Nepali investors utilize technical analysis to navigate the complexities of the local stock market, capitalize on emerging opportunities, and mitigate risks. By focusing on the Nepali context, the study provides valuable insights that can inform both local investors and international observers about the dynamics of investment decision-making in an evolving market landscape.

1.2 Problem Statement

Technical analysis serves as a cornerstone for investment decision-making across global financial markets. However, several key challenges and discrepancies persist within this realm, necessitating a comprehensive examination of its efficacy and implications on a global scale.

Technical analysis, grounded in the belief that historical price movements can forecast future trends, stands in apparent contradiction to the Efficient Market Hypothesis (EMH). According to EMH, stock prices reflect all available information, rendering technical analysis redundant. Yet, the persistent application of technical analysis strategies globally raises questions regarding the coexistence of these methodologies and their impact on market efficiency (Fama, 1970). Investor behavior, influenced by cognitive biases such as overconfidence and herd mentality, poses a significant challenge to the efficacy of technical analysis globally. Despite the availability of historical data and sophisticated technical

indicators, investors often deviate from rational decision-making, leading to market anomalies and inefficiencies that undermine the reliability of technical analysis strategies (Barberis & Thaler, 2003).

The effectiveness of technical analysis is hindered by challenges related to data availability and information transparency across global financial markets. Limited access to reliable data sources, coupled with inconsistent disclosure practices by corporations, undermines the robustness of technical analysis tools (Botosan,1997). This raises concerns about the validity and reliability of investment decisions based solely on historical price patterns.

Addressing these global challenges and discrepancies is paramount for investors, regulators, and market participants to enhance the integrity and effectiveness of technical analysis in investment decision-making. By fostering greater transparency, investor education, and interdisciplinary collaboration, global financial markets can navigate the complexities of technical analysis and promote informed and efficient investment strategies. Following has been the research questions asked for this study.

1. Do Nepali investors use technical analysis in investment decision-making?
2. Is there a relationship between technical analysis and investment decision-making?
3. What is the impact of technical analysis on investment decision-making?

1.3 Objectives of the Study

The primary aim of this study has been to conduct a comprehensive analysis of investment decision-making among Nepali investors, focusing specifically on the utilization of technical analysis techniques. By delving into the strategies employed by Nepali investors in the stock market, this research seeks to elucidate the extent to which technical analysis influences their investment decisions. Through empirical investigation and data analysis, this study endeavors to uncover patterns, trends, and challenges associated with the application of technical analysis methodologies in the Nepali context. Furthermore, by identifying factors influencing investor behavior and decision-making processes, this research aims to provide insights that can inform both investors and policymakers in Nepal. Ultimately, the findings of this study aspire to contribute to a deeper understanding of investment dynamics in Nepal and offer practical implications for enhancing the effectiveness and efficiency of investment strategies based on technical analysis. The objectives of this study are as follows.

1. To assess the use of technical analysis in investment decision-making.
2. To examine the relationship between technical analysis and investment decision-making.
3. To analyze the impact of technical analysis on investment decision-making.

1.4 Rationale of the Study

The study holds significant importance for various stakeholders within the Nepali financial landscape. With the burgeoning interest in the stock market among Nepali investors and the increasing complexity of investment decisions, understanding the technical analysis is paramount. This study seeks to shed light on how Nepali investors utilize technical analysis in their investment decision-making processes. By investigating this aspect, the study aims to provide valuable insights that can benefit following investors, policymakers, researchers, students, and academicians alike.

- **Investor:** For Nepali investors, this study offers insights into the effectiveness and implications of technical analysis in the context of the Nepali Stock Market. Understanding the technical analysis can help investors make more informed decisions, manage risks effectively, and potentially enhance their investment returns.
- **Government Bodies:** Government entities and policymakers can benefit from understanding the impact of technical analysis on investment decision-making. Insights from this study can inform regulatory frameworks and policies aimed at fostering a more transparent, efficient, and investor-friendly stock market environment in Nepal.
- **Researchers:** Researchers in finance and related fields can use the findings of this study as a basis for further exploration and analysis. By contributing to the existing body of knowledge on technical analysis and investment decision-making, this study can pave the way for future research endeavors aimed at addressing gaps and advancing theoretical understanding.
- **Students:** Students pursuing finance, economics, or related disciplines can gain valuable insights into real-world investment practices and strategies through this study. Understanding how technical analysis influences investment decisions in the

Nepali Stock Market can enrich their academic learning and prepare them for careers in the financial sector.

- **Academicians:** Academicians and educators can incorporate the findings of this study into their curriculum, enriching the learning experience for students. By integrating real-world examples and applications of technical analysis in investment decision-making, academic programs can better equip students with practical knowledge and skills relevant to the financial industry.

Overall, the study on technical analysis and investment decision-making in the Nepali Stock Market holds significant implications for a diverse array of stakeholders. By providing insights into the usage, relationship, and impact of technical analysis, this study aims to empower investors, inform policymakers, inspire further research, enrich academic learning, and contribute to the overall development of the Nepali financial landscape. Through collaborative efforts and a deeper understanding of investment dynamics, stakeholders can work towards fostering a more efficient, transparent, and resilient stock market ecosystem in Nepal.

1.5 Limitations of the Study

The limitation of this study is as follows.

- Primary data has been used, so inherent limitation of primary data is always present.
- The sample size of this study is limited to 400 investors.
- This study only focuses on education, experience, time horizon, trading frequency, and accessibility of information factors in evaluating the technical analysis of investors.
- This study is focused only on the technical analysis of investors located in the Kathmandu Valley and might not cover the perception of the whole country.
- The sampling method used in this study is convenience sampling, which may limit the generalizability of the findings due to potential biases in participant selection.

CHAPTER II

LITERATURE REVIEW

The literature review is a comprehensive examination of existing research and theoretical frameworks relevant to a particular study. It encompasses a detailed review of related concepts and terminologies, an analysis of previous articles and journals, and a discussion of relevant theories. Additionally, the literature review identifies and evaluates research gaps, providing a context for the current study by highlighting areas that require further investigation. This critical analysis helps to situate the research within the broader academic discourse and supports the development of a well-grounded research framework.

2.1 Conceptual Review

2.1.1 History of Technical Analysis

Technical analysis, a method of analyzing financial markets by studying historical price and volume data, has a rich history dating back to the 1600s in Japan. The quote by Nison (1994) aptly illustrates the importance of charts in guiding traders towards their investment goals. Initially used by Japanese traders in the rice futures market, technical analysis evolved over centuries, driven by insights into market psychology and the recognition of emotional influences on price movements (Manic, 2017).

The roots of technical analysis can be traced back to Japan's rice futures market in the 1600s. Following a period of internal warfare, General Tokugawa emerged victorious and became the Shogun of Japan. With rice serving as a primary commodity for trade and taxation, the emergence of futures contracts for rice marked a significant development in financial markets (Nison, 1994). These early futures contracts, known as "empty rice contracts," laid the foundation for the future evolution of technical analysis.

In the 1700s, a pivotal figure in the development of technical analysis emerged in the form of Homma, a renowned trader of rice futures. Homma's insights went beyond simple supply and demand dynamics, as he recognized the role of emotions in driving market movements. His groundbreaking realization that market sentiment could influence prices laid the groundwork for modern technical analysis techniques (Nison, 1994).

One of the most enduring contributions to technical analysis is the introduction of candlestick charting, originating from Japan in the 1700s. Although the technique was introduced to the Western world by Steve Nison in the late 1980s, its roots can be traced back centuries. The enduring relevance of candlestick charting highlights its effectiveness

in capturing market sentiment and price action, transcending time and geographic boundaries.

Over time, charting systems have undergone significant advancements to enhance investors' understanding of financial markets. From rudimentary charts used in the early days of technical analysis to the sophisticated tools available today, each iteration has contributed to a deeper comprehension of market dynamics. These incremental improvements have empowered investors to make more informed decisions and navigate the complexities of modern financial markets (Manic, 2017). Despite its centuries-old origins, technical analysis remains a cornerstone of financial market analysis. The enduring principles established by early pioneers like Homma continue to shape contemporary trading strategies. As technological advancements and big data analytics continue to reshape the landscape of financial markets, the principles of technical analysis remain relevant, providing traders with valuable insights into market behavior and opportunities for profit (Manic, 2017).

2.1.2 Type of Technical Analysis Indicators

There are various type of technical analysis indicators in stock market. Out of them some of the indicators are mentioned below.

2.1.2.1 Moving Averages

Moving averages are essential trend indicators used by stock traders to smooth out price data and identify trends. By calculating the average price of a security over a specified period, moving averages help traders discern the overall direction and strength of a trend. They're useful for identifying trend reversals and establishing support and resistance levels. While they're lagging indicators, providing signals after a trend has begun, they're crucial for navigating market trends and making informed trading decisions.

2.1.2.2 Moving Average Convergence Divergence (MACD)

The MACD is a versatile momentum indicator used to identify changes in trend strength, direction, momentum, and duration. Comprising two lines – the MACD line and signal line – it measures the relationship between two moving averages. Crosses above the signal line indicate bullish momentum, while crosses below suggest bearish momentum. Traders also analyze MACD divergence from price to identify potential reversals or continuations. It's essential for generating trend-following and momentum signals in technical analysis.

2.1.2.3 Parabolic Stop and Reverse (Parabolic SAR)

The Parabolic SAR is a trend-following indicator designed to identify potential reversals in market price direction. Developed by Welles Wilder, it places dots above or below price bars to indicate trend changes. Switches from above to below suggest bullish trend reversals, while switches from below to above indicate bearish reversals. Traders use it with other indicators to confirm signals and manage risk.

2.1.2.4 Stochastic Oscillator

The Stochastic Oscillator is a momentum indicator used to predict potential trend reversals by comparing the closing price of a security to its price range over a specified period. It consists of two lines, %K and %D, which oscillate between 0 and 100. Readings above 80 indicate overbought conditions, suggesting a potential downturn, while readings below 20 suggest oversold conditions, indicating a potential upturn. Traders use it to identify entry and exit points in the market.

2.1.2.5 Commodity Channel Index (CCI)

The Commodity Channel Index (CCI) is an oscillator used to identify price reversals, extremes, and trend strength. Developed by Donald Lambert, it measures a security's current price relative to its average price over a specified period, adjusted for volatility. Readings above +100 indicate overbought conditions, suggesting a potential downturn, while readings below -100 suggest oversold conditions, indicating a potential upturn. Traders use it to confirm trends and detect trend changes.

2.1.2.6 Relative Strength Index (RSI)

The Relative Strength Index (RSI) is a momentum oscillator that measures the recent strength and velocity of price movements in a security. It oscillates between 0 and 100 and is calculated based on the ratio of upward and downward price movements over a specified period. Readings above 70 indicate overbought conditions, suggesting a potential downturn, while readings below 30 suggest oversold conditions, indicating a potential upturn. Traders use it to identify entry and exit points and to confirm trends.

2.1.2.7 Bollinger Bands

Bollinger Bands are a volatility indicator that consists of a simple moving average (SMA) and two standard deviations plotted above and below the SMA. The bands expand and contract based on market volatility, indicating the "highness" or "lowness" of prices relative to previous trades. When prices touch or move outside the bands, it may signal overbought or oversold conditions, suggesting potential reversals or continuation of trends.

2.1.2.8 Average True Range (ATR)

The Average True Range (ATR) is a volatility indicator that measures the degree of price volatility in a security over a specified period. It considers the true range of price movement, accounting for gaps and limit moves. A higher ATR value indicates higher volatility, while a lower value indicates lower volatility. Traders use ATR to set stop-loss orders and determine position sizing based on market volatility.

2.1.2.9 On-Balance Volume (OBV)

On-Balance Volume (OBV) is a momentum indicator that attempts to measure the level of accumulation or distribution in a security. It is calculated by adding the volume on up days and subtracting the volume on down days. The resulting OBV line can help traders confirm price trends: rising OBV confirms uptrends, while falling OBV confirms downtrends. Divergences between OBV and price movements can signal potential reversals. Traders use OBV to assess the strength of price trends and identify potential buying or selling opportunities.

2.1.2.10 Volume Rate of Change

Volume Rate of Change (VROC) is a technical indicator that highlights changes in trading volume over a specified period. It measures the percentage change in volume from one period to the next, helping traders identify increases or decreases in volume. High positive values of VROC suggest rising trading activity, often occurring at market tops, bottoms, or breakouts. Conversely, negative values indicate declining trading activity. Traders use VROC to confirm price trends and assess the strength of market moves based on changes in trading volume.

2.1.2.11 Candlestick Patterns

Candlestick patterns are graphical representations of price movements in the form of candlesticks on a chart. Each candlestick typically represents the open, high, low, and close prices for a specific period, such as one day. Different candlestick patterns, such as doji, hammer, shooting star, and engulfing patterns, convey information about market sentiment and potential trend reversals. Traders use candlestick patterns to identify entry and exit points, as well as to confirm other technical indicators' signals.

2.1.2.12 Bar Chart

A bar chart is a type of chart that represents price movements for a financial asset over a specified period. Each bar on the chart displays the opening, high, low, and closing prices for that period. Bar charts provide traders with visual insights into price action, including

the range and direction of price movements. By analyzing patterns and trends in bar charts, traders can make informed decisions about buying or selling assets.

2.1.2.13 Chart Patterns

Chart patterns are formations that appear on price charts and indicate potential future price movements. Common chart patterns include head and shoulders, triangles, flags, and double tops and bottoms. Each pattern has specific characteristics that traders use to predict market direction. For example, a head and shoulders pattern typically signals a trend reversal, while a triangle pattern suggests a continuation of the existing trend. By recognizing chart patterns, traders can anticipate market movements and adjust their trading strategies accordingly.

2.1.3 Trading Versus Investing

Distinguishing between trading and investing is akin to understanding diverse exercise routines catering to different objectives. Trading resembles a sprint, focusing on quick gains through short bursts of activity, while investing mirrors a marathon, emphasizing long-term endurance and gradual growth. When investing, individuals commit to assets for extended periods, akin to building endurance over time. Conversely, trading involves frequent transactions to capitalize on short-term price fluctuations, akin to sprinting for immediate gains (Pitters & Oberlechner, 2014).

Investing typically adopts a long-term outlook, with investors holding assets for months or years to achieve gradual growth. This approach aligns with marathon runners, who pace themselves for extended periods. Conversely, trading operates on a short-term horizon, with traders entering and exiting positions swiftly, often within minutes or days. This short-term focus resembles the rapid movements of sprinters during a race (Frans et al., 2022).

Investing is generally perceived as less risky than trading due to its long-term orientation and focus on stable, diversified portfolios. Investors aim to withstand market fluctuations over time, much like enduring challenges in a marathon. In contrast, trading carries higher risks, especially during volatile market conditions. Traders must navigate rapid price movements and employ risk management strategies to mitigate potential losses, akin to maneuvering through obstacles in a sprint (Waisi, 2020).

Trading often entails higher costs compared to investing due to frequent transactions and brokerage fees associated with each trade. These costs can accumulate significantly, particularly for active traders executing multiple transactions. In contrast, investing tends to be more cost-efficient, with fewer transactions and lower expenses, making it akin to a

frugal approach to marathon training, where every expenditure is carefully managed for long-term sustainability (Pitters & Oberlechner, 2014).

Investors typically employ fundamental analysis, focusing on a company's financial health, management quality, and industry prospects when making investment decisions. This method mirrors the meticulous planning and preparation of marathon runners, who analyze terrain and pacing strategies for optimal performance. Conversely, traders often rely on technical analysis, studying price charts and indicators to identify short-term trends and trading opportunities. This approach resembles the agility and adaptability of sprinters, who adjust their strategies based on real-time conditions (Frans et al., 2022).

2.2 Theoretical Review

2.2.1 Greater Fool Theory

The Greater Fool Theory is a controversial concept in investing that revolves around the belief that one can profit from buying investments at any price, regardless of their underlying value, because there will always be someone else willing to pay an even higher price in the future (Sun, 2011). This theory essentially suggests that investors can rely on finding a "greater fool" who will be willing to purchase their overvalued assets, allowing them to sell at a profit. However, this approach disregards traditional valuation methods and relies solely on the expectation of finding someone else to purchase the investment at a higher price.

Proponents of the Greater Fool Theory argue that in dynamic and rapidly changing markets, there will always be individuals who are willing to pay a premium for assets based on their future growth potential or speculative hype (Goldring, 2020). These investors believe that they can capitalize on market momentum and investor sentiment to profit from short-term price fluctuations without necessarily considering the fundamental value of the asset. In this view, the key to success lies in timing the market and being able to sell to the next investor at a higher price.

However, critics of the Greater Fool Theory warn against the dangers of speculative bubbles and irrational exuberance in financial markets (Holt, 2017). They argue that relying on finding a greater fool to buy overpriced assets is a risky strategy that can lead to significant losses when market sentiment changes or when the underlying fundamentals of the investment are exposed. In essence, this approach amounts to little more than gambling, as it does not involve careful analysis of the investment's intrinsic value or potential risks.

Moreover, the Greater Fool Theory can contribute to market inefficiency and volatility, as it encourages investors to engage in herd behavior and follow the crowd without regard for underlying fundamentals (Goldring, 2020). When investors focus solely on finding someone else to sell to at a higher price, it can create artificial demand for assets, driving prices even higher and potentially creating asset bubbles that eventually burst, leading to sharp market corrections.

The Greater Fool Theory has been associated with speculative frenzies and market manias, such as the dot-com bubble of the late 1990s and the housing bubble of the mid-2000s (Holt, 2017). In both cases, investors poured money into overvalued assets based on the belief that prices would continue to rise indefinitely, only to suffer significant losses when the bubbles inevitably burst. These episodes serve as cautionary tales about the dangers of relying on the Greater Fool Theory as an investment strategy.

2.2.2 Dow Theory

The Dow Theory, originating from the writings of Charles H. Dow, a prominent journalist and co-founder of Dow Jones & Company, lays the foundation for understanding stock price movements through technical analysis (Brown et al., 1998). Developed from Dow's editorials in the Wall Street Journal, this theory hypothesizes that the stock market does not operate randomly but instead follows discernible trends. These trends are categorized into three main types: primary, secondary, and minor trends.

The primary trend, also known as the major trend, represents the overarching movement of the market and can persist for varying durations, ranging from less than a year to several years (Schannep, 2008). This trend can either be bullish, characterized by upward price movements, or bearish, marked by downward price movements. Primary trends are crucial for investors as they provide insight into the broader direction of the market over the long term. Identifying and understanding primary trends is fundamental to successful investment decision-making.

In contrast, secondary trends are shorter-term movements that occur within the primary trend (Yadav, 2017). While they can last for weeks or months, secondary trends are considered corrective phases within the broader primary trend. These movements may appear as corrections or retracements against the primary trend's direction. Secondary trends provide opportunities for traders to capitalize on short-term price fluctuations while remaining mindful of the overarching primary trend.

Additionally, the Dow Theory recognizes minor trends, which encompass the day-to-day fluctuations or short-term movements in stock prices (Prabakaran & Krishnaveni, 2016). These trends are of very brief duration and may not necessarily reflect the broader primary or secondary trends. While minor trends may present trading opportunities for day traders or short-term investors, they are often subject to greater volatility and noise, making them less significant for long-term investment strategies.

Scholars such as Brown et al. (1998) have extensively studied the Dow Theory's principles and their applications in financial markets. Their research contributes to a deeper understanding of how investors interpret and utilize Dow's insights to navigate the complexities of the stock market. Similarly, authors like Schannep (2008), Yadav (2017), and Prabakaran and Krishnaveni (2016) have explored various aspects of the Dow Theory, including its historical significance, practical implications for investment strategies, and adaptations in modern financial markets. The Dow Theory remains a cornerstone of technical analysis, providing investors with valuable insights into market trends and price movements. By understanding the dynamics of primary, secondary, and minor trends, investors can make more informed decisions and capitalize on opportunities while managing risks effectively.

2.2.3 Random Walk Theory

The Random Walk Theory posits that financial market price movements, whether in stocks, commodities, or other assets, follow a random distribution. Advocates of this theory argue that traditional analysis tools like technical and fundamental analysis are unreliable due to the unpredictable nature of market movements. According to Oluwafemi et al. (2020), technical analysis lacks reliability because historical price data cannot accurately predict established trends in a market characterized by randomness. Similarly, fundamental analysis is considered unreliable due to the poor quality and misinterpretation of information available.

Malkiel (2016) supports this perspective by suggesting that while price patterns in the stock market may appear to repeat, the variety of these patterns makes it difficult to confidently predict future outcomes based on past behavior. He refutes the notion of predictable cycles, such as uptrends and downtrends, comparing them to the random runs of luck experienced by gamblers. Malkiel (2016) conducted an experiment with his students involving a hypothetical stock priced at $50. Using a coin toss to determine daily closing prices, they

observed apparent patterns in the resulting stock price chart. However, they concluded that the distribution was entirely random, as each day's closing price was determined by chance. Malkiel (2016) aligns with the Efficient Market Hypothesis, which asserts that markets instantly incorporate all relevant information regarding a stock, rendering attempts to outperform the market futile. According to this hypothesis, investors are better off investing in passive index funds rather than attempting to select individual stocks (Malkiel, 2016).

2.2.4 Zero Sum Game

The concept of a zero-sum game, rooted in economic theory, posits that any gains made by one player or entity result in equivalent losses experienced by another player or entity. In essence, the net effect of gains and losses on both sides should sum up to zero. An illustrative example commonly cited to explain this concept is Poker, where the winnings of one player directly correspond to the losses incurred by another player (Ibrahim & Raahemifar, 2016).

In the realm of financial markets, trading often mirrors the dynamics of a zero-sum game. When an investor purchases an asset, another investor must sell it, creating a situation where gains for one party are offset by losses for the other. However, it is crucial to recognize that this dynamic does not necessarily translate into a simple winner-loser scenario. Engle (2008) highlights that while one party may profit from a transaction, the other party may also have previously realized gains or may continue to profit from subsequent market movements.

To delve deeper into the nuanced nature of trading as a zero-sum game, it's essential to consider the broader context of market dynamics. Caloni (2009) emphasizes that the stock market differs from classic zero-sum games like Poker because participants have the potential to increase their net worth. Unlike in Poker, where one player's loss directly reduces their net holdings, both buyers and sellers in the stock market can enhance their overall wealth through strategic decision-making and market movements.

Dolgopolov (2012) further elaborates on the implications of the zero-sum game theory within the stock market context. While individual transactions may exhibit zero-sum characteristics, the aggregate effect of market activities is more complex. Market participants have varying investment horizons, risk tolerances, and strategies, leading to diverse outcomes. Moreover, factors such as market efficiency, informational advantages, and regulatory influences shape the dynamics of trading, influencing the distribution of gains and losses among participants.

While the zero-sum game concept offers valuable insights into the competitive nature of trading, its application in the stock market requires a nuanced understanding. Engle (2008), Caloni (2009), and Dolgopolov (2012) collectively underscore the multifaceted nature of market interactions, where participants strive to optimize their positions while navigating a complex web of factors. Recognizing the potential for both gains and losses, investors can adopt informed strategies to navigate the dynamic landscape of the stock market.

2.3 Empirical Review

Pheng et al. (2024) analyzed optimizing stock trend prediction by developing a comprehensive multi-technical indicator strategy. In the context of the Malaysian stock market, technical analysis (TA) is often underutilized despite its potential for identifying price trends. The researchers sought to address this gap by proposing a balanced approach that combines various technical indicators to enhance short-term price trend prediction. The model considered factors such as trend, volatility, momentum, volume, and market sentiment, integrating them to overcome the limitations of individual indicators. Through multiple regression analysis, the researchers evaluated the predictive power of these indicators and their combinations, ultimately developing a four-factor model that strikes a balance between complexity and predictive accuracy. The study yielded promising results, demonstrating a profit ROI of 87.45% within a six-month period, highlighting the effectiveness of the proposed multi-technical indicator strategy in enhancing trading tactics. This research contributes valuable insights into the potential of technical analysis in the Malaysian stock market, emphasizing the importance of adopting a comprehensive approach to improve trading performance.

Khan et al. (2024) examined an approach to portfolio selection by proposing an automatic trading system that incorporates an investor's trading strategy, whether aggressive, conservative, or neutral. The system utilizes technical indicators to forecast future price behavior of assets and clusters them into three groups: "Buy," "Sell," and "Hold." A gradient-based fuzzy rule system is developed to identify these groups based on the technical indicator values of the cluster centers. Additionally, a labelling algorithm is devised to address instances where the fuzzy rule-based system identifies multiple groups for buy, sell, or hold. The clustered assets are then inputted into a credibilistic portfolio optimization model, which models asset returns using coherent fuzzy numbers. To solve the optimization model, a genetic algorithm is employed, leveraging the problem's special structure. The proposed methodology is demonstrated through a case study involving the

components of the NASDAQ-100 index. The study's objective is to provide investors with an automated trading system that effectively selects portfolios based on their preferred trading strategies and technical analysis indicators, ultimately aiming to enhance portfolio performance and profitability.

Pasaribu (2024) examined stock investment decisions within the telecommunications sector listed on the Indonesia Stock Exchange, employing a technical analysis approach. Utilizing a quantitative descriptive research design without hypotheses, the study employed purposive sampling to select a representative sample of telecommunications companies listed on the exchange. The research focused on analyzing monthly stock price movements of three issuers in the fourth quartile of 2023, specifically from October to December. The findings of the study indicate that while MACD crossovers are commonly used as signals, they often yield false signals without confirmation from momentum indicators like RSI. Specifically, in the cases of TLKM, ISAT, and EXCL, although MACD crossovers occurred, the RSI did not exhibit significant movement to validate the signals, suggesting a potential for reversal. The study underscores the importance of multi-factor validation, indicating that MACD crossovers should be confirmed by other indicators to strengthen their reliability before being used as references for entry or exit positions. Overall, the research contributes valuable insights into the complexities of technical analysis in stock investment decisions, particularly within the telecommunications sector of the Indonesian Stock Exchange.

Inani et al. (2024) explored the landscape of technical analysis in stock markets through bibliometric and topic modeling approaches. The primary objective was to provide insights into the various themes and trends within this domain over the last two decades. Utilizing a dataset comprising 589 English-language journal articles indexed in Scopus from 2003 to 2023, the study employed keyword co-occurrence analysis and structural topic modeling to identify and analyze thematic clusters. Through these methodologies, five prominent thematic clusters were uncovered: pattern-based forecasting, rule-based trading, algorithmic trading, techno-fundamental trading, and machine learning & sentiment analysis. Each cluster represents a distinct aspect of technical analysis, ranging from traditional pattern-based forecasting to the application of advanced machine learning techniques for predicting stock prices. The findings revealed that rule-based trading, machine learning & sentiment analysis, and algorithmic trading were the three predominant topics within the dataset, underscoring their significance in current research discussions.

This study contributes valuable insights into the evolving landscape of technical analysis in stock markets, highlighting the diverse approaches and methodologies employed by researchers to navigate and understand market dynamics.

Riaz and Zubair (2024) investigated the influence of self-control and over-confidence on investment decision-making, focusing on the mediating fundamental and technical analysis. The study targeted institutional investors operating within the Pakistan Stock Exchange Market, encompassing the Lahore, Karachi, and Islamabad Stock Exchanges. Using a sample of 375 institutional investors, selected through stratified and cluster sampling techniques, the researchers assessed the behavioral impact of stock market fluctuations on investment decisions. Data collection was conducted using a 5-point Likert scale, enabling respondents to express their agreement or disagreement on a continuum. The study aimed to elucidate the behavioral consequences of integrating self-control and over-confidence into investment decisions, especially in relation to market instability and the application of fundamental and technical analysis. The findings revealed that both self-control and over-confidence significantly influenced investment decisions, with fundamental and technical analysis serving as important mediators.

Karki et al. (2023) evaluated the performance of five widely used technical indicators in the context of the Nepal Stock Exchange (NEPSE) indexes. Their research aimed to assess indicators such as the simple moving average, moving average convergence and divergence, relative strength index, stochastic oscillator, and Bollinger Band. Employing a descriptive and quantitative research design, the study analyzed daily closing index data of NEPSE and its sub-indices over a significant period from September 1, 2012, to August 31, 2022. By incorporating technical trading rules into the modeling process and utilizing various performance metrics, the researchers evaluated the effectiveness of these indicators through modeling, backtesting, and statistical analysis. Additionally, the predictability of the indicators was assessed using standard statistical analysis and bootstrap techniques with a random walk model. The findings of the study suggest that the technical strategies represented by the analyzed indicators generally support the effectiveness of technical analysis in the NEPSE. However, an exception was observed with the relative strength index, which yielded negative returns. Furthermore, certain indices showed that the simple moving average, relative strength, and Bollinger band failed to generate significant returns. Contradictory results were also obtained from bootstrap techniques, casting doubt on the forecasting ability of technical strategies in the Nepali stock market. These findings

underscore the importance of critically evaluating the performance of technical indicators and raise questions about their real efficacy in guiding investment strategies in the NEPSE.

Almeida and Vieira (2023) assessed the academic understanding of decision support tools for investments in the capital market, specifically focusing on fundamental analysis, technical analysis, and Ichimoku dynamics. Utilizing bibliometric analysis, they evaluated scientific production over the last thirty years, employing Bradford's Law, Lotka's Law, and Zipf's Law to identify publication patterns, gaps, and collaboration networks. Analyzing 1710 relevant academic publications retrieved from the Web of Science database from 1990 to May 22, 2023, the study aimed to advance scientific knowledge by uncovering gaps in research, particularly in the limited literature on Ichimoku. Their findings revealed a growing trend of research in this area and identified emerging research topics and areas of interest, as well as collaboration networks among authors, institutions, and countries. The study's significance lies in providing valuable insights for financial professionals and investors interested in applying these methodologies for price forecasting, thereby supporting investment decision-making, trading strategies, and portfolio management.

Singh et al. (2022) explored stock market prediction accuracy by leveraging advanced neural network methodologies. The study focused on technical analysis, utilizing neural networks to predict stock market trends, specifically examining the purchasing and selling prices of stocks on the Bombay Stock Exchange (BSE). The researchers employed a Long-Short-Term Memory (LSTM) neural network model with an embedded layer and LSTM neural network to forecast market movements. Their experimental design demonstrated that the deep LSTM model with multiple layers significantly improved prediction accuracy, yielding more precise results. This enhanced prediction capability provided a robust framework for achieving substantial profits in stock trading. The findings highlighted the effectiveness of deep LSTM models in capturing complex market patterns and trends, reinforcing the potential of neural networks in financial forecasting (Singh et al., 2022).

Jashan (2022) examined significance of technical analysis in rationalizing investment decisions in equities within the Abu Dhabi Stock Exchange. Utilizing a descriptive analytical approach, Jashan employed a comprehensive inventory method to select a study population of 120 investors, from which a sample of 90 investors was drawn. Data collection was facilitated through a questionnaire, the validity and reliability of which were confirmed, and subsequent data analysis was conducted using the Statistical Package for

the Social Sciences (SPSS). The study found that the participants agreed on the importance of technical analysis and the the technical analyst in guiding investors' decisions. Additionally, the study highlighted the economic sectors in which investments were predominantly made based on technical indicators, revealing a high degree of consensus among respondents. Based on these findings, the research concluded with several recommendations and proposals aimed at enhancing the application of technical analysis for investment decisions in the stock market.

Levi et al. (2021) evaluated the advantages of using both fundamental and technical analysis in making systematic investment decisions in stock market equities. The study focused on the significance of equity investments in generating additional income and managing future risks, particularly in the context of Indian portfolio investors. The researchers reviewed past literature to analyze how fundamental research, which examines factors influencing stock prices, and technical analysis, which assesses market behavior through performance indicators, contribute to investment decisions. They highlighted that advancements in technology, including machine learning algorithms like ANN and SNV, have enhanced the processing of data for decision-making. The findings indicated that a combined use of fundamental and technical analysis aids in determining intrinsic value, identifying patterns, and making informed buy/sell decisions to achieve better profits.

Prasad and Seetharaman (2021) analyzed the importance of machine learning in making investment decisions in the stock market. The study set out to gather and review machine learning research articles focusing on investment decisions, evaluate the performance of various algorithms, identify key feature variables, and assess the fitness of these models using root mean squared error (RMSE) and accuracy metrics. This qualitative study relied on secondary data collected from well-ranked journals. The authors reviewed over 50 research papers to analyze the feature variables and the performance of different algorithms. They found that models incorporating financial news, trading volume, and technical indicators significantly improved prediction accuracy. Among the machine learning models analyzed, Long Short-Term Memory (LSTM) displayed superior accuracy, while reinforcement learning was deemed best due to its complexity and independence from target variables. The study concluded that machine, deep, and reinforcement learning algorithms are reliable and instrumental for predicting stock movements and making investment decisions.

Ayala et al. (2021) evaluated technical analysis strategies in stock market indices using a machine learning approach. The objective was to address the challenge of forecasting price values or movements in the stock market by proposing a hybrid approach that combines machine learning techniques with technical analysis indicators. The researchers proposed applying a technical indicator alongside a machine learning approach to generate trading signals, with a focus on simplicity and effectiveness. They tested different machine learning techniques including Linear Model, Artificial Neural Network, Random Forests, and Support Vector Regression, in combination with technical strategies such as Triple Exponential Moving Average (TEMA) and Moving Average Convergence/Divergence (MACD). The study utilized daily trading data from major indices like Ibex35, DAX, and Dow Jones Industrial to evaluate the performance of the proposed technique. The findings indicated that integrating machine learning techniques into technical analysis strategies improved the quality of trading signals and enhanced the competitiveness of the proposed trading rules. This research contributes to the advancement of stock market prediction methodologies by demonstrating the effectiveness of hybrid approaches combining machine learning and technical analysis.

Nti et al. (2020) examined systematic and critical review of research on stock market prediction using machine learning, focusing on fundamental and technical analysis. The study reviewed 122 relevant academic works published over an 11-year period (2007–2018). The researchers categorized the techniques from these reports into technical, fundamental, and combined analyses based on criteria such as dataset nature, number of data sources, data timeframe, machine learning algorithms used, machine learning tasks, accuracy and error metrics, and software packages used for modeling. The review revealed that 66% of the documents focused on technical analysis, while 23% and 11% were based on fundamental and combined analyses, respectively. Additionally, 89.34% of the reviewed documents utilized single data sources, whereas 8.2% and 2.46% used two and three sources, respectively. Support vector machines and artificial neural networks emerged as the most frequently used machine learning algorithms for stock market prediction. The findings highlighted the predominance of technical analysis in stock market prediction and underscored the effectiveness of specific machine learning algorithms in this domain (Nti, Adekoya, & Weyori, 2020).

Nuzula et al. (2019) investigated the influence of technical analysis, sources of information, and emotions on investment decisions in capital markets. The study utilized questionnaires

to gather data from respondents, focusing on how these behavioral aspects impact investors' decisions. To analyze the data, the authors applied a 0.25 quantile regression due to the non-normal distribution patterns of the data. The results revealed that among the three independent variables examined, only the source of information had a significant impact on investment decisions. Technical analysis and emotions did not significantly influence investment decisions, indicating that investors in East Java Province still relied more on fundamental analysis despite the noted use of technical analysis. This finding suggests that while technical analysis and emotions play a role, they are not the primary determinants of investment decisions in the region.

Edwards et al. (2018) explored investors with comprehensive tools and concepts for making informed and profitable trading decisions through technical analysis. The primary objective of their study was to explore and explain various technical theories, such as The Dow Theory, reversal patterns, consolidation formations, and trend analysis, alongside practical trading tactics. Their methodology included a detailed examination of both long- and short-term stock trends, technical analysis of commodity charts, and advancements in investment technology. The authors introduced a comprehensive guide to trading tactics that covered stock selection, charting, risk management, and portfolio diversification. Additionally, the updated edition incorporated new material on Pragmatic Portfolio Theory as an alternative to Modern Portfolio Theory and presented a simpler, yet more powerful, alternative to Dow Theory. Their findings emphasized the efficacy of technical trading concepts and the importance of balancing and diversifying stock portfolios. The study concluded that these technical analysis tools and concepts could significantly enhance investors' ability to craft long-term successful trading strategies.

Utami and Nugroho (2017) analyzed whether investors in Indonesia preferred technical or fundamental analysis for their investment decisions and to identify the factors influencing this preference. The research employed a questionnaire-based survey with 125 participants, focusing on six independent variables: investor's education, experience, information accessibility, time horizon, trading activity frequency, and perception toward corporate disclosure. The findings indicated that Indonesian investors predominantly favored technical analysis over fundamental analysis. Additionally, the study revealed that investor's experience and time horizon were significant factors influencing the choice of investment analysis method. These results provided insights into the preferences and

behaviors of investors in the Indonesian stock market, emphasizing the experience and time horizon in shaping their analytical approaches.

Shen and Tzeng (2015) examined investment decision-making based on technical analysis by developing a hybrid soft computing model. This model sought to address the inconsistency and down-side risk associated with various technical indicators by retrieving imprecise patterns through a Variable Consistency Dominance-based Rough Set Approach (VC-DRSA) combined with fuzzy inference-enhanced signal discretization. Initially, the study categorized trading signals into straightforward and complicated groups. Straightforward signals, determined by precise rules, were evaluated using trading strategies to assess indicator outcomes. Complicated signals, requiring imprecise judgments from experts, were enhanced using fuzzy inference techniques and similarly tested. The second stage involved combining signals and outcomes for VC-DRSA modeling to derive decision rules. The model was empirically tested on the Taiwan stock market from 2002 to 2014, achieving nearly 80% classification accuracy. The findings indicated that considering multiple technical indicators simultaneously provides practical and reliable decision rules for investors.

Stanković et al. (2015) examined the efficacy of technical analysis and predictive modeling in optimizing investment strategies in emerging markets. The research focused on trading strategies based on various technical indicators, including moving averages, Moving Average Convergence-Divergence (MACD), and Relative Strength Index (RSI). The study utilized two moving averages—a long period and a short period—to generate simple trading rules. These technical indicators served as features for defining a predictive model based on Least Squares Support Vector Machines (LS-SVMs). The LS-SVM classifier predicted trends in stock indices' values, producing binary signals for trading strategies. The researchers compared the LS-SVM model's results with traditional statistical methods for predicting financial series trends. They concluded that machine learning techniques, particularly the LS-SVM model, better captured the non-linear patterns dominant in financial markets. The application of LS-SVM in the decision-making process for financial market investments significantly outperformed the Buy & Hold strategy and traditional technical trading strategies, thereby enhancing investment profitability.

Bonga (2015) explored the importance of conducting thorough fundamental analysis when investing in various securities. The study aimed to demonstrate that one does not need to be a financial analyst to identify high-risk assets or assets with potential for good future

returns. Bonga explored the two primary approaches traders use in financial markets: technical analysis and fundamental analysis. Technical analysis involves using historical stock statistics, such as price and volume data, to forecast future prices. In contrast, fundamental analysis seeks to predict a stock's intrinsic value and identify opportunities where the live price deviates from the calculated intrinsic price. The study emphasized that efficient investment requires the use of both fundamental and technical analysis. By combining these approaches, investors can better detect mispriced securities and make more informed investment decisions. Bonga concluded that a dual approach enhances the ability to achieve profitable investment outcomes by balancing risk and return considerations.

Ghobadi and Torabi (2015) investigated the use of a fuzzy multi-criteria decision-making (FMCDM) approach to optimize investment rankings on the Tehran Stock Exchange. The main objective was to address the complexities investors face when evaluating numerous criteria, such as Overall Trend, Buying/Selling Pressure, Reward to Risk Ratio, and Potential Entry Levels for new long positions. The study employed a fuzzy hierarchical analytic approach to ascertain the weighting of subjective judgments, using triangular fuzzy numbers to establish weights and anticipated achievement values. Additionally, a non-additive fuzzy integral technique was applied to evaluate the technical analysts, demonstrating its effectiveness in dealing with the interdependencies among criteria. The research findings indicated that by ranking fuzzy weights and synthetic performance values, investors could determine the relative importance of various criteria and select optimal investment strategies. This fuzzy integral method proved particularly suitable for evaluating complex and interrelated investment criteria, providing a robust framework for making informed investment decisions.

Wang and Chan (2007) investigated the potential profitability of bull flag technical trading rules utilizing pattern recognition-based template matching techniques for the Nasdaq Composite Index (NASDAQ) and Taiwan Weighted Index (TWI). Their primary objective was to discover stock market trading rules using pattern recognition and technical analysis. To minimize data snooping bias, the study conducted various experiments to assess the effectiveness of their proposed method. The empirical findings revealed that all technical trading rules correctly predicted the direction of changes in both the NASDAQ and TWI indices. This discovery suggests valuable insights for investors regarding asset allocation strategies. Additionally, the study observed that better bull flag template price fit correlated

with higher average returns. Notably, the average return of trading rules conditioned on bull flag signals significantly outperformed the strategy of buying every day during the study period, particularly for the TWI index. Through their research design and analysis, Wang and Chan provided evidence supporting the effectiveness of pattern recognition and technical analysis in discovering profitable trading rules in stock markets.

Wong et al. (2003) examined the effectiveness of technical analysis in timing stock market entry and exit in the Singapore Stock Exchange (SES). Their objective was to evaluate the two prominent technical indicators, namely the Moving Average and the Relative Strength Index, in generating returns. The researchers introduced test statistics to assess the performance of these indicators. Using Singaporean data, their findings suggest that both indicators can indeed be used to produce significantly positive returns. Specifically, member firms of the SES were observed to achieve substantial profits by employing technical analysis techniques. This observation sheds light on why many member firms maintain dedicated trading teams that heavily rely on technical analysis. The study contributes to the understanding of the practical application of technical analysis in real-world investment contexts, particularly within the Singaporean stock market. By demonstrating the profitability of technical analysis strategies, the research underscores the importance of considering such tools in investment decision-making processes. Additionally, the use of test statistics provides a robust methodological approach for evaluating the performance of technical indicators, enhancing the credibility of the study's findings within the realm of financial economics.

Dourra and Siy (2002) explored the application of fuzzy logic engineering tools in the field of technical analysis within finance. The primary objective was to enhance the traditional technical analysis methods, which rely on indicators used by experts to evaluate stock prices. Their approach involved mapping these indicators into new inputs suitable for a fuzzy logic system, with past sequences of stock prices serving as the only required inputs. By utilizing fuzzy logic, the system was designed to formulate decision-making processes based on specific price movements or formations. The efficacy of this new stock evaluation method was measured by comparing its outputs against actual stock price movements. The results demonstrated that the fuzzy logic-based system outperformed market performance, proving to be a superior tool in the technical analysis domain. Additionally, the flexibility of the system was highlighted, showcasing its adaptability and effectiveness in various market conditions.

Table 1
Summary of Empirical Review

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
1	Pheng et al. (2024)	Optimizing Stock Trend Prediction with a Comprehensive Multi-Technical Indicator Strategy	To develop a balanced multi-technical indicator strategy for enhancing short-term price trend prediction in the Malaysian stock market	Employed multiple regression analysis	Achieved a profit ROI of 87.45% within six months, demonstrating the efficiency of the proposed multi-technical indicator strategy.
2	Khan et al. (2024)	A Fuzzy Rule-based System for Portfolio Selection using Technical Analysis	To develop an automatic trading system for portfolio selection incorporating different investor trading strategies	Employed technical indicators and a fuzzy rule-based system for clustering assets	Proposed methodology demonstrated enhanced portfolio selection based on preferred trading strategies and technical analysis
3	Pasaribu (2024)	Technical Analysis of Stock Investment Decisions in Telecommunication Companies Listed on the Indonesian Stock Exchange	To examine stock investment decisions within the telecommunications sector listed on the Indonesia Stock Exchange	Utilized quantitative descriptive research design without hypotheses and purposive sampling	MACD crossovers without confirmation from momentum indicators like RSI tend to yield weak and inaccurate signals, requiring multi-factor validation for reliability
4	Inani et al. (2024)	Navigating the technical analysis in stock markets: Insights from bibliometric and topic modeling approaches	To explore the landscape of technical analysis in stock markets over the last two decades using bibliometric and topic modeling approaches	Utilized a dataset comprising 589 English-language journal articles indexed in Scopus from 2003 to 2023; employed keyword co-occurrence analysis and structural topic modeling	Uncovered five thematic clusters: pattern-based forecasting, rule-based trading, algorithmic trading, techno-fundamental trading, and machine learning & sentiment analysis; identified rule-based trading, machine learning & sentiment analysis, and algorithmic trading as predominant topics

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
5	Riaz and Zubair (2024)	Does Self-Control and Over-Confidence Influence Investment Decision: The Mediating Fundamental and Technical Analysis	To investigate the influence of self-control and over-confidence on investment decisions, mediated by fundamental and technical analysis	Stratified and cluster sampling; sample of 375 institutional investors; data collected using a 5-point Likert scale	Self-control and over-confidence significantly influenced investment decisions, with fundamental and technical analysis serving as mediators.
6	Karki et al. (2023)	Performance evaluation of technical analysis in the Nepali stock market: Implications for investment strategies	To examine the performance of widely used technical indicators on NEPSE indexes	Utilized a descriptive and quantitative research design. Analyzed daily closing index data of NEPSE and its sub-indices.	Technical strategies generally support effectiveness in NEPSE. Relative strength index yielded negative returns. Certain indicators failed to generate significant returns in certain indices. Bootstrap techniques raised doubts on forecasting ability.
7	Almeida and Vieira (2023)	Technical Analysis, Fundamental Analysis, and Ichimoku Dynamics: A Bibliometric Analysis	To contribute to academic knowledge on decision support tools for investments, focusing on fundamental analysis, technical analysis, and Ichimoku	Utilized bibliometric analysis to evaluate scientific production and identify publication patterns, gaps, and collaboration networks	Revealed a growing trend of research in Ichimoku dynamics. Identified emerging research topics, areas of interest, and collaboration networks.
8	Singh et al.(2022)	Application of neural network to technical analysis of stock market prediction	To develop a neural network-based approach for stock market prediction using LSTM	Experimental comparison of LSTM models	Deep LSTM model with multiple layers provides accurate predictions, potentially leading to higher profits in stock market trading.

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
9	Jashan (2022)	Technical analysis as a tool to rationalize investment decision in equities: an application study on the Abu Dhabi Stock Exchange	To identify the importance of technical analysis and its applications in rationalizing investment decisions in equities within the Abu Dhabi Stock Exchange	Descriptive analytical approach; questionnaire; statistical analysis using SPSS	The study highlighted the significance of technical analysis and technical analysts in guiding investment decisions, with strong consensus among participants regarding the prominent economic sectors for investment based on technical indicators.
10	Levi et al. (2021)	Fundamental and technical analysis leads to a systematic investment decision in stock market equities	To demonstrate the advantages of using both fundamental and technical analysis for systematic investment decisions in stock market equities	Review of past literature; analysis of fundamental and technical analysis techniques; use of machine learning algorithms	Combined use of fundamental and technical analysis helps in determining intrinsic value, identifying patterns, and making informed buy/sell decisions for better profits.
11	Prasad and Seetharaman (2021)	Importance of machine learning in making investment decision in stock market	To evaluate the importance of machine learning algorithms in making investment decisions in the stock market	Qualitative study based on data collected from well-ranked journals, reviewed over 50 research papers	Found LSTM models to have superior accuracy and reinforcement learning to be the best; machine learning algorithms are instrumental and reliable for investment decisions.
12	Ayala et al. (2021)	Technical analysis strategy optimization using a machine learning approach in stock market indices	To optimize technical analysis strategies using a machine learning approach in stock market indices	Hybrid approach combining machine learning techniques with technical analysis	Machine learning techniques enhance the quality of trading signals and competitiveness of technical analysis strategies
13	Nti et al. (2020)	A systematic review of fundamental and technical analysis of stock market predictions	To review stock market prediction studies using machine learning, focusing on fundamental	Systematic review of 122 academic works from 2007-2018	Technical analysis is predominant (66%); support vector machines and artificial neural networks are most used; machine learning techniques

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
			and technical analysis		improve stock market prediction accuracy.
14	Nuzula et al. (2019)	The use of technical analysis, source of information and emotion and its influence on investment decisions	To investigate the influence of technical analysis, sources of information, and emotions on investment decisions	Quantitative research with the help of a Questionnaires survey	Only the source of information significantly influenced investment decisions; technical analysis and emotions did not.
15	Edwards et al. (2018)	Technical analysis of stock trends	To provide investors with comprehensive tools and concepts for making informed and profitable trading decisions	Examination of technical theories, trading tactics, and advancements in investment technology.	Technical analysis tools and concepts can enhance investors' long-term success. New material on Pragmatic Portfolio Theory and an alternative to Dow Theory were also presented.
16	Utami and Nugroho (2017)	Fundamental versus technical analysis of investment: Case study of investors' decision in Indonesia stock exchange	To determine whether investors prefer technical or fundamental analysis and identify factors influencing their choice of analysis method	Quantitative research with a Questionnaire with 125 participants; analyzed six independent variables: education, experience, information accessibility, time horizon, trading frequency	Indonesian investors preferred technical analysis; significant factors influencing choice were investor's experience and time horizon.
17	Shen and Tzeng (2015)	Fuzzy inference-enhanced VC-DRSA model for technical analysis: Investment decision aid	To enhance investment decision-making using a hybrid model combining VC-DRSA and fuzzy	Categorized trading signals into straightforward and complicated groups, evaluated using VC-DRSA and fuzzy inference	Achieved nearly 80% classification accuracy, indicating that considering multiple technical indicators simultaneously provides reliable decision rules for investors.

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
			inference techniques		
18	Stankovic et al. (2015)	Investment strategy optimization using technical analysis and predictive modeling in emerging markets	To examine the efficacy of technical analysis and predictive modeling in optimizing investment strategies in emerging markets	Utilized technical indicators (moving averages, MACD, RSI) and LS-SVM classifier for predictive modeling	LS-SVM model outperformed traditional statistical methods and the Buy & Hold strategy, significantly enhancing investment profitability.
19	Bonga (2015)	The need for efficient investment: Fundamental analysis and technical analysis	To clarify the importance of conducting a thorough fundamental analysis for investing in various securities	Explored the roles of fundamental and technical analysis in financial markets	Efficient investment requires the use of both fundamental and technical analysis to identify mispriced securities and balance risk and return.
20	Ghobadi and Torabi (2015)	Investment Rankings Based on Technical Analysis by Fuzzy MCDM in the Tehran Stock Exchange	To optimize investment rankings by addressing complexities investors face when evaluating numerous criteria in the Tehran Stock Exchange using a fuzzy MCDM approach	A fuzzy hierarchical analytic approach using triangular fuzzy numbers and non-additive fuzzy integral technique	Effective use of fuzzy hierarchical analytic approach and non-additive fuzzy integral technique in determining the relative importance of various criteria and selecting optimal investment strategies
21	Wang and Chan (2007)	Stock market trading rule discovery using pattern recognition and technical analysis	To discover stock market trading rules using pattern recognition	Pattern recognition-based template matching technique	All technical trading rules correctly predicted the direction of changes in the NASDAQ and TWI indices.

S.N.	Researcher(s)	Title	Objective	Methodology	Findings
22	Wong et al. (2003)	How rewarding is technical analysis? Evidence from the Singapore stock market.	To evaluate the technical analysis indicators in stock market timing	Test statistics and analysis of Singapore data	Technical indicators can be used to generate significantly positive returns, indicating substantial profits for member firms of the Singapore Stock Exchange.
23	Dourra and Siy (2002)	Investment using technical analysis and fuzzy logic	To enhance traditional technical analysis methods by applying fuzzy logic engineering tools	Mapped technical indicators into inputs for a fuzzy logic system using past stock price sequences	The fuzzy logic-based system outperformed market performance and proved to be a flexible and superior tool for technical analysis.

2.4 Research Gap

Previous research has provided valuable insights into various aspects of technical analysis and investment decision-making across different stock markets and contexts. Studies such as those by Pheng et al. (2024), Khan et al. (2024), and Pasaribu (2024) have explored the optimization of stock trend prediction strategies, development of fuzzy rule-based systems for portfolio selection, and examination of technical analysis in specific market sectors. However, a notable context gap exists concerning the technical analysis in investment decision-making within the Nepali Stock Market.

In the context gap, there is a significant dearth of research focusing on the specific influence of technical analysis on investment decisions within the Nepali Stock Market. While studies have explored technical analysis in other markets such as Malaysia, Indonesia, and Singapore, there remains a critical need to understand its implications and effectiveness in the unique context of Nepal.

Furthermore, there is a noticeable time gap in the literature, with existing studies often relying on data preceding the year 2024. Given the dynamic nature of financial markets and the evolving landscape of technical analysis techniques, there is a need for research that utilizes the latest available data to provide current insights into investment decision-making practices.

Moreover, the variable gap in previous research highlights the limited consideration of key factors that may influence investment decisions, such as education, experience, time horizon, trading frequency, accessibility of information, and the perception of investors. While some studies have examined technical indicators and trading strategies, few have

comprehensively investigated the multifaceted aspects that contribute to investment decision-making.

Additionally, there is a methodology gap in the literature, with a lack of studies employing both descriptive statistics and causal effect research designs to analyze the intricacies of technical analysis and investment decision-making. Integrating these methodologies allows for a more comprehensive understanding of the factors influencing investment decisions and their implications.

Overall, the identified research gaps underscore the need for a study that specifically examines the technical analysis on investment decision-making in the Nepali Stock Market, utilizing the latest data and considering a comprehensive set of variables. This study aims to address these gaps by providing insights into the dynamics of investment decision-making practices in Nepal and contributing to the broader body of knowledge in the field of financial analysis and decision-making.

CHAPTER III
RESEARCH METHODOLOGY

This chapter outlines the overall research methodology, detailing the research design, population, and sample, along with the sampling design. It covers the nature and sources of data, the instrument of data collection, and the method of analysis. Additionally, the chapter presents the research framework and provides definitions for the key variables used in the study.

3.1 Research Design

In this research, both descriptive research design and causal effect research design have been used. Descriptive statistics have been employed to assess the intricacies of technical analysis and investment decision-making, providing valuable insights into the patterns, trends, and behaviors observed within the market. Additionally, the application of causal-comparative research design has allowed for a deeper analysis of the impact of technical analysis on investment decision-making.

3.2 Population and Sample, and Sampling Design

Given the focus of this study on Kathmandu Valley, where the individual investors investing in the Nepali Stock Market have constituted the total population under examination, a sample size of 400 individual investors has been selected as per the convenience sampling method for data collection ease. This approach has acknowledged the practical constraints of data collection while ensuring that a representative sample has been obtained from the population of interest. By selecting individual investors from Kathmandu Valley, the study has aimed to capture a diverse range of perspectives and behaviors within this specific geographical area, thereby enhancing the generalizability of the findings to the broader context of investment decision-making in Nepal. Additionally, convenience sampling has enabled efficient data collection and has facilitated access to participants who have been readily available and willing to participate in the study.

3.3 Nature and Sources of Data and the Instrument of Data Collection

In this study, a quantitative approach has been adopted to analyze the data, emphasizing the numerical representation and statistical analysis of investment decision-making patterns among individual investors in the Nepali Stock Market. The primary sources of data have included information gathered directly from the investors through a questionnaire survey.

Utilizing a questionnaire survey has allowed for the collection of firsthand insights and perceptions from the target population, thereby offering a comprehensive understanding of their investment behaviors and preferences. The questionnaire has been designed to incorporate a five-point Likert scale, enabling respondents to express their opinions and attitudes towards various aspects of technical analysis and investment decision-making with a range of responses from strongly disagree to strongly agree.

3.4 Method of Analysis

Following the completion of data collection, the gathered data has undergone meticulous analysis using statistical software tools such as Microsoft Excel and SPSS (Statistical Package for the Social Sciences). This step involved organizing and presenting the data in a structured format conducive to statistical analysis. The utilization of various statistical tools, including descriptive statistics, correlation analysis, and multivariate regression models, has enabled a comprehensive examination of the relationships and patterns within the dataset. Descriptive statistics have provided insights into the central tendencies and variability of the variables under investigation, offering a summary overview of key characteristics. Correlation analysis has facilitated the exploration of associations between different variables, elucidating potential interdependencies and connections. Additionally, employing multivariate regression models has allowed for the identification of significant predictors and their respective impacts on investment decision-making outcomes. By leveraging these advanced statistical techniques, this study has aimed to uncover meaningful insights into the factors influencing investment decision-making in the Nepali Stock Market. The following statistical tools has been used in this study.

3.4.1 Mean

In statistical analysis, the mean, also known as the arithmetic average, is a measure of central tendency that represents the average value of a set of data points. In the context of this study, the mean is used to analyze the investor perception regarding the use of technical analysis in investment decision-making. By calculating the mean of responses obtained from investors through surveys or questionnaires, researchers can determine the typical or average perception among the sample population. This helps in understanding the consensus or prevailing sentiment regarding the effectiveness, relevance, or utility of technical analysis in making investment decisions.

$$\text{Mean} = \frac{\sum x}{n}$$

Where,

X = Value of responses of each independent or dependent variable

n = Number of responses

3.4.2 Standard Deviation (S.D.)

The standard deviation is a statistical measure of the dispersion or variability of a set of data points around the mean. It quantifies the extent to which individual data points deviate from the mean of the data set. In the context of this study, the standard deviation (S.D.) is used to analyze the fluctuation or difference in opinions among investors regarding the use of technical analysis in investment decision-making. A higher standard deviation indicates greater variability among responses, suggesting a wider range of opinions or perceptions among investors regarding the effectiveness, reliability, or applicability of technical analysis in guiding investment decisions.

$$\text{Standard Deviation}(\sigma) = \sqrt{\frac{\sum(X - \overline{X})^2}{n}}$$

Where,

X = Value of responses of each dependent or independent variable

$\overline{X}$ = Mean value of responses of each dependent or independent variable

n= Number of responses

3.4.3 Correlation Analysis

Correlation analysis is a statistical technique used to measure the strength and direction of the relationship between two variables. It assesses how changes in one variable are associated with changes in another variable. In the context of this study, correlation analysis is employed to examine the relationship between the extent of technical analysis usage and the quality or effectiveness of investment decisions made by investors. By calculating correlation coefficients, researchers can determine whether there is a positive, negative, or no correlation between the adoption of technical analysis techniques and the outcomes of investment decisions. This helps in understanding the degree to which technical analysis practices influence investors' decision-making processes.

The correlation coefficient between two variables is also calculated by using the following formula:

$$\text{Correlation Coefficient}(r) = \frac{n\sum XY - \sum X \sum Y}{\sqrt{n\sum X^2 - (\sum X)^2}\sqrt{n\sum Y^2 - (\sum Y)^2}}$$

Where,

n = Number of responses

X = Value of independent variable

Y= Value of dependent variable

3.4.4 Regression Analysis

Regression analysis is a statistical method used to analyze the relationship between a dependent variable and one or more independent variables. It helps in understanding how changes in the independent variables affect the dependent variable. In the context of this study, regression analysis is utilized to assess the impact of technical analysis on investment decision-making. By examining how variations in technical analysis practices (independent variables) affect the quality, accuracy, or profitability of investment decisions (dependent variable), researchers can quantify the significance and magnitude of this impact. Regression analysis allows for controlling other relevant factors or variables, enabling researchers to isolate the specific influence of technical analysis on investment decisions from other potential determinants. The regression equation of this study is as follows.

$$Y_{IND} = \alpha + \beta_1 EDU + \beta_2 EXP + \beta_3 TIM + \beta_4 FRE + \beta_5 AOI + \beta_6 POI \ldots\ldots\ldots\ldots\ldots\ldots \text{ Eq (1)}$$

Where,

IND = Investment Decision Making

EDU = Education

EXP = Experience

TIM = Time Horizon

FRE = Trading Frequency

AOI = Accessibility of Information

POI = Perception of Investor

E = Error Term

α = Intercept term

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ = Coefficients

3.5 Reliability Test

To ensure the reliability of the data and findings, this study utilized SPSS software. The consistency of the data was evaluated using Cronbach's Alpha Test of Reliability within SPSS. This test measures the repeatability of results and yields a value between 0 and 1. A value below 0.60 signifies low reliability, whereas values between 0.90 and 0.99 indicate excellent reliability. Generally, a value exceeding 0.7 is considered good (Nunnally, 1978).

Table 2
Reliability Test

Code	Variables	Cronbach's Alpha	N of Items
EDU	Education	0.876	6
EXP	Experience	0.822	6
TIM	Time Horizon	0.735	6
FRE	Trading Frequency	0.806	6
AOI	Accessibility of Information	0.797	6
POI	Perception of Investor	0.823	6
IND	Investment Decision Making	0.828	6
Overall Reliability		0.945	56

Table 2 presents the results of the reliability test conducted on the variables included in this study. The Cronbach's Alpha values for Education, Experience, Time Horizon, Trading Frequency, Accessibility of Information, Perception of Investor, and Investment Decision Making are 0.876, 0.822, 0.735, 0.806, 0.797, 0.823, and 0.828, respectively. All these values surpass the acceptable threshold of 0.70, indicating good internal consistency for each variable. Additionally, the overall Cronbach's Alpha for all variables combined is 0.945, reflecting very high internal consistency across the entire dataset. This high overall value further confirms the reliability of the data collected for this study.

3.6 Normality Test

In this study, a normality test was performed to evaluate whether the data followed a normal distribution. This assessment is essential to confirm that the assumptions required for various statistical analyses are satisfied. The Kolmogorov-Smirnov and Shapiro-Wilk tests

were utilized to determine if the data collected for variables such as Education, Experience, Time Horizon, Trading Frequency, Accessibility of Information, Perception of Investor, and Investment Decision Making adhered to normal distribution.

Table 3
Normality Test

Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
EDU	0.080	400	0.000	0.968	400	0.000
EXP	0.085	400	0.000	0.968	400	0.000
TIM	0.077	400	0.000	0.970	400	0.000
FRE	0.091	400	0.000	0.970	400	0.000
AOI	0.092	400	0.000	0.978	400	0.000
POI	0.087	400	0.000	0.973	400	0.000
IND	0.108	400	0.000	0.965	400	0.000

Table 3 presents the results of the normality test conducted on the variables included in this study. The Kolmogorov-Smirnov and Shapiro-Wilk tests were used to evaluate the normality of the data for Education (EDU), Experience (EXP), Time Horizon (TIM), Trading Frequency (FRE), Accessibility of Information (AOI), Perception of Investor (POI), and Investment Decision Making (IND). For all variables, the Kolmogorov-Smirnov statistics are significant with p-values of 0.000, indicating deviations from normality. The Shapiro-Wilk statistics also show significant p-values, with all values being below the threshold of 0.05. Consequently, the data for all variables do not follow a normal distribution, suggesting that assumptions for parametric tests might not be fully met.

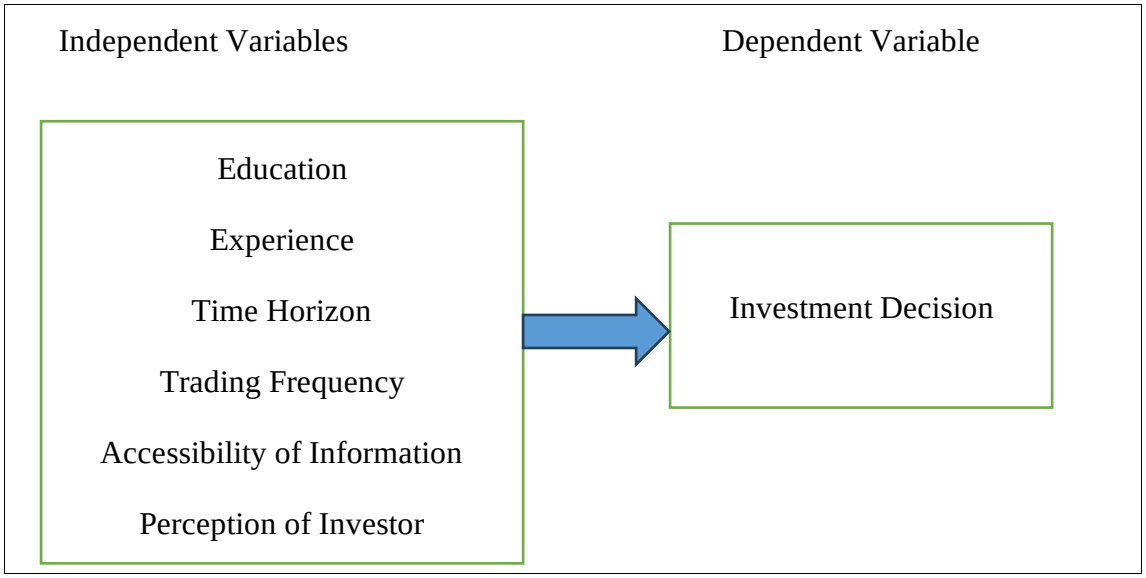
3.7 Research Framework and Definition of Variables

3.7.1 Research Framework

The research framework of this study delineates the overarching structure and methodology guiding the investigation into the relationship between technical analysis and investment decision-making in the context of the Nepali Stock Market.

Drawing from the framework proposed by Utami and Nugroho (2017), this study incorporates key independent variables related to investor characteristics and perceptions, namely education, experience, time horizon, trading frequency, accessibility of information, and perception of investor. These variables serve as the foundation for understanding the factors that influence investment decision-making in the Nepali Stock Market. Education and experience reflect the knowledge and expertise of investors, while

time horizon and trading frequency capture their investment preferences and behaviors. Accessibility of information pertains to the availability and ease of access to market-related data, while perception of investor encapsulates subjective beliefs and attitudes towards investment strategies.



Source: Utami and Nugroho (2017)

Figure 1. Research Framework of this Study

3.7.2 Operational Definition of Variables

Education

Education refers to the level of formal schooling or academic qualifications attained by individual investors participating in the Stock Market (Utami & Nugroho, 2017). This variable encompasses factors such as educational degrees, diplomas, certifications, and specialized training related to finance, economics, or investment analysis. Higher levels of education may indicate a greater understanding of financial concepts, analytical skills, and familiarity with investment strategies, potentially influencing the decision-making processes of investors in evaluating stocks and employing technical analysis methods.

Experience

Experience represents the cumulative knowledge, skills, and practical exposure gained by individual investors through their participation in the stock market over time (Utami & Nugroho, 2017). This variable considers factors such as the duration of involvement in investing, previous investment successes or failures, and familiarity with market dynamics and trends. Investors with extensive experience may demonstrate greater confidence in

their decision-making abilities, relying on past experiences to inform their investment strategies and interpretations of technical analysis indicators.

Time Horizon

Time horizon refers to the duration or timeframe over which individual investors intend to hold their investment positions in the Stock Market (Utami & Nugroho, 2017). This variable encompasses short-term, medium-term, and long-term investment objectives, reflecting investors' preferences for capital appreciation, income generation, or wealth preservation. Investors with shorter time horizons may prioritize short-term price movements and trading opportunities, while those with longer time horizons may adopt a more patient and strategic approach, considering fundamental factors alongside technical analysis indicators.

Trading Frequency

Trading frequency denotes the frequency or rate at which individual investors engage in buying and selling activities within the Stock Market (Utami & Nugroho, 2017). This variable encompasses factors such as the number of trades executed per day, week, month, or year, as well as the turnover rate of investment portfolios. High trading frequency may indicate an active trading strategy characterized by frequent adjustments to investment positions based on technical analysis signals, while low trading frequency may suggest a more passive or buy-and-hold approach.

Accessibility of Information

Accessibility of information refers to the ease with which individual investors can access relevant market data, financial reports, news updates, and research insights pertinent to their investment decisions in the Stock Market (Utami & Nugroho, 2017). This variable encompasses factors such as the availability of online trading platforms, financial news channels, research reports, and investor education resources. Investors with greater accessibility to information may be better equipped to conduct thorough analyses and make informed decisions, including the utilization of technical analysis tools.

Perception of Investor

Perception of the investor relates to individual investors' subjective beliefs, attitudes, and biases towards the Nepali Stock Market, investment strategies, and the efficacy of technical analysis (Utami & Nugroho, 2017). This variable encompasses factors such as risk

tolerance, confidence in market predictions, behavioral biases, and sentiments towards market trends. Investors' perceptions may influence their interpretation of technical analysis signals, with optimistic or pessimistic outlooks shaping their investment decisions and risk management approaches.

Investment Decision Making

Investment decision making refers to the process through which individual investors evaluate available investment opportunities, assess risks and rewards, and make informed choices regarding the allocation of their capital in the Stock Market (Utami & Nugroho, 2017). This variable encompasses factors such as the selection of investment instruments, timing of buy or sell decisions, portfolio diversification strategies, and the integration of fundamental and technical analysis techniques. Effective investment decision making involves weighing various factors, including financial goals, market conditions, and risk preferences, to optimize investment returns and mitigate potential losses.

CHAPTER IV
RESULTS AND DISCUSSION

This chapter presents the results of the study, which are analyzed to provide insights into technical analysis and investment decision-making in the Nepali Stock Market. The results are systematically outlined and examined to reveal key findings and patterns. Following the results, the discussion section compares and contrasts these findings with conclusions from previous research. This comparative effect analysis helps contextualize the study's outcomes within the broader academic discourse, highlighting consistencies and discrepancies with existing literature.

4.1 Results

In this section, the results of the descriptive study, normality test, reliability test, correlation analysis, and regression analysis are presented in tabular form and analyzed. The descriptive study provides an overview of the data, while the normality and reliability tests assess the distribution and consistency of the data, respectively. Correlation analysis examines the relationships between variables, and regression analysis explores the impact of independent variables on the dependent variable. Each set of results is discussed to highlight key findings and their implications for the study.

4.1.1 Demographic Profile of Respondents

In this section, the demographic profile of respondents is examined, covering key aspects such as gender, age, educational background, investment experience, frequency of trading, sources of information for investment decisions, and investment goals. This profile provides a comprehensive understanding of the respondent's characteristics and their influence on investment behaviors. Analyzing these demographic factors helps in contextualizing the study's findings and assessing how different demographic variables might impact investment decisions in the context of technical analysis.

Table 4

Demographic Profile of Respondents

Gender			
Variables		Frequency	Percent
Gender	Male	239	59.75
	Female	161	40.25
	Total	400	100
Age	Below 25 Years	54	13.50
	25-34 years	128	32.00
	35-44 years	172	43.00
	45 years and above	46	11.50
	Total	400	100
Educational Background	High School or equivalent	96	24.00
	Bachelor's Degree	197	49.25
	Master's Degree or above	107	26.75
	Total	400	100
Investment Experience	Less than 1 year	26	6.50
	1-3 years	108	27.00
	4-6 years	173	43.25
	7-10 years	49	12.25
	More than 10 years	44	11.00
	Total	400	100
Frequency of Trading	Daily	44	11.00
	Weekly	86	21.50
	Monthly	165	41.25
	Quarterly	52	13.00
	Annually	53	13.25
	Total	400	100
Source of Information for Investment Decisions	Financial News and Media	63	15.75
	Technical Analysis Tools	103	25.75
	Recommendations from Financial Advisors	89	22.25
	Peer Discussions and Forums	83	20.75
	Company Reports and Filings	62	15.50
	Total	400	100
Investment Goals	Short-term gains	99	24.75
	Long-term growth	141	35.25
	Income generation (e.g., dividends)	50	12.50
	Diversification	58	14.50
	Speculative opportunities	52	13.00
	Total	400	100

Source: Opinion Survey,2024

Table 4 presents the demographic profile of respondents. The profile includes various aspects such as gender, age, educational background, investment experience, frequency of trading, sources of information for investment decisions, and investment goals.

Out of the total respondents, 239 (59.75%) are male, while 161 (40.25%) are female. The age distribution shows that 54 respondents (13.50%) are below 25 years, 128 (32.00%) are between 25-34 years, 172 (43.00%) are between 35-44 years, and 46 (11.50%) are 45 years and above. Among the respondents, 96 (24.00%) have a high school education or equivalent, 197 (49.25%) hold a bachelor's degree, and 107 (26.75%) have a master's degree or higher.

Respondents' investment experience is as follows: 26 (6.50%) have less than 1 year, 108 (27.00%) have 1-3 years, 173 (43.25%) have 4-6 years, 49 (12.25%) have 7-10 years, and 44 (11.00%) have more than 10 years. Trading frequency varies with 44 respondents (11.00%) trading daily, 86 (21.50%) trading weekly, 165 (41.25%) trading monthly, 52 (13.00%) trading quarterly, and 53 (13.25%) trading annually.

The sources of information are distributed as follows: 63 respondents (15.75%) rely on financial news and media, 103 (25.75%) use technical analysis tools, 89 (22.25%) follow recommendations from financial advisors, 83 (20.75%) consult peer discussions and forums, and 62 (15.50%) use company reports and filings. The respondents' investment goals are 99 (24.75%) aiming for short-term gains, 141 (35.25%) focusing on long-term growth, 50 (12.50%) seeking income generation through dividends, 58 (14.50%) aiming for diversification, and 52 (13.00%) looking for speculative opportunities.

4.1.2 Descriptive Statistics

In this study, descriptive statistics have been employed to analyze the use of technical analysis in investment decision-making. By summarizing and presenting key characteristics of the data, such as means, standard deviations, and frequencies, descriptive statistics offer insights into how technical analysis is utilized among investors. This approach helps in identifying common practices, preferences, and trends within the dataset, providing a clear overview of how technical analysis influences investment decisions. Through these statistical summaries, the study aims to explore the extent and manner in which technical analysis is integrated into the decision-making processes of investors.

4.1.2.1 Summary of Descriptive Statistics

In this section, the summary of descriptive statistics has been conducted to analyze the overall summary of factors including Education, Experience, Time Horizon, Trading Frequency, Accessibility of Information, Perception of Investor, and Investment Decision Making. Using mean and standard deviation, this analysis provides a comprehensive overview of each factor's central tendency and variability. The mean offers insight into the average level or extent of each factor among the respondents, while the standard deviation measures the dispersion or spread of responses around the mean. This statistical summary aids in understanding the general trends and variations within the data, helping to contextualize how these factors collectively influence investment decision-making.

Table 5

Summary of Descriptive Statistics

Code	Variables	Mean	S.D.
EDU	Education	3.680	0.824
EXP	Experience	3.637	0.691
TIM	Time Horizon	3.529	0.618
FRE	Trading Frequency	3.449	0.659
AOI	Accessibility of Information	3.587	0.655
POI	Perception of Investor	3.639	0.666
IND	Investment Decision Making	3.739	0.669

Source: Appendix I & III

Table 5 presents the summary of descriptive statistics of investor perception towards technical analysis on investment decision making. The mean scores and standard deviations for each variable provide an overview of how investors perceive various aspects related to technical analysis and its impact on their investment decisions.

For education (EDU), the mean score is 3.680 with a standard deviation of 0.824. This suggests that investors generally perceive their educational background as moderately influential in their understanding of technical analysis. The relatively high mean indicates a positive perception, implying that investors believe their education supports their ability to apply technical analysis effectively.

For experience (EXP), the mean score is 3.637 with a standard deviation of 0.691. This indicates that investors view their experience in the stock market as somewhat beneficial for using technical analysis. The moderate mean reflects a positive but not overwhelmingly

strong perception, suggesting that while experience is valued, its impact is viewed as supportive rather than central.

For time horizon (TIM), the mean score is 3.529 with a standard deviation of 0.618. This score shows that investors have a moderate view of how their investment time horizon affects their use of technical analysis. The mean suggests that investors perceive technical analysis as somewhat more relevant for shorter time horizons, but it is not the primary factor in their decision-making process.

For trading frequency (FRE), the mean score is 3.449 with a standard deviation of 0.659. This implies that investors generally view frequent trading as moderately important for applying technical analysis. The mean indicates that while trading frequency is considered beneficial, it is not seen as crucial for making investment decisions.

For accessibility of information (AOI), the mean score is 3.587 with a standard deviation of 0.655. This reflects that investors have a somewhat positive perception of how access to financial data and research tools influences their use of technical analysis. The relatively high mean score suggests that having good access to information is seen as important but not the sole determinant of investment decisions.

For perception of investor (POI), the mean score is 3.639 with a standard deviation of 0.666. This indicates that investors have a moderately positive view of how technical analysis can provide insights into market sentiment and behavior. The mean suggests a general confidence in the effectiveness of technical analysis in understanding market dynamics.

For investment decision making (IND), the mean score is 3.739 with a standard deviation of 0.669. This shows that investors generally have a positive perception of how technical analysis affects their investment decisions. The highest mean among the variables indicates that technical analysis is viewed as a significant tool in shaping investment choices and strategies.

4.1.2.2 Descriptive Study of Education on Investment Decision

This section describes the influence of investor perception on the descriptive study of education in relation to investment decisions. The analysis highlights how investor perception, shaped by their educational background, affects their approach to making investment choices. It examines the role of education in shaping perceptions of technical analysis and its impact on investment strategies. By analyzing descriptive statistics, the

study provides insights into how educational qualifications and investor perception intersect to influence investment decision-making processes.

Table 6
Descriptive Study of Education on Investment Decision

Statements	Mean	S.D.
My education has prepared me well to understand technical analysis.	3.563	1.214
Higher education positively influences my ability to interpret stock market data.	3.680	1.039
I feel confident applying technical analysis principles due to my educational background.	3.820	0.998
Formal education in finance is essential for successful implementation of technical analysis.	3.633	1.042
Continuous learning is crucial for improving proficiency in technical analysis.	3.695	1.000
My academic knowledge guides my investment decisions in the stock market.	3.690	0.980

Source: Appendix I & III

Table 6 presents the descriptive study of education on investment decision. The analysis reflects respondents' perceptions regarding how their educational background impacts their ability to use technical analysis in making investment decisions.

Among the statements, "I feel confident applying technical analysis principles due to my educational background" has the highest mean score of 3.820 with a standard deviation of 0.998. This suggests that respondents generally feel confident in their ability to apply technical analysis principles because of their educational qualifications. The relatively high mean indicates a strong perception of confidence linked to educational background, despite the variation in responses.

Conversely, the statement "My education has prepared me well to understand technical analysis" has the lowest mean score of 3.563 with a standard deviation of 1.214. This lower mean indicates that respondents are less certain about the extent to which their education has specifically prepared them for understanding technical analysis. The higher standard deviation also reflects a wider range of opinions about the adequacy of their education in this regard.

Overall, the descriptive study shows a generally positive perception of the role of education in technical analysis and investment decision-making. Respondents value their educational

background and continuous learning in enhancing their technical analysis skills, though there is some variability in opinions about the direct preparation provided by their education.

4.1.2.3 Descriptive Study of Experience on Investment Decision

This section describes the impact of investor perception on the descriptive study of experience in relation to investment decisions. It explores how investors' experiences in the stock market influence their perceptions and decision-making processes.

Table 7
Descriptive Study of Experience on Investment Decision

Statements	Mean	S.D.
Past experiences significantly influence my reliance on technical analysis.	3.698	0.950
My trading experience is sufficient for effectively using technical analysis.	3.648	0.925
Over time, I've developed a strong intuition for interpreting technical indicators.	3.450	1.007
Experience has taught me to identify trends and patterns in the stock market accurately.	3.695	0.969
I've learned valuable lessons from past successes and failures in technical analysis.	3.645	0.944
Practical experience in trading is essential for mastering technical analysis.	3.688	0.904

Source: Appendix I & III

Table 7 presents the descriptive study of experience on investment decision. The analysis reflects respondents' perceptions regarding how their trading experience impacts their use of technical analysis in investment decision-making.

Among the statements, "Past experiences significantly influence my reliance on technical analysis" has the highest mean score of 3.698 with a standard deviation of 0.950. This suggests that respondents strongly believe that their past experiences have a notable impact on their use of technical analysis. The high mean indicates a positive view of how past experiences shape their reliance on technical analysis, while the relatively low standard deviation shows consistency in this perception.

Conversely, the statement "Over time, I've developed a strong intuition for interpreting technical indicators" has the lowest mean score of 3.450 with a standard deviation of 1.007. This lower mean indicates that respondents are less confident about having developed a

strong intuition for interpreting technical indicators through experience. The higher standard deviation reflects greater variability in opinions about the development of intuitive skills in technical analysis.

Overall, the descriptive study demonstrates that respondents generally perceive their trading experience as influential in their use of technical analysis for investment decisions. They value the practical experience in mastering technical analysis and believe that past experiences significantly affect their reliance on this method, although there is some variability in the confidence regarding intuitive skills in interpreting technical indicators.

4.1.2.4 Descriptive Study of Time Horizon on Investment Decision

This section describes the influence of investor perception on the descriptive study of time horizon with regard to investment decisions. It examines how investors' views on the time horizon affect their investment choices and strategies. The analysis highlights how different time horizons, whether short-term or long-term, shape investors' expectations and decision-making processes. By evaluating descriptive statistics, the study provides insights into how perceptions of time impact investment strategies and the application of technical analysis in making investment decisions.

Table 8
Descriptive Study of Time Horizon on Investment Decision

Statements	Mean	S.D.
I prefer short-term investments to capitalize on immediate market movements.	3.610	0.917
Technical analysis is more useful for my short-term trading strategies than for long-term investments.	3.593	0.927
I frequently adjust my investment portfolio based on short-term price trends identified through technical analysis.	3.565	0.950
Long-term investment goals are less important to me compared to short-term profit opportunities.	3.648	0.941
My investment strategy focuses more on short-term gains rather than long-term stability.	3.380	0.945
I am more interested in short-term market trends than in long-term growth prospects when making investment decisions.	3.383	0.974

Source: Appendix I & III

Table 8 presents the descriptive study of time horizon on investment decision. This analysis examines how respondents' preferences for different investment time horizons influence their use of technical analysis in making investment decisions.

The statement "Long-term investment goals are less important to me compared to short-term profit opportunities" has the highest mean score of 3.648 with a standard deviation of 0.941. This indicates that respondents generally place more emphasis on short-term profit opportunities over long-term investment goals. The relatively high mean score and standard deviation suggest a strong and somewhat varied inclination towards short-term gains rather than long-term stability.

In contrast, the statement "My investment strategy focuses more on short-term gains rather than long-term stability." has the lowest mean score of 3.380 with a standard deviation of 0.945. This lower mean reflects that respondents are less focused on short-term market trends compared to long-term growth prospects. The higher standard deviation indicates greater variability in how respondents prioritize short-term trends versus long-term growth. Overall, the descriptive study reveals that respondents have a general preference for short-term investments and find technical analysis more relevant for short-term trading strategies. Despite this general trend, there is notable variability in how respondents balance short-term versus long-term investment considerations.

4.1.2.5 Descriptive Study of Trading Frequency on Investment Decision

This section describes the impact of investor perception on the descriptive study of trading frequency concerning investment decisions. It explores how investors' attitudes towards trading frequency influence their investment choices and strategies.

Table 9

Descriptive Study of Trading Frequency on Investment Decision

Statements	Mean	S.D.
I prefer to actively trade stocks on a daily basis.	3.410	0.927
Frequent trading allows me to capitalize on short-term price movements.	3.470	0.952
My investment strategy involves making multiple trades within a single day.	3.470	0.925
High trading frequency is essential for implementing technical analysis strategies.	3.398	0.968
I am comfortable with the level of risk associated with frequent trading.	3.458	0.860
I regularly review and adjust my trading strategy based on frequent market movements.	3.490	0.915

Source: Appendix I & III

Table 9 presents the descriptive study of trading frequency on investment decision. This analysis examines how respondents' trading frequency impacts their use of technical analysis and investment strategies.

The statement "I regularly review and adjust my trading strategy based on frequent market movements" has the highest mean score of 3.490 with a standard deviation of 0.915. This suggests that respondents frequently revisit and refine their trading strategies in response to market changes. The relatively low standard deviation indicates that this behavior is consistent among respondents.

Conversely, the statement "High trading frequency is essential for implementing technical analysis strategies." has the lowest mean score of 3.398 with a standard deviation of 0.968. This lower mean reflects that respondents are less inclined to engage in high trading activities. The standard deviation here is slightly higher, indicating more variation in how often respondents prefer to trade daily.

Overall, the descriptive study reveals that while respondents value the ability to adjust their trading strategies based on market movements, there is less enthusiasm for daily trading. The results suggest a moderate preference for frequent trading without a strong inclination towards daily transactions.

4.1.2.6 Descriptive Study of Accessibility of Information on Investment Decision

This section describes the impact of investor perception on the descriptive study of accessibility of information regarding investment decisions. It examines how investors' views on the availability and timeliness of financial information influence their decision-making processes. The analysis focuses on how easily accessible information, such as market data and research tools, affects investors' use of technical analysis and their overall investment strategies. By reviewing the descriptive statistics, this study highlights the critical role that information accessibility plays in shaping investment choices and the effectiveness of technical analysis in the decision-making process.

Table 10
Descriptive Study of Accessibility of Information on Investment Decision

Statements	Mean	S.D.
I have access to a wide range of financial data and research tools.	3.490	0.966
Timely access to market information is critical for making informed decisions.	3.608	0.957
Online trading platforms and research resources enhance my ability to conduct analysis.	3.643	0.893
Access to real-time market data gives me a competitive edge in executing trades.	3.635	0.888
I am satisfied with the accessibility of financial information provided by my brokerage.	3.585	0.946
I find that having easy access to historical data is important for effective technical analysis.	3.563	0.926

Source: Appendix I & III

Table 10 presents the descriptive study of accessibility of information on investment decision. This analysis explores how respondents' access to financial data and resources affects their investment decisions. The statement "Online trading platforms and research resources enhance my ability to conduct analysis" has the highest mean score of 3.643 with a standard deviation of 0.893. This suggests that respondents believe online trading platforms and research resources significantly improve their ability to perform technical analysis. The relatively low standard deviation indicates that respondents are generally consistent in their view regarding the usefulness of these tools for analysis.

On the other hand, the statement "I have access to a wide range of financial data and research tools" has the lowest mean score of 3.490 with a standard deviation of 0.966. This reflects that respondents feel less strongly about having access to a broad range of financial data and research tools. The higher standard deviation indicates greater variability in how respondents perceive the accessibility of these resources.

Overall, the descriptive study reveals that while respondents recognize the importance of online trading platforms and research resources for conducting technical analysis, there is some variability in their satisfaction with the overall range of financial data and tools available to them.

4.1.2.7 Descriptive Study of Perception of Investor on Investment Decision

This section describes the impact of investor perception on the descriptive study of perception of investor regarding investment decisions. It explores how investors' attitudes

and beliefs about technical analysis influence their investment choices and strategies. The analysis highlights how investors' perceptions of the effectiveness of technical analysis, including their confidence in using indicators and patterns, affect their decision-making process.

Table 11
Descriptive Study of Perception of Investor on Investment Decision

Statements	Mean	S.D.
Investors who prioritize technical analysis tend to achieve higher returns.	3.598	0.910
Successful investors effectively use technical analysis to time market entry and exit points.	3.693	0.818
Technical analysis is essential for gaining insights into market sentiment and behavior.	3.535	0.973
Investors who incorporate technical analysis are adaptable to changing market conditions.	3.640	0.907
Proficiency in interpreting chart patterns and technical indicators defines experienced investors.	3.648	0.928
Investors who rely on technical analysis are better equipped to manage investment risks and uncertainties.	3.725	0.942

Source: Appendix I & III

Table 11 presents the descriptive study of perception of investor on investment decision. The statement "Investors who rely on technical analysis are better equipped to manage investment risks and uncertainties" has the highest mean score of 3.725 with a standard deviation of 0.942. This indicates that respondents strongly believe that technical analysis enhances their ability to manage risks and uncertainties in their investments, reflecting a high level of confidence in the effectiveness of technical analysis for risk management.

Conversely, the statement "Technical analysis is essential for gaining insights into market sentiment and behavior" has the lowest mean score of 3.535 with a standard deviation of 0.973. Although this score is still positive, it suggests that respondents view technical analysis as somewhat less critical for understanding market sentiment compared to other aspects of investment decision-making. The higher standard deviation indicates a wider variation in opinions on this aspect of technical analysis.

Overall, the descriptive study reveals that respondents generally perceive technical analysis as a valuable tool for managing investment risks and adapting to market conditions.

4.1.2.8 Descriptive Study of Investment Decision Making on Technical Analysis

This section describes the influence of investor perception on the descriptive study of investment decision making related to technical analysis. It examines how investors' views and beliefs about the efficacy of technical analysis impact their overall investment decisions.

Table 12
Descriptive Study of Investment Decision Making on Technical Analysis

Statements	Mean	S.D.
I prioritize technical analysis over fundamental analysis in my investment decision-making process.	3.710	0.926
I believe that past price movements and chart patterns are reliable indicators for future market trends.	3.675	0.931
Technical indicators such as moving averages and RSI significantly influence my buy or sell decisions.	3.770	0.922
I actively seek out information on technical analysis strategies to enhance my investment decisions.	3.745	0.873
I am comfortable with taking calculated risks based on technical signals to achieve investment goals.	3.760	0.911
I regularly review historical market data and perform technical analysis to adjust my investment portfolio.	3.773	0.913

Source: Appendix I & III

Table 12 presents the descriptive study of investment decision making on technical analysis. This analysis examines how respondents prioritize and use technical analysis in their investment decision-making processes.

The statement "I regularly review historical market data and perform technical analysis to adjust my investment portfolio" has the highest mean score of 3.773 with a standard deviation of 0.913. This indicates that respondents frequently use historical market data and technical analysis to make adjustments to their investment portfolios. The relatively low standard deviation suggests a consistent approach among respondents in using technical analysis for portfolio adjustments.

Conversely, the statement "I believe that past price movements and chart patterns are reliable indicators for future market trends" has the lowest mean score of 3.675 with a standard deviation of 0.931. This lower mean reflects that respondents are somewhat less confident in relying solely on past price movements and chart patterns as indicators of

future trends. The standard deviation being relatively high indicates more variability in respondents' confidence regarding these indicators.

Overall, the descriptive study reveals that respondents place considerable importance on technical analysis for making investment decisions and adjusting their portfolios. While they generally value technical analysis, there is some variation in their confidence regarding the reliability of past price movements and chart patterns for predicting future market trends.

4.1.3 Correlation Analysis

In this section, correlation analysis has been used to analyze the relationship between technical analysis and investment decision-making. This analysis examines the strength and direction of the association between the use of technical analysis and various aspects of investment decisions. By calculating correlation coefficients, this section reveals how closely related the application of technical analysis is to different investment outcomes. This helps in understanding whether increased reliance on technical analysis corresponds with changes in investment decision-making patterns, providing valuable insights into how technical analysis impacts investor behavior and choices.

Table 13

Correlation Matrix

Variables		EDU	EXP	TIM	FRE	AOI	POI	IND
EDU	Pearson Correlation	1						
	Sig. (2-tailed)							
EXP	Pearson Correlation	.694**	1					
	Sig. (2-tailed)	0.000						
TIM	Pearson Correlation	.514**	.693**	1				
	Sig. (2-tailed)	0.000	0.000					
FRE	Pearson Correlation	.176**	.307**	.536**	1			
	Sig. (2-tailed)	0.000	0.000	0.000				
AOI	Pearson Correlation	.463**	.544**	.523**	.367**	1		
	Sig. (2-tailed)	0.000	0.000	0.000	0.000			
POI	Pearson Correlation	.434**	.586**	.546**	.298**	.667**	1	
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		
IND	Pearson Correlation	.463**	.576**	.517**	.275**	.554**	.662**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	

Source: Appendix I & IV

Table 13 presents the correlation between the independent variables (education, experience, time horizon, trading frequency, accessibility of information, and perception of investor) and the dependent variable (investment decision making).

The correlation between education and investment decision making is 0.463, which is a moderate positive correlation. This indicates that higher levels of education are associated with better investment decision making, and this relationship is statistically significant at the 5 percent level. The correlation is considered moderate in strength, suggesting a meaningful but not overly strong association.

Experience shows a correlation of 0.576 with investment decision making, reflecting a strong positive relationship. This implies that greater investment experience is significantly associated with more effective decision making. The correlation is significant at the 5 percent level, underscoring the importance of experience in enhancing investment decisions.

The variable time horizon has a correlation of 0.517 with investment decision making, indicating a moderate to strong positive relationship. This suggests that having a longer-term investment perspective is positively associated with improved decision making, with the correlation being significant at the 5 percent level.

Trading frequency exhibits a correlation of 0.275 with investment decision making, which is a weak positive correlation. This indicates that while there is a positive relationship between trading frequency and investment decisions, it is relatively weak and statistically significant at the 5 percent level.

Accessibility of information has a correlation of 0.554 with investment decision making, demonstrating a moderate to strong positive relationship. This means that better access to financial information is associated with more effective investment decision making, with the correlation being significant at the 5 percent level.

Finally, perception of investor shows a correlation of 0.662 with investment decision making, which is a strong positive correlation. This suggests that a more favorable perception of technical analysis is strongly associated with improved investment decisions. This relationship is significant at the 5 percent level, indicating a robust link between investor perception and decision making.

The correlation analysis reveals that education, experience, time horizon, and accessibility of information all positively influence investment decision making, with experience and perception of investor having the most significant impact. Trading frequency, while still positive, has a less substantial effect. Overall, the results emphasize the importance of these factors in enhancing the effectiveness of investment decisions, with perception and experience playing particularly critical roles.

4.1.3 Regression Analysis

In this section, multivariate regression analysis has been used to analyze the impact of technical analysis on investment decision-making. This analysis examines how multiple independent variables, such as technical indicators and analysis methods, simultaneously influence the dependent variable of investment decision-making. By assessing the relationship between these variables, the regression analysis determines the extent to which technical analysis contributes to variations in investment decisions, while controlling for other influencing factors. This approach provides a comprehensive understanding of how technical analysis affects investment choices and strategies in a nuanced manner.

Table 14

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.712	0.507	0.500	0.473

Source: Appendix I & V

Table 14 presents the model summary of the regression analysis conducted. The regression model shows an R value of 0.712, indicating a strong positive correlation between the predictors and the dependent variable (investment decision making (IND)). The R square value of 0.507 suggests that approximately 50.7% of the variability in investment decision making is explained by the predictors, including perception of investor (POI), trading frequency (FRE), education (EDU), accessibility of information (AOI), time horizon (TIM), and experience (EXP). The adjusted R square of 0.500, which is slightly lower than the R square value, accounts for the number of predictors in the model. The standard error of the estimate is 0.473, reflecting the average distance between the observed and predicted values.

Table 15

ANOVA Table of Regression Model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	90.686	6	15.114	67.429	0.00
	Residual	88.092	393	0.224		
	Total	178.777	399			

Source: Appendix I & V

Table 15 presents the ANOVA results for the regression model. The regression model shows a significance level of 0.00, which is less than the threshold of 0.05. This indicates that the model is statistically significant and well-fitted for analysis. The F-value of 67.429 further supports the validity of the regression model, demonstrating that the predictors significantly contribute to explaining the variability in the dependent variable (investment decision making, IND).

Table 16

Beta Coefficient of Regression Model

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.695	0.171		4.075	0.000		
	EDU	0.063	0.041	0.078	1.558	0.120	0.499	2.004
	EXP	0.161	0.059	0.166	2.712	0.007	0.334	2.991
	TIM	0.080	0.062	0.074	1.301	0.194	0.385	2.594
	FRE	0.007	0.044	0.007	0.160	0.873	0.676	1.479
	AOI	0.111	0.052	0.108	2.132	0.034	0.485	2.061
	POI	0.418	0.052	0.416	8.077	0.000	0.473	2.112

Source: Appendix I & V

Table 16 presents the unstandardized and standardized beta coefficients, significance levels, and variance inflation factors (VIF) for each independent variable in the regression model.

For education (EDU), the unstandardized beta coefficient is 0.063, and the standardized beta coefficient is 0.078. The significance value is 0.12, which is greater than the 0.05 threshold, indicating that education does not significantly impact investment decision making (IND) at the 5 percent level. The VIF for education is 2.004, which is below 10,

suggesting that multicollinearity is not a concern for this variable. Although education has a positive effect on investment decisions, its impact is not statistically significant.

Experience (EXP) has an unstandardized beta coefficient of 0.161 and a standardized beta coefficient of 0.166. The significance value of 0.007 is below the 0.05 threshold, demonstrating that experience has a significant positive impact on investment decision making. The VIF for experience is 2.991, indicating no multicollinearity issues. This suggests that greater experience positively influences investment decisions and is a key factor to consider.

The time horizon (TIM) shows an unstandardized beta coefficient of 0.08 and a standardized beta coefficient of 0.074. With a significance value of 0.194, which is above 0.05, time horizon does not significantly impact investment decision making. The VIF for time horizon is 2.594, which is acceptable and shows no multicollinearity. This implies that while time horizon has a positive effect, its impact on investment decisions is not statistically significant.

Trading frequency (FRE) has an unstandardized beta coefficient of 0.007 and a standardized beta coefficient of 0.007. The significance value of 0.873 is well above 0.05, indicating that trading frequency does not significantly affect investment decision making. The VIF for trading frequency is 1.479, which is well below 10, suggesting no multicollinearity issues. Hence, trading frequency has minimal impact on investment decisions.

Accessibility of information (AOI) has an unstandardized beta coefficient of 0.111 and a standardized beta coefficient of 0.108. The significance value is 0.034, which is below the 0.05 threshold, indicating a significant positive impact on investment decision making. The VIF for accessibility of information is 2.061, suggesting no multicollinearity concerns. This suggests that easier access to information is crucial for making informed investment decisions.

Perception of investor (POI) has an unstandardized beta coefficient of 0.418 and a standardized beta coefficient of 0.416. The significance value of 0.000 is well below 0.05, demonstrating a highly significant positive impact on investment decision making. The VIF for perception of investor is 2.112, indicating no multicollinearity. This implies that a positive perception of technical analysis strongly enhances investment decision making.

The overall conclusion of the study is that certain variables have a significant impact on investment decision making, while others do not. Specifically, experience, perception of investor, and accessibility of information are found to significantly influence investment decisions, emphasizing their importance in the decision-making process. On the other hand, education, time horizon, and trading frequency do not show a significant effect on investment decision-making. This suggests that while experience and investor perception are crucial for making informed and effective investment choices, the role of education, time horizon, and trading frequency may be less critical. The findings highlight the need for investors to focus on acquiring relevant experience, leveraging investor perception, and ensuring access to comprehensive information to enhance their investment decisions.

4.1.4 Major Findings

- The survey results reveal a diverse demographic profile among the respondents. A majority are male (59.75%), with a significant proportion being between 35-44 years old (43.00%). In terms of education, nearly half hold a bachelor's degree (49.25%), and most have between 4-6 years of investment experience (43.25%). This distribution suggests a well-educated and experienced respondent base.

- Regarding trading behaviors, the majority of respondents trade on a monthly basis (41.25%), with a smaller segment engaging in daily trading (11.00%). This pattern indicates a preference for less frequent trading among the respondents, aligning with their varied investment experiences. Additionally, the sources of information show a strong reliance on technical analysis tools (25.75%) and financial news (15.75%), highlighting a preference for a combination of analytical and media sources for investment decisions.

- The respondents' investment goals are primarily focused on long-term growth (35.25%), followed by short-term gains (24.75%). This indicates a balanced approach towards achieving both immediate and future financial objectives. The distribution of investment goals reflects a strategic mix of long-term planning and short-term opportunities, with a smaller focus on income generation and speculative investments.

- The survey reveals that educational background (EDU) has a moderately positive impact on investors' ability to use technical analysis, with a mean score of 3.680 and a standard deviation of 0.824. This suggests that investors believe their

education plays a supportive role in their understanding of technical analysis, enhancing their application of analytical techniques.

- Experience (EXP) in the stock market is viewed as beneficial but not central to technical analysis, as indicated by a mean score of 3.637 and a standard deviation of 0.691. While investors value their experience, it is seen as a supportive factor rather than a primary one in utilizing technical analysis for investment decisions.
- The time horizon (TIM) is perceived to have a moderate effect on the relevance of technical analysis, with a mean score of 3.529 and a standard deviation of 0.618. Investors consider technical analysis somewhat more pertinent for shorter investment time horizons but do not view it as a dominant factor in their decision-making process.
- Trading frequency (FRE) is also regarded as moderately important, with a mean score of 3.449 and a standard deviation of 0.659. While frequent trading is seen as beneficial for applying technical analysis, it is not considered crucial for making investment decisions, reflecting a balanced view of its impact.
- Accessibility of information (AOI) has a somewhat positive impact on technical analysis, with a mean score of 3.587 and a standard deviation of 0.655. This indicates that good access to financial data and research tools is important but not the only determinant of effective investment decisions.
- Perception of investor (POI) reflects a moderate positive view of technical analysis in understanding market sentiment, with a mean score of 3.639 and a standard deviation of 0.666. This suggests a general confidence in the effectiveness of technical analysis for grasping market dynamics.
- Overall, the highest mean score is for investment decision making (IND), at 3.739 with a standard deviation of 0.669, highlighting that investors view technical analysis as a significant tool in shaping their investment strategies. This indicates a strong belief in the effectiveness of technical analysis for guiding investment choices.
- The correlation analysis shows that education (EDU) has a moderate positive correlation of 0.463 with investment decision making (IND). This suggests that higher education levels are associated with more effective investment decisions,

though the strength of this relationship is moderate. The correlation is statistically significant at the 5 percent level, indicating that education plays a meaningful, though not overwhelming, role in investment decision making.

- Experience (EXP) exhibits a strong positive correlation of 0.576 with investment decision making. This strong relationship implies that more extensive investment experience significantly enhances the quality of decision making. The correlation is significant at the 5 percent level, highlighting the crucial role that experience plays in shaping effective investment strategies.
- Time horizon (TIM) has a moderate to strong positive correlation of 0.517 with investment decision-making. This indicates that investors with a longer-term perspective tend to make better investment decisions. The relationship is statistically significant at the 5 percent level, suggesting that the time horizon contributes positively to the effectiveness of investment decisions.
- Trading frequency (FRE) shows a weak positive correlation of 0.275 with investment decision-making. This weaker correlation suggests that while there is a positive relationship between how frequently investors trade and their decision-making effectiveness, the impact is relatively minor. The correlation remains significant at the 5 percent level, though its effect on decision-making is less substantial compared to other factors.
- Accessibility of information (AOI) demonstrates a moderate to strong positive correlation of 0.554 with investment decision-making. This indicates that better access to financial information is associated with more effective investment decisions. The significance of this correlation at the 5 percent level underlines the importance of having good information access in improving investment outcomes.
- Perception of investor (POI) reveals a strong positive correlation of 0.662 with investment decision-making. This strong relationship highlights that a more favorable view of technical analysis significantly enhances decision-making effectiveness. The correlation is statistically significant at the 5 percent level, emphasizing the critical role of investor perception in shaping successful investment strategies.

- Overall, the findings underscore that education, experience, time horizon, and accessibility of information positively influence investment decision making, with experience and perception of investor having the most pronounced impact. Trading frequency, although positively correlated, has a less significant effect. These results highlight the importance of experience and perception in improving investment decisions, while also recognizing the supportive roles of education, time horizon, and information accessibility.

- The model summary of the regression analysis, revealing that the predictors explain approximately 50.7% of the variability in investment decision making (IND), as indicated by an R square value of 0.507. The strong positive correlation, with an R value of 0.712, suggests that the predictors, including perception of investor (POI), trading frequency (FRE), education (EDU), accessibility of information (AOI), time horizon (TIM), and experience (EXP), have a substantial influence on investment decisions. The adjusted R square of 0.500, slightly lower than the R square, adjusts for the number of predictors, confirming that the model's explanatory power remains robust.

- For education (EDU), the unstandardized beta coefficient is 0.063, and the standardized beta coefficient is 0.078. The significance value of 0.12 is greater than the 0.05 threshold, indicating that education does not have a statistically significant impact on investment decision making (IND) at the 5 percent level. Despite its positive effect, education's influence on investment decisions is not substantial enough to be considered significant. The variance inflation factor (VIF) for education is 2.004, which is well below 10, showing that multicollinearity is not an issue for this variable.

- Experience (EXP) shows an unstandardized beta coefficient of 0.161 and a standardized beta coefficient of 0.166, with a significance value of 0.007, which is below the 0.05 threshold. This indicates that experience has a significant positive effect on investment decision-making. The VIF for experience is 2.991, suggesting that there are no concerns about multicollinearity. The results imply that greater investment experience is crucial for making more effective investment decisions.

- The time horizon (TIM) has an unstandardized beta coefficient of 0.08 and a standardized beta coefficient of 0.074. With a significance value of 0.194, which is

above the 0.05 threshold, time horizon does not significantly impact investment decision-making. The VIF for the time horizon is 2.594, indicating no issues with multicollinearity. This shows that while time horizon has a positive effect, its impact on investment decisions is not statistically significant.

- Trading frequency (FRE) has an unstandardized beta coefficient of 0.007 and a standardized beta coefficient of 0.007. The significance value is 0.873, which is well above the 0.05 threshold, meaning that trading frequency does not significantly affect investment decision making. The VIF for trading frequency is 1.479, well below 10, indicating no multicollinearity problems. Consequently, trading frequency appears to have a minimal impact on investment decisions.
- Accessibility of information (AOI) has an unstandardized beta coefficient of 0.111 and a standardized beta coefficient of 0.108, with a significance value of 0.034, which is below the 0.05 threshold. This indicates a significant positive impact on investment decision making. The VIF for accessibility of information is 2.061, suggesting no issues with multicollinearity. The findings suggest that having easy access to financial data and research tools plays a crucial role in enhancing investment decisions.
- Perception of investor (POI) has an unstandardized beta coefficient of 0.418 and a standardized beta coefficient of 0.416. The significance value of 0.000 is well below 0.05, demonstrating a highly significant positive impact on investment decision making. The VIF for perception of investor is 2.112, indicating no multicollinearity. This implies that a positive perception of technical analysis significantly improves investment decision making.
- Overall, the study reveals that experience, perception of investor, and accessibility of information have a significant impact on investment decision making. In contrast, education, time horizon, and trading frequency do not significantly influence investment decisions. The results highlight that focusing on gaining relevant experience, having a positive perception of technical analysis, and ensuring access to comprehensive information are crucial for making effective investment decisions.

4.2 Discussion

The first objective of this study is to explore the use of technical analysis in investment decision-making. The findings reveal that investors view technical analysis as a crucial tool for developing their investment strategies, with a strong belief in its effectiveness. This perception is supported by moderate views on education, experience, and accessibility of information, which are seen as beneficial but not critical. Trading frequency and time horizon are considered relevant but not central to the decision-making process. Overall, technical analysis is recognized as a significant, though not exclusive, factor in investment decisions. Pheng et al. (2024) also found technical analysis to be effective but emphasized the need for a multi-technical indicator approach for improved performance, which aligns with the current study's recognition of technical analysis as valuable but not exclusive. Khan et al. (2024) focused on an automated trading system incorporating technical indicators, similar to the current study's view of technical analysis as crucial yet not sole, demonstrating a more integrated use. Pasaribu (2024) highlighted the need for confirmation of technical signals, contrasting with the current study's more straightforward acknowledgment of technical analysis, indicating a more cautious approach. Inani et al. (2024) found diverse themes within technical analysis, reflecting a broader scope than the current study's focus on its perceived importance, while Riaz and Zubair (2024) noted the impact of behavioral factors alongside technical analysis, contrasting with the current study's more straightforward assessment of technical analysis alone.

The second objective of this study is to analyze the relationship between technical analysis and investment decision-making. The analysis has found that experience and perception of technical analysis have a strong positive relationship with investment decision-making, indicating they significantly enhance decision-making. Education and accessibility of information have shown moderate to strong positive correlations, suggesting they positively influence decisions but to a lesser extent. Time horizon also exhibits a moderate to strong positive relationship, contributing positively to decision-making. Trading frequency, however, has only a weak positive correlation, indicating its minor effect. Pheng et al. (2024) supports the current findings by highlighting the effectiveness of a comprehensive multi-technical indicator strategy in enhancing trading performance. This aligns with the study's conclusion on the importance of experience and perception but extends it to a broader strategy involving multiple indicators. Khan et al. (2024) also resonate with the current research by emphasizing the integration of technical indicators in

an automatic trading system, which underscores the positive role of technical analysis in decision-making. However, Pasaribu (2024) contrasts this by indicating that while MACD crossovers are used, their effectiveness can be questionable without confirmation from other indicators, suggesting a more cautious approach compared to the current study's moderate to strong correlations. Inani et al. (2024) provides a broader view, revealing various themes and trends in technical analysis over time, which adds context to the current study's findings but does not directly compare with the specific relationships observed. Riaz and Zubair (2024) introduce behavioral factors, revealing that self-control and over-confidence also influence investment decisions, indicating that technical analysis is one of several influential factors, thus providing a nuanced view compared to the current study's focus on technical indicators alone.

The third objective of this study is to analyze the impact of technical analysis and investment decision-making. The analysis has found that experience, perception of investors, and accessibility of information significantly impact investment decisions. Experience has a strong positive effect, emphasizing its critical role in improving decision-making. Perception of investors shows a highly significant positive impact, indicating that a favorable view of technical analysis greatly enhances investment decisions. Accessibility of information also has a significant positive effect, highlighting the importance of easy access to financial data for informed decisions. In contrast, education, time horizon, and trading frequency do not significantly influence investment decisions. Education and time horizon have positive but statistically insignificant effects, suggesting their limited role, while trading frequency has a minimal effect, indicating it is not a major factor in investment choices. Inani et al. (2024) highlight various themes in technical analysis but do not directly address the influence of personal factors like experience or perception on investment decisions. Riaz and Zubair (2024) similarly stress the technical analysis but focus on self-control and over-confidence rather than the direct effects of experience or perception. Karki et al. (2023) and Almeida and Vieira (2023) focus on evaluating technical indicators and bibliometric analysis, respectively, without specifically addressing the impact of investor experience or perception. Singh et al. (2022) supports the significance of technical analysis but uses neural networks for prediction rather than personal investor factors which supports the result of this study.

CHAPTER V
SUMMARY AND CONCLUSION

This chapter provides a comprehensive summary of the study, highlighting that experience, perception of investors, and accessibility of information significantly influence investment decision-making, while education, time horizon, and trading frequency do not. The findings underscore the importance of gaining relevant experience, maintaining a positive view of technical analysis, and having good access to financial data for effective investment decisions. The implications of this study suggest that investors should prioritize these factors to enhance their decision-making process, and future research could further explore the nuanced impacts of less influential variables.

5.1 Summary

This study has examined, technical analysis and investment decision-making among Nepali investors, focusing on its effectiveness and applicability in the Nepali Stock Market. It has addressed several key challenges and discrepancies, including the contradiction between technical analysis and the Efficient Market Hypothesis (EMH), the influence of cognitive biases on investor behavior, and issues related to data availability and transparency. The objectives of this research have been to explore how Nepali investors utilize technical analysis, analyze its relationship with investment decision-making, and evaluate its impact on investment choices. Through this investigation, the study aims to provide valuable insights into the dynamics of investment strategies in Nepal, offering implications for both local investors and international observers.

The literature review of this study has been categorized into four main sections: conceptual review, theoretical review, empirical review, and research gap. The conceptual review has examined the history and types of technical analysis indicators, including moving averages, MACD, and RSI, among others. This section has provided a comprehensive overview of technical analysis tools and their applications in investment decision-making. The theoretical review has explored various theories relevant to technical analysis, such as the greater fool theory, dow theory, random walk theory, and zero-sum game, which have contributed to the understanding of market behavior and investor decision-making. The empirical review has summarized previous research findings on the impact of technical analysis on investment decisions, highlighting key results and methodologies used in related studies. Lastly, the research gap has identified areas where existing literature has

been insufficient, pointing out the need for further investigation into the application of technical analysis in different market contexts and among diverse investor groups.

The research has employed both descriptive statistics and a causal effect research design to analyze the impact of technical analysis and investment decision-making. Descriptive statistics have been used to explore the patterns, trends, and behaviors related to technical analysis and investment decisions, while the causal-comparative design has facilitated a deeper understanding of how technical analysis influences investment choices. The study has focused on individual investors in the Kathmandu Valley, with a sample of 400 investors selected through convenience sampling. This approach has enabled the collection of a representative sample while addressing practical constraints. The data collection has been conducted using a quantitative approach, primarily through a questionnaire survey designed with a five-point Likert scale. This survey has gathered firsthand insights from investors, providing a comprehensive understanding of their behaviors and preferences regarding technical analysis and investment decision-making.

In this study, the method of analysis involved the use of statistical software tools, including Microsoft Excel and SPSS, to meticulously analyze the data. Descriptive statistics have provided insights into central tendencies and variability, while correlation analysis has explored associations between variables. Multivariate regression models have been employed to identify significant predictors and their impacts on investment decision-making outcomes. The research framework, based on Utami and Nugroho (2017), incorporates key independent variables such as education, experience, time horizon, trading frequency, accessibility of information, and perception of investors. These variables are examined about the dependent variable, investment decision-making, to understand the factors influencing investment decisions in the Nepali Stock Market.

Based on the findings of this study, it is evident that the independent variables significantly influence the dependent variable, investment decision-making, albeit to varying extents. The analysis has highlighted that experience, perception of investors, and accessibility of information are key determinants of effective investment decision-making. Experience has been identified as a crucial factor, demonstrating a significant positive impact, which underscores the importance of investor expertise in making sound investment choices. Similarly, the perception of investors has shown a highly significant positive effect, reflecting that a favorable view of technical analysis strongly contributes to improved decision-making. Accessibility of information also plays a significant role, with better

access to financial data facilitating more informed decisions. In contrast, education, time horizon, and trading frequency have shown less pronounced impacts on investment decision-making. While education and time horizon exhibit positive effects, they are not statistically significant, suggesting their roles are less critical in the decision-making process. Trading frequency has had a minimal effect, indicating it is not a significant determinant of investment decisions. Overall, the study emphasizes that while experience, perception, and access to information are major determinants of investment decision-making, the influence of education, time horizon, and trading frequency is comparatively weaker. This indicates that investors should focus on gaining experience, fostering a positive perception of technical analysis, and ensuring robust access to information to enhance their investment decision-making processes.

This study has highlighted several practical and theoretical implications. Practically, investors in the Nepali Stock Market can benefit from understanding the significance of technical analysis and its components in improving investment decisions. Theoretical implications underscore the importance of integrating investor characteristics and market behaviors into investment models. Recommendations include enhancing investor education on technical analysis and promoting tools that facilitate better access to market data. Future research should explore the impact of additional variables on investment decision-making and extend findings to different market contexts.

5.2 Conclusion

The first objective of this study is to assess the use of technical analysis in investment decision-making. The findings indicate that investors generally perceive technical analysis as an important tool for shaping their investment strategies. The high mean score for investment decision-making reflects a strong belief in the effectiveness of technical analysis in guiding their choices. This positive perception is supported by moderate views on factors such as education, experience, and accessibility of information, which are considered beneficial but not solely decisive. Although trading frequency and time horizon are seen as moderately relevant, they do not dominate the decision-making process. Overall, technical analysis has been viewed as a significant, though not the only, factor influencing investment decisions.

The second objective of this study is to examine the relationship between technical analysis and investment decision-making. The analysis has revealed varying strengths of relationships between different variables and investment decision-making. Education has

shown a moderate positive correlation with investment decision-making, indicating that higher education levels are associated with better decision-making, though the relationship is not extremely strong. Experience has exhibited a strong positive correlation, highlighting that greater experience significantly enhances investment decisions. Time horizon has demonstrated a moderate to strong positive relationship, suggesting that a longer-term investment perspective contributes positively to decision-making. Trading frequency has had a weak positive correlation, implying that while frequent trading has a positive effect, it is relatively minor. Accessibility of information has shown a moderate to strong positive correlation, emphasizing that better access to financial data improves investment decisions. Lastly, the perception of investors has exhibited a strong positive relationship, indicating that a favorable perception of technical analysis is strongly linked to improved decision-making. Overall, the study has emphasized the significant, experience, and perception in enhancing investment decision-making, with moderate influences from education, time horizon, and accessibility of information, and a weaker influence from trading frequency.

The third objective of this study is to analyze the impact of technical analysis on investment decision-making. The analysis has revealed that experience, perception of investors, and accessibility of information significantly impact investment decision-making. Experience has a significant positive effect, highlighting its crucial role in enhancing decision-making. Perception of investors shows a highly significant positive impact, indicating that a favorable view of technical analysis strongly improves investment decisions. Accessibility of information also demonstrates a significant positive impact, emphasizing that ease of access to financial data is essential for informed decision-making. Conversely, education, time horizon, and trading frequency do not significantly impact investment decisions. Education and time horizon have positive effects, but their impacts are not statistically significant, suggesting that they are less critical in the decision-making process. Trading frequency has a minimal effect, indicating it is not a significant factor in influencing investment choices. Overall, the findings emphasize the importance of experience, perception, and access to information in making effective investment decisions, while the role of education, time horizon, and trading frequency appears to be less influential.

5.3 Implications

5.3.1 Theoretical Implications

The study's findings contribute significantly to the theoretical understanding of investment decision-making, particularly regarding the technical analysis. By emphasizing the impact

of investor experience, perception, and information accessibility on investment choices, this research extends traditional theories in technical analysis and behavioral finance. Conventional models often prioritize technical indicators and algorithms for forecasting market trends, focusing on quantitative measures. However, this study integrates subjective elements like investor experience and perception, which are less frequently addressed in established theories. This incorporation offers a more comprehensive view of how personal factors influence decision-making, blending technical analysis with behavioral insights. It highlights that cognitive biases and behavioral patterns significantly shape investment strategies, enriching the theoretical framework by connecting the technical and psychological dimensions of investor behavior. This nuanced understanding helps bridge the gap between technical analysis and behavioral finance, offering a more holistic approach to analyzing investment decisions.

5.3.2 Practical Implications

Practically, the study's results have meaningful implications for both investors and financial advisors. The identification of experience, perception, and information accessibility as key factors influencing investment decisions underscores the need for tailored investment strategies. Investors can benefit from focusing on enhancing their experience and understanding of technical analysis, which can lead to more informed and effective decision-making. Financial advisors and investment platforms should prioritize improving investors' access to relevant information and offer educational resources to deepen their technical knowledge. The findings suggest that while traditional factors such as education and trading frequency may have less impact, practical applications of technical indicators and personalized advice based on individual profiles can improve investment outcomes. Financial institutions should consider developing tools and resources that accommodate different levels of investor experience and perception. By integrating these practical insights, financial advisors can better support investors in making informed choices, potentially leading to improved investment performance and greater satisfaction.

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APPENDICES

Appendix I

Questionnaire

Dear Sir/Mam,

I am conducting research for my master's degree dissertation titled " Technical Analysis and Investment Decision-Making in the Nepali Stock Market." I am reaching out to request your valuable assistance with this study. Your insights and experiences in the stock market are incredibly important to my research, and I would greatly appreciate your participation in a brief survey. The survey aims to gather perspectives on how technical analysis influences investment decisions.

Your responses will contribute significantly to understanding the impact of technical analysis in the Nepali stock market and will help provide more comprehensive insights into the factors affecting investment decision-making.

The survey is designed to be brief and should take no more than 10 minutes of your time. Rest assured that all responses will be kept confidential and used solely for academic purposes. Thank you very much for considering this request. Your participation would be immensely helpful for the success of my research.

Part I: Demographic Profile

Please put a tick mark (✓) in the box in an appropriate option for each of the following.

Age

- Below 25 Years
- 25-34 years
- 35-44 years
- 45 years and above

Gender

- Male
- Female
- Other

Educational Background

- High School or equivalent
- Bachelor's Degree
- Master's Degree or above

Investment Experience

- Less than 1 year

1-3 years
4-6 years
7-10 years
More than 10 years

Frequency of Trading

Daily
Weekly
Monthly
Quarterly
Annually

Source of Information for Investment Decisions

Financial News and Media
Technical Analysis Tools
Recommendations from Financial Advisors
Peer Discussions and Forums
Company Reports and Filings

Investment Goals

Short-term gains
Long-term growth
Income generation (e.g., dividends)
Diversification
Speculative opportunities

Part II: Core Questions of Technical Analysis

Please put a tick mark (✓) in the box in an appropriate option for each of the following.

S.N.	Education	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
EDU1	My education has prepared me well to understand technical analysis.					
EDU2	Higher education positively influences my ability to interpret stock market data.					
EDU3	I feel confident applying technical analysis principles due to my educational background.					
EDU4	Formal education in finance is essential for successful implementation of technical analysis.					
EDU5	Continuous learning is crucial for improving					

	proficiency in technical analysis.					
EDU6	My academic knowledge guides my investment decisions in the stock market.					

S.N.	Experience	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
EXP1	Past experiences significantly influence my reliance on technical analysis.					
EXP2	My trading experience is sufficient for effectively using technical analysis.					
EXP3	Over time, I've developed a strong intuition for interpreting technical indicators.					
EXP4	Experience has taught me to identify trends and patterns in the stock market accurately.					
EXP5	I've learned valuable lessons from past successes and failures in technical analysis.					
EXP6	Practical experience in trading is essential for mastering technical analysis.					

S.N.	Time Horizon	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
TIM1	I prefer short-term investments to capitalize on immediate market movements.					
TIM2	Technical analysis is more useful for my short-term trading strategies than for long-term investments.					
TIM3	I frequently adjust my investment portfolio based on short-term price trends identified through technical analysis.					

TIM4	Long-term investment goals are less important to me compared to short-term profit opportunities.					
TIM5	My investment strategy focuses more on short-term gains rather than long-term stability.					
TIM6	I am more interested in short-term market trends than in long-term growth prospects when making investment decisions.					

S.N.	Trading Frequency	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
FRE1	I prefer to actively trade stocks on a daily basis.					
FRE2	Frequent trading allows me to capitalize on short-term price movements.					
FRE3	My investment strategy involves making multiple trades within a single day.					
FRE4	High trading frequency is essential for implementing technical analysis strategies.					
FRE5	I am comfortable with the level of risk associated with frequent trading.					
FRE6	I regularly review and adjust my trading strategy based on frequent market movements.					

S.N.	Accessibility of Information	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
AOI1	I have access to a wide range of financial data and research tools.					
AOI2	Timely access to market information is critical for making informed decisions.					
AOI3	Online trading platforms and research resources enhance my ability to conduct analysis.					

AOI4	Access to real-time market data gives me a competitive edge in executing trades.					
AOI5	I am satisfied with the accessibility of financial information provided by my brokerage.					
AOI6	I find that having easy access to historical data is important for effective technical analysis.					

S.N.	Perception of Investor	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
POI1	Investors who prioritize technical analysis tend to achieve higher returns.					
POI2	Successful investors effectively use technical analysis to time market entry and exit points.					
POI3	Technical analysis is essential for gaining insights into market sentiment and behavior.					
POI4	Investors who incorporate technical analysis are adaptable to changing market conditions.					
POI5	Proficiency in interpreting chart patterns and technical indicators defines experienced investors.					
POI6	Investors who rely on technical analysis are better equipped to manage investment risks and uncertainties.					

Appendix II

Frequency Table

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	239	59.8	59.8	59.8
	Female	161	40.3	40.3	100.0
	Total	400	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 25 Years	54	13.5	13.5	13.5
	25-34 years	128	32.0	32.0	45.5
	35-44 years	172	43.0	43.0	88.5
	45 years and above	46	11.5	11.5	100.0
	Total	400	100.0	100.0	

Educational Background

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High School or equivalent	96	24.0	24.0	24.0
	Bachelor's Degree	197	49.3	49.3	73.3
	Master's Degree or above	107	26.8	26.8	100.0
	Total	400	100.0	100.0	

Investment Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	26	6.5	6.5	6.5
	1-3 years	108	27.0	27.0	33.5
	4-6 years	173	43.3	43.3	76.8
	7-10 years	49	12.3	12.3	89.0
	More than 10 years	44	11.0	11.0	100.0
	Total	400	100.0	100.0	

Frequency of Trading

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Daily	44	11.0	11.0	11.0
	Weekly	86	21.5	21.5	32.5
	Monthly	165	41.3	41.3	73.8
	Quarterly	52	13.0	13.0	86.8

	Annually	53	13.3	13.3	100.0
	Total	400	100.0	100.0	

Source of Information for Investment Decisions

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Financial News and Media	63	15.8	15.8	15.8
	Technical Analysis Tools	103	25.8	25.8	41.5
	Recommendations from Financial Advisors	89	22.3	22.3	63.8
	Peer Discussions and Forums	83	20.8	20.8	84.5
	Company Reports and Filings	62	15.5	15.5	100.0
	Total	400	100.0	100.0	

Investment Goals

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Short-term gains	99	24.8	24.8	24.8
	Long-term growth	141	35.3	35.3	60.0
	Income generation (e.g., dividends)	50	12.5	12.5	72.5
	Diversification	58	14.5	14.5	87.0
	Speculative opportunities	52	13.0	13.0	100.0
	Total	400	100.0	100.0	

Appendix III

Descriptive Statistics

	N	Mean	Std. Deviation
My education has prepared me well to understand technical analysis.	400	3.5625	1.21441
Higher education positively influences my ability to interpret stock market data.	400	3.6800	1.03938
I feel confident applying technical analysis principles due to my educational background.	400	3.8200	0.99754
Formal education in finance is essential for successful implementation of technical analysis.	400	3.6325	1.04171
Continuous learning is crucial for improving proficiency in technical analysis.	400	3.6950	0.99974
My academic knowledge guides my investment decisions in the stock market.	400	3.6900	0.98046
Past experiences significantly influence my reliance on technical analysis.	400	3.6975	0.95040
My trading experience is sufficient for effectively using technical analysis.	400	3.6475	0.92487
Over time, I've developed a strong intuition for interpreting technical indicators.	400	3.4500	1.00749
Experience has taught me to identify trends and patterns in the stock market accurately.	400	3.6950	0.96919
I've learned valuable lessons from past successes and failures in technical analysis.	400	3.6450	0.94404
Practical experience in trading is essential for mastering technical analysis.	400	3.6875	0.90382
I prefer short-term investments to capitalize on immediate market movements.	400	3.6100	0.91652
Technical analysis is more useful for my short-term trading strategies than for long-term investments.	400	3.5925	0.92660
I frequently adjust my investment portfolio based on short-term price trends identified through technical analysis.	400	3.5650	0.95028
Long-term investment goals are less important to me compared to short-term profit opportunities.	400	3.6475	0.94099
My investment strategy focuses more on short-term gains rather than long-term stability.	400	3.3800	0.94490
I am more interested in short-term market trends than in long-term growth prospects when making investment decisions.	400	3.3825	0.97394
I prefer to actively trade stocks on a daily basis.	400	3.4100	0.92685
Frequent trading allows me to capitalize on short-term price movements.	400	3.4700	0.95203

My investment strategy involves making multiple trades within a single day.	400	3.4700	0.92533
High trading frequency is essential for implementing technical analysis strategies.	400	3.3975	0.96790
I am comfortable with the level of risk associated with frequent trading.	400	3.4575	0.86026
I regularly review and adjust my trading strategy based on frequent market movements.	400	3.4900	0.91487
I have access to a wide range of financial data and research tools.	400	3.4900	0.96552
Timely access to market information is critical for making informed decisions.	400	3.6075	0.95694
Online trading platforms and research resources enhance my ability to conduct analysis.	400	3.6425	0.89257
Access to real-time market data gives me a competitive edge in executing trades.	400	3.6350	0.88811
I am satisfied with the accessibility of financial information provided by my brokerage.	400	3.5850	0.94605
I find that having easy access to historical data is important for effective technical analysis.	400	3.5625	0.92641
Investors who prioritize technical analysis tend to achieve higher returns.	400	3.5975	0.90970
Successful investors effectively use technical analysis to time market entry and exit points.	400	3.6925	0.81830
Technical analysis is essential for gaining insights into market sentiment and behavior.	400	3.5350	0.97270
Investors who incorporate technical analysis are adaptable to changing market conditions.	400	3.6400	0.90689
Proficiency in interpreting chart patterns and technical indicators defines experienced investors.	400	3.6475	0.92757
Investors who rely on technical analysis are better equipped to manage investment risks and uncertainties.	400	3.7250	0.94159
I prioritize technical analysis over fundamental analysis in my investment decision-making process.	400	3.7100	0.92631
I believe that past price movements and chart patterns are reliable indicators for future market trends.	400	3.6750	0.93088
Technical indicators such as moving averages and RSI significantly influence my buy or sell decisions.	400	3.7700	0.92153
I actively seek out information on technical analysis strategies to enhance my investment decisions.	400	3.7450	0.87286
I am comfortable with taking calculated risks based on technical signals to achieve investment goals.	400	3.7600	0.91075
I regularly review historical market data and perform technical analysis to adjust my investment portfolio.	400	3.7725	0.91259
EDU	400	3.6801	0.82407

EXP	400	3.6370	0.69113
TIM	400	3.5294	0.61808
FRE	400	3.4491	0.65888
AOI	400	3.5869	0.65477
POI	400	3.6394	0.66611
IND	400	3.7388	0.66938
Valid N (listwise)	400		

Appendix IV

Correlation Analysis

Correlations[b]

		EDU	EXP	TIM	FRE	AOI	POI	IND
EDU	Pearson Correlation	1	.694**	.514**	.176**	.463**	.434**	.463**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000	0.000
EXP	Pearson Correlation	.694**	1	.693**	.307**	.544**	.586**	.576**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000
TIM	Pearson Correlation	.514**	.693**	1	.536**	.523**	.546**	.517**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000
FRE	Pearson Correlation	.176**	.307**	.536**	1	.367**	.298**	.275**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000	0.000
AOI	Pearson Correlation	.463**	.544**	.523**	.367**	1	.667**	.554**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000	0.000
POI	Pearson Correlation	.434**	.586**	.546**	.298**	.667**	1	.662**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000		0.000
IND	Pearson Correlation	.463**	.576**	.517**	.275**	.554**	.662**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).

b. Listwise N=400

Appendix V

Regression Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.712[a]	0.507	0.500	0.47345

a. Predictors: (Constant), POI, FRE, EDU, AOI, TIM, EXP

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	90.686	6	15.114	67.429	.000[b]
	Residual	88.092	393	0.224		
	Total	178.777	399			

a. Dependent Variable: IND

b. Predictors: (Constant), POI, FRE, EDU, AOI, TIM, EXP

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.695	0.171		4.075	0.000		
	EDU	0.063	0.041	0.078	1.558	0.120	0.499	2.004
	EXP	0.161	0.059	0.166	2.712	0.007	0.334	2.991
	TIM	0.080	0.062	0.074	1.301	0.194	0.385	2.594
	FRE	0.007	0.044	0.007	0.160	0.873	0.676	1.479
	AOI	0.111	0.052	0.108	2.132	0.034	0.485	2.061
	POI	0.418	0.052	0.416	8.077	0.000	0.473	2.112

a. Dependent Variable: IND

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ii ABSTRACT This study explores the role of technical analysis in investment decision-making among Nepalese investors, addressing

the effectiveness and applicability **of technical analysis in the Nepalese** Stock **Market**

. It identifies key challenges such as the contradiction with the Efficient Market Hypothesis (EMH), cognitive biases, and issues with data availability. The primary objective is to investigate how technical analysis influences investment decisions and its practical relevance in the Nepalese context. The research employs a quantitative approach with a causal-comparative design. Data were collected from a sample of 400 individual investors in the Kathmandu Valley, selected through convenience sampling. A structured questionnaire using a five-point Likert scale served as the primary instrument for gathering data, focusing on investors' behaviors and perceptions regarding technical analysis. Statistical analysis was conducted using Microsoft Excel and SPSS, with tools including descriptive statistics, correlation analysis, and multivariate regression models. The research framework examines key independent variables—education, experience, time horizon, trading frequency, accessibility of information, and perception of investor— against the dependent variable of investment