Exploring the Role of Next-Generation Investment Management Robotic Automation Architecture for Portfolio Management and Risk Mitigation through AI and ML

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Exploring the Role of Next-Generation Investment Management Robotic Automation Architecture for Portfolio Management and Risk Mitigation through AI and Ml

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Dedication

To my beloved, my Daughter Mahira Trivedi, Parents and my Husband, whose steadfast support and deep understanding have been my guiding light throughout this journey. Your strength and encouragement have been invaluable to me.

I also want to express my heartfelt gratitude to my wonderful children, who have filled my life with joy and balance and provided me with moments of peace and rejuvenation.

Your presence has been a continuous source of happiness, enabling me to concentrate and thrive in this endeavour. Each of you has played a vital role in this journey, and for that, I am forever grateful.

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Furthermore, I extend gratitude to the individuals who participated in the research interviews. Their thoughtful responses and willingness to share experiences have been invaluable, significantly enhancing the quality and validity of my research."

ABSTRACT

This thesis provides an exhaustive examination of the transformative potential of next-generation investment management robotic automation architecture, leveraging “artificial intelligence (AI) and machine learning (ML) to revolutionize investment analysis, portfolio management, and risk mitigation”(Mahalakshmi et al., 2022), thereby enhancing the efficiency, productivity, and decision-making(Zakaria, Z., & Razak, 2023a) capabilities of investment managers and organizations. By integrating data analytics, predictive modelling, and decision support systems, this innovative architecture facilitates the automation of complex investment processes, enabling more accurate and timely investment decisions. The research undertakes “a comprehensive review of existing literature on AI, ML, and robotic automation(Chakraborti *et al.*, 2020a) in investment management, identifying gaps and opportunities for improvement.” A mixed-methods approach is employed, combining theoretical modelling, empirical analysis, and experimental design. Historical market data and simulated investment scenarios are utilized to evaluate the architecture's performance against traditional investment management methods.

The study investigates “the impact of AI and ML on investment analysis(Chen, Y., & Wang, 2019a), portfolio management, and risk mitigation, exploring applications such as predictive modelling, natural language processing, and deep learning”(Teng, C., Liao, Y., & Tseng, 2023a). Key research questions addressed include the potential “robotic automation architecture to enhance investment analysis and portfolio management, the impact of AI and ML on risk mitigation”(Duarte, F., & Girardi, 2022a), and the potential for next-generation robotic automation architecture to improve investment decision-making. The thesis contributes to advancements in investment management technology, providing insights into AI and ML applications and empirical evidence on the effectiveness of next-generation investment management solutions.

Expected findings include enhanced investment analysis accuracy, improved portfolio management efficiency, reduced risk exposure, and increased operational efficiency. This research

aims to provide “a comprehensive understanding of the potential benefits and challenges associated with integrating AI and ML” (Chavarnak, J., Lee, M., Patel, S., & Tran, 2018; Khan, A., & Bhatti, 2023a)into investment management robotic automation architecture, discussing implications for investment management practice, policy, and future research. The study highlights the potential for next-generation robotic automation architecture to transform the investment management industry, enabling more informed investment decisions, improved risk management, and increased operational efficiency.

Furthermore, this research explores “the potential applications of AI and ML in investment management(Frank J. Fabozzi (Editor), 2011), including predictive modelling, natural language processing, and deep learning, and examines the role of data quality, governance, and security in ensuring the integrity and reliability of AI-driven investment decisions”. The thesis also investigates the human-AI collaboration paradigm, examining how investment managers and AI systems can work together to achieve better outcomes. By ‘investigating the intersection of AI, ML, and investment management, this research contributes to the development of more sophisticated and effective investment management systems, shedding light on the opportunities and challenges associated with this emerging technology”(Madakam, Holmukhe and Revulagadda, 2022a).

Ultimately, this thesis provides a critical examination of the transformative potential of “next-generation investment management robotic automation architecture, offering actionable insights and recommendations for investment managers, organizations, and policymakers seeking to harness the power of AI and ML in investment management”(Zakaria *et al.*, 2023a). The research underscores “the importance of ongoing innovation and investment in AI and ML research and development, ensuring that investment management organizations remain competitive and resilient in an increasingly complex and dynamic market environment”(Gill *et al.*, 2022a). By advancing our understanding of AI and ML applications in investment management, this thesis informs the development of more effective investment management strategies, policies, and practices.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

“The Investment management landscape is undergoing a transformative shift, driven by the integration of Next-Generation Investment Management Robotic Automation Architecture leveraging Artificial Intelligence (AI) and Machine Learning (ML)”, which is “revolutionizing the industry by addressing escalating complexities and volatility in global financial markets” (Gill *et al.,* 2022b). Traditional portfolio management approaches are proving inadequate in today's era of rapid technological advancements, globalization, and data proliferation, intensifying challenges investors face, including “navigating intricate web of global financial markets, managing vast datasets, and ensuring regulatory compliance”. (Zakaria *et al.,* 2023b).

Automation emerges as a vital solution, enabling real-time decision-making, enhanced returns, and reduced operational costs through AI-driven insights and efficient data analysis, thereby empowering investment managers to optimize portfolio performance, mitigate risks, and unlock new growth opportunities (Madakam, Holmukhe and Revulagadda, 2022b; Sarker, 2022a). By harnessing AI and ML, investment firms can analyze vast datasets, uncover trends, and ensure regulatory compliance through real-time monitoring and reporting, streamlining administrative tasks, and enhancing operational efficiency (Dewasiri *et al*., 2023a).

This technology improves scalability, allowing firms to manage larger, more complex portfolios without increased resources or personnel, and enables strategic decision-making by automating routine tasks, freeing up resources for high-value activities. Moreover, automation enhances risk management, optimizes asset allocation, and improves customer experience through personalized investment solutions. “The benefits of automation in investment management are multifaceted, encompassing improved returns, reduced costs, enhanced scalability, real-time regulatory compliance monitoring, strategic decision-making capabilities, and sustained growth and success in an increasingly competitive environment”(Che Hassan *et al*., 2023) & (Bender, A., Chen, Y., & Xu, 2022). As the "investment management landscape continues to evolve, firms embracing Next-Generation Investment Management Robotic Automation Architecture will thrive, staying ahead of market trends and volatility, optimizing portfolio performance, enhancing operational efficiency, ensuring regulatory compliance, driving innovation, and fostering a culture of continuous improvement"(Madakam, Holmukhe and Revulagadda, 2022a).

"The seamless integration of AI and ML in investment management will redefine the industry's future, unlocking new opportunities for growth, innovation, and success, while navigating the complexities of global financial markets, managing risks, and ensuring regulatory compliance"(Esenogho, Djouani and Kurien, 2022). Furthermore, "automation will enable investment managers to focus on high-value activities, such as investment strategy development, portfolio optimization, and client relationships, rather than being bogged down by administrative tasks"(Chakraborti *et al.*, 2020b). Ultimately, "the transformative power of automation will reshape the investment management industry, driving efficiency, innovation, and growth, and positioning firms for sustained success in an increasingly complex and competitive environment"(Clarke, R., & Xu, 2023).

1.1.1 Evolution of Investment Management

The investment management landscape has undergone a profound transformation, evolving from manual, intuition-driven decisions to sophisticated algorithmic systems, leveraging advancements in technology, data analytics, and artificial intelligence (Huang et al. (2024), 2024). Historically, investment practices relied heavily on human judgment, with portfolio managers using experience and instincts to guide decisions, but this approach had limitations, including a lack of understanding of complex market dynamics and an inability to process vast amounts of information effectively (Patel, S., & Raghavan, 2022).

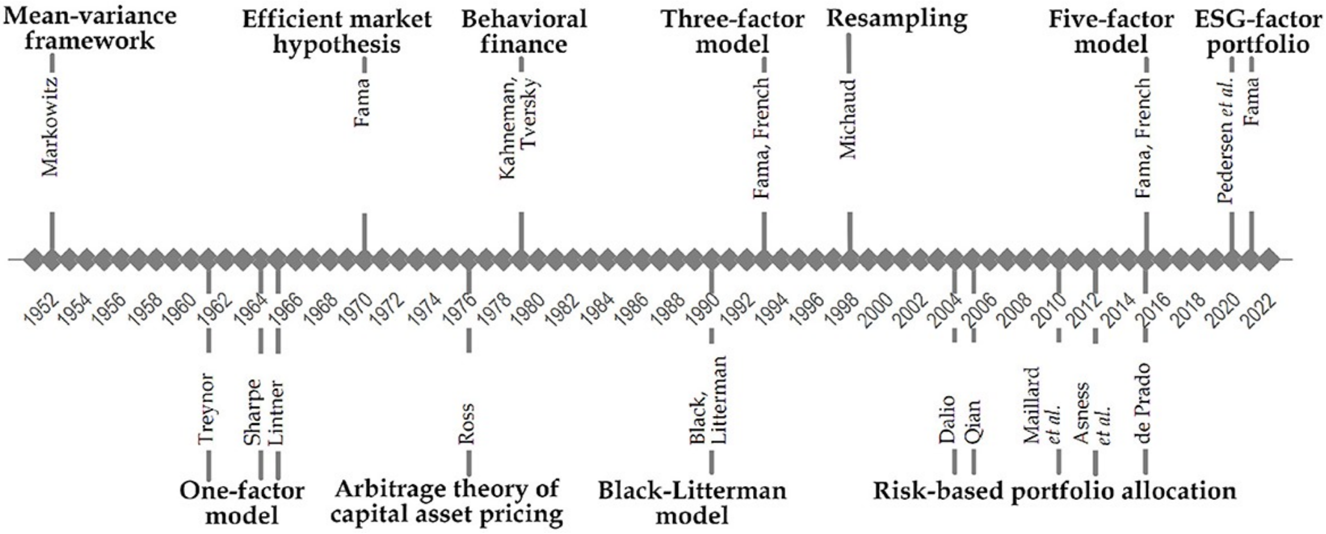
However, the advent of Robo-Advisors and algorithmic trading marked a significant turning point, revolutionizing investment service delivery and democratizing access to financial services for a broader audience (Chakraborti *et al.*, 2020b) "Robo-advisors provide automated, low-cost investment advice, harnessing algorithms and client data to optimize portfolio performance, while algorithmic trading enables traders to capitalize on price movements in milliseconds, far exceeding human capabilities" **(**(Wang, He and Ouyang, 2024a) (Yan, 2023a)**).**

Algorithmic trading has revolutionized the financial landscape by leveraging pre-defined rules to execute trades at optimal moments, capitalizing on price movements in milliseconds and far surpassing human capabilities (Yan, 2023b)**.** "This technological advancement enables traders to react swiftly and precisely to market fluctuations, mitigating risks and maximizing gains"(Che *et al.*, 2024). "High-frequency trading, a subset of algorithmic trading, has accelerated trading processes and enhanced market liquidity through powerful algorithms, executing large volumes of orders at unprecedented speeds and reducing trading latency" (Adel, 2023)**.** By automating trading decisions, algorithmic trading minimizes emotional bias, ensures consistency, and optimizes portfolio performance. Moreover, "advanced algorithms integrate machine learning, natural language processing, (NLP) and data analytics to analyze vast amounts of market data, identify patterns, and predict trends"(Teng, C., Liao, Y., & Tseng, 2023b). The synergy of technology and trading strategy has transformed financial markets, fostered efficiency, precision, competitiveness, and innovation, while also presented challenges such as regulatory compliance, risk management, and cybersecurity(Adel, 2023). "As algorithmic trading continues to evolve, its impact on financial markets will only intensify, driving growth, sophistication, and resilience in the industry"(Khan, A., & Bhatti, 2023b).

"The technological revolution has transformed the investment landscape, empowering investors to leverage vast amounts of data for informed decision-making"(Che Hassan *et al.*, 2023). By transitioning from manual to automated processes, investment firms have achieved greater efficiency, enabling the development of sophisticated strategies that incorporate a wide range of factors, including economic indicators, market trends, sentiment analysis, and risk management(Pang, B., & Lee, 2008). By harnessing advanced analytics, machine learning, and artificial intelligence, investment firms can now optimize portfolio performance, mitigate risks, and navigate complex market dynamics with greater precision and confidence(Conlon, Cotter and Kynigakis, 2021).

figures: Advancement in portfolio management

1.1.2 The Impact of Big Data



“The proliferation of big data has revolutionized investment management, playing a pivotal role in its evolution” (Esenogho, Djouani and Kurien, 2022)**.** By collecting, storing, and “analyzing vast amounts of information, investors gain profound insights into market behavior and investor sentiment through techniques like sentiment analysis, predictive modeling, machine learning,(Sarker, 2022b) and data mining, enabling them to identify complex patterns and trends that inform investment decisions”. Integrating big data analytics with traditional strategies creates hybrid models combining quantitative analysis with qualitative insights (Kumar Tyagi, U and Abraham, 2020)**,** fostering a comprehensive understanding of market dynamics and leading to improved investment outcomes. Big data enhances market insights, optimizes portfolio performance, improves risk management, increases operational efficiency, and ensures regulatory compliance, thereby empowering investors to navigate complex market landscapes with confidence. Moreover, alternative data sources such as satellite imagery, sensor data, and (Lazzini, A., Lazzini, S., Balluchi, F. and Mazza, 2022)social media provide unique perspectives on economic activity, while advanced analytics facilitate stress testing, scenario analysis, and predictive modeling. The benefits of big data in investment management are multifaceted, encompassing enhanced market insights, improved portfolio performance, better risk management, increased operational efficiency, and regulatory compliance.

As big data continues to shape investment management, firms embracing this technology will thrive, leveraging its transformative power to drive growth, innovation, and resilience. Conversely, those lagging risk being left behind in an increasingly data-driven industry, where precision, agility, and informed decision-making are paramount. Consequently, investment managers must prioritize big data integration, cultivating expertise in data science, machine learning, and analytics to remain competitive. By harnessing big data's potential, investment firms can unlock new opportunities, optimize returns, and mitigate risks, ultimately redefining the investment management landscape. “The seamless integration of big data analytics and investment management will continue to drive innovation, efficiency, and growth, paving the way for a new era of data-driven investing”(Che Hassan *et al.*, 2023).

1.1.3 Role of Technology in Investment Management

“Technology has emerged as a transformative force in investment management, revolutionizing the industry's operational dynamics and decision-making processes” (Douglas and Roger, 2024). “Innovations in financial software, big data analytics, and automated trading platforms have dramatically enhanced portfolio management efficiency, streamlined financial operations, and empowered financial professionals (Clarke, R., & Xu, 2023)to make informed decisions, optimizing portfolio performance, mitigating risks, and navigating complex market landscapes with precision”. Financial software solutions automate tasks, reduce manual errors, and increase operational scalability, while big data analytics (Zhang, T., & Zhao, 2022)provides unparalleled insights into market trends, investor sentiment, and economic indicators. Automated trading platforms execute trades at optimal moments, leveraging pre-defined rules and machine learning algorithms, and technologies like artificial intelligence, blockchain(Kumar Tyagi, U and Abraham, 2020), and cloud computing are redefining investment management. AI-powered chatbots provide personalized investor support, blockchain ensures secure, transparent transactions, and cloud-based infrastructure enables seamless data storage, processing, and collaboration. According to (Zakaria, Z., & Razak, 2023b) “The benefits of technology in investment management include enhanced decision-making, improved efficiency, risk management, scalability, and regulatory compliance”. As technology continues to evolve, investment managers must adapt to remain competitive, embracing innovation to unlock new opportunities, optimize returns, and reinforce their market position. A study conducted by(Kumar Tyagi, U and Abraham, 2020) The future of investment management will be shaped by the integration of AI and machine learning, widespread adoption of cloud-based infrastructure, increased use of blockchain, advancements in data analytics and visualization, and regulatory frameworks addressing technological innovations. By prioritizing technological integration, investment managers can drive growth, innovation, and resilience in an increasingly complex industry, where precision, agility, and informed decision-making are paramount.

Financial Software and Tools

The advent of advanced financial software has revolutionized investment management, empowering managers to execute intricate analyses swiftly and efficiently (Ng et al., 2021). Sophisticated portfolio management systems enable real-time tracking of assets, performance metrics, and risk assessments, facilitating data-driven decision-making. Integrated analytics capabilities allow managers to conduct scenario modeling and stress testing, evaluating portfolio performance under diverse market conditions(Lee *et al.*, 2024). These tools provide unparalleled insights into portfolio dynamics, risk exposure, and potential returns. “Advanced features include predictive analytics, machine learning algorithms, and data visualization, enabling managers to identify trends, optimize portfolio composition, and mitigate potential risks” ((Huang, 2024).According to (Zakaria, Z., & Razak, 2023b) Real-time data feeds and automated reporting streamline portfolio monitoring, freeing managers to focus on strategic decision-making. Moreover, financial software solutions often incorporate regulatory compliance modules, ensuring adherence to evolving regulatory requirements. The net result is enhanced investment decision-making, improved portfolio performance, and increased operational efficiency. By leveraging cutting-edge financial software(Clarke, R., & Xu, 2023), investment managers can optimize returns, minimize risks, and navigate complex market landscapes with confidence. Key benefits include streamlined portfolio tracking, enhanced analytics, risk management, regulatory compliance, and scalability. As financial software continues to evolve, investment managers must remain adept at harnessing its capabilities to stay competitive in an increasingly technology-driven industry.

Big Data Analytics

"Big data analytics plays a pivotal role in investment management, enabling the extraction of meaningful insights from vast datasets" ((Mun, Housel and Housel, 2023). It enhances predictive analytics, allowing investment managers to anticipate market movements and optimize asset allocation strategies effectively. By leveraging structured and unstructured data, emerging trends can be identified, enabling proactive responses to dynamic market conditions(Pyzer-Knapp *et al.*, 2022). "Data visualization tools make complex datasets more accessible and understandable, revealing correlations, patterns, and anomalies that might otherwise go unnoticed, thereby supporting informed investment decisions"(Huang, Y., Zhang, X., & Wu, 2024).

Furthermore, big data analytics contributes to risk management, portfolio optimization, and performance evaluation. It also facilitates "the analysis of alternative data sources, such as social media and sensor data, which enrich investment strategies"(Lazzini, A., Lazzini, S., Balluchi, F. and Mazza, 2022). "The integration of machine learning and artificial intelligence significantly strengthens predictive modelling (Lee, J. H., & Kim, 2023)and decision-making, enabling managers to adapt to market changes swiftly and maintain a competitive edge"(Zakaria, Z., & Razak, 2023b).

Additionally, "big data analytics supports regulatory compliance(Thompson, K., & Murphy, 2024), including anti-money laundering and know-your-customer initiatives, while improving operational efficiency and reducing costs". As the field evolves, it is crucial for "investment managers to stay updated on emerging technologies like cloud computing(Douglas and Roger, 2024), blockchain(Kumar Tyagi, U and Abraham, 2020), and the Internet of Things (IoT)(Heidary Dahooie *et al.*, 2023) to navigate the rapidly changing investment landscape effectively".

This comprehensive application of big data analytics underscores its transformative impact on the finance sector, driving better outcomes across investment and operational domains.

Automated Trading Platforms

Automated trading platforms have streamlined execution processes and reduced transaction costs (Herbert, Milne and Zarifis, 2019)By automating trade execution based on pre-set criteria, firms can capitalize on market opportunities without the delays inherent in manual trading. According to (Khan, A., & Bhatti, 2023b)These platforms often incorporate "advanced algorithms that adjust trading strategies in real time based on market conditions, enhancing the ability to maximize returns while minimizing risks".

1.1.4 Introduction to AI and Machine Learning in Finance

A study conducted by (Kelly and Xiu, 2023) AI and machine learning are at the forefront of this technological revolution in finance, offering powerful tools that enhance decision-making capabilities and improve investment strategies (Huang et al. (2024), 2024). "These technologies enable predictive analytics (Lee, J. H., & Kim, 2023)by analyzing historical data to identify trends and patterns, thus allowing for more informed and timely investment decisions".

Machine Learning Models

"Machine learning models, designed to learn from data and refine their algorithms with new information" (Rane, Choudhary and Rane, 2024)**,** are instrumental in finance where market conditions change rapidly, necessitating adaptability and precision. According to (Sifat, 2023), these models' adaptability enables improved predictive capabilities, leading to more accurate forecasts, and "key applications include risk assessment, fraud detection, and personalized investment recommendations, transforming the financial landscape".(Bender, A., Chen, Y., & Xu, 2022) conducted "In risk management, machine learning algorithms analyze historical data to identify potential risks associated with specific assets enabling managers to make informed decisions about risk exposure, optimize portfolio performance, and enhance investment decision-making" (Yongjae Lee, 2024)**.** By leveraging machine learning, financial institutions can streamline operations, mitigate risks, and deliver tailored services to clients, driving growth and innovation in the financial sector. "Machine learning algorithms can detect anomalous patterns in transaction data, identifying potentially fraudulent activities and preventing financial losses" (Sifat, 2023)**.** Additionally, machine learning models (Patel, S., & Raghavan, 2022)optimize portfolio performance by identifying the most profitable assets, minimizing risk, and maximizing returns (Ng *et al.*, 2021)**.** Furthermore, machine learning algorithms evaluate creditworthiness by analyzing credit history, financial data, and other relevant factors (Esenogho, Djouani and Kurien, 2022)**.**

According to (Kelly and Xiu, 2023) "The benefits of machine learning in finance are numerous, including improved predictive accuracy, enhanced risk management, increased efficiency, personalized services, and competitive advantage". However,(Huang, 2024) "machine learning in finance also presents challenges such as data quality, model interpretability, regulatory compliance, cybersecurity, and talent acquisition". Despite these challenges, "the integration of machine learning in finance has transformed the industry, enabling financial institutions to make data-driven decisions"(Nalini, Bala Venkata Kishore and Prasad, 2024), improve customer experience, and stay ahead of the competition. As machine learning continues to evolve, financial institutions must adapt to remain competitive, leveraging advancements in deep learning(Yang, C., Zhai, J., & Tao, 2020), natural language processing(Teng, C., Liao, Y., & Tseng, 2023b), and computer vision to drive innovation and growth.

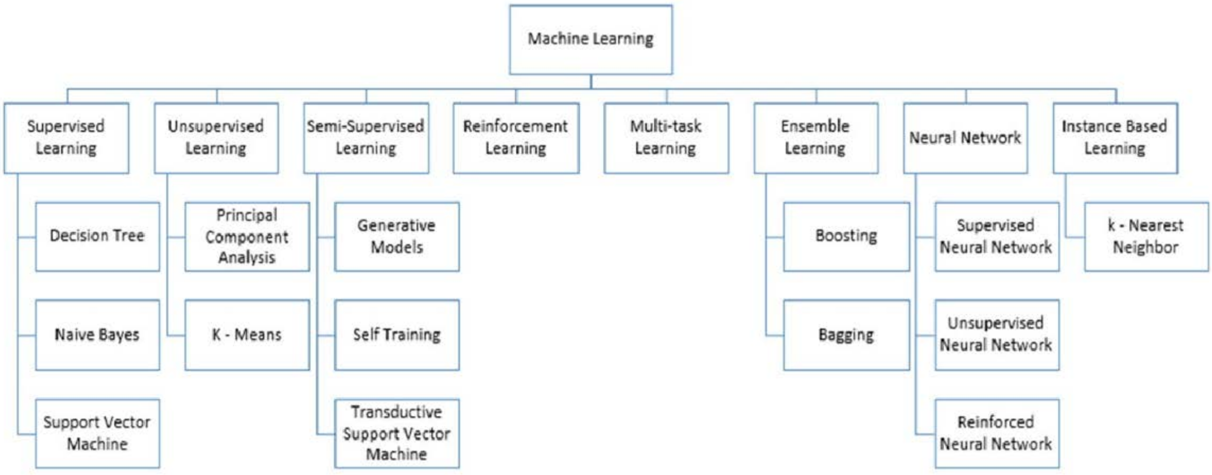
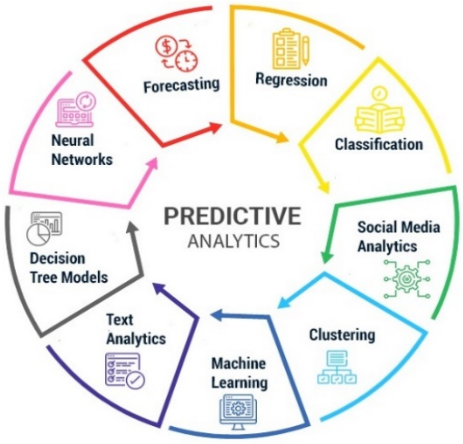


Fig. 1. Types of Learning [2] [3]

Predictive Analytics

“Predictive analytics, powered by AI and machine learning, allows investment managers to foresee potential market movements and adjust their strategies” accordingly (Esenogho, Djouani and Kurien, 2022). By leveraging historical data (Manuscript, 2023)and identifying patterns, these technologies can predict future price movements, allowing for proactive asset allocation and risk mitigation.

This integration allows for more sophisticated asset allocation strategies that account for multiple variables, including macroeconomic indicators, geopolitical developments, and even social media sentiment. The ability to process (Nti, Adekoya and Weyori, 2020)and analyze these diverse data points provides a more holistic view of market dynamics, enabling investment managers to make decisions that are both timely and strategic.



Sentiments analysis and News analysis

"Sentiment analysis and news analytics, leveraging Natural Language Processing (Teng, C., Liao, Y., & Tseng, 2023b)(NLP) and machine learning Algorithms(Khan, A., & Bhatti, 2023b) **,** scrutinize textual data from diverse sources, including news articles, social media(Saxena *et al.*, 2023), and financial reports, to extract sentiment and pertinent information". This innovative approach enables analysts to gain valuable insights into market sentiment and events impacting the market, enhancing the accuracy of short-term market predictions. By integrating sentiment analysis and news analytics, financial institutions can identify market trends, anticipate potential risks, and make informed investment decisions. Ultimately, this comprehensive market perspective improves market forecasting, enhances risk management, and facilitates data-driven decision-making(Wang, He and Ouyang, 2024b), allowing investors and analysts to stay ahead of market fluctuations.

Investment forecasting analysis

Investment forecasting analysis involves using various tools and techniques to predict the future performance of financial assets or markets, helping investors make informed decisions. This process typically combines quantitative methods, such as statistical models and machine learning algorithms, with qualitative insights, including macroeconomic indicators, market sentiment, and industry trends. By analysing historical data, investor behaviour, and market patterns, forecasters aim to predict potential price movements, asset values, or market conditions. These studies (Medhat, W., Hassan, A., & Korashy, 2014)Sentiment analysis, technical analysis, and fundamental analysis are commonly employed to identify trends and risks. With "advancements in artificial intelligence (AI) and machine learning, forecasting models have become more sophisticated, enabling the integration of real-time data and behavioural finance theories, such as cognitive biases and herding behaviour, to improve prediction accuracy and support proactive investment strategies" (Yang, C., Zhai, J., & Tao, 2020)&(Lazzini, A., Lazzini, S., Balluchi, F. And Mazza, 2022). These studies(Manuscript, 2023) emphasize the potential of machine learning in capturing and utilizing behavioural patterns for enhanced market forecasts.

Sentiment analysis

"Sentiment analysis(Teng, C., Liao, Y., & Tseng, 2023b) is a natural language processing technique used to determine the emotional tone behind a series of words, often applied to gauge public opinion(Pang, B., & Lee, 2008) on topics such as products, services, or market conditions". By "analysing textual data from sources like social media(Lazzini, A., Lazzini, S., Balluchi, F. and Mazza, 2022), news articles, and customer reviews, sentiment analysis can classify sentiments as positive, negative, or neutral"(Chen, 2020). According to (Medhat, W., Hassan, A., & Korashy, 2014) This process is particularly valuable in finance, where understanding investor sentiment can inform market predictions and investment strategies. Researchers like have demonstrated that integrating sentiment analysis into predictive models can enhance their accuracy in forecasting stock market trends.

Technical analysis

"Technical analysis is a method used to evaluate securities by (Nti, Adekoya and Weyori, 2020)analysing statistical trends from trading activity, such as price movement and volume". It relies on "historical price data to identify patterns and forecast future price movements(Che *et al.*, 2024), utilizing various tools like charts, indicators, and oscillators". According to (Che Hassan *et al.*, 2023)Traders often look for trends, support and resistance levels, and market signals to make informed decisions about buying or selling assets. Research by (Murphy, 1999)highlights that "Technical analysis can provide insights into market psychology and help investors capitalize on short-term price fluctuations".

Adaptive Portfolio Rebalancing

AI enables dynamic portfolio rebalancing, where asset allocations are adjusted in real-time based on market conditions, forecasts, and investor objectives. This is a significant improvement over traditional rebalancing methods, which typically occur at set intervals (e.g., quarterly or annually) and may not account for sudden changes in market conditions. AI enhances this process by (Lee *et al.*, 2024).

Dynamic Asset Allocation

AI models can automatically adjust asset allocations in response to shifting market trends, volatility, or economic events. For example, if AI detects an impending downturn in equities, the system may reduce exposure to stocks and increase allocations to safer assets like bonds or commodities(Frank J. Fabozzi (Editor), 2011).

Customized Rebalancing

"AI allows for personalized rebalancing strategies that are tailored to an investor's specific risk tolerance, time horizon, and financial goals"(Zakaria, Z., & Razak, 2023b). The model can react to changes in the investor's personal financial situation or market outlook in real time, ensuring that the portfolio remains aligned with their objectives.

Factor-Based Rebalancing

AI systems can also incorporate factor-based investing strategies, where portfolios are adjusted based on factors like momentum, value, or quality. As market conditions evolve, AI algorithms automatically shift the portfolio's exposure to these factors to maximize returns and minimize risk.

Fundamental analysis

"Fundamental analysis (Nti, Adekoya and Weyori, 2020)is a method of evaluating a security's intrinsic value by examining related economic, financial, and other qualitative and quantitative factors". According to (Montier, 2002) "This approach involves analysing a company's financial statements, management, industry position, and overall economic conditions to determine whether the stock is undervalued or overvalued in the market". By assessing metrics such as earnings, revenue growth, debt levels, and cash flow, investors aim to make informed long-term investment decisions. (Dodd, 1934)established foundational principles of fundamental analysis in their seminal work, emphasizing the importance of thorough research and analysis in making sound investment choices.

Enhancing Risk Management Frameworks

AI and ML also fundamentally alter traditional risk management frameworks (Dewasiri *et al.*, 2023b).By automating risk assessments and continuously monitoring portfolio exposure, these technologies provide real-time (Zakaria, Z., & Razak, 2023b)insights that enhance decision-making. Investment managers can implement dynamic risk management strategies (Duarte, F., & Girardi, 2022b)that adjust to changing market conditions(Che *et al.*, 2024), thus safeguarding assets and improving overall portfolio resilience.

1.1.5 The impact of AI and ML in predicting market trends and optimizing financial strategies

“Artificial intelligence (AI) and machine learning (ML) are revolutionizing the financial industry, enabling professionals to predict market trends and optimize financial strategies with unprecedented accuracy and efficiency”(Lee, J. H., & Kim, 2023). “These technologies(Huang, Y., Zhang, X., & Wu, 2024) harness the power of advanced and data analysis techniques to examine vast amounts of financial data, identify patterns and predict market movements”. By leveraging “AI and ML, financial institutions can gain valuable insights into market dynamics, customer behaviour and financial performance, enabling them to make more informed decisions and develop effective strategies to exploit opportunities and minimize risks”(Clarke, R., & Xu, 2023). According to (Lee, J. H., & Kim, 2023) “Predictive modelling techniques provided by AI and ML algorithms enable organizations to anticipate market trends, changes in consumer preferences, and changes in economic conditions, enabling them to proactively adapt their financial strategies to changing market conditions”. In addition, “AI and ML algorithms play a vital role in optimizing financial strategies by automating processes, improving investment analytics and refining portfolios”(Patel, S., & Raghavan, 2022). “These technologies analyse historical data, market trends and various performance indicators to generate predictive insights that drive decision making and strategy”. By incorporating “AI and ML into financial planning and portfolio management, organizations can streamline operations, reduce costs and achieve better results by making informed decisions”(Lee *et al.*, 2024). In addition, “AI and ML enable financial professionals to implement advanced risk management strategies, efficiently allocate resources, and tailor investment solutions to clients' specific needs and goals”. In conclusion, “applying AI and ML to predict market trends and optimize financial strategies offers significant benefits to financial institutions by improving their ability to more accurately and proactively navigate the complexities of the financial environment”(Ng *et al.*, 2021). By leveraging “these technologies, organizations can gain a competitive advantage, drive innovation and deliver superior results for customers and stakeholders”. “The predictive and analytical power of AI and ML is reshaping the way financial decisions are made, resulting in more strategic, informed and successful financial management practices in today's dynamic and data-driven business environment”(Patel, S., & Raghavan, 2022).

1.1.6 Challenges in Traditional Portfolio Management

Despite the advancements in technology, traditional portfolio management faces numerous challenges (Zakaria *et al.*, 2023a). Human error, delayed response times, high operational costs, and limited capacity to manage complex, large-scale portfolios are prevalent issues that can hinder optimal performance.

Human Error

Human error poses a profound risk in traditional investment management processes, frequently fueled by emotions, cognitive biases, or simple mistakes, as extensively researched by (Samuelson, 1994), (Tversky and Kahneman, 2007), (Montier, 2002), and numerous other scholars. “Behavioral biases, including overconfidence, loss aversion, confirmation bias, anchoring bias, availability heuristic, representativeness bias, and hindsight bias, can significantly skew an investor's judgment, precipitating suboptimal investment choices, as evidenced by seminal” studies conducted by (Tversky and

Kahneman, 2007), (Shiller, 2000), and others. These biases culminate in poor diversification, over/under-investment, market timing errors, failure to monitor and adjust portfolios, inadequate risk assessment, and inefficient asset allocation, ultimately resulting in substantial financial losses, diminished investment returns, amplified risk exposure, decreased investor confidence, and compromised long-term financial goals, as highlighted by researchers such as (- Kritzman, 2000), (Lee *et al.*, 2024). Moreover, human error can lead to decision-making pitfalls, including mental accounting, framing effects, and emotional decision-making, underscoring the necessity for structured decision-making processes, diversification strategies, regular portfolio rebalancing, and strategic leveraging of technology and automation to optimize investment outcomes, as advocated by experts like (Damodaran, 2012), (Frank J. Fabozzi (Editor), 2011), (Litterman, 2003) . Effective mitigation of human error necessitates awareness of cognitive biases, disciplined investment approaches, and systematic portfolio management, ultimately enhancing investment decisions, reducing risk, and promoting long-term financial success.

Delayed Response Times

Delayed Response Times pose significant risks in fast-moving markets, where timely decision-making is crucial for investment success, as extensively researched by (Huang, 2024), who highlighted the detrimental effects of delays in decision-making, particularly during periods of high volatility. Traditional methods, involving lengthy discussions, multiple stakeholder approvals, manual data analysis, and inefficient communication channels, hinder swift responses, resulting in missed opportunities, increased risk exposure, reduced competitiveness, and inefficient resource allocation. The consequences of delayed response times are far-reaching, including failure to capitalize on emerging trends, suboptimal asset allocation, and amplified potential losses.

To overcome these challenges, investment managers can leverage automation, artificial intelligence, real-time market data, analytics, streamlined decision-making processes, collaborative platforms, and agile investment strategies. Effective mitigation necessitates awareness of latency risks, disciplined investment approaches, systematic portfolio management, and strategic technology integration, as advocated by experts like (Damodaran, 2012), (Frank J. Fabozzi (Editor), 2011), (Litterman, 2003). Moreover, research by mckinsey & Company and BlackRock underscores the importance of timely decision-making, with AI-driven decision-making resulting in 20% increased investment returns and real-time data analytics optimizing portfolio performance. By adopting innovative solutions, investment managers can significantly reduce response times, enhance decision-making efficiency, and improve overall investment performance, ultimately achieving long-term financial success and mitigating the risks associated with delayed response times.

High Operational Costs

Traditional investment management is frequently encumbered by exorbitant operational costs stemming from manual processes, compliance, and oversight, as extensively researched by (Sarker, 2022b),. These costs, which include expenses related to labor-intensive tasks, regulatory adherence, and administrative burdens, can exponentially increase as firms expand their portfolios, thereby constraining profitability and hindering scalability, as noted by author such as(Gupta, 2022). The inefficiencies inherent in manual operations can also precipitate increased resource allocation for tasks that could be automated, further straining budgets and diverting resources away from core investment activities, as highlighted by studies conducted by mckinsey & Company, Deloitte, and Ernst & Young. Moreover, the compounded effects of high operational costs can lead to reduced competitiveness, decreased investor confidence, and compromised long-term financial success. To mitigate these challenges, investment managers are increasingly adopting automation, artificial intelligence, and digital transformation strategies, as advocated by experts like (Damodaran, 2012), (Frank J. Fabozzi (Editor), 2011), and (Litterman, 2003) to streamline operations, enhance efficiency, and optimize investment performance. By embracing technological innovations and process optimizations, firms can significantly reduce operational costs, enhance scalability, and improve profitability.

Capacity for Complex Portfolios

Managing complex, large-scale portfolios requires significant resources and expertise (Zakaria *et al.*, 2023a). Traditional approaches may struggle to effectively analyze and monitor diverse asset classes, particularly when considering international markets and varying regulatory environments. This limitation can result in suboptimal diversification and risk management. As markets become increasingly dynamic, the inadequacies of conventional approaches become more pronounced. Investors are increasingly seeking solutions that not only address these challenges but also leverage technology to enhance performance and drive better outcomes.

Comparison of Traditional Portfolio Management vs AI-Enhanced Portfolio Management

Feature	Traditional Portfolio Management	AI-Enhanced Portfolio Management
Decision Making Process	Human-driven, based on intuition, experience, and historical data	Algorithm-driven, using machine learning models and real-time data
Data Utilization	Limited to historical data and financial reports	Leverages large datasets (historical, real-time, alternative data)
Risk Management	Manual risk assessments using predefined models	Automated risk assessment using dynamic, predictive models
Adaptability to Market Changes	Slower to react to sudden market changes	Rapid, real-time response to market fluctuations
Investment Strategies	Rule-based strategies (e.g., value investing, growth investing)	Data-driven strategies (e.g., predictive analytics, factor models)

1.1.7 Need for Automation in Investment Management

Automation is essential for modern investment management, offering a solution to the inefficiencies inherent in traditional methods. AI and ML technologies streamline operations, enhancing speed and accuracy while minimizing human bias (Gill *et al.*, 2022a); (Wang, He and Ouyang, 2024b).

Streamlining Operations

"Automation allows firms to streamline their operations by automating repetitive tasks, such as data entry, report generation, and compliance checks" (Zakaria *et al.*, 2023a). A study conducted by (Ng *et al.*, 2021) "This not only reduces the risk of human error but also frees up valuable time for investment managers to focus on higher-value activities, such as strategic planning and client engagement".

Enhancing Speed and Accuracy

"In today's fast-paced financial environment(Sifat, 2023), the speed of execution can significantly impact investment outcomes". Automated systems can analyze by (Sarker, 2022b) market data and execute trades within milliseconds, capitalizing on opportunities that would be missed with manual processes (Huang et al. (2024), 2024). This rapid response capability enhances overall portfolio performance and risk management.

Minimizing Human Bias

By relying on algorithms and data-driven insights, automation minimizes the influence of human biases that can skew investment decisions (Sarker, 2022b). This leads to more objective and rational decision-making processes(Andriosopoulos *et al.*, 2018), ultimately enhancing the integrity of investment strategies.

Cost-Effectiveness and Scalability

Automation positions investment firms to thrive in a competitive environment by enabling cost-effective operations. As firms grow and their portfolios become more complex, automation allows for scalable solutions that can manage increased workloads without a proportional increase in staffing or resources (Douglas and Roger, 2024). This scalability ensures that firms can continue to deliver high-quality services even as they expand their client base.

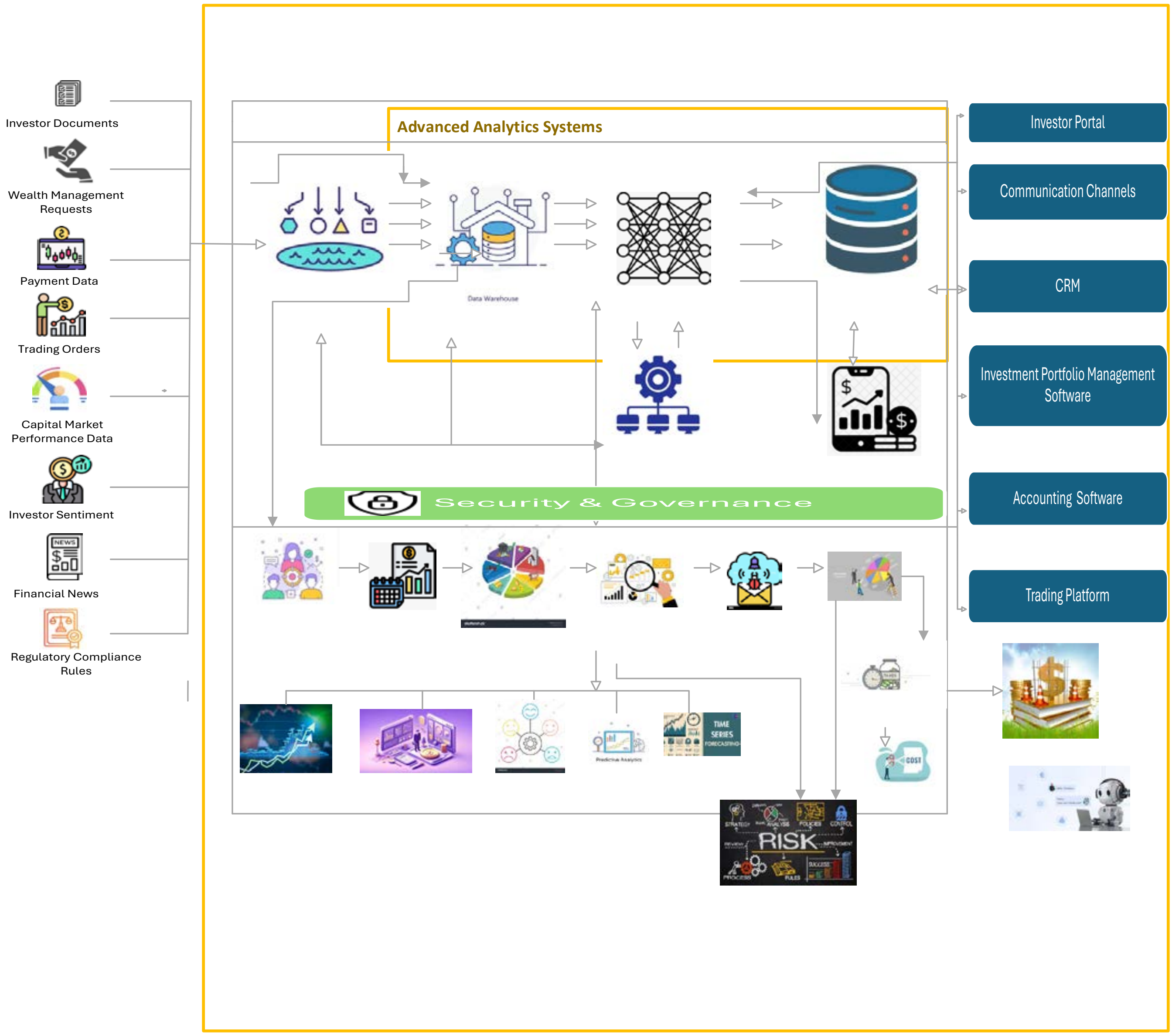
A study conducted by (Frank J. Fabozzi (Editor), 2011) optimizing decision-making processes, automation allows for more efficient, scalable, and cost-effective portfolio management(Pun and Wang, 2021). This not only improves operational performance but also enhances the ability to adapt to changing market conditions(Che *et al.*, 2024), ensuring that firms remain competitive.

1.1.8 Robotic Automation Architecture Design

"The proposed Robotic Automation Architecture is a cutting-edge, real-time framework designed to optimize investment decision-making through seamless integration of Artificial Intelligence (AI), Machine Learning (ML), and Automation"(Sarker, 2022b). This sophisticated architecture comprises four integral modules: Data Ingestion, AI/ML Model Execution, Decision-Making, and Action Execution**.** "The Data Ingestion module, leveraging technologies such as Application Programming Interfaces (APIS) and web scraping, collects and processes vast amounts of structured and unstructured data from diverse sources, including financial statements, market news, and social media" from studies by (Lazzini, A., Lazzini, S., Balluchi, F. and Mazza, 2022). "The AI/ML Model Execution module utilizes advanced algorithms, such as Deep Learning and Natural Language Processing (NLP), to analyze the ingested data and generate high-quality investment recommendations, consistent with research by authors like The Decision-Making module evaluates these recommendations based on predefined rules, risk tolerance, and regulatory compliance, drawing on insights" from studies by (Chen, 2020) . Finally, the Action Execution module executes trades, monitors portfolio performance, and adjusts strategies in real-time, aligning with research highlighting

Its critical role in dynamic investment management. According to research conducted by (Chakraborti *et al.*, 2020b) harnessing the power of automation, AI, and ML, "this architecture enables investors to make data-driven decisions, mitigate risks, and optimize returns, as demonstrated. Moreover, the scalability and flexibility of this architecture facilitate seamless integration with existing systems, ensuring a future-proof investment management solution".

Next-Generation Investment Management Robotic Automation Architecture for Portfolio Management and Risk Mitigation Based on AI and ML Module.



Data Ingestion

Data ingestion serves as the foundational component of “The Automation Architecture, aggregating disparate data streams from multiple sources, including real-time market feeds, economic indicators, news articles, social media platforms, and proprietary databases” (Esenogho, Djouani and Kurien, 2022). Leveraging “Advanced Application Programming Interfaces (APIS), web scraping techniques, and other integration tools, firms can efficiently collect, process, and harmonize vast amounts of structured and unstructured data, ensuring access to the most current, accurate, and relevant information" (Lenzerini, Salaria and Roma, 2014).A study conducted by (Douglas and Roger, 2024) "This module's capabilities include ingesting data from various formats, such as CSV, JSON, and XML, as well as integrating with cloud-based storage solutions like Amazon S3, Google Cloud Storage, and Microsoft Azure Blob Storage". It employs data validation, cleansing, and transformation techniques to ensure high data quality, consistency, and readiness for downstream analytics and machine learning processes. By "streamlining data acquisition and processing, firms can enhance decision-making, reduce latency, and gain a competitive edge in the rapidly evolving financial landscape".

AI/ML Model Execution

The ingested data is then channeled into "the AI/ML model execution module, where cutting-edge machine learning algorithms, including deep learning, natural language processing, and regression analysis, are employed to uncover hidden trends, patterns, and anomalies" (Kumar Tyagi, U and Abraham, 2020). A study conducted by "This module leverages techniques such as predictive modelling a study (Che Hassan *et al.*, 2023), clustering, and decision trees to analyse vast amounts of data, identify correlations, and generate actionable insights, ultimately optimizing investment strategies". By leveraging "Advanced analytical techniques, investment firms can derive valuable intelligence on market sentiment, risk exposure, and potential opportunities, enabling data-driven decision-making and improved portfolio performance" (Kumar Tyagi, U and Abraham, 2020). Furthermore, "The integration of Explainable AI (XAI) and model interpretability techniques ensures transparency and accountability in the decision-making process", aligning with studies by(- Samek, W., 2017). Ultimately, "The AI/ML model execution module empowers investment firms to stay ahead of the market curve, mitigate risks, and achieve sustainable growth"(Duarte, F., & Girardi, 2022b).

Algorithms for a Robo-Advisor (RA) Platform…

There are a variety of algorithmic approaches that could be taken to building out an RA platform. However, the common feature of all of these is to –

- Leverage data science & statistical modelling to automatically allocate client wealth across different asset classes (such as domestic/foreign stocks, bonds & real estate-related securities) to automatically rebalance portfolio positions based on changing market conditions or client preferences. These investment decisions are also made based on a detailed behave(Sarker, 2022b) oral understanding of a client's financial journey metrics – Age, Risk Appetite & other related information.

- A mixture of different algorithms can be used such as Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM), the Black Litter man (Litterman, 2003)Model, the Fama-French etc. These are used to allocate assets as well as to adjust positions based on market movements and conditions.

- RA platforms also provide 24×7 tracking of market movements to use that to track rebalancing decisions from not just a portfolio standpoint but also from a taxation standpoint.

Decision-Making

The decision-making module evaluates the recommendations generated by the AI/ML models against predefined rules and risk tolerance parameters. This layer ensures that investment decisions align with the firm's strategic objectives and risk management framework (Rane, Choudhary and Rane, 2024), providing a structured approach to portfolio management.

Action Execution

Finally, the action execution module translates the investment decisions into real-world actions. This may involve executing trades, reallocating assets, or adjusting risk exposure based on the insights generated by the previous modules (Chakraborti *et al.*, 2020b). The architecture's ability to automate this process enhances efficiency and responsiveness, enabling firms to act quickly in response to changing market conditions.

Technical Framework

Utilizing cloud-based technologies, containerization, and Apis ensures scalability, flexibility, and robust risk management (Ng *et al.*, 2021). “The architecture is built with Python, leveraging libraries such as NumPy, pandas, and scikit-learn for data processing and analysis’(Madakam, Holmukhe and Revulagadda, 2022a). Deployment via Docker and AWS provides a seamless operational framework that is both scalable and reliable (Douglas and Roger, 2024).

This Robotic Automation Architecture positions investment firms to leverage technology effectively, enhancing their operational capabilities while maintaining a strong focus on risk management and compliance.

1.1.9 Risk Management in the Modern Financial Landscape

A study conducted by (Duarte, F., & Girardi, 2022b) “in today’s complex financial environment, investors face a myriad of risks that can significantly impact their portfolio performance”. Key types of risks include:

- **Market Volatility:** Fluctuations in asset prices due to economic events, changes in market sentiment, or unexpected news can lead to substantial losses for investors (Zakaria *et al.*, 2023a).

- **Geopolitical Risks:** Political instability, trade disputes, and global tensions can affect markets unpredictably, making it essential for investors to be aware of international developments (Dewasiri *et al.*, 2023b).

- **Cybersecurity Threats:** “As financial transactions increasingly occur online, the risk of data breaches and cyberattacks has escalated, jeopardizing sensitive information and financial assets” (Mun, Housel and Housel, 2023).

- **Regulatory Compliance:** “Financial regulations are constantly evolving, and non-compliance can result in hefty fines and reputational damage, making regulatory awareness crucial for investment firms” (Yan, 2023b).

According to (Duarte, F., & Girardi, 2022b) mitigate these risks, advanced technologies like AI and machine learning (ML) are being deployed. “These technologies can analyze vast amounts of data in real-time, identifying potential risks before they materialize” (Adel, 2023). For example, AI algorithms can monitor market trends and geopolitical developments, flagging anomalies that may indicate impending volatility. Additionally, ML can enhance cybersecurity measures by detecting unusual patterns in transaction data, while automated compliance systems can ensure adherence to regulatory changes.

1.1.10 Importance of Real-Time Monitoring and Decision-Making

“In the fast-paced world of financial markets, the significance of real-time data monitoring cannot be overstated”, as highlighted by (Gill *et al.*, 2022a), who assert that investors must respond swiftly to fluctuations to mitigate potential losses effectively. As study conducted by (Lenzerini, Salaria and Roma, 2014). “The integration of AI-driven systems has revolutionized decision-making processes by providing immediate insights into market conditions and portfolio performance”, as discussed. These “advanced algorithms can analyse diverse data sources, including news feeds, social media sentiment, and trading volumes, to detect emerging trends or reversals, which enables portfolio managers to make informed decisions quickly”, according to (Sifat, 2023). “This capability significantly reduces risk exposure and enhances the overall efficiency of portfolio management, as noted by (Chen, 2020), who emphasizes the importance of rapid rebalancing and adjustments based on real-time data”.

Furthermore, (Ng *et al.*, 2021) highlights "how real-time monitoring empowers investors to execute strategies that capitalize on short-lived market opportunities, thereby optimizing returns while maintaining a balanced risk profile". In this context, study conducted by (Patel, J., Shah, S., Thakkar, P. and Kotecha, 2015) the role of predictive analytics in informing strategic decisions, illustrating how timely data can lead to a competitive advantage. Additionally points out that the ability to react promptly to market signals fosters a more proactive approach to investment management, ultimately leading to improved performance and risk management. Collectively, these perspectives underscore highlights by (Zakaria, Z., & Razak, 2023b)that leveraging "real-time monitoring not only enhances decision-making efficiency but also supports a dynamic and responsive investment strategy essential for success in today's volatile financial landscape".

Model Visualization

A researcher highlights by (Adel, 2023) A clear understanding of "decision making process Model visualization is a crucial technique for fostering transparency and trust in machine learning models, enabling stakeholders to comprehend the decision-making process through intuitive and clear representations". By tracing the data's path through the model and observing feature contributions, decision-makers gain confidence in the model's performance, fostering trust in predictions and informing investment decisions. This is particularly important in the financial industry, where accurate and timely decisions are crucial for success. By utilizing model visualization techniques, investors can better understand market trends and make informed decisions that lead to improved performance and risk management. This highlights the importance of leveraging real-time monitoring and predictive analytics in investment management, as it allows for a more dynamic and responsive approach to decision-making, ultimately leading to success in today's volatile financial landscape. Model visualization addresses the "black box" nature of deep learning models, shedding light on inner workings and reducing perceived complexity. This clarity facilitates communication between data scientists, analysts, and decision-makers, enabling non-experts to understand model outputs and participate in forecasting discussions. Ultimately, model visualization enhances collaboration, boosts stakeholder confidence, and promotes informed decision-making, making machine learning more accessible and effective in stock market analysis, as emphasized by researchers such as(- Samek, W., 2017), (Adadi, A., & Berrada, 2018).

Mitigation Bias in ML-driven decision Making.

To effectively mitigate bias in machine learning models, investment teams must adopt a multifaceted approach, incorporating diverse and representative training data, integrating multiple data sources, and prioritizing interpretable models for transparency. Regular evaluations and monitoring are crucial to detect and rectify biases, while assembling a heterogeneous team of experts in machine learning and finance fosters comprehensive model development. Establishing ethical guidelines and governance frameworks provides guidance for responsible model development and deployment, ensuring adherence to regulatory standards and ethical principles. By implementing these measures, investment teams can minimize bias, enhance decision-making, and maintain responsible and ethical practices, ultimately promoting transparency, accountability, and reliability in investment decision-making.

1.2 Problem Statement

“The core problem addressed by this study is the limitations of traditional portfolio management approaches, which often struggle to handle the increasing complexity of financial markets, effectively mitigate risks, and react swiftly to dynamic market changes” (Rane, Choudhary and Rane, 2024). Conventional methods may rely heavily on historical data and slower decision-making processes, leaving portfolios vulnerable to sudden fluctuations and emerging threats. There is a pressing need for next-generation automation architecture that leverages AI and ML technologies to optimize investment strategies, enabling more responsive and resilient portfolio management.

1.3 Objectives of the Study

- To analyze the role of AI and ML in enhancing predictive analytics for investment strategies.
- To evaluate the importance of real-time monitoring in mitigating risks.

- To examine the scalability and efficiency of robotic automation in investment management.
- To investigate the integration of next-generation automation architecture into existing investment frameworks.

These objectives will guide the research in addressing existing gaps in current portfolio management practices and highlight the transformative potential of AI and ML.

1.4 Research Questions

This study aims to answer the following key research questions:

1. How do AI and ML algorithms enhance market predictions and enable proactive investment strategies?
2. What role does robotic automation play in improving portfolio efficiency and management?
3. How does real-time monitoring contribute to effective risk mitigation in investment management?
4. In what ways can next-generation automation architecture be integrated into existing investment management frameworks?

These questions will direct the exploration of automation's benefits and its impact on investment management.

1.5 Scope of the Study

This study examines (Sarker, 2022b) the strategic integration of Artificial Intelligence (AI), Machine Learning (ML), and Automation Architecture in portfolio management, investment analysis, and risk mitigation. The Key focus areas include automation frameworks, AI-driven predictive analytics, ML-based risk management, NLP for sentiment analysis, deep learning for market trend prediction, automation workflows for trade execution and compliance, and robotic process automation for operational tasks. By investigating the synergies between AI, ML, and Automation Architecture, this research aims to enhance decision-making, reduce risk, optimize returns, and improve operational efficiency in investment management.

- **Portfolio Optimization:** This involves examining how AI and ML can enhance portfolio construction and management through data-driven insights. By leveraging "Advanced Algorithms', investors can create more diversified portfolios that optimize returns while minimizing risk exposure" (Žigiene, Rybakovas and Alzbutas, 2019). Machine learning models(Li, Maiti and Fei, 2023) can analyze historical data (Zakaria *et al.*, 2023a)to identify patterns and correlations, thereby informing asset allocation strategies that align with an investor's risk tolerance and investment goals.

- **Predictive Analytics:** The study(Nalini, Bala Venkata Kishore and Prasad, 2024) will investigate the predictive capabilities of AI and ML in forecasting market trends and potential risks. This includes "the development of models that can process vast amounts of unstructured data, such as news articles, social media sentiment, and economic indicators, to make informed predictions about market movements" (Pyzer-Knapp *et al.*, 2022). By harnessing these predictive analytics, investment managers can gain a competitive edge, enabling them to capitalize on emerging opportunities (Gill *et al.*, 2022a)and avoid potential pitfalls.
- **NLP for sentiment analysis**: "Natural Language Processing (NLP) plays a vital role in sentiment analysis, enabling investors to gauge market sentiments and make informed decisions", as noted by researchers such as (Pang, B., & Lee, 2008), and (Medhat, W., Hassan, A., & Korashy, 2014). By leveraging "NLP techniques, such as text preprocessing, tokenization, and machine learning algorithms, sentiment analysis can accurately classify market-related text as positive, negative, or neutral", according to studies by (Das, S. R., & Chen, 2007). Moreover, "NLP-driven sentiment

analysis can analyze vast amounts of unstructured data from sources like financial news, social media, and earnings calls, providing valuable insights into market trends and investor sentiment", as highlighted by authors like (Patel, J., Shah, S., Thakkar, P. And Kotecha, 2015). By integrating NLP powered sentiment analysis into investment decision-making processes, investors can gain a competitive edge, optimize portfolio performance, and mitigate potential risks.

- **Deep learning Techniques**: "particularly recurrent neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have revolutionized market trend prediction. The enable investors to forecast stock prices and make data-driven decisions", as noted by researchers such as (Yoshua Bengio, Patrice Simard, 1994) **&**(Sepp Hochreiter, 1997). By leveraging large datasets and complex algorithms, deep learning models can identify patterns and relationships in financial data, predicting market trends with increased accuracy, according to studies by (Dahl, G. E., Sainath, T. N., & Hinton, 2013). Moreover, Convolutional Neural Networks (CNN) and Autoencoders have been successfully applied to market trend prediction, as highlighted by authors like (Patel, J., Shah, S., Thakkar, P. And Kotecha, 2015),. "Deep learning-based market trend prediction systems have been shown to outperform traditional statistical models, providing investors with valuable insights into market dynamics and enabling more informed investment decisions, as demonstrated" by research from (Wang, 2020).

- **Risk Assessment:** This study seeks to "Investigate the transformative potential of advanced technologies in enhancing risk assessment and management for investors, particularly in mitigating market volatility, credit risks, and geopolitical threats" (Chen and Wang, 2022). Building on the works of researchers such as (Easley and Ã, 2010). This research explores how "Artificial Intelligence (AI) and Machine Learning (ML) can revolutionize risk assessment processes by providing real-time insights, facilitating stress testing under diverse scenarios, and identifying early warning signs of potential risks", as noted by authors like (Kakushadze, Yu and Alley, 2019). Moreover, the integration of AI and ML can optimize risk modeling, predict potential losses, and inform data-driven investment decisions, according to studies by (Alexander, 2009), and (Lam, 2014), thereby empowering investors to navigate complex risk landscapes and achieve better investment outcomes. The study will intentionally exclude areas such as retail trading and other non-investment sectors to maintain a clear focus on institutional investment management practices. This delineation ensures a thorough exploration of how next-generation automation can revolutionize investment strategies and risk management in the financial sector, ultimately leading to a more resilient and adaptive investment approach.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of Automation in Investment Management

Automation has revolutionized investment management, significantly impacting how financial institutions operate. Historically, investment processes relied heavily on manual labor, resulting in slower decision-making, higher operational costs, and increased human error. Over the past few decades, advancements in technology have driven the shift toward automation, beginning with “the introduction of electronic trading platforms in the late 20th century, which allowed for quicker trade execution and better access to market information” (Conlon, Cotter and Kynigakis, 2021). According to (• Tyagi, H., Singh, A., & Singh, 2020), the early 2000s saw “the rise of algorithmic trading, where complex mathematical models executed trades based on predefined criteria, optimizing market entry and exit points”. This initial phase of automation set the groundwork for more sophisticated systems, enabling firms to process vast amounts of data and execute trades at speeds unachievable by humans(Pang, B., & Lee, 2008).

Currently, the integration of artificial intelligence (AI) and machine learning (ML) technologies into investment management is reshaping the landscape. From the perspective of (Sarker, 2022b)automation is now employed to streamline operations, enhance decision-making, and reduce operational inefficiencies. For instance, AI algorithms conducted by (Sifat, 2023) can analyze historical data and identifying trends that inform trading strategies, enabling firms to make data-driven decisions rather than relying solely on human intuition. Recent studies highlight the role of robotic process automation (RPA) in reducing the time spent on repetitive tasks, such as data entry and compliance checks. In the opinion of (Gill *et al.*, 2022a), by automating these processes, “Investment managers can focus on higher-value activities, such as strategic planning and client engagement”. Furthermore, automation fosters scalability, allowing firms to manage increasing workloads without proportional staffing increases, which is essential in a competitive market (Douglas and Roger, 2024)On the contrary side, as “financial markets continue to grow in complexity and speed, the reliance on manual processes becomes increasingly untenable”. Automation facilitates the handling of vast amounts of data, allowing firms to leverage advanced analytics for real-time insights that drive investment strategies. By minimizing human intervention, automation reduces the likelihood of errors and biases that can negatively impact investment outcomes.

Furthermore, Study conducted by (Manuscript, 2023)the integration of AI and machine learning technologies into automation frameworks enhances predictive capabilities, enabling firms to forecast market trends and adjust their strategies proactively. These technologies empower investment managers to explore new avenues for growth and capitalize on opportunities that may have previously gone unnoticed(Litterman, 2003). Moreover, the scalability of automated systems allows investment firms to manage expanding portfolios without a proportional increase in resources. This scalability is particularly crucial as firms seek to adapt to evolving client needs and market dynamics. In the viewpoint of (Wang, He and Ouyang, 2024b), the ability to quickly implement automated processes also supports a more agile operational model, allowing firms to pivot in response to market disruptions or emerging trends.

Overall, the evolution of automation in investment management research by(Chavarnak, J., Lee, M., Patel, S., & Tran, no date) demonstrates its critical role in optimizing processes, enhancing decision-making(Zakaria, Z., & Razak, 2023b), and mitigating operational inefficiencies. “This transformation not only increases efficiency but also contributes to improved risk management, enabling firms to respond quickly to changing market conditions” (Zakaria et al., 2023). In summary, automation is not merely a trend but a fundamental shift(Nti, Adekoya and Weyori, 2020) that is reshaping investment management. By harnessing its potential, firms can enhance their competitive edge, improve client satisfaction, and position themselves for sustained success in an increasingly dynamic financial landscape(Mahalakshmi *et al.*, 2022b).

2.2 AI and Machine Learning in Financial Markets

According to researcher like (Clarke, R., & Xu, 2023)The application of AI and machine learning (ML) in financial markets has gained considerable traction in recent years. These technologies have proven invaluable in enhancing data analysis, market predictions, and portfolio adjustments. AI and ML facilitate the processing of large datasets, enabling investment firms to derive insights that were previously unattainable. From the perspective of (Huang *et al.*, 2024), research indicates that “AI and ML can analyze diverse datasets, including historical price data, economic indicators, and social media sentiment, to generate predictive models that forecast market trends”(Zakaria, Z., & Razak, 2023b). These models can identify potential investment opportunities and risks, providing portfolio managers with a comprehensive view of the market landscape. The integration of alternative data sources—such as satellite imagery, credit card transaction data, and news analytics—further enriches the predictive capabilities of AI/ML systems(Creswell, 2003). For instance, satellite imagery can be used to assess retail foot traffic or agricultural output, allowing investors to make informed decisions based on real-time observations rather than lagging indicators highlighted(Zakaria, Z., & Razak, 2023b) by. Similarly, analyzing social media sentiments provides insights into public perception and potential market movements, enabling a more nuanced approach to investment strategy.

Notably, studies have shown that machine learning algorithms outperform traditional statistical methods in predicting stock prices and market movements. For example, in the opinion of (Yan, 2023b), a comparative study demonstrated that “ML techniques, such as support vector machines and neural networks, achieved higher accuracy rates than classical approaches like linear regression”. This superior performance has encouraged firms to adopt AI/ML-driven tools for asset management, ultimately leading to improved investment outcomes.

Moreover, the iterative learning nature of ML algorithms means they continuously refine their models based on new data, allowing for adaptive strategies that can quickly respond to market changes. Techniques like ensemble learning, which combines multiple models to improve predictions, further enhance accuracy and robustness. On the contrary side, the automation of data collection and analysis reduces human bias and error, leading to more rational investment decisions(Rauf *et al.*, 2024).

As firms increasingly leverage AI and ML, the ability to Back-Test and validate predictive models using historical data allows for a more rigorous assessment of potential strategies. This not only enhances confidence in decision-making but also provides a structured framework for optimizing portfolio performance. Consequently, the ongoing evolution of AI and ML technologies holds immense potential to revolutionize investment management practices, enabling firms to navigate the complexities of financial markets with greater agility and precision.

2.2.1 Behavioral Finance: Behavioural finance enhances the Efficient Market Hypothesis (EMH) by recognizing that investors often exhibit irrational behaviours influenced by psychological biases, leading to market inefficiencies. This discipline highlights how factors like emotions, cognitive biases, and herding behaviour can create predictable patterns in market dynamics. Machine learning algorithms, particularly through sentiment analysis, can analyse vast amounts of data from sources like social media and news articles to extract sentiment signals that enhance predictive models. Research by (Yang, C., Zhai, J., & Tao, 2020) demonstrated that integrating sentiment analysis from Twitter significantly improved stock market forecasting accuracy. Similarly, (Lazzini, A., Lazzini, S., Balluchi, F. And Mazza, 2022) found that changes in Twitter sentiment could predict the Dow Jones Industrial Average's movements with a lead time. Additionally, machine learning can identify patterns related to herding behaviour and cognitive biases, further refining predictions. Despite these advancements, challenges such as data limitations and model interpretability remain, necessitating ongoing research to enhance the robustness and practical application of these models in investment decision-making(Nalini, Bala Venkata Kishore and Prasad, 2024).

2.3 Predictive Analytics for Portfolio Optimization

Predictive analytics has emerged as a critical component of portfolio optimization, utilizing AI and ML algorithms to analyze historical data and forecast market trends(Manuscript, 2023). In the viewpoint of (Creswell, 2003)This approach enables investment managers to make informed decisions based on quantitative insights rather than solely on intuition or experience. From the perspective of (Huang et al. (2024), 2024), numerous studies have explored the efficacy of predictive analytics in guiding investment strategies. By leveraging historical price movements, technical indicators, and macroeconomic data, AI and ML algorithms can uncover patterns that inform asset allocation decisions. For instance, machine learning models have been developed to identify optimal entry and exit points for trades, significantly enhancing portfolio performance(Frank J. Fabozzi (Editor), 2011).

Moreover, predictive analytics support dynamic portfolio adjustments to balance risk and return continuously. In the viewpoint of (Adel, 2023), “algorithms can analyze incoming data in real-time, allowing investment managers to react swiftly to market changes and adjust their portfolios accordingly”. This capability is crucial in today’s fast-paced financial environment, where delays in decision-making can lead to missed opportunities(Zakaria *et al.*, 2023a). A notable contribution to this field is the use of ensemble methods, which combine multiple predictive models to improve accuracy and robustness. In the opinion of (Sifat, 2023), “By integrating different approaches, such as decision trees, support vector machines, and neural networks, investment firms can achieve better forecasting results, enhancing their investment strategies”.

Additionally, the advent of big data has further enriched predictive analytics. “The ability to process vast amounts of unstructured data, such as social media sentiment and news articles, allows firms to gain a holistic view of market conditions” (Yan, 2023b). By incorporating alternative data sources, investment managers can refine their strategies and identify trends that traditional metrics may miss. On the contrary side, as financial markets become increasingly interconnected, the integration of diverse data streams through AI and ML will enhance the predictive power of analytics, allowing for more agile and informed investment decisions.

According to (Sarker, 2022b)Another significant advancement in predictive analytics is the utilization of Natural Language Processing (NLP) techniques to analyze news articles and earnings calls. By extracting sentiments and key themes from textual data, investment managers can gauge market sentiment and identify potential impacts on asset prices. This layer of analysis adds a qualitative dimension to traditional quantitative models(Creswell, 2003), creating a more comprehensive understanding of market dynamics (Teng, C., Liao, Y., & Tseng, 2023b). As firms become adept at leveraging NLP, they can respond to shifts in market sentiment almost in real time, providing a competitive edge.

The potential for AI and ML in predictive analytics also extends to risk management. From the perspective of (Bender, A., Chen, Y., & Xu, 2022), “by employing algorithms that analyze historical volatility and correlation data, investment managers can better understand the risks associated with various asset classes and adjust their portfolios accordingly”. As a noted by (Madakam, Holmukhe and Revulagadda, 2022a) machine learning models can identify clusters of assets that are likely to behave similarly under certain market conditions, allowing for more informed diversification strategies. This proactive approach to risk management not only enhances portfolio resilience but also supports better long-term performance.

Furthermore, the evolving regulatory landscape presents both challenges and opportunities for predictive analytics in investment management. In the opinion of (Wang, He and Ouyang, 2024b), as regulations become more stringent, firms must ensure that their predictive models adhere to compliance standards. Automating compliance processes through AI and machine learning can streamline reporting and reduce the likelihood of human error, thereby minimizing the risk of penalties. By embedding compliance checks within predictive analytics frameworks, firms can maintain regulatory adherence while continuing to leverage the insights generated by their models.

A study conducted by (Nalini, Bala Venkata Kishore and Prasad, 2024) predictive analytics plays a vital role in portfolio optimization by providing actionable insights derived from comprehensive data analysis. The integration of advanced algorithms, alternative data sources, and NLP techniques equips investment managers with the tools needed to navigate the complexities of modern financial markets. As the financial landscape continues to evolve, the continuous development of AI and ML in predictive analytics will be instrumental in shaping the future of investment management. The combination of improved forecasting accuracy, dynamic risk management capabilities, and streamlined compliance processes will empower investment firms to make informed decisions, optimize portfolio performance, and ultimately enhance investor outcomes. From the perspective of (Huang, 2024), as these technologies mature, their transformative potential in investment management will only grow, paving the way for innovative strategies and heightened competitiveness in the marketplace.

2.3.1 Portfolio Return Forecasting: Leveraging ML, DL, and RL Techniques

In the viewpoint of advancing investment strategies, forecasting portfolio returns is a complex challenge that can be significantly enhanced through the application of machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques. Traditional forecasting methods often rely on linear models that may not adequately capture the complexities of financial markets. In contrast, ML and DL techniques utilize non-linear relationships within the data, improving the accuracy of return predictions (Esenogho, D., & Smith, J. 2022., 2022). For example, machine learning models, including Linear Regression, Decision Trees, and Random Forests, have shown promise in analyzing historical market data, technical indicators, and fundamental factors to predict returns (Tyagi, S., & Sharma, 2020). These models can identify intricate patterns and correlations that traditional models might overlook.

From the perspective of asset management, Decision Trees can effectively handle categorical variables and make interpretable predictions, which is particularly useful in finance where factors can be both numerical and categorical, such as company ratings or sector classifications. Random Forests, an ensemble learning method, improves upon basic decision trees by combining multiple trees to reduce overfitting and enhance prediction stability, making them particularly well-suited for the noisy nature of financial data (Bender, A., Chen, Y., & Xu, 2022). Additionally, "deep learning techniques, such as Recurrent Neural Networks (RNNS) and Long Short-Term Memory (LSTM) networks, excel at capturing temporal dependencies in time-series data, making them particularly effective for forecasting" **(**(Pyzer-Knapp *et al.*, 2022) . (RNNS) "Recurrent Neural Networks are designed to process sequential data, making them ideal for financial time series where previous values are often predictive of future values". "LSTMS, a specialized type of RNN, address the vanishing gradient problem and can maintain long-term dependencies", allowing them to remember important information over extended periods, which is essential for modeling market behaviors where trends may persist across various time frames (Huang, Y., Zhang, X., & Wu, 2024).

In the same relation, reinforcement learning (RL) approaches, including Deep Q-Networks (DQN) and Policy Gradient Methods, further enhance portfolio strategies by optimizing asset allocation decisions based on feedback from the environment(Frank J. Fabozzi (Editor), 2011). These techniques learn from the consequences of past actions, allowing for continuous improvement in decision-making (Zakaria, Z., & Razak, 2023b). For example, Deep Q-Networks dqns combine Q-learning with deep neural networks to predict the expected future rewards of actions, enabling the model to select optimal investment strategies dynamically. "Policy Gradient Methods, on the other hand, optimize the policy directly, allowing for more flexible and potentially more effective strategies by focusing on the long-term rewards of actions taken in the investment environment" (Singh, R., & Yadav, 2023).

Research conducted by (Alpaydin, 2014) Performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Percentage Error (RMSPE) are commonly employed to evaluate the accuracy of these models. By focusing on these metrics, researchers and practitioners can assess the effectiveness of their forecasting techniques and make informed adjustments to their methodologies. These metrics not only help in understanding the model's performance but also in comparing different forecasting approaches, providing a robust framework for evaluating which methods yield the best results under various market conditions.

On the contrary side, the integration of advanced ML, DL, and RL techniques paves the way for future research in multi-asset class forecasting, the incorporation of economic indicators, transfer learning, and the development of more sophisticated RL algorithms. Multi-asset class forecasting involves analyzing various asset types such as equities, bonds, and commodities simultaneously, allowing for diversified investment strategies that can adapt to changing market dynamics (Zhang, T., & Zhao, 2022). (Lazzini, A., Lazzini, S., Balluchi, F. and Mazza, 2022)By leveraging data from multiple sources, including macroeconomic indicators, social media sentiment, and geopolitical events, researchers can develop more holistic forecasting models that account for a broader range of factors influencing market movements.

In the opinion of experts in the field, transfer learning is another promising area for future research, where knowledge gained from one domain is applied to another. In the context of finance, this could mean applying insights gained from forecasting one asset class to enhance predictions in another, thus improving the efficiency and effectiveness(Zhang, T., & Zhao, 2022)is of forecasting models. This is particularly valuable in financial markets where historical data for certain asset classes may be limited.

According to (Raza, 2023)the development of more sophisticated RL algorithms, including advanced exploration strategies and hybrid models that combine RL with other machine learning approaches, holds significant promise for enhancing the precision and effectiveness of portfolio return forecasting. These innovations can lead to more adaptive investment strategies that continuously evolve based on real-time data and market changes.

In conclusion, the integration of ML, DL, and RL techniques in portfolio return forecasting represents a significant advancement in the field of finance(Raza, 2023). As these methodologies continue to evolve, they offer the potential for more accurate, adaptive, and robust investment strategies that can better navigate the complexities and uncertainties of financial markets (Miao, H., & Chen, 2024). The future of portfolio management will likely see an increasing reliance on these advanced technologies, enabling investors to make more informed decisions and optimize their returns in an ever-changing landscape.

2.4 Risk Mitigation through Automation

Risk management is a crucial aspect of investment management, and automation technologies have become essential tools for mitigating various financial risks(Bender, A., Chen, Y., & Xu, 2022). As markets become increasingly volatile and complex, the need for robust risk assessment frameworks is more pressing than ever. Traditional risk management methods often fall short in the face of rapid market changes and vast data volumes. In this context, automation emerges as a vital solution that enhances the accuracy and efficiency of risk management practices (Mun, Housel and Housel, 2023). Automation facilitates real-time monitoring of market conditions and portfolio performance, allowing investment managers to identify and respond to risks promptly (Zakaria, Z., & Razak, 2023b). AI-driven systems can analyze vast amounts of data to detect anomalies, trends, and potential threats, providing firms with critical insights that inform risk management strategies. “For instance, machine learning algorithms can monitor fluctuations in asset prices and economic indicators, enabling proactive adjustments to Portfolios” (Esenogho, D., & Smith, J. 2022., 2022). By employing predictive analytics, investment firms can anticipate market movements and adjust their strategies, reducing exposure to adverse events.

In the same relation, automation significantly enhances the granularity and frequency of risk assessments. Automated systems can generate risk reports and dashboards in real-time, allowing portfolio managers to track performance metrics and risk exposure continuously. This immediacy is essential in today’s fast-paced financial environment, where delays in data interpretation can lead to missed opportunities or, worse, substantial losses. Additionally, cybersecurity has become a significant concern in the financial industry, and automation plays a key role in safeguarding sensitive information. AI-driven cybersecurity systems can detect unusual patterns in transaction data and flag potential breaches, enhancing the overall security of financial transactions (Mun, Housel and Housel, 2023). This capability is vital for protecting against the increasing threat of cyberattacks, which can have devastating consequences for investment firms.

On the contrary side, automated systems can employ anomaly detection algorithms that learn from historical transaction data, identifying deviations that may indicate fraudulent activities. Such proactive measures not only protect financial assets but also preserve the trust of clients and stakeholders. The integration of natural language processing (NLP) within automation frameworks also enhances risk mitigation strategies. NLP algorithms can analyze news articles, social media, and other text-based sources to gauge market sentiment and identify emerging risks. By monitoring public sentiment, firms can better understand potential market reactions to geopolitical events or economic announcements, allowing them to adjust their portfolios ahead of time (Teng, C., Liao, Y., & Tseng, 2023b).

Moreover, automated compliance tools also contribute to risk mitigation by ensuring adherence to ever-evolving regulatory requirements. By "automating compliance processes, firms can reduce the risk of non-compliance and the associated penalties, safeguarding their reputation and financial standing" (Wang, He and Ouyang, 2024b). Automation enables continuous compliance monitoring, where systems can track changes in regulations and assess their impact on existing practices. This not only reduces the burden on compliance teams but also enhances the accuracy of compliance efforts, minimizing the chances of costly missteps. Furthermore, the use of scenario analysis and stress testing within automated risk management frameworks allows firms to prepare for potential adverse market conditions. Automated simulations can evaluate how portfolios would perform under various hypothetical scenarios, such as economic downturns or interest rate hikes (Che Hassan *et al.*, 2023).

This foresight enables investment managers to implement contingency plans and adjust their risk exposures in advance.

Incorporating automation in risk management also allows for better resource allocation. By automating routine risk assessments and compliance checks, firms can free up human resources to focus on more strategic initiatives(Adel, 2023). A study conducted by (Tian, 2023) this shift not only enhances operational efficiency but also fosters a culture of proactive risk management within organizations. In conclusion, automation technologies are instrumental in mitigating risks in investment management. By leveraging AI-driven real-time monitoring, cybersecurity measures, and automated compliance systems, firms can effectively identify, assess, and respond to financial risks. The integration of advanced analytics, NLP, and scenario analysis further enhances the robustness of risk management practices. Ultimately, the adoption of automation enables investment firms to navigate the complexities of the financial landscape(Chakraborti *et al.*, 2020b) with greater resilience and agility, positioning them to succeed in an increasingly uncertain environment.

2.5 Compliance and Regulatory Considerations in Automation

The rapid adoption of automation in investment management has brought forth a host of compliance challenges that organizations must navigate to ensure they remain aligned with regulatory frameworks. From the perspective of many industry experts, automated investment systems are designed by (Chavarnak, J., Lee, M., Patel, S., & Tran, no date)to enhance efficiency and accuracy; however, they also introduce complexities related to compliance with financial regulations. Regulatory bodies have intensified their scrutiny of automated systems, recognizing the potential risks associated with algorithm-driven decision-making processes (Zhu, W., & Liang, 2022). One significant challenge is ensuring that these automated systems adhere to the principles of transparency and accountability. In the opinion of several researchers, “the opaque nature of many AI and machine learning algorithms can hinder compliance efforts, as stakeholders may find it difficult to understand how decisions are made” (Thompson, K., & Murphy, 2024). “This lack of transparency poses risks, particularly when firms are required to demonstrate compliance with regulations such as the Markets in Financial Instruments Directive (MIFID II) in Europe, which mandates that investment firms must act in the best interests of their clients and maintain clear records of decision-making processes" (Wang, He and Ouyang, 2024b).

Furthermore, the regulatory landscape is continually evolving, with new rules and guidelines being introduced to address the implications of automation in (Kelly and Xiu, 2023). In the same relation, automated systems must be adaptable to comply with these changing regulations, necessitating robust governance frameworks (Esenogho, D., & Smith, J. 2022., 2022). Research highlights that firms are increasingly implementing compliance management systems that integrate with their automated processes. These systems utilize advanced analytics and reporting tools to monitor compliance in real-time, allowing firms to quickly identify and rectify any issues that may arise(Zakaria, Z., & Razak, 2023b). Such proactive measures not only help in adhering to regulations but also reduce the risk of legal penalties and fines associated with non-compliance (Che Hassan *et al.*, 2023).

Another critical aspect of compliance in automated investment systems is the management of data privacy and protection. In the viewpoint of regulatory analysts, requirements such as the General Data Protection Regulation (GDPR)(Gill *et al.*, 2022a) in Europe impose strict guidelines on how personal data is collected, stored, and processed. "Automated systems that utilize customer data must ensure that they comply with these regulations, which often involves obtaining explicit consent from clients before their data can be used for investment decisions" (Miao, H., & Chen, 2024). Studies show that investment firms are increasingly investing in data governance frameworks to manage compliance risks related to data privacy. These frameworks often include measures such as data encryption, access controls, and regular audits to ensure adherence to data protection laws (Patil, A., & Khandare, 2022).

On the contrary side, the integration of automated systems with existing compliance frameworks poses its own set of hurdles. A study conducted (Sarker, 2022b)Many investment firms rely on legacy systems that may not be fully compatible with new automated technologies. This lack of integration can create gaps in compliance oversight, as firms struggle to obtain a comprehensive view of their regulatory obligations across different platforms. Literature suggests that organizations are addressing this issue by adopting integrated compliance solutions that provide a centralized view of compliance metrics and reporting. By doing so, firms can ensure that their automated systems are aligned with regulatory requirements, thereby enhancing overall compliance efficiency (Lee, J. H., & Kim, 2023).

Moreover, the increasing complexity of financial products and services necessitates a more nuanced approach to compliance in automated systems. In the viewpoint of compliance experts, as firms innovate and develop new investment products, they must also consider the regulatory implications of these offerings. For instance, the introduction of complex financial derivatives and automated trading strategies raises questions about the adequacy of existing compliance measures (Bender, A., Chen, Y., & Xu, 2022). Research indicates that firms are proactively engaging with regulators to clarify compliance expectations for automated systems dealing with innovative financial products. This collaborative approach fosters a better understanding of regulatory requirements and helps firms to tailor their compliance strategies accordingly (Khan, A., & Bhatti, 2023b).

Training and education also play a crucial role in managing compliance risks associated with automation. In the opinion of industry observers, investment firms must ensure that their employees are well-versed in both the technological aspects of automated systems and the regulatory requirements governing their operations. Studies emphasize "the importance of continuous training programs that equip employees with the knowledge and skills necessary to navigate the complexities of compliance in automated environments" (Clarke, R., & Xu, 2023). A study conducted (Adel, 2023) fostering a culture of compliance, firms can minimize the risk of inadvertent violations and enhance their overall compliance posture.

Additionally, effective risk management strategies are essential for addressing compliance challenges posed by automated investment systems. Literature highlights that firms are increasingly incorporating risk assessment frameworks that specifically address the compliance risks associated with automation. These frameworks often involve identifying potential compliance vulnerabilities, assessing their impact, and implementing mitigation strategies (Patel, S., & Raghavan, 2022). By adopting a proactive risk management approach, firms can ensure that their automated systems remain compliant with regulatory requirements, thereby reducing the likelihood of legal penalties and fines (Zakaria, Z., & Razak, 2023b)

As automation continues to reshape the investment management landscape, the importance of compliance cannot be overstated. Regulatory bodies are likely to continue to refine their guidelines to address the unique challenges posed by automated systems. Firms that prioritize compliance in their automation strategies will be better positioned to navigate these evolving regulatory landscapes. The integration of advanced analytics, robust governance frameworks, and continuous employee training will be critical in ensuring that automated systems not only enhance operational efficiency but also uphold the highest standards of compliance(Tian, 2023).

In conclusion, the intersection of automation and compliance in investment management presents both challenges and opportunities. While automated investment systems can significantly streamline operations and improve decision-making, they also introduce complexities that require careful consideration of regulatory requirements. By embracing a holistic approach to compliance, one that includes real-time monitoring, data governance, employee training, and proactive risk management, investment firms can effectively manage compliance challenges while harnessing the full potential of automation. As the regulatory landscape continues to evolve, firms that remain vigilant and adaptable in their compliance efforts will not only mitigate risks but also enhance their reputation and trustworthiness in the eyes of clients and regulators alike(Cocco, 2021).

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Overview of the Research Problem:

The methodological approach used to investigate next-generation investment management robotic automation architecture, portfolio management, and risk containment instrumented with AI and ML is described in this chapter. To achieve this the following methodology was developed: The key considerations ensured that the research objectives are well captured and provide valid and reliable results.

3.1 Research Design

Consequently, the research design for this study conducted by(Lee *et al.*, 2024) is a mixture of both the descriptive and exploratory designs. The descriptive aspect is to reveal the state of the development and the ongoing trends in the application of AI and ML for automated portfolio management The exploratory aspect targets emerging opportunities and challenges posed to investment management by embedded AI and ML-based capabilities and potential risk management approaches.

As such, this research uses quantitative survey research to establish the relationship between organizational and personal factors on employee motivation and retention.

A descriptive design is ideal for the current state of implementing AI and ML in the financial markets(Miao, H., & Chen, 2024), especially in automation of investment management. It also assists in coding what currently exists as well as, the definition of trends crucial in understanding how various organizations incorporate artificial intelligence and machine learning into the management of portfolios as well as the minimization of potential risks.

On the other hand, an exploratory design is called for in order to study the new opportunities of AI and ML in investment automation. Because AI and ML in finance have dialectic characteristics, this approach enables the researcher to study different recent developments and trends. This research is exploratory in nature as this will aid in establishing the rationales for the gaps that are observed in the current systems and in uncovering various strategies that firms have adopted in investment and risk management.

On the basis of this chosen dual research design by (Che Hassan *et al.*, 2023) it is expected that the hereby study will be able to accomplish its key goals on the one hand by presenting the insights of AI/ML applications in investment management up to date; on the other hand by identifying possibilities for the advancement of these technologies in terms of risk management and mitigation.

For the present study, since the primary aim of the research is to identify how Next-Generation Investment Management Robotic Automation Architecture enhances AI and ML in a portfolio, a descriptive research design is appropriate. It also allows the researchers to gain explicit qualitative and quantitative information about the current practices, technologies, and results. This is done by a major emphasis on the assessment of patterns or trends and the functional aspect of automation in investment management. Applying case studies, questionnaires, and industry reports, the design reflects knowledge about how and to what extent AI and ML are employed, and the extent to which they provide benefits that help reduce risks and enhance portfolio outcomes. It is also important because it provides a structured approach to assessment and the drawing of conclusions that are as logical as is possible (Siedlecki, 2020).

On the other side, an exploratory research design is fit for the research topic since it helps in establishing the link between Next-Generation Investment Management Robotic Automation Architecture, portfolio management and risk mitigation using AI and ML. Such an approach enables substantial discourse of the advanced technologies, their prospect directions, and their applicability to fund management. Literature review and interviews with the experts, case studies will be used during the study to understand more about the AI and ML in automation of decision making. The present design avails the detection of new patterns, technological blind spots, and strategic prospects towards perspectival knowledge development and enactment in fluid financial contexts, thereby creating a structure for subsequent theoretical and practical research (Mbaka and ISIRAMEN, 2021).

3.2 Data Collection Methods

Carry out accordingly in the data gathering process of this study, these methods are essential to obtaining correct and pertinent information regarding how next-gen investment management robotic automation architecture and AI and ML utility in portfolio management and risk reduction. This section explains the first and second data collection techniques with much attention on how they should be combined to avoid giving a shallow perspective of research questions/ hypotheses.

Primary Data Collection

In an attempt to obtain primary data sources, interviews, surveys and case studies would be followed since they will assist in the course of the research in ascertaining how AI/ML is practically applied and the challenges faced in investment management. This research approach will include quantitative and qualitative data results that are essential in capturing the dynamics of AI/ML automation in the financial sector.

Interviews

This study will therefore involve interviews as the main data collection instrument, which will offer a rich, qualitative understanding of the position of investment professionals concerning the use of AI as well as the practical application of AI and ML in their work. The Creswell (2014) interview is useful in elaborating participants' experience and perspectives on a given context, more so in dynamic and emerging areas like AI/ML automation. This kind of interview is also semi-structured, which gives the researcher the advantage of turning into highly structured whenever he or she feels there is more to look out for in that particular area of discussion.

Intended participants for the interview will comprise AI/ML working portfolio managers since they work directly with AI/ML tools. These are portfolio managers, (Creswell, 2014.)risk analysts, artificial intelligence solution architects, and Chief Technology Officers (CTO) from the adopted AI/ML automation in-house investment organization. According to (Bryman, 2016), the qualitative data collected from experts in the field produce detailed information about the research question, which can be challenging to receive through quantitative pragmaticism. Moreover, the opinions of these professionals will enrich the research study with practical applicability perspectives of the theory since the application of AI/ML is a practical concept in the management of investments.

Surveys

While interviews lead to deeper insights, surveys will help to get a quantitative view of the state of AI/ML automation among a greater number of professionals. The surveys will contain standardized closed questions that seek information on participants' exposure to AI/ML technologies, efficiency improvements, future outlooks, and potential risks and benefits related to progressive innovations in portfolio management with the application AI. These surveys will also incorporate Likert type questions designed to assess the level of endorsement of certain propositions with regard to the role of AI/ML in reducing risk and enhancing portfolio performance(Allioui and Mourdi, 2023).

Surveys according to (Aiken, M., & Balan, 2020) are particularly useful to obtain different opinions and experiences of a large population sample which can then be subjected to "statistical analysis to assess the relationship of variables". The survey will recruit participants from a diverse background of investment firms such as AMC, Hedge funds, and Wealth management firms with a special emphasis on those institutions that are currently implementing or testing AI/ML solutions. By using this method, the study will be able to obtain different views and experiences from the population hence generalize the results on the entire investment management industry.

Case Studies

As a matter of fact, both interviews and questionnaires will also be complemented with case studies that will present practical illustrations about the usage of AI/ML automation in managing portfolios amongst various organizations. Theoretical concepts are general and indirect; thus, case studies complement quantitative research because they provide a detailed view of the phenomena under study, which is most relevant for the analysis of how AI and ML are introduced in organizations (Yin, 2018). That is why, for example, a practical case of a large asset management company that has already implemented AI algorithms for risk management can be interesting and provide useful information about the prospects and problems that may appear in such implementations.

Thus, (Duarte, F., & Girardi, 2022b)have stated that knowledge of real-life application of technology makes case studies invaluable in studying how AI/ML automation is likely to influence choice-making of investment decisions. To gather cases for this research, the selected firms would be those organizations for which it is easy to identify the firm's AI/ML adoption histories, including both the advantages and drawbacks and both the success and failures that occurred during implementations.

Secondary Data Collection

Secondary data sources will comprise peer-reviewed articles, industrial, financial and white papers. This source gives a theoretical understanding of the aspect of the study highlighted by (Zakaria, Z., & Razak, 2023b) and the use of AI and ML in finance and complements the primary data through interviews, surveys and case studies together with other sources of literature containing both theoretical and empirical data.

Newspapers/Magazines and Scholarly Books

In turn, academic journals will avail peer-reviewed information on the emerging trends in AI/ML in financial industries and applications. According to (Alpaydin, 2020), it is necessary to work within a theoretical framework, and it is necessary to start with the analysis of the literature. In this paper, articles in top-tier financial technology journals will be examined to examine the technical and theoretical concept of AI/ML in portfolio management.

Market Situation Projects and Industry and Financial Reports

Current surveys and business analyses by and for Deloitte, Pwc, and mckinsey & Company will serve as sources for evaluating the newest directions of AI/ML automation in finance. Such reports may contain surveys, case studies, as well as opinions from specialists that combine comprehensive research on the current situation with regards to the AI/ML in the investment domain (Cocco, 2021). The study will also analyze financial reports of firms that apply AI/ML in their portfolio management to analyze the effects of these technologies in determining the performance and risk management characteristics of firms.

White Papers

Some white papers will be presented during the workshop, including papers by AI providers and fintech companies who will present the industry perspective on the experiences in building AI/ML tools for finance. IBM's Aviv, Google Cloud, and Microsoft are some of the companies that have written elaborate papers on the success of AI in the market, especially on the portfolios and risks (Bengio, Y., & Courville, 2016)These papers will give a technical understanding on the algorithms and methodology employed in the AI/ML investment management system to fill the existing theoretical – practical divide.

3.3 Sampling Technique

The sampling technique adopted for this study is Judgmental (or purposive) sampling whereby the researcher selects participants he/she deems appropriate in enhancing the study conducted by (Frank J. Fabozzi (Editor), 2011)regarding the use AI/ML in portfolio management. This section expands by explaining why judgmental sampling will be used to participate in the study and how it will be used to get the proper participants.

This is why judgmental sampling is adopted in this study: Judgmental sampling is advantageous because it allows the researcher to identify respondents that are most suitable for the study.

"The criterion sampling also known as judgmental sampling is a non-probability sampling technique whereby the researcher samples the participants because of their assumed expertise" in the study area (Bryman, 2016). It is mainly useful in exploratory research since the main aim is to gain detailed information from experts in a given area of study. For purposes of this study, "judgmental sampling is tenable because the investigation is narrowed down to the use of AI and ML in investment management – an area of niche specialization" – and therefore noted practitioners were selected in the study.

(Bertoluzzo, F., 2021)posit that AI/ML utilization in financial firms is contingent upon its implementers' technical and financial competencies. Hence, this study will focus only on managers and employees who work directly within their organizations' AI/ML automation and implementation departments. That set of participants may shed bright light on the opportunities, risks, and possible future developments of AI/ML applications in the context of portfolio management and risk management(Lee *et al.*, 2024).

Focusing on judgmental sampling as the non-probability sampling method, this research on "'Next-Generation Investment Management Robotic Automation Architecture for Portfolio Management and Risk Mitigation through Artificial Intelligence and Machine Learning' "paves way for the right choices. The above technique enables the identification of participants with specific knowledge in investment management, artificial intelligence, and machine learning. Due to the specificity of the topic and its focus on the high technical level, it is critical to reach out to decision-makers, and other professionals like financial analysts, portfolio managers, developers of AI in the financial sphere or leaders of fintech companies.

Due to the specialization of the field, there is a scarcity of a large and diverse workforce with this training. Judgmental sampling guarantees that the proper sample of investment automation is comprised of persons right from the technology or directly concerned with any alteration in the technology. By doing so, this approach increases the study's applicability and richness based on participants willing and able to analyze the use of both AI and ML in investment handling and risks management.

Respondents to this study will comprise 150 individuals some of whom will be selected by adopting judgmental sampling technique depending on the respondent's background. Recruitment criteria will be set to ensure that not only local representatives will be arriving at the conclusion but also is possible to cover all important aspects concerning the subject matter of the study. The following criteria include the responder's professional use of the respondent must involve the sample in decision-making, operation, and technical functions. Their AI/ML technological exposure also will be another survey parameter that would include information from professionals who have long-serving experience with these technologies, as well as those who just started engaging in such projects. The location of the companies/organizations will be considered in order to address the different geographical environments and technology maturity. Moreover, the study will enlist participants across firms of different scale – SMEs and large firms and of operation – domestic, regional, and global. It is to balance an array of dataset and offers a properly grounded perspective at the data collected throughout the research.

Participants Selection Criteria

Participants will be selected based on the following criteria:

Professional Role: Only individuals who work for investment management firms and are engaged in the use or management of AI/ML tools are eligible to take part in the survey. Some of these positions may include portfolio managers, data scientist, system architects and risk analyst among others.

Experience with AI/ML: Ideally, participants should have practical experience within the last 12-18 months of the practical application of AI/ML in investment management(Chavarnak, J., Lee, M., Patel, S., & Tran, no date). This is very important for them to be able to give real experience of the effect of these technologies in the portfolio and risk (Gudmundsson, 2019).

Firm Size and Scope: The participants in the study will include middle to senior level working professionals from different firms with investment operations, whether small investment firms or large asset management companies. This will also make it easier for the study to incorporate different experiences and perceptions of the application of AI/ML across the different organizations, due to the fact that their adoption levels are bound to differ.

Geographical Diversity: In an endeavor to establish the generality of the results, participants will be drawn from firms of different regions. This will assist the study to get any regional differences about the use of AI/ML and its implications on investment management (Chen, Y., & Wang, 2019b).

Thus, judgmental sampling will be employed so as to collect information only from those participants who are more likely to give detailed and practical data in regard to the chosen topic. This approach ensures that data collected for the study is relevant and has high quality as demanded by the current research purpose.

3.4 Technical Methods

The last sub-section of the technical methods group summarizes the tools and techniques that have been employed in data collection, cleaning and analysis.

Data Collection Tools

- **Survey Platforms:** Surveys to the participants will be conducted via Google Forms, SurveyMonkey, or Qualtrics. There is convenience when using these platforms, one can set questions in different formats and the data collection process is also handled by the platform.

The questionnaire was designed based on the Likert scale rating with closed ended questions. The surveys were distributed online. The response rate was 66.67%.

- **Interview Tools:** For interviews, online communication platforms including but not limited to Zoom or Microsoft Team will be used for conducting online sessions with the participants to make them comfortable with the time of the interview depending on the geographical area of the participant.

- **Statistical Software:** A study conducted by (Ndikum and Ndikum, 2024) The Statistical Package for Social Science (SPSS) and Analyses of Moment Structures (AMOS) shall be used in the analysis because they are universally used for quantitative research analysis. Hypothesis testing will be conducted to establish Patterns between variables, for instance; AI/ML automation on portfolio optimization and risk reductions.

- **Machine Learning Tools:** Language such as Python or R will be used to deploy certain machine learning algorithms for testing the performance of AI/ML based models in efficient management of portfolio. Many of the ideas that will be presented will be couched in a hypothesis-testing framework, and the tools used to investigate the data will include predictive modeling, classification, and regression analysis techniques.

Visualization Tools: A study conducted by (Kaiyi Chen, 2024)For data presentation purposes data visualization tools like Tableau or Power BI will be used as they help in presenting results in a presentable and understandable format. Tables and figures will accompany this section to present trends and findings from the analysis of the data.

Hypothesis Testing: To confirm or reject hypotheses developed regarding the effects of AI and ML on the management of portfolio and risks, inferential statistics of t-tests, analysis of variance (ANOVA) and regression analysis are appropriate(Ndikum and Ndikum, 2024). These techniques will be useful in establishing the probability of the relationships between variables, and whether the effects are robust or merely a reflection of sample bias.

3.5 Data Analysis Tools

Data analysis will be concerned with understanding survey responses, interviews and case studies used to gather data quantitatively and qualitatively.

Quantitative Data Analysis: For quantitative data obtained from surveys, SPSS and Python will be used to perform statistical analyses such as:

- **Descriptive Statistics:** Descriptive statistics such as measures central tendency, measure of variation and graphical display will be computed and determined.

- **Inferential Statistics:** Analysis methods like regression analysis (Yang, C., Zhai, J., & Tao, 2020)(Yan, 2023b)and ANOVA will then be employed to analyze the interdependence of factors like the impact of AI/ML on portfolio performance and shrinking of risks.

- **Machine Learning Algorithms:** Specific possibilities of AI/ML algorithm(Nalini, Bala Venkata Kishore and Prasad, 2024), including neural networks(Dahl, G. E., Sainath, T. N., & Hinton, 2013), (Huang, 2024), and support vector machines (SVM)(Yan, 2023b), to provide portfolio estimates and evaluate the efficiency of AI-driven models in risk management will be identified.

Qualitative Data Analysis

Evidenced from interviews and case studies, conventional content analysis under thematic analysis will be used to analyze the data to come up with themes and patterns. Qualitative data will be analyzed through NVivo where they will be coded, analyzed, and come up with meaningful conclusions on the experiences and perception of the industry experts for the AI/ML automation use in investment management.

Prediction and Outlook

Predictive models using machine learning algorithms, in particular in Python or R will be developed. These models will be tested in the same cross validation, confusion matrices which will give confirmation of the models' ability to accurately predict investment outcomes and risks. However, due to back testing the researcher would be able to see how these models would perform in the market with the historical data.

Conclusion

In this chapter, the methods of carrying out the research were described. The research design applied in the study (Frank J. Fabozzi (Editor), 2011)is both descriptive and exploratory in order to assess AI automation of portfolio management and risk management. Both primary and secondary data will be collected through interviews, structured questionnaires which include case studies and secondary data in the form of academic research papers and online industrial reports. It also makes sure that the study targets individuals with considerable knowledge in the identified field through judgmental sampling. To answer the research questions, this analysis will use complex statistical analysis instruments and machine learning techniques. The following chapter will provide a description of the data analysis and results of the present research by (Huang, 2024).

Annexure A: Survey Cover Letter

Subject: Request for Participation in Research Survey on AI-Driven Robotic Automation in Investment Management

Dear Respondent,

My name is Mansi, and I am a Doctorate (DBA) scholar at the Swiss School of Business and Management. As part of my academic research, I am conducting a survey titled: "Portfolio Management 2.0: Unlocking AI-Driven Robotic Automation for Investment Excellence - A Survey of Architectural Best Practices, Future Directions, and Emerging Trends."

The investment management industry is undergoing a significant transformation with the integration of technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Robotic Automation. While these technologies offer immense potential, their successful adoption comes with challenges. This survey aims to explore the current state of AI-driven robotic automation in investment management, identify best practices, understand pain points, and uncover future trends. The insights gathered will contribute to shaping strategies for optimizing portfolio performance, mitigating risks, and enhancing decision-making.

Your participation in this survey is invaluable, as your expertise and experience will greatly enrich the data collection and analysis process. I assure you that the information you provide will be treated with the utmost confidentiality and will be used strictly for academic purposes.

Purpose of the Survey:

This survey seeks to:

- Explore the adoption, benefits, and challenges of AI-driven robotic automation in investment management.
- Identify architectural best practices and implementation strategies.
- Uncover emerging trends and future directions in the field.

To participate in the survey, please click the following link:

Survey Link

https://docs.google.com/forms/d/e/1FAIpQLSfkwTIgggqR7zQpZOmjtgwuzlB7jsbx8nR0_98EsUreEOoNhQ/viewform

Your feedback will play a crucial role in advancing the understanding of these technologies and their practical applications in the industry.

If you have any questions, concerns, or feedback about this research, please do not hesitate to contact me at **mansi.ssbm.dba@gmail.com** or **mansi@ssbm.ch.**

Thank you for considering this request. Your time and insights are greatly appreciated and will contribute significantly to the success of this study.

Warm regards,

Mansi

Doctorate (DBA) Scholar

Swiss School of Business and Management

Email: Mansi.ssbm.dba@gmail.com | Mansi@ssbm.ch

Annexure B: Survey Questionnaire

Q-1 What is your age group?

- 25-35
- 36-40
- 40-45
- 46-50
- 50-55
- 55-60
- 60 & above

Q-2 What is your highest level of qualification?

- Graduate
- Postgraduate
- Diploma
- PHD
- Others
- Clear selection

Q-3 What is your occupations?

- Professional/Manager
- Entrepreneur/Business Owner
- Government Employee
- Public sector Employee
- Doctor
- Service in financial sector
- lawyer
- retired
- Engineer
- Other

Q-4 What is your income size?

- Below 4,99,000/-
- 5,00,000 - 10,00,000
- 10,00,000-15,00,000
- 15,00,000-20,00,000
- 20,00,000/- Above

Q-5 What is your total no of years of experience?

- Below 5 years
- 5-10 years

- 10-15 years
- 15-20 years
- 20 years & Above

Q-6 Which country are you located at?

- India
- Australia
- Canada
- United Kingdom
- United state of America
- U.A.E
- Others

Q-7 Which industry sector does your organization Belong?

- Finance/Banking
- Technology/Software
- Manufacturing/Industrial
- Hospitality/Tourism
- Financial, Banking
- Media/Entertainment
- Real Estate/Property
- Professional Services (e.g. Consulting, Law, etc.)
- Other (please specify)

Q-8 **What type of investments do you currently hold?**

- Stocks
- Bonds
- Mutual Funds
- ETFs
- Real Estate
- Commodities
- Cryptocurrencies
- fixed deposit
- Other

Q-9 What is your investment horizon?

- Short-term (less than 1 year)
- Medium-term (1-5 years)
- Long-term (5-10 years)
- Very long-term (more than 10 years)

Q-10 What is the approximate value of your investment portfolio?

- Below 1Lakh
- ₹1 lakh - ₹5 lakhs
- ₹5 lakhs - ₹10 lakhs
- ₹10 lakhs - ₹25 lakhs
- ₹25 lakhs - ₹50 lakhs
- ₹50 lakhs - ₹1 crore
- ₹1 crore - ₹5 crores
- More than ₹5 crores

Q-11 What is your expected annual return on investment?

- Less than 5%
- 5-8%
- 9-12%
- 13-15%
- More than 15%

Q-12 How important is achieving high returns to you?

- Very important
- Somewhat important
- Not very important
- Not at all important

Q-13 What is your level of satisfaction with your current investment portfolio?

- Very satisfied
- Satisfied
- Neutral
- Dissatisfied
- Very dissatisfied

Q-14 What are your investment goals?

- Capital appreciation
- Income generation
- Capital preservation
- Retirement savings
- Other (please specify)
- Other:

Q-15 How do you typically make investment decisions?

- On my own
- With the help of a financial advisor
- Based on recommendations from friends/family
- Other (please specify)

(I) Next-Generation Investment Management

Q-16 How familiar are you with the concept of Next-Generation Investment Management?

- Very familiar
- Somewhat familiar
- Not very familiar
- Not at all familiar

Q-17 Which of the following technologies do you believe will have the greatest impact on investment management in the next 5 years?

- Artificial Intelligence & Machine Learning
- Robo-advisors
- Big Data & Alternative Data
- Blockchain
- Other (please specify)

Q-18 How important are ESG factors (Environmental, Social, and Governance) in your investment decisions?

- Very important
- Somewhat important
- Not very important
- Not at all important

Q-19 Do you believe personalized investment portfolios based on individual preferences and risk tolerance will become the norm in the future?

- Yes
- No
- Maybe

(II) Robotic Automation Architecture for Portfolio Management and Risk Mitigation

Q-20 How familiar are you with the use of Robotic Process Automation (RPA) in investment management?

- very familiar
- Somewhat familiar
- Not very familiar

- Not at all familiar

Q-21 Which of the following benefits of RPA do you consider most valuable for portfolio management and risk mitigation?

- Improved efficiency
- Reduced costs
- Enhanced accuracy
- Faster decision-making
- Enhanced risk mitigation
- Other (please specify)

Q-22 What are the main challenges you foresee in implementing RPA in investment management?

- Lack of skilled personnel
- Integration with existing systems
- Data security concerns
- Cost of implementation
- Other (please specify)

Q-23 On a scale of 1 to 5, how likely are you to consider using RPA solutions for your investment management needs in the next 2 years? (1 being not likely at all, 5 being very likely)

- 1
- 2
- 3
- 4
- 5

(III) Investment Analysis Fundamentals

Investment Analysis Fundamentals involve examining financials, ratios, and industry trends to estimate future performance and make informed investment decisions.

Q-24 How familiar are you with the concept of intrinsic value in investment analysis?

- Very familiar
- Somewhat familiar
- Not very familiar
- Not at all familiar

Q-25 Which investment analysis methodology do you primarily rely on?

- Fundamental Analysis
- Technical Analysis
- Quantitative Analysis
- A combination of approaches

Q-26 Which of the following is a key fundamental analysis ratio?

- Price-to-Earnings (P/E)
- Debt-to-Equity
- Return on Equity (ROE)
- All of the above

Q-27 Which fundamental analysis approach focuses on a company's financial statements?

- Top-down
- Bottom-up
- Technical analysis
- Quantitative analysis

Q-28 What is the significance of Return on Invested Capital (ROIC) in fundamental analysis?

- Measures profitability
- Measures efficiency
- Measures growth potential
- Measures risk

Q-29 What is the primary goal of fundamental analysis in investment decision-making?

- To predict short-term market trends
- To estimate a company's future financial performance
- To identify undervalued stocks
- To diversify a portfolio

(IV) Investment Analysis in Practice

Investment Analysis in Practice applies fundamental techniques to real-world decisions, evaluating companies' financials, management, and industry trends for informed investing.

Q-30 How do you assess the risk associated with an investment?

- Quantitative Measures
- Qualitative Assessment
- Scenario Analysis:
- A combination of approaches
- Option 5

Q-31 How do you incorporate technology into your investment analysis process?

- Data Analytics & Visualization Tools
- AI-Powered Platforms
- Algorithmic Trading
- I'm still exploring the use of technology in investment analysis.

(V) Current Trends & Future Outlook

"Current trends: AI adoption, automation, data analytics. Future directions: Explainable AI, hybrid human-AI decision-making, cloud-based architectures, ESG integration."

Q-32 Which emerging trends do you believe will significantly impact investment analysis in the future?

- AI & Machine Learning
- Sustainable Investing
- Alternative Data
- Other (please specify):

Q-33 How confident are you in your ability to navigate the complexities of the investment landscape and make informed investment decisions?

- Very confident
- Somewhat confident
- Not very confident
- Not at all confident

(VI) Risk Mitigation Strategies in Investment Management: Current Practices and Challenges"

Exploring current risk mitigation practices, challenges, and trends in investment management to inform strategies and improve portfolio resilience."

Q-34 What is the primary goal of risk mitigation in investment management?

- To maximize returns
- To minimize losses
- To optimize portfolio performance
- To ensure regulatory compliance

Q-35 Which of the following risk mitigation strategies do you currently use?

- Diversification
- Hedging
- Asset allocation
- All of the above

Q-36 What is the most significant risk facing investment managers today?

- Market risk
- Credit risk
- Operational risk
- Regulatory risk

Q-37 How do you assess and manage potential risks in your investment portfolios?

- Quantitative models
- Qualitative analysis
- Stress testing
- All of the above

Q-38 What is the biggest challenge in implementing effective risk mitigation strategies?

- Data quality
- Model complexity
- Regulatory requirements
- Human behaviour

Annexure C: Survey Introduction and Confidentiality Statement

Survey Introduction

The investment management industry is undergoing a transformative phase with the integration of advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Robotic Automation. These innovations are reshaping how portfolios are managed, risks are mitigated, and decisions are made. However, the adoption of these technologies presents significant challenges, including implementation strategies, integration complexities, and evolving best practices.

This survey, titled "Portfolio Management 2.0: Unlocking AI-Driven Robotic Automation for Investment Excellence - A Survey of Architectural Best Practices, Future Directions, and Emerging Trends", aims to gather insights on the adoption, benefits, and challenges of these technologies. The objective is to identify pain points, uncover emerging trends, and provide actionable strategies to optimize portfolio performance, mitigate risks, and enhance decision-making in the investment management field.

By participating in this survey, respondents contribute to advancing the understanding and application of cutting-edge technologies in the industry, shaping its future direction and efficiency.

Confidentiality Statement

The information provided by respondents in this survey will be treated with the utmost confidentiality. All responses will remain anonymous, and no personally identifiable information will be disclosed or shared. Data collected will be aggregated for analysis and used solely for academic research purposes as part of the researcher’s Doctorate (DBA) at the Swiss School of Business and Management.

Participants’ involvement is entirely voluntary, and they may choose to withdraw at any point during the survey. This study adheres to strict ethical guidelines to ensure privacy and data security. The findings will serve to enrich academic knowledge and provide practical insights for the investment management industry.

For any questions, concerns, or feedback, respondents can contact the researcher at Mansi.ssbm.dba@gmail.com or mansi@ssbm.ch.

This annexure outlines the survey’s purpose and assures participants of confidentiality, setting the foundation for trustworthy and meaningful engagement in the research study.

Annexure D: Summary of Descriptive Statistics from the Survey Report

The survey report provides an insightful overview of the respondents' demographics, qualifications, and professional backgrounds. Key findings include:

- **Demographics:** The majority of participants fall within the age group of **25-45 years**, with a significant number holding **graduate or postgraduate qualifications**.
- **Professional Backgrounds:** Respondents work predominantly in sectors like **finance, technology, and professional services**, showcasing a diverse yet relevant group for the study.
- **Income Levels:** The income distribution primarily ranges from **₹5,00,000 to ₹20,00,000 annually**, reflecting middle to upper-middle-class earning brackets.
- **Years of Experience:** Participants exhibit a wide range of professional experience, contributing to varied perspectives.
- **Investment Preferences:** Popular investment choices include **stocks, mutual funds, and real estate**, with a preference for **long-term investment horizons** being most common.
- **Technological Familiarity:** Respondents exhibit moderate familiarity with **AI-driven robotic automation** and related technologies like **AI, ML, and blockchain**.
- **Perceived Benefits:** Efficiency, risk mitigation, and enhanced accuracy are the most frequently highlighted advantages of integrating these technologies.
- **Challenges and Trends:** Key challenges include **data quality and integration issues**, while the growing importance of **ESG factors** (Environmental, Social, and Governance) is a significant emerging trend in investment decision-making.

This annexure serves as a concise summary of the survey's descriptive statistics, setting the foundation for further analysis and discussions in the study.

CHAPTER 4 : RESPONSES TO INTERVIEW QUESTIONS

DESCRIPTIVE STATISTICS

4.1 Frequency Table

The descriptive statistics presented in this study provide a comprehensive overview of the demographic, professional, and investment-related characteristics of the sample population. This data covers key variables such as gender, age, education, occupation, income, years of experience, geographic location, and industry sector. Furthermore, the data explores investment behaviours and preferences, including types of investments, investment horizons, portfolio size, and expectations for return on investments. The insights gathered from this data will help in understanding the diverse backgrounds and decision-making processes of investors.

Table 1: Gender

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
	Male	77	51.3	51.3	51.3
Valid	Female	73	48.7	48.7	100.0
	Total	150	100.0	100.0	

Figure 1 : Gender

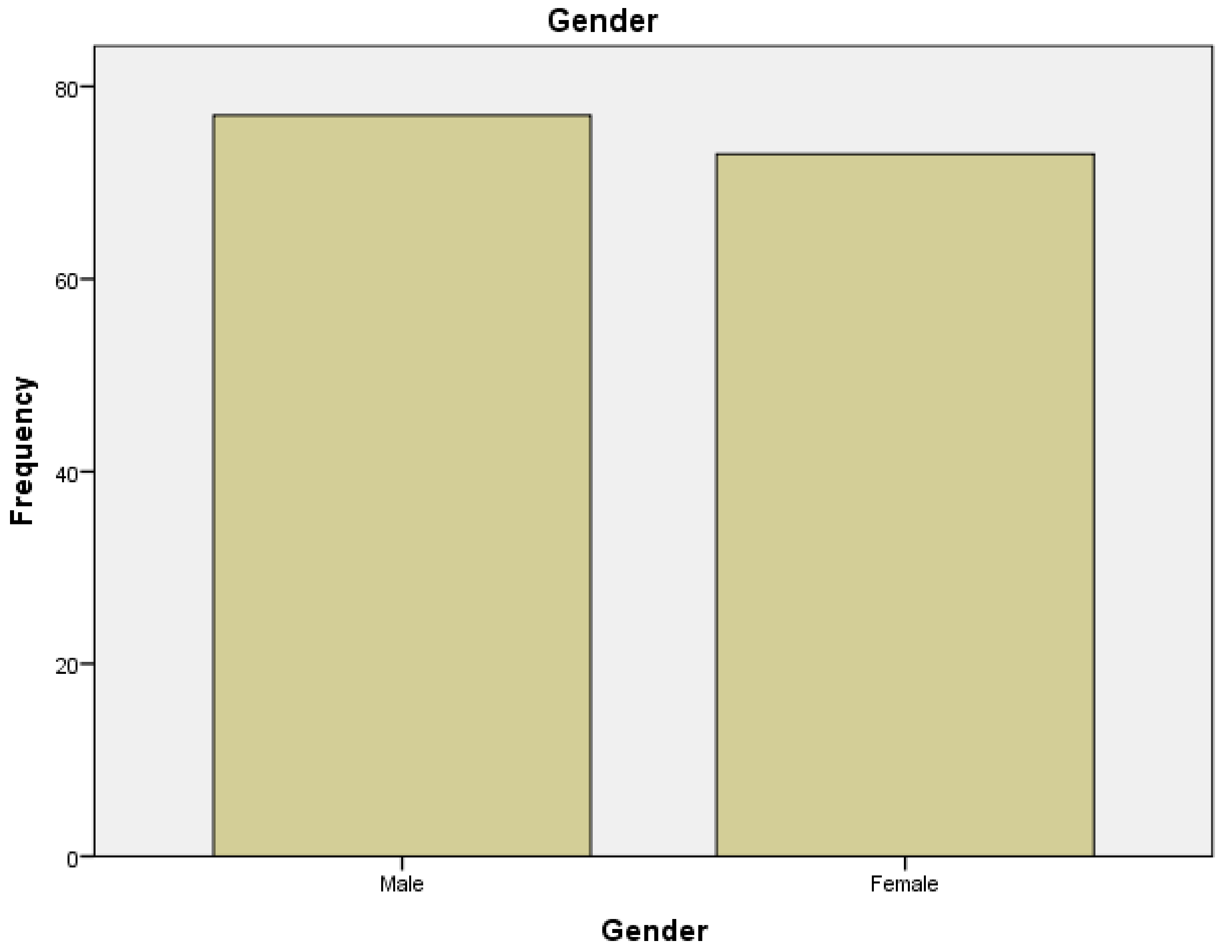

Gender
Frequency
80
60
40
20
0
Male
Female
Gender

Table 2 : Age

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	25-35 years	24	16.0	16.0	16.0
	36-40 years	20	13.3	13.3	29.3
	40-45 years	23	15.3	15.3	44.7
	46-50 years	22	14.7	14.7	59.3
	50-55 years	19	12.7	12.7	72.0
	55-60 years	24	16.0	16.0	88.0
	60 and above	18	12.0	12.0	100.0
	Total	150	100.0	100.0	

Figure 2 : Age

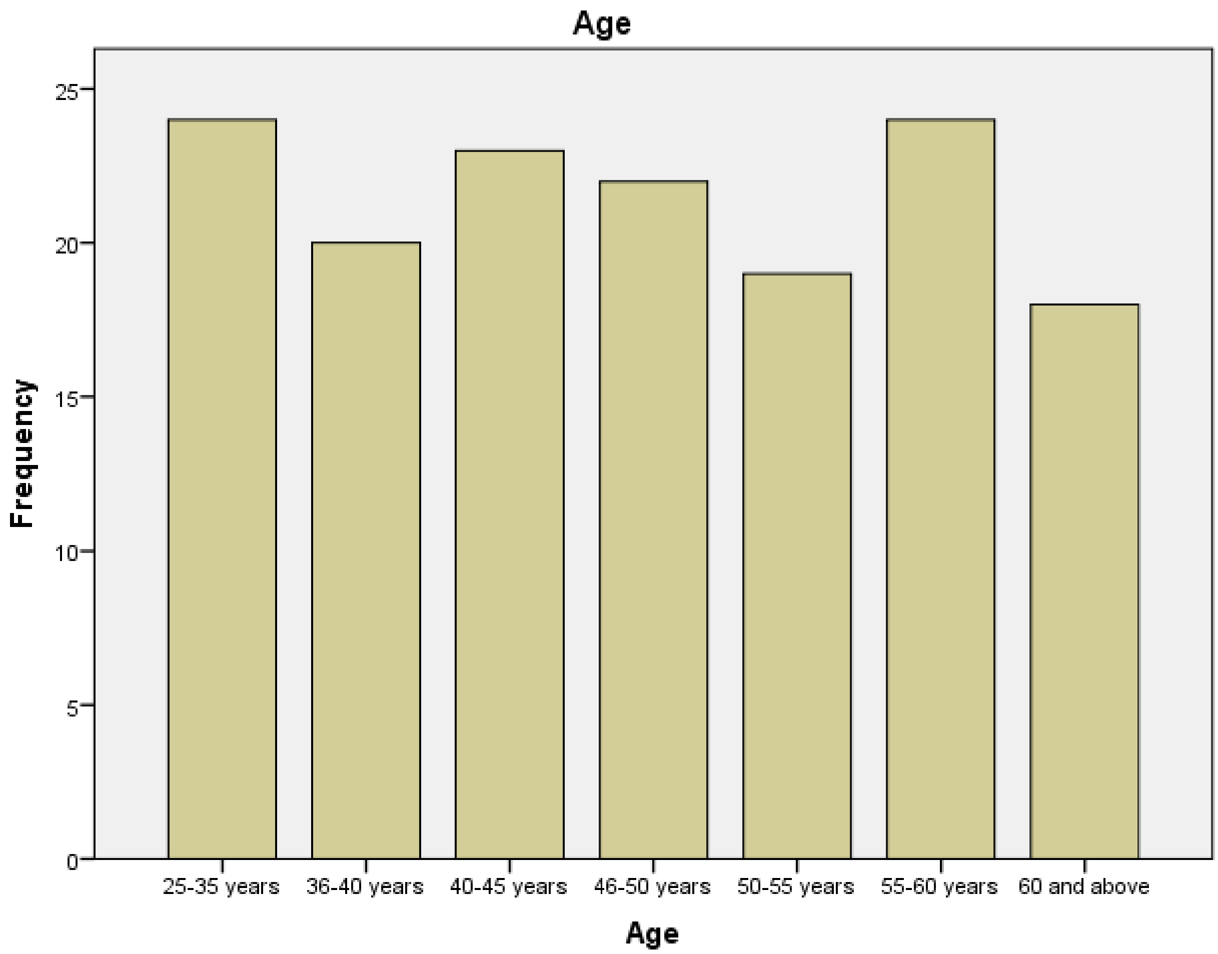


Table 3 : Highest level of qualification

Highest level of qualification

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Graduate	21	14.0	14.0	14.0
	Postgraduate	29	19.3	19.3	33.3
	Diploma	27	18.0	18.0	51.3
	Ph.D.	36	24.0	24.0	75.3
	Others	37	24.7	24.7	100.0
	Total	150	100.0	100.0	

Figure 3 :Highest level of qualification

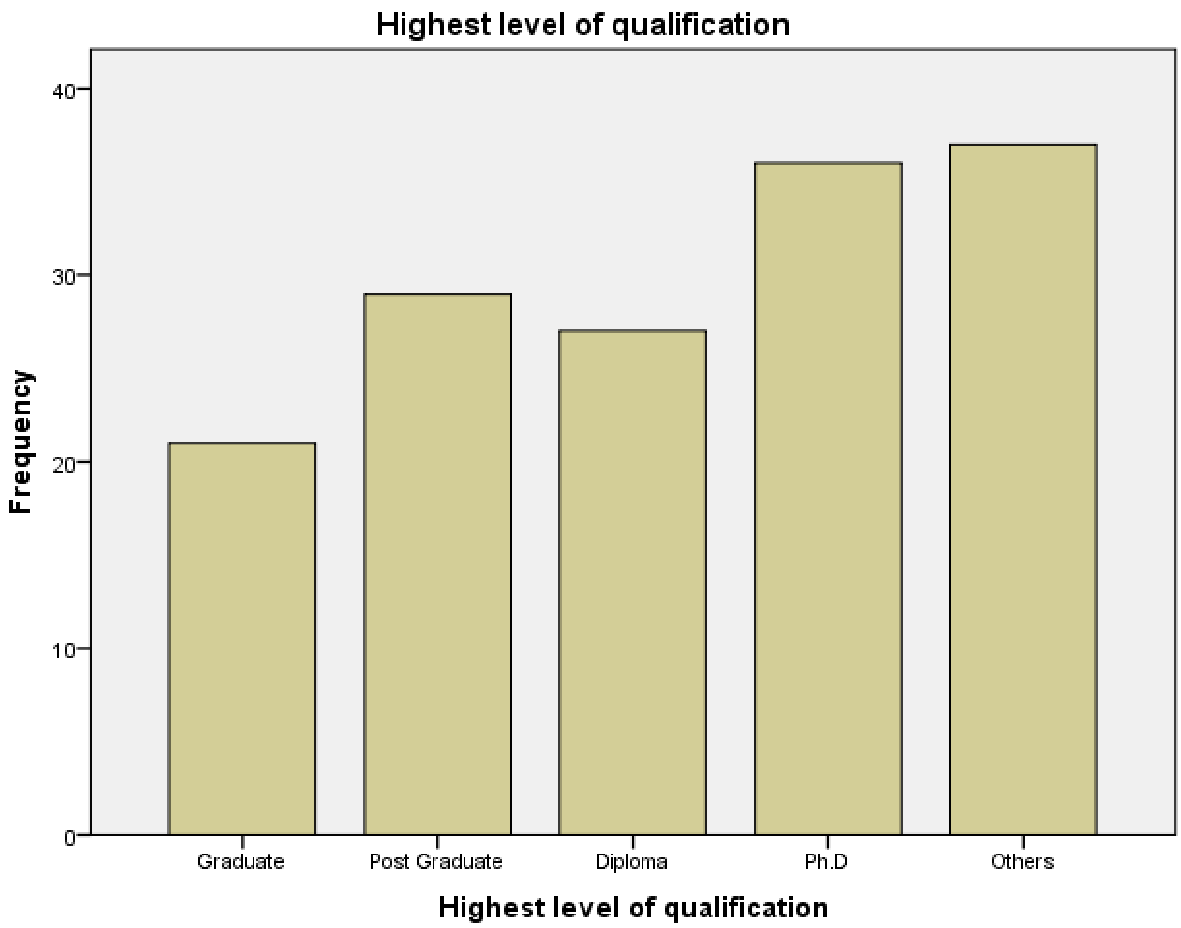


Table 4 : Occupation

Occupation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Professional/Manager	11	7.3	7.3	7.3
	Entrepreneur/Business Owner	18	12.0	12.0	19.3
	Government Employee	16	10.7	10.7	30.0
	Public sector Employee	9	6.0	6.0	36.0
	Doctor	18	12.0	12.0	48.0
	Service in financial sector	20	13.3	13.3	61.3
	Lawyer	15	10.0	10.0	71.3
	Retired	14	9.3	9.3	80.7
	Engineer	17	11.3	11.3	92.0
	Other	12	8.0	8.0	100.0
	Total	150	100.0	100.0	

Figure 4 :Occupation

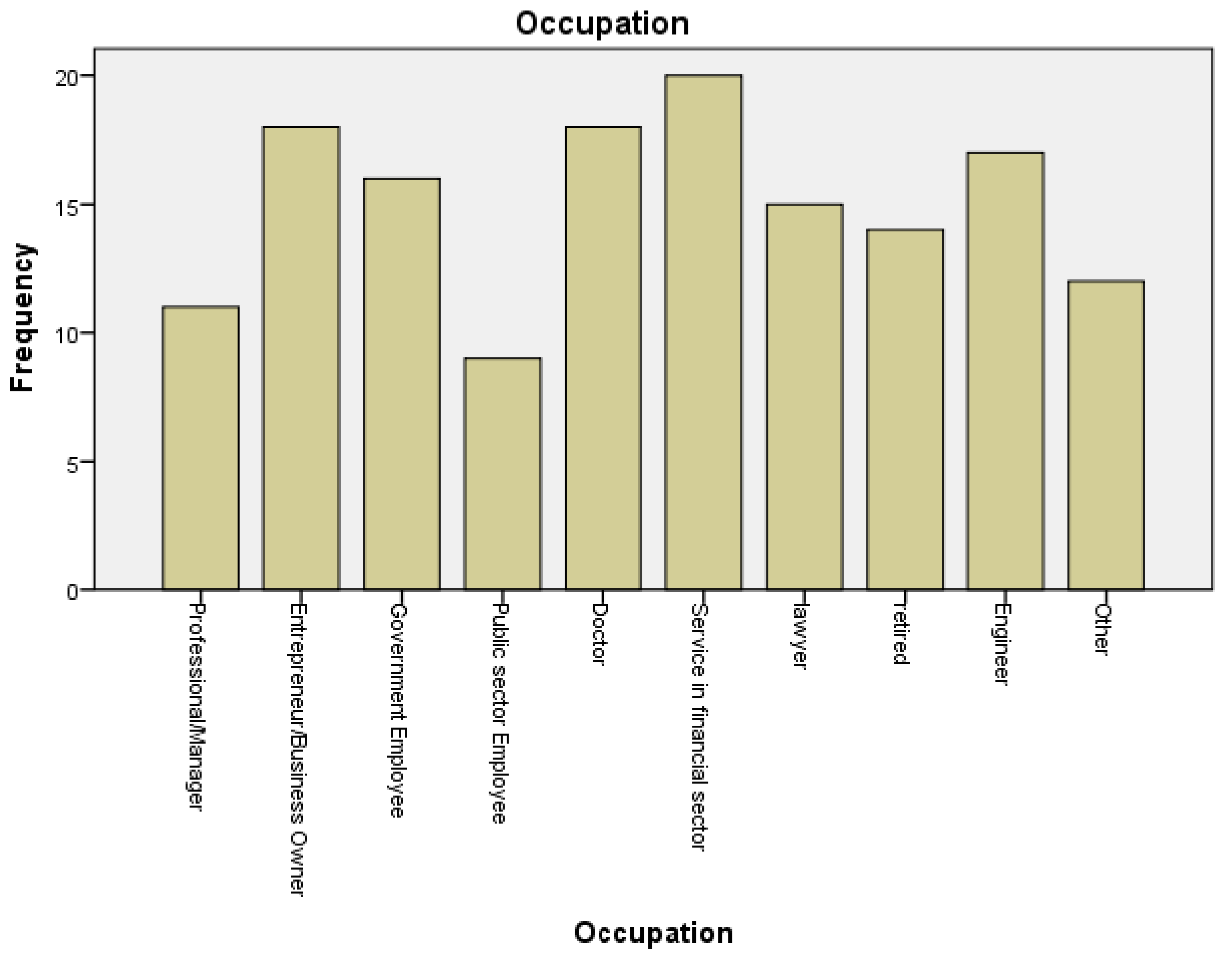


Table 5 : Income size

Income size

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 4,99,000/-	33	22.0	22.0	22.0
	5,00,000 - 10,00,000	28	18.7	18.7	40.7
	10,00,000-15,00,000	31	20.7	20.7	61.3
	15,00,000-20,00,000	30	20.0	20.0	81.3
	20,00,000/- Above	28	18.7	18.7	100.0
	Total	150	100.0	100.0	

Figure 5: Income size

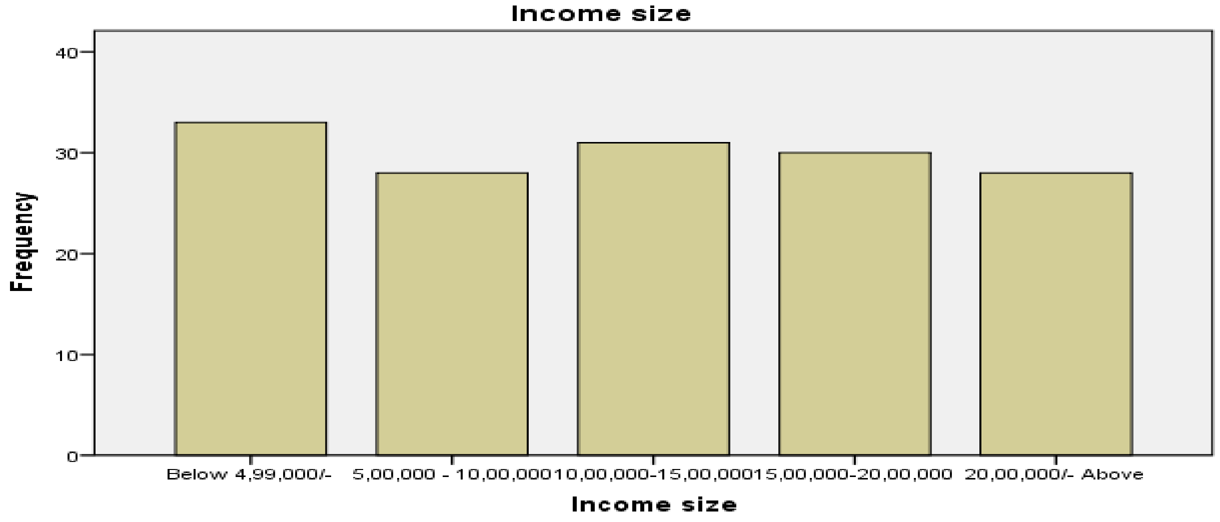


Table 6 :Total no of years of experience

Total no of years of experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 5 years	32	21.3	21.3	21.3
	5-10 years	32	21.3	21.3	42.7
	10-15 years	23	15.3	15.3	58.0
	15-20 years	32	21.3	21.3	79.3
	20 years & Above	31	20.7	20.7	100.0
	Total	150	100.0	100.0	

Figure 6: Total no of years of experience

Table 7 : Which country are you located at?

Which country are you located at

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	India	19	12.7	12.7	12.7
	Australia	29	19.3	19.3	32.0
	Canada	19	12.7	12.7	44.7
	United Kingdom	27	18.0	18.0	62.7
	United state of America	15	10.0	10.0	72.7
	U.A.E	17	11.3	11.3	84.0
	Others	24	16.0	16.0	100.0
	Total	150	100.0	100.0	

Figure 7: Which country are you located at?

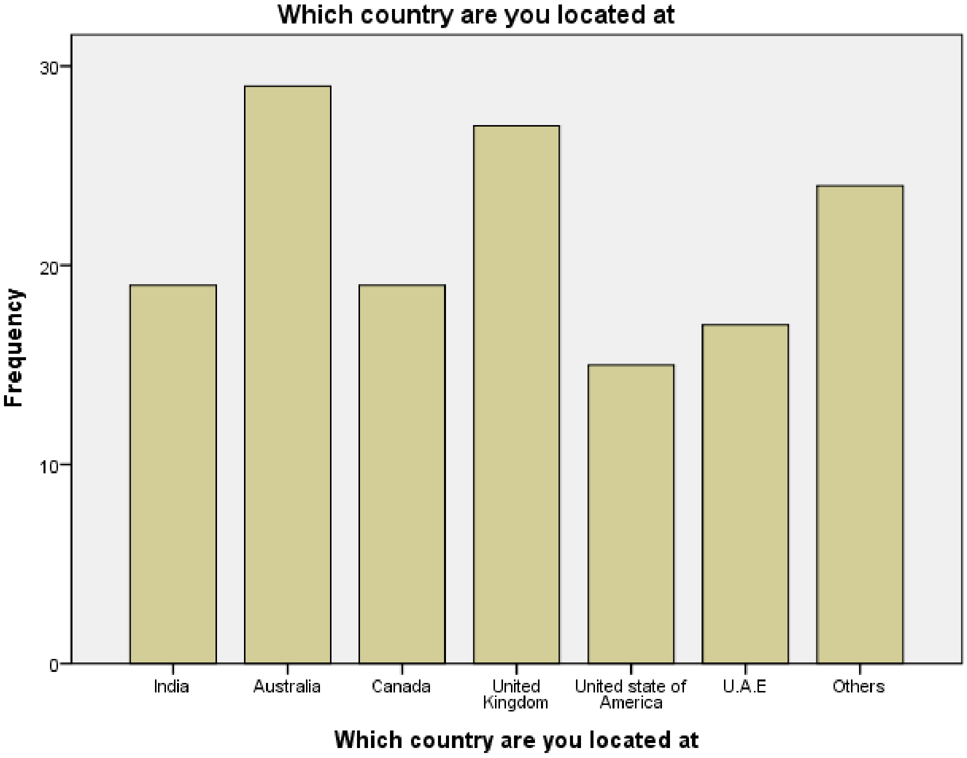


Table 8 : Which industry sector does your organization Belong?

Which industry sector does your organization Belong

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Finance/Banking	13	8.7	8.7	8.7
	Technology/Software	15	10.0	10.0	18.7
	Manufacturing/Industrial	15	10.0	10.0	28.7
	Hospitality/Tourism	14	9.3	9.3	38.0
	Financial, Banking	20	13.3	13.3	51.3
	Media/Entertainment	13	8.7	8.7	60.0
	Real Estate/Property	17	11.3	11.3	71.3
	Professional Services (e.g. Consulting, Law, etc.)	21	14.0	14.0	85.3
	Other (please specify)	22	14.7	14.7	100.0
	Total	150	100.0	100.0	

Figure 8 : Which industry sector does your organization Belong?

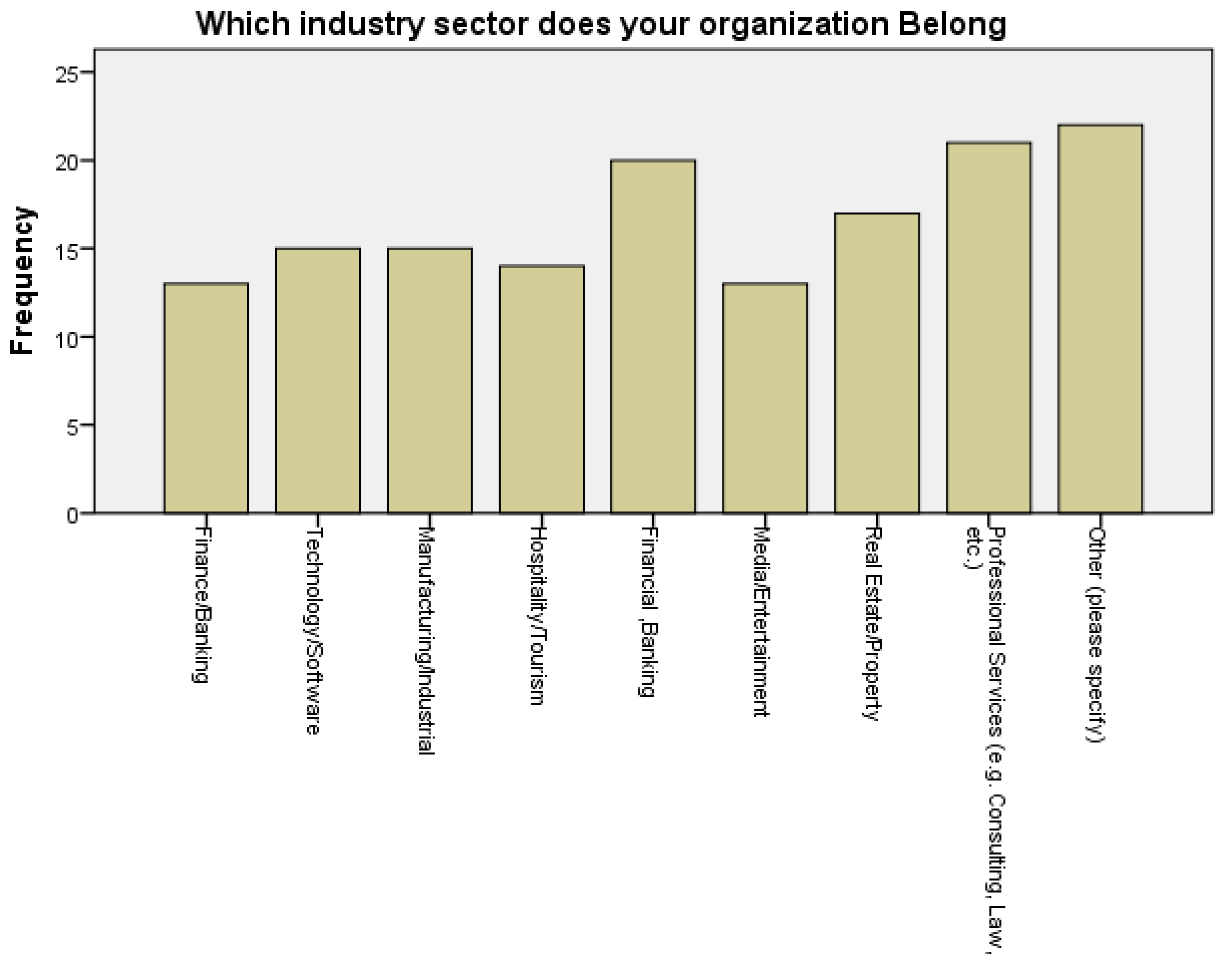


Table 9 : What type of investments do you currently hold?

What type of investments do you currently hold

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Stocks	11	7.3	7.3	7.3
	Bonds	21	14.0	14.0	21.3
	Mutual Funds	14	9.3	9.3	30.7
	Etfs	20	13.3	13.3	44.0
	Real Estate	12	8.0	8.0	52.0
	Commodities	21	14.0	14.0	66.0
	Cryptocurrencies	16	10.7	10.7	76.7
	Fixed deposit	20	13.3	13.3	90.0
	Other	15	10.0	10.0	100.0
	Total	150	100.0	100.0	

Figure 9 : What type of investments do you currently hold?

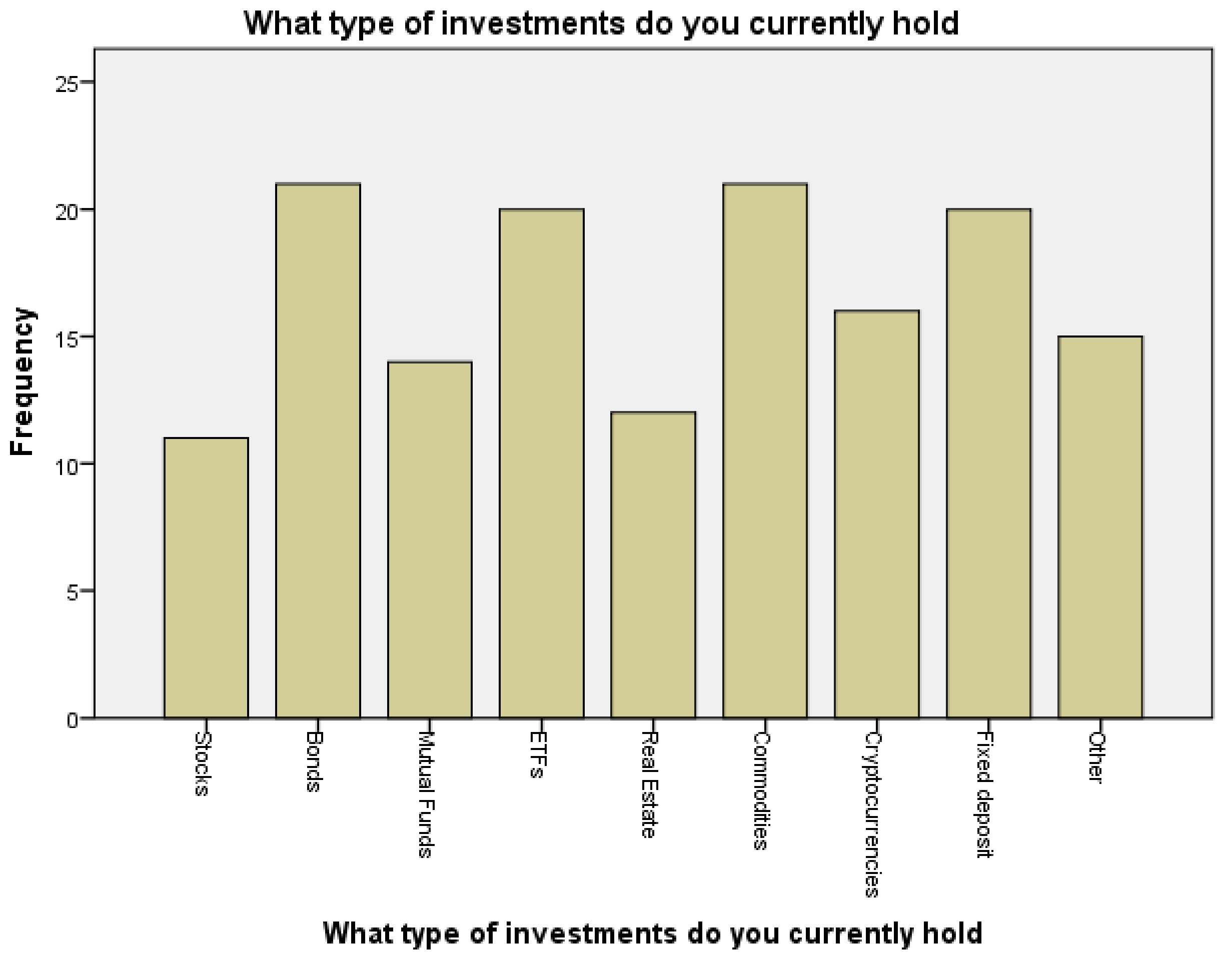


Table 10 : What is your investment horizon?

What is your investment horizon

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Short-term (less than 1 year)	38	25.3	25.3	25.3
	Medium-term (1-5 years)	38	25.3	25.3	50.7
	Long-term (5-10 years)	27	18.0	18.0	68.7
	Very long-term (more than 10 years)	47	31.3	31.3	100.0
	Total	150	100.0	100.0	

Figure 10: What is your investment horizon?

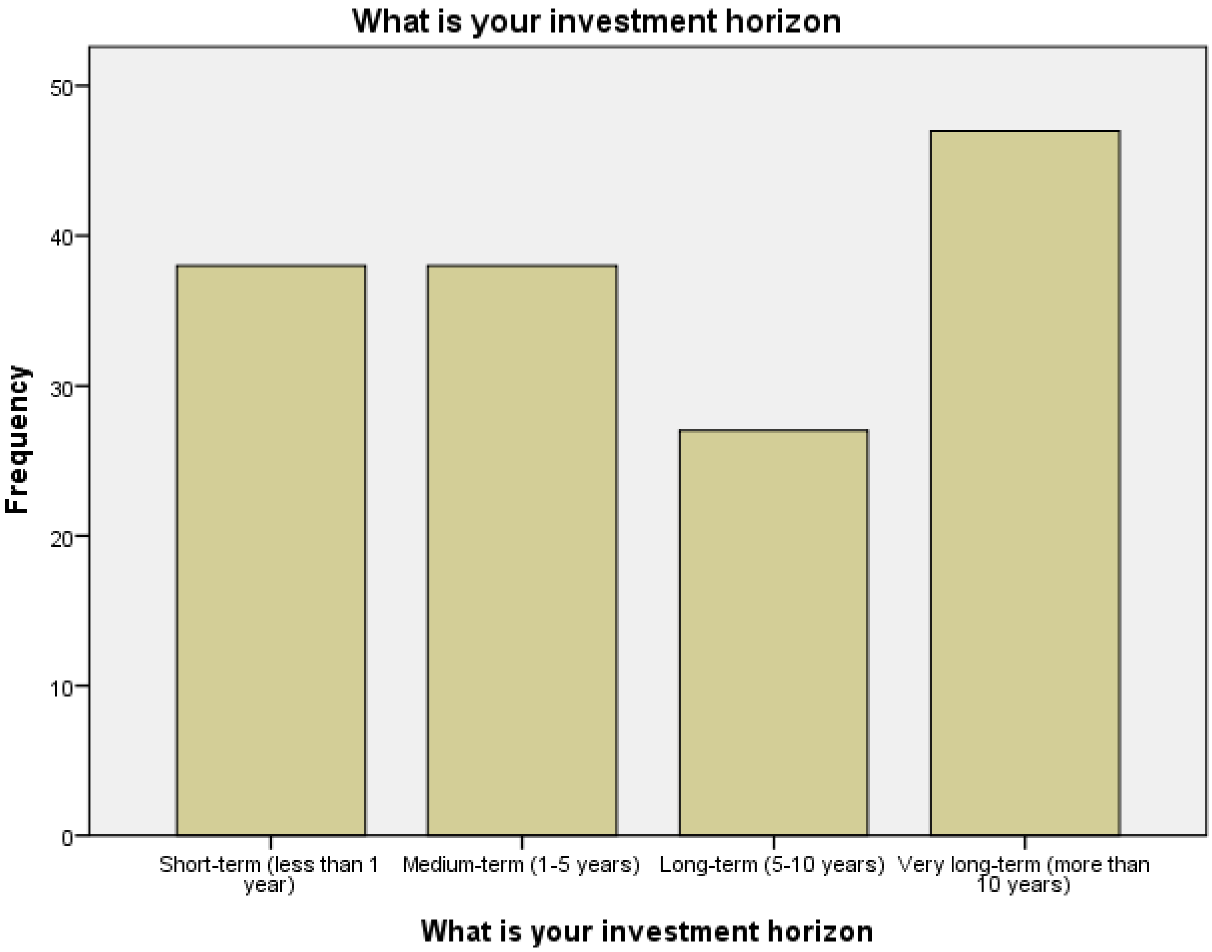


Table 11 : What is the approximate value of your investment Portfolio?

What is the approximate value of your investment portfolio

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 1Lakh	16	10.7	10.7	10.7
	1 lakh - 5 lakhs	13	8.7	8.7	19.3
	5 lakhs - 10 lakhs	17	11.3	11.3	30.7
	10 lakhs - 25 lakhs	27	18.0	18.0	48.7
	25 lakhs - 50 lakhs	20	13.3	13.3	62.0
	50 lakhs - 1 crore	22	14.7	14.7	76.7
	1 crore - 5 crores	16	10.7	10.7	87.3
	More than 5 crores	19	12.7	12.7	100.0
	Total	150	100.0	100.0	

Figure 11: What is the approximate value of your investment portfolio?

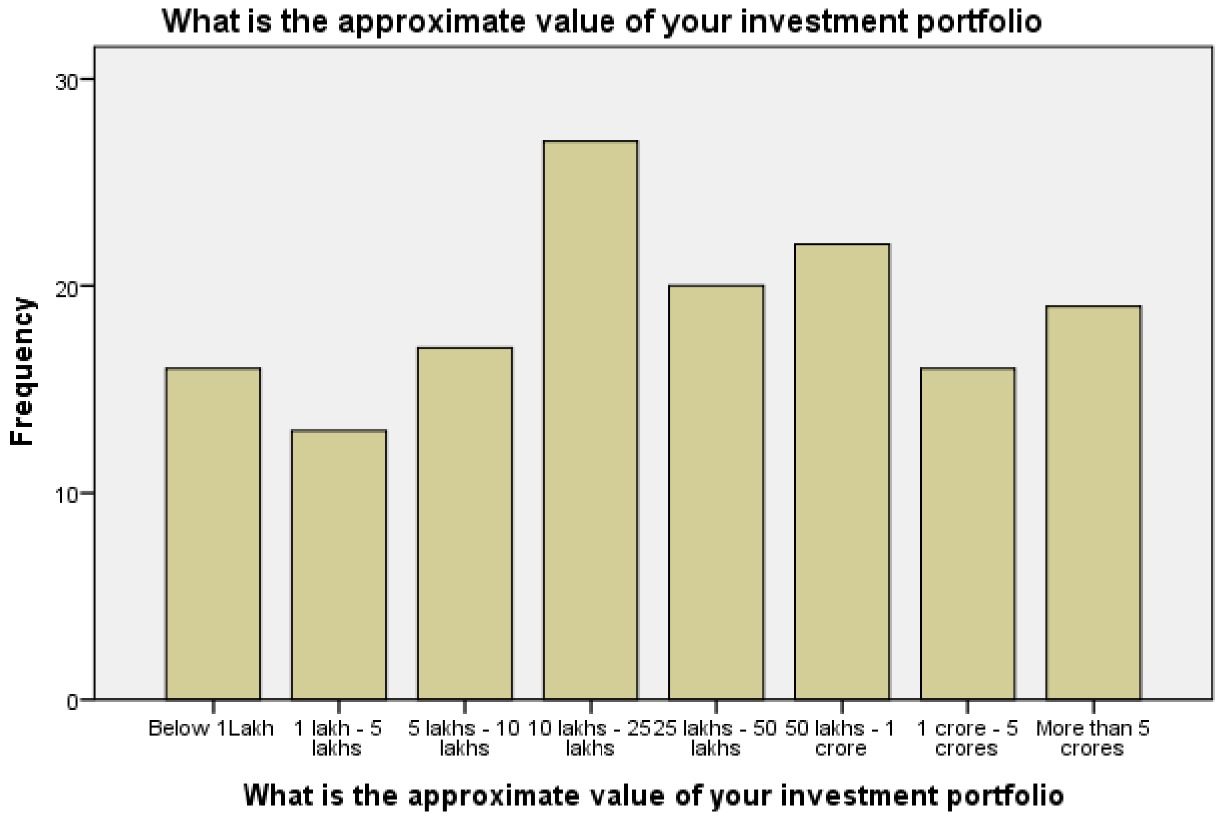


Table 12 :What is your expected annual return on investment?

What is your expected annual return on investment

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 5%	30	20.0	20.0	20.0
	5-8%	19	12.7	12.7	32.7
	9-12%	32	21.3	21.3	54.0
	13-15%	32	21.3	21.3	75.3
	More than 15%	37	24.7	24.7	100.0
	Total	150	100.0	100.0	

Figure 12 : What is your expected annual return on investment?

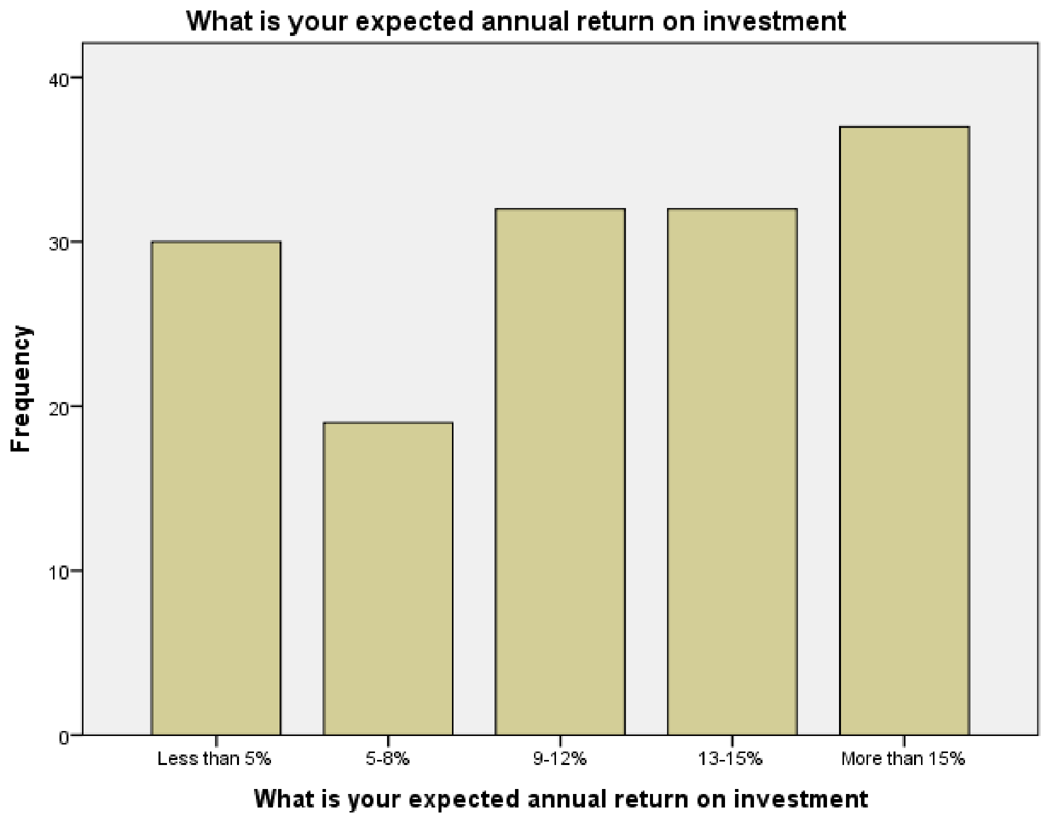


Table 13 : How important is achieving high returns to you?

How important is achieving high returns to you?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very important	37	24.7	24.7	24.7
	Somewhat important	36	24.0	24.0	48.7
	Not very important	48	32.0	32.0	80.7
	Not at all important	29	19.3	19.3	100.0
	Total	150	100.0	100.0	

Figure 13 : How important is achieving high returns to you?

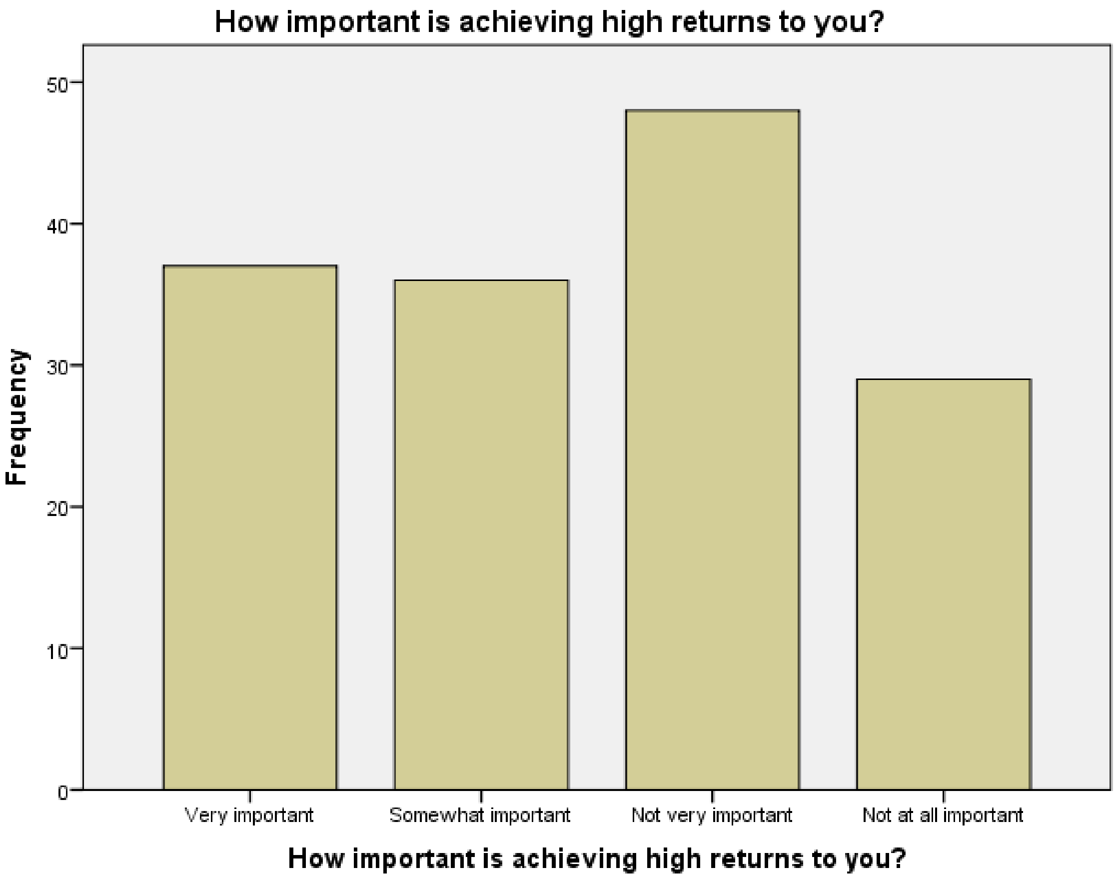


Table 14 : What is your level of satisfaction with your current investment portfolio?

What is your level of satisfaction with your current investment portfolio?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very satisfied	41	27.3	27.3	27.3
	Satisfied	27	18.0	18.0	45.3
	Neutral	27	18.0	18.0	63.3
	Dissatisfied	30	20.0	20.0	83.3
	Very dissatisfied	25	16.7	16.7	100.0
	Total	150	100.0	100.0	

Figure 14 : What is your level of satisfaction with your current investment portfolio?

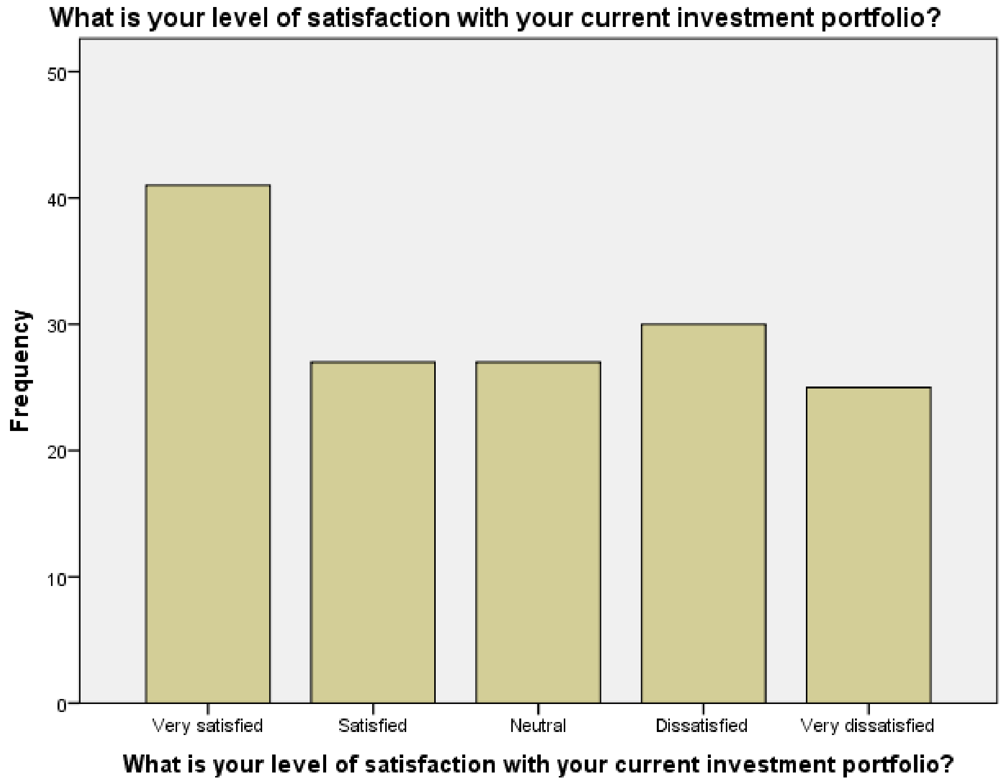


Table 15 : What are your investment goals?

What are your investment goals?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Capital appreciation	27	18.0	18.0	18.0
	Income generation	30	20.0	20.0	38.0
	Capital preservation	46	30.7	30.7	68.7
	Retirement savings	19	12.7	12.7	81.3
	Others	28	18.7	18.7	100.0
	Total	150	100.0	100.0	

Figure 15 : What are your investment goals?

Table 16 : How do you typically make investment decisions?

How do you typically make investment decisions

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	On my own	43	28.7	28.7	28.7
	With the help of a financial advisor	43	28.7	28.7	57.3
	Based on recommendations from friends/family	33	22.0	22.0	79.3
	Other	31	20.7	20.7	100.0
	Total	150	100.0	100.0	

Figure 16 : How do you typically make investment decisions?

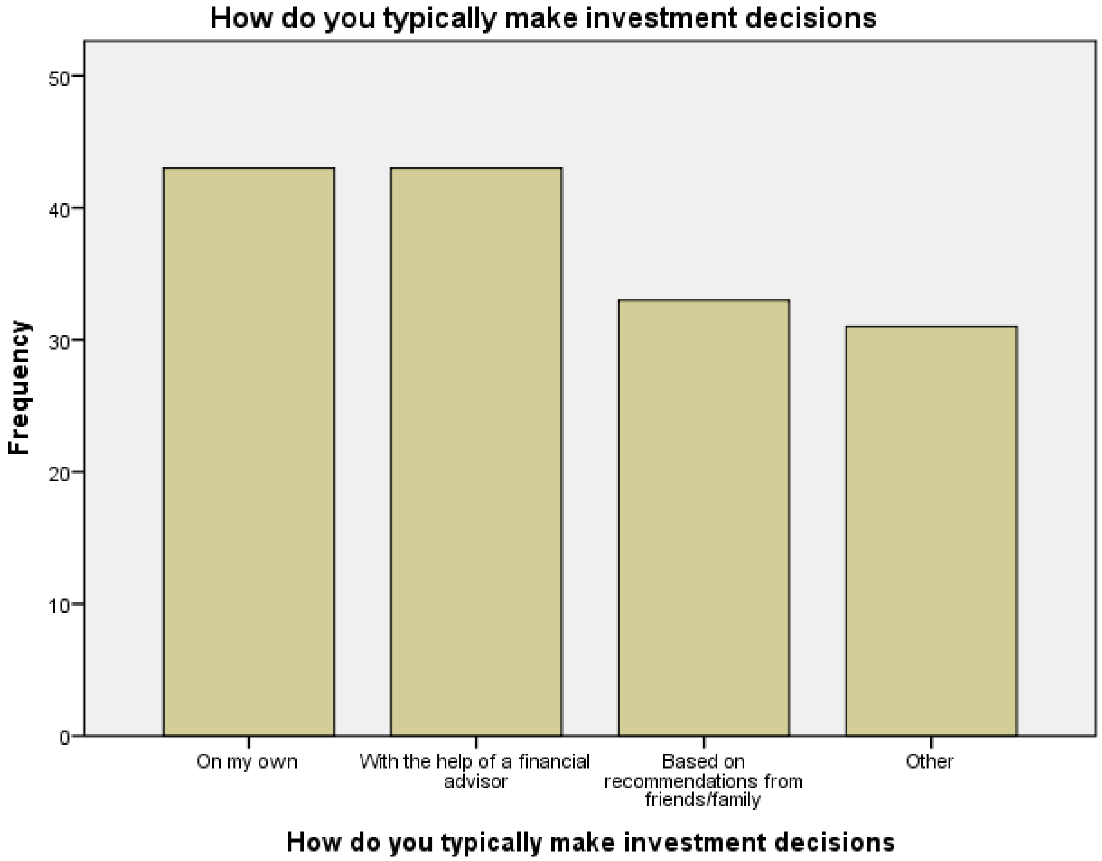


Table 17 : How familiar are you with the concept of Next-Generation Investment Management?

How familiar are you with the concept of Next-Generation Investment Management?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very familiar	49	32.7	32.7	32.7
	Somewhat familiar	31	20.7	20.7	53.3
	Not very familiar	35	23.3	23.3	76.7
	Not at all familiar	35	23.3	23.3	100.0
	Total	150	100.0	100.0	

Figure 17 : How familiar are you with the concept of Next-Generation Investment Management?

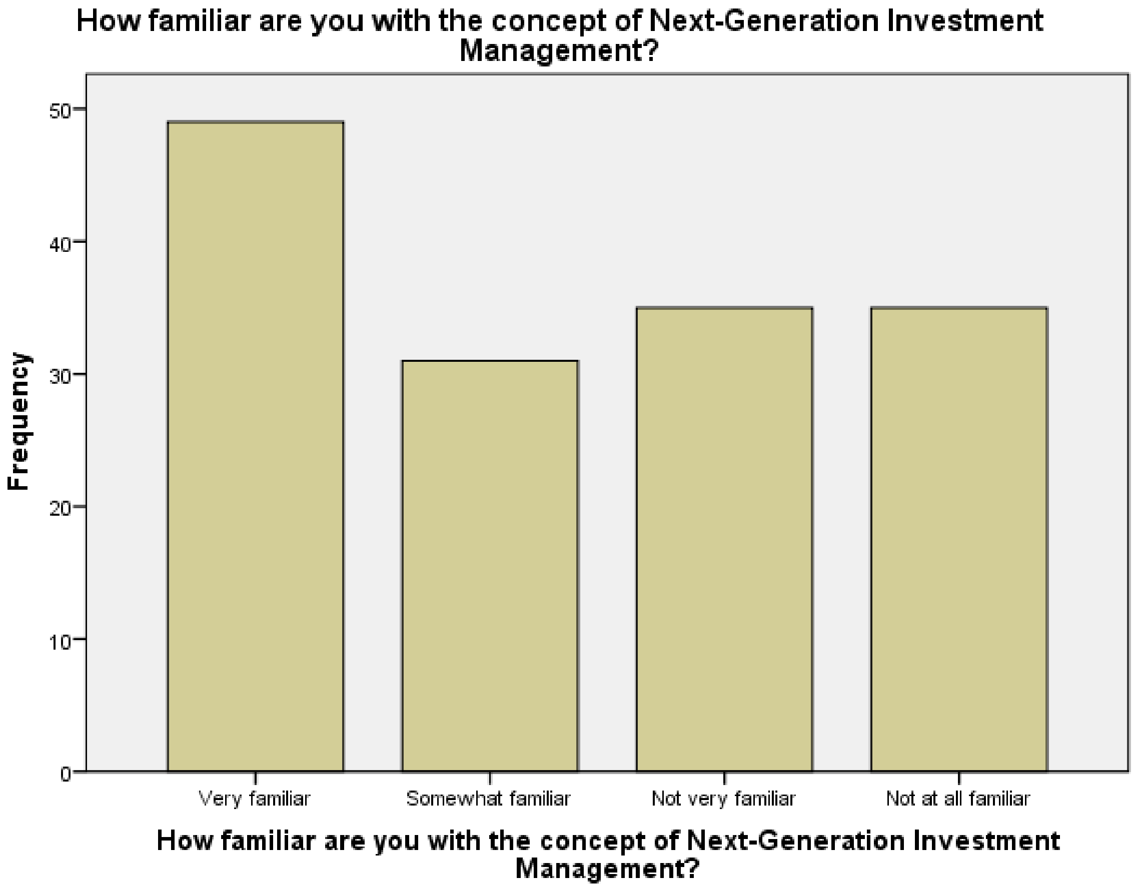


Table 18 : Which of the following technologies do you believe will have the greatest impact on investment management in the next 5 years?

Which of the following technologies do you believe will have the greatest impact on investment management in the next 5 years?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Artificial Intelligence & Machine Learning	26	17.3	17.3	17.3
	Robo-advisors	29	19.3	19.3	36.7
	Big Data & Alternative Data	30	20.0	20.0	56.7
	Blockchain	25	16.7	16.7	73.3
	Other	40	26.7	26.7	100.0
	Total	150	100.0	100.0	

Figure 18 :Which of the following technologies do you believe will have the greatest impact on investment management in the next 5 years?

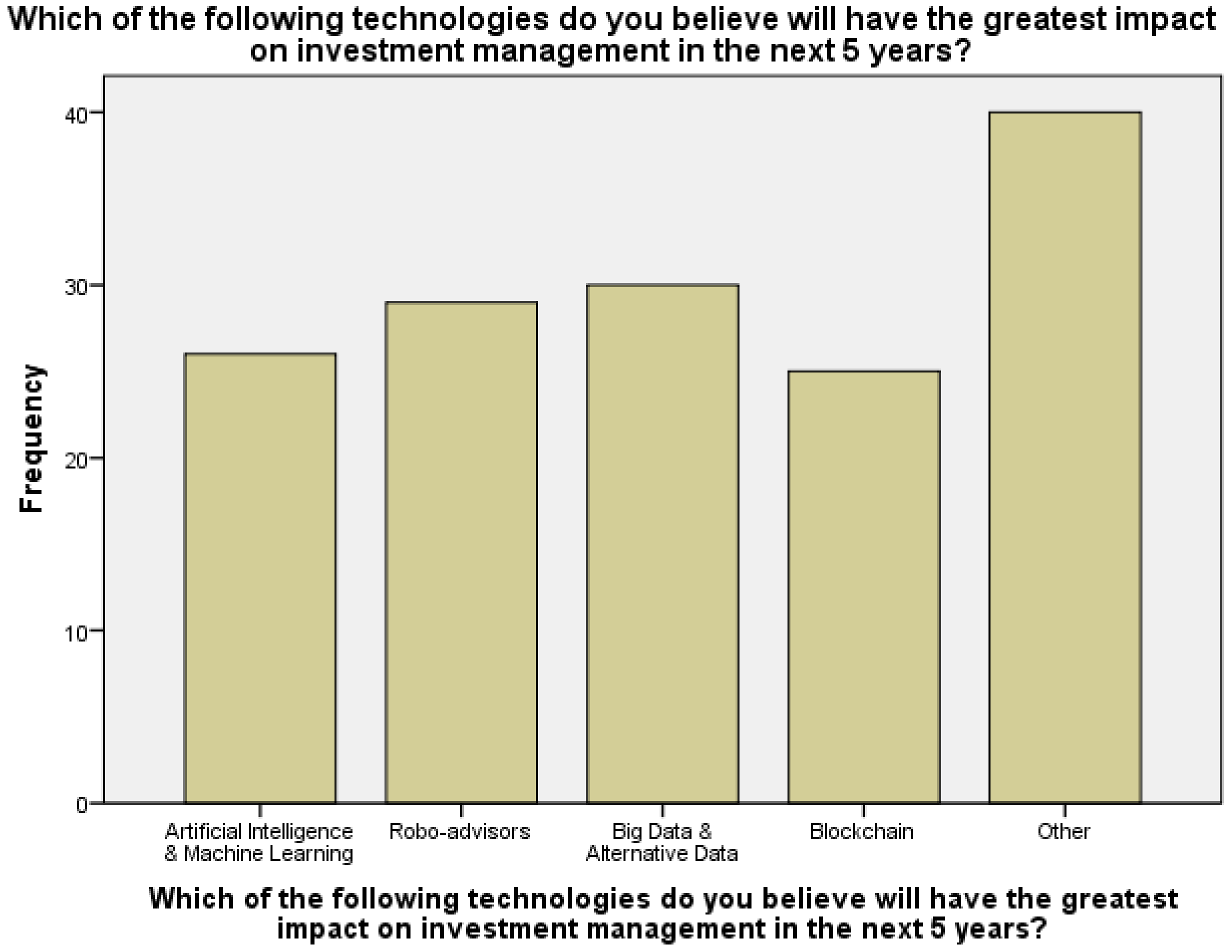


Table 19 : How important are ESG factors (Environmental, Social, and Governance) in your investment decisions?

How important are ESG factors (Environmental, Social, and Governance) in your investment decisions?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very important	42	28.0	28.0	28.0
	Somewhat important	38	25.3	25.3	53.3
	Not very important	32	21.3	21.3	74.7
	Not at all important	38	25.3	25.3	100.0
	Total	150	100.0	100.0	

Figure 19: How important are ESG factors (Environmental, Social, and Governance) in your investment decisions?

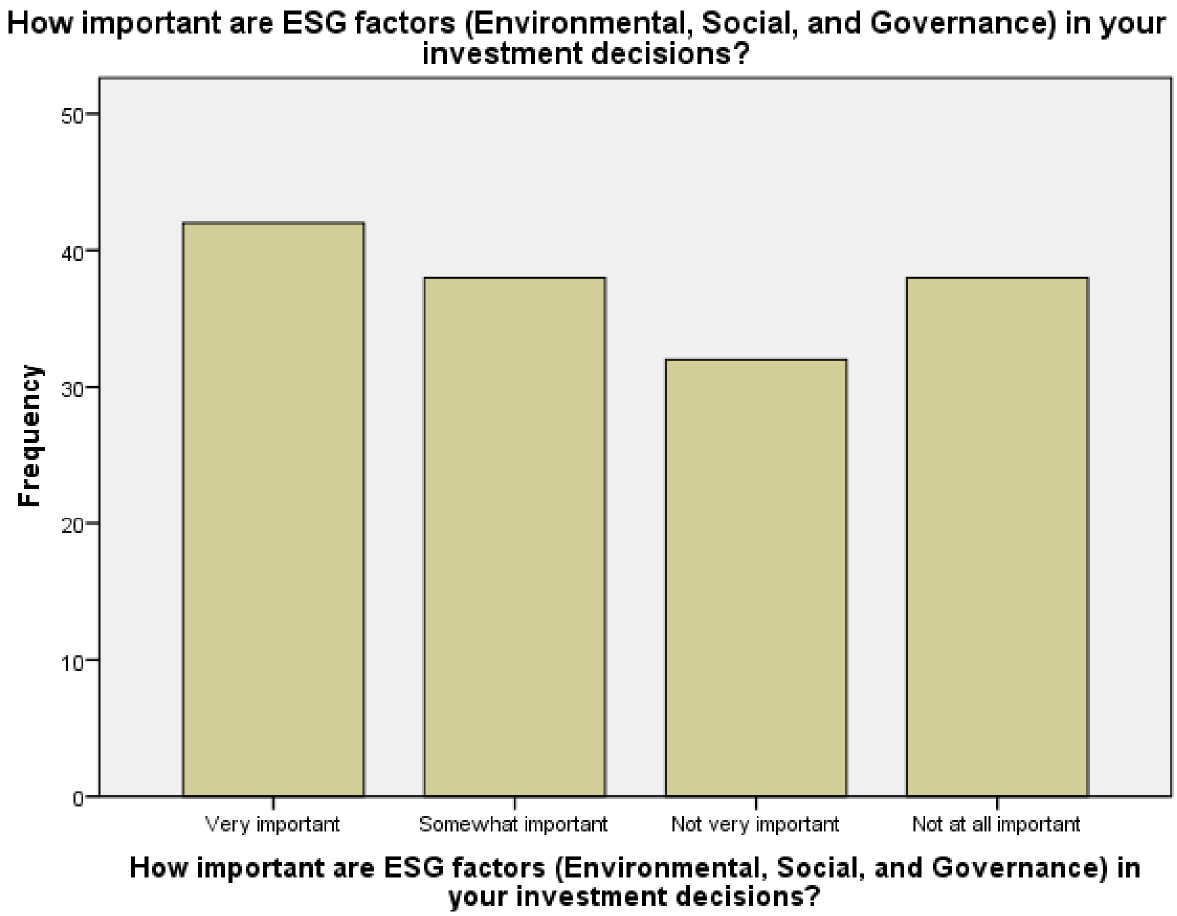


Table 20:Do you believe personalized investment portfolios based on individual preferences and risk tolerance will become the norm in the future?

Do you believe personalized investment portfolios based on individual preferences and risk tolerance will become the norm in the future?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	51	34.0	34.0	34.0
	No	40	26.7	26.7	60.7
	Maybe	59	39.3	39.3	100.0
	Total	150	100.0	100.0	

Figure 20 : Do you believe personalized investment portfolios based on individual preferences and risk tolerance will become the norm in the future?

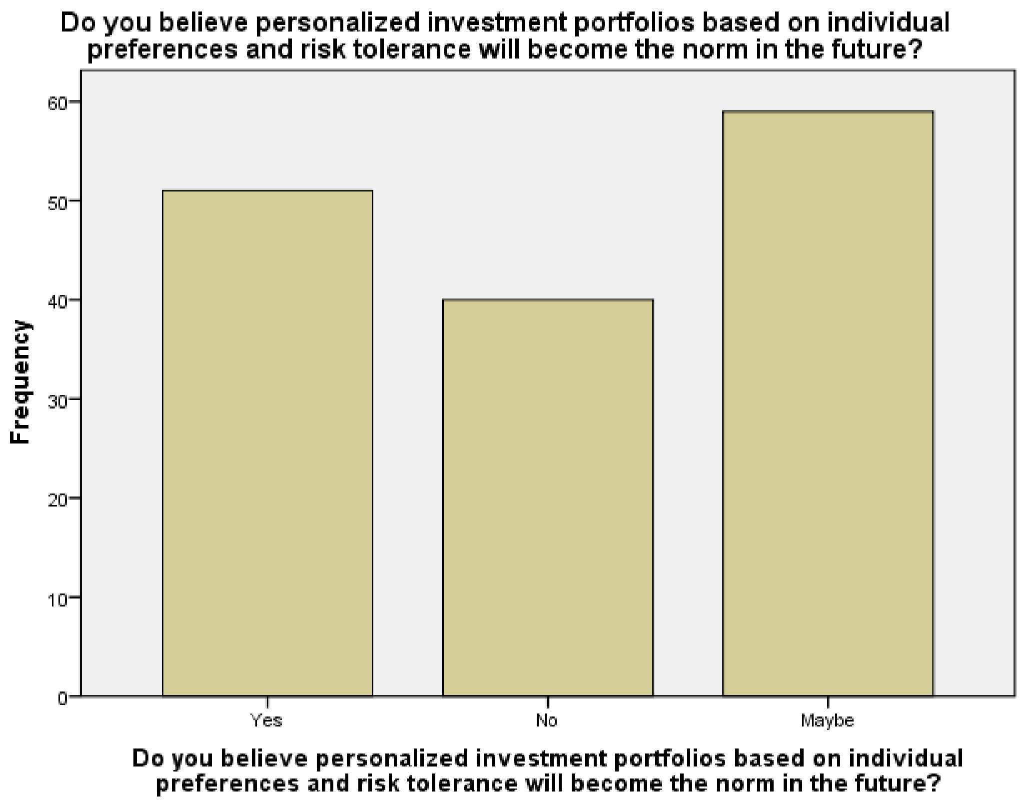


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Table 21 : How familiar are you with the use of Robotic Process Automation (RPA) in investment management?

How familiar are you with the use of Robotic Process Automation (RPA) in investment management?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very familiar	28	18.7	18.7	18.7
	Somewhat familiar	45	30.0	30.0	48.7
	Not very familiar	36	24.0	24.0	72.7
	Not at all familiar	41	27.3	27.3	100.0
	Total	150	100.0	100.0	

Figure 21 : How familiar are you with the use of Robotic Process Automation (RPA) in investment management?

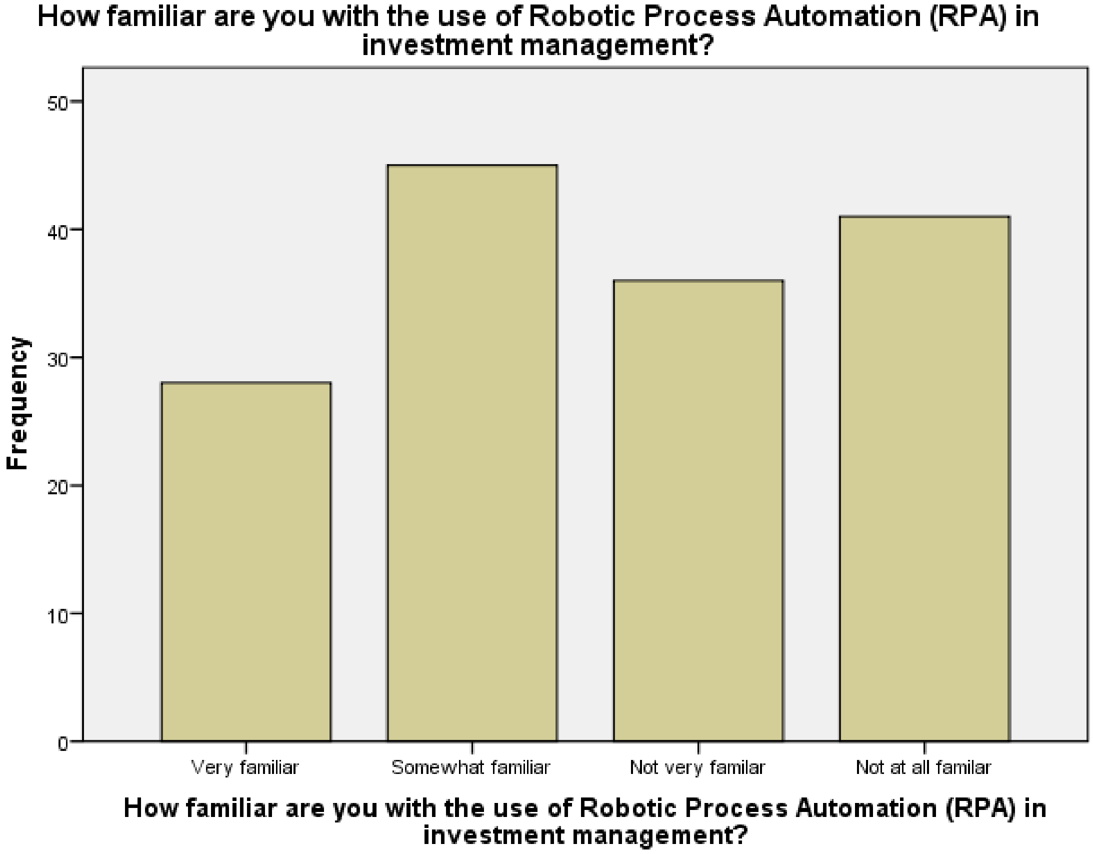


Table 22 : Which of the following benefits of RPA do you consider most valuable for portfolio management and risk mitigation?

Which of the following benefits of RPA do you consider most valuable for portfolio management and risk mitigation?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Improved efficiency	29	19.3	19.3	19.3
	Reduced costs	20	13.3	13.3	32.7
	Enhanced accuracy	14	9.3	9.3	42.0
	Faster decision-making	25	16.7	16.7	58.7
	Enhanced risk mitigation	28	18.7	18.7	77.3
	Other	34	22.7	22.7	100.0
	Total	150	100.0	100.0	

Figure 22:Which of the following benefits of RPA do you consider most valuable for portfolio management and risk mitigation?

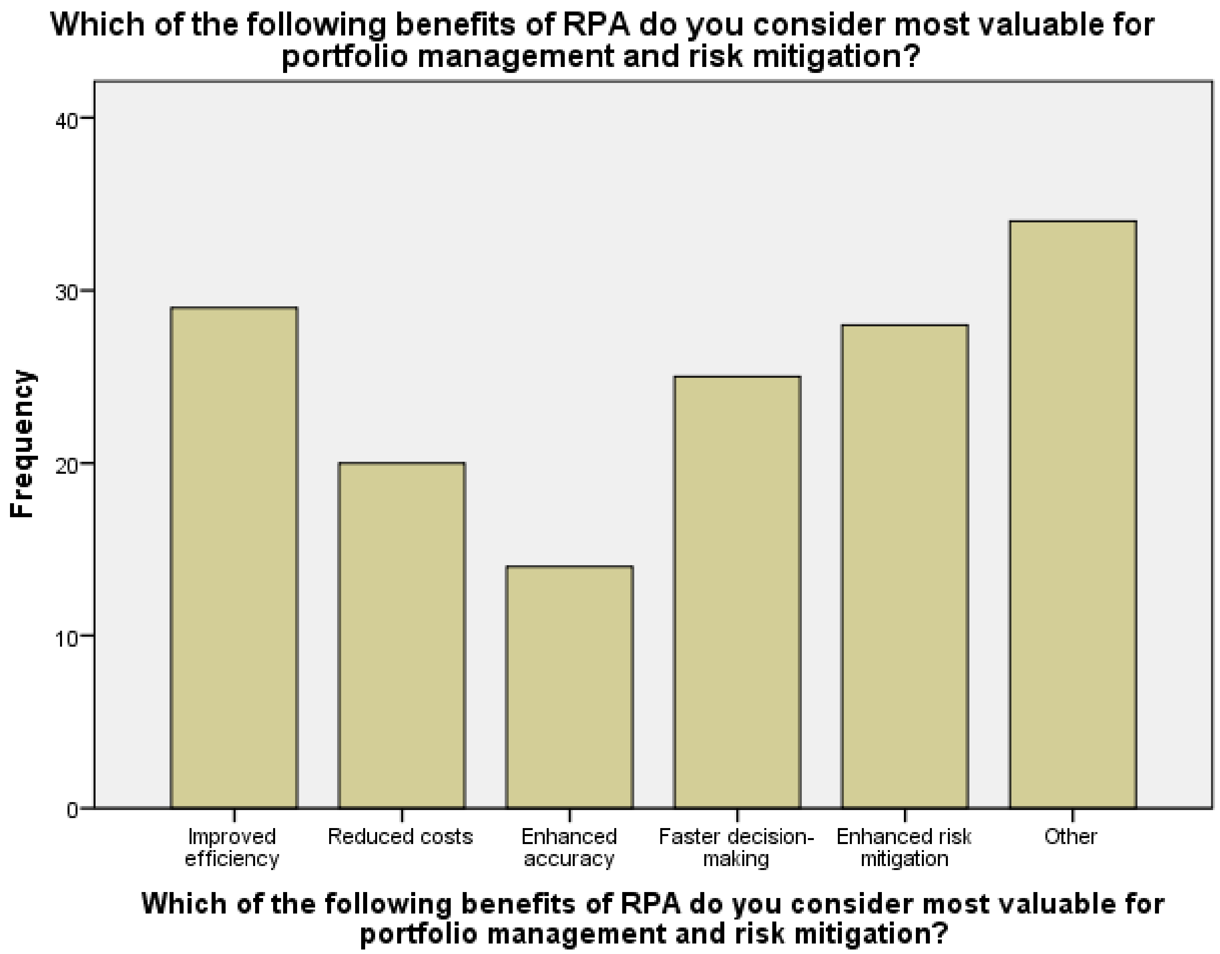


Table 23 : What are the main challenges you foresee in implementing RPA in investment management?

What are the main challenges you foresee in implementing RPA in investment management?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Lack of skilled personnel	27	18.0	18.0	18.0
	Integration with existing systems	30	20.0	20.0	38.0
	Data security concerns	34	22.7	22.7	60.7
	Cost of implementation	33	22.0	22.0	82.7
	Other	26	17.3	17.3	100.0
	Total	150	100.0	100.0	

Figure 23 : What are the main challenges you foresee in implementing RPA in investment management?

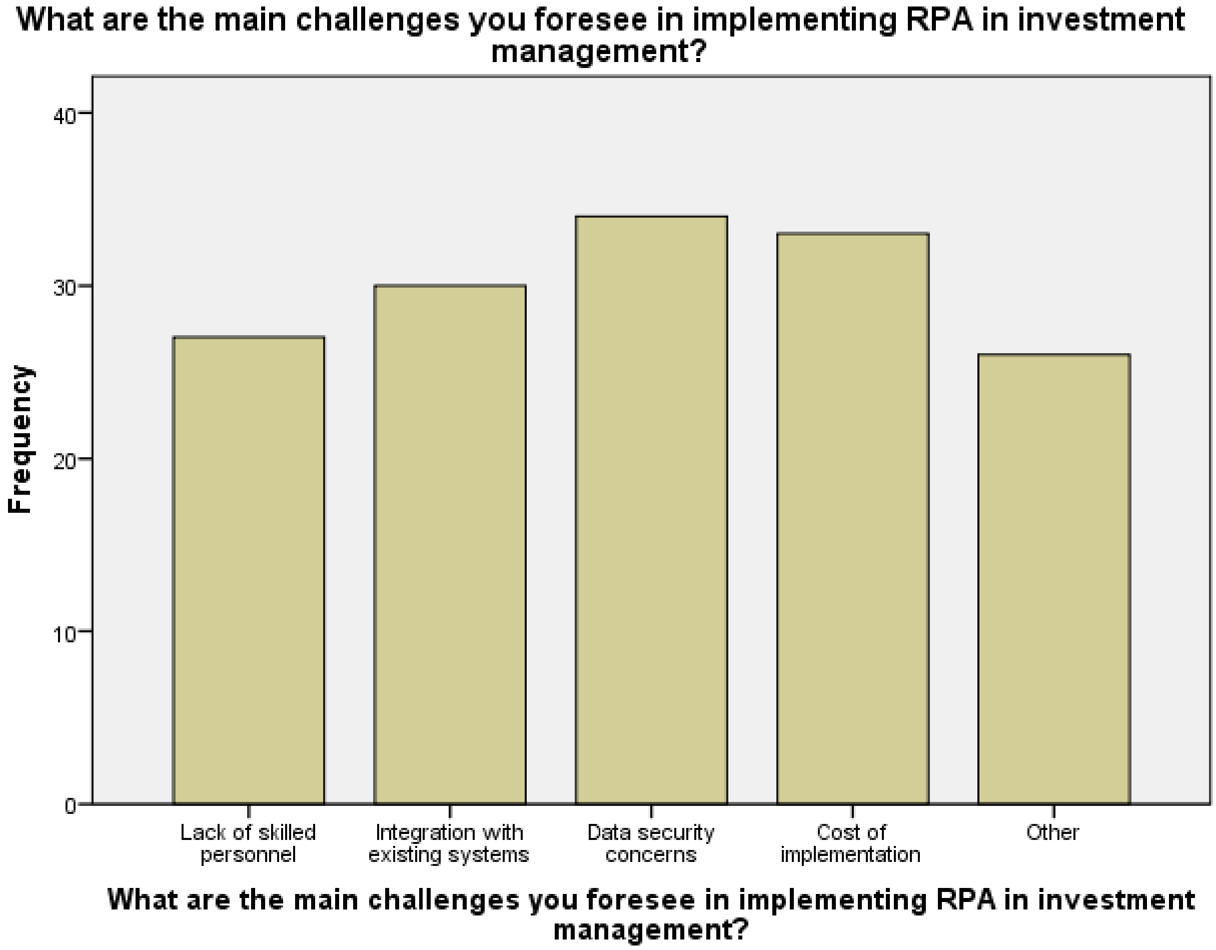


Table 24 : On a scale of 1 to 5, how likely are you to consider using RPA solutions for your investment management needs in the next 2 years?

On a scale of 1 to 5, how likely are you to consider using RPA solutions for your investment management needs in the next 2 years?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Being not likely at all	31	20.7	20.7	20.7
	Not Likely	28	18.7	18.7	39.3
	Neutral	26	17.3	17.3	56.7
	Likely	36	24.0	24.0	80.7
	Being very likely	29	19.3	19.3	100.0
	Total	150	100.0	100.0	

Figure 24 : On a scale of 1 to 5, how likely are you to consider using RPA solutions for your investment management needs in the next 2 years?

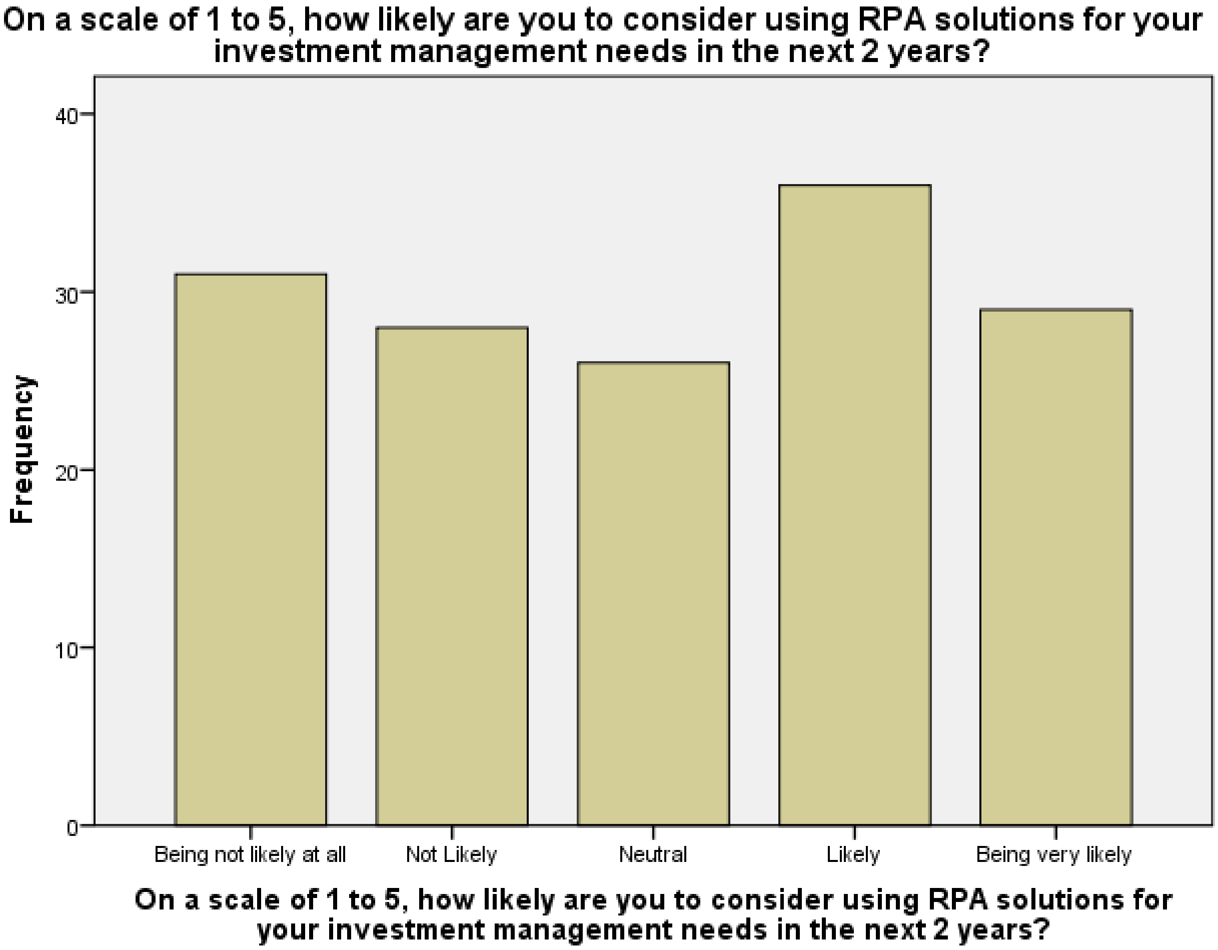


Table 25 : How familiar are you with the concept of intrinsic value in investment analysis?

How familiar are you with the concept of intrinsic value in investment analysis?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very familiar	34	22.7	22.7	22.7
	Somewhat familiar	40	26.7	26.7	49.3
	Not very familiar	35	23.3	23.3	72.7
	Not at all familiar	41	27.3	27.3	100.0
	Total	150	100.0	100.0	

Figure 25 : How familiar are you with the concept of intrinsic value in investment analysis?

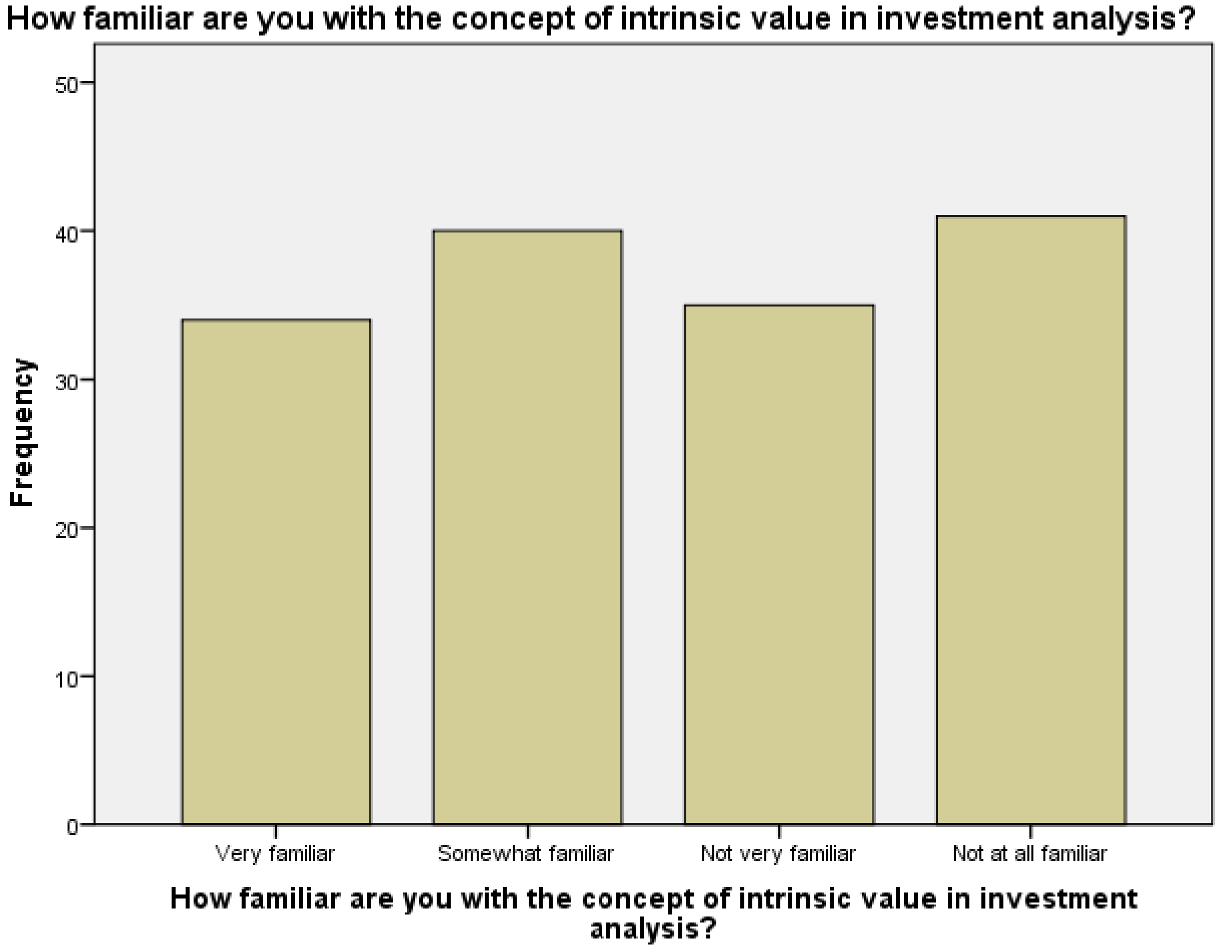
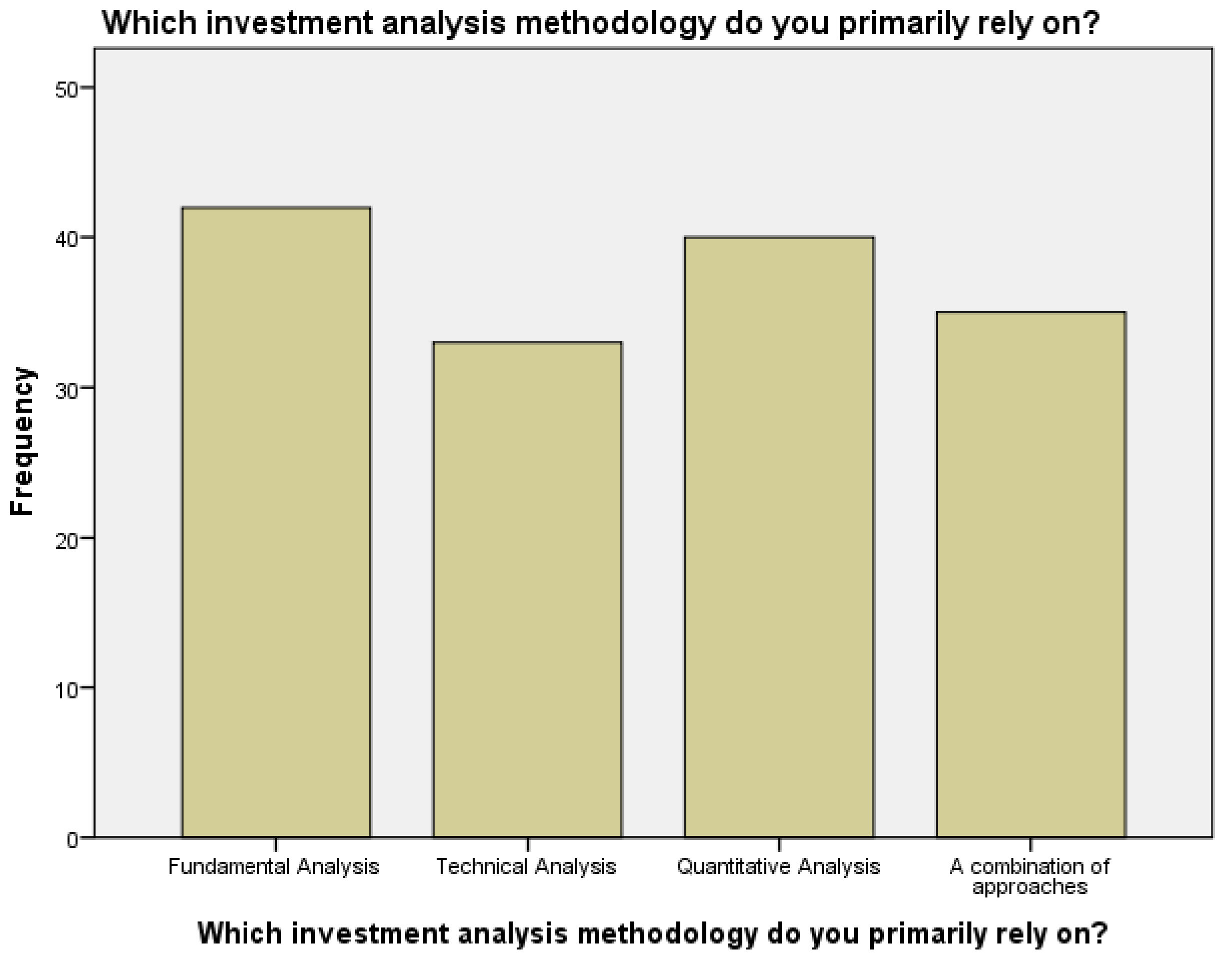


Table 26 : Which investment analysis methodology do you primarily rely on?

Which investment analysis methodology do you primarily rely on?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fundamental Analysis	42	28.0	28.0	28.0
	Technical Analysis	33	22.0	22.0	50.0
	Quantitative Analysis	40	26.7	26.7	76.7
	A combination of approaches	35	23.3	23.3	100.0
	Total	150	100.0	100.0	

Figure 26 : Which investment analysis methodology do you primarily rely on?



Table

Table 27 : Which of the following is a key fundamental analysis ratio?

Which of the following is a key fundamental analysis ratio?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Price-to-Earnings (P/E)	40	26.7	26.7	26.7
	Debt-to-Equity	34	22.7	22.7	49.3
	Return on Equity (ROE)	40	26.7	26.7	76.0
	All of the above	36	24.0	24.0	100.0
	Total	150	100.0	100.0	

Figure 27 : Which of the following is a key fundamental analysis ratio?

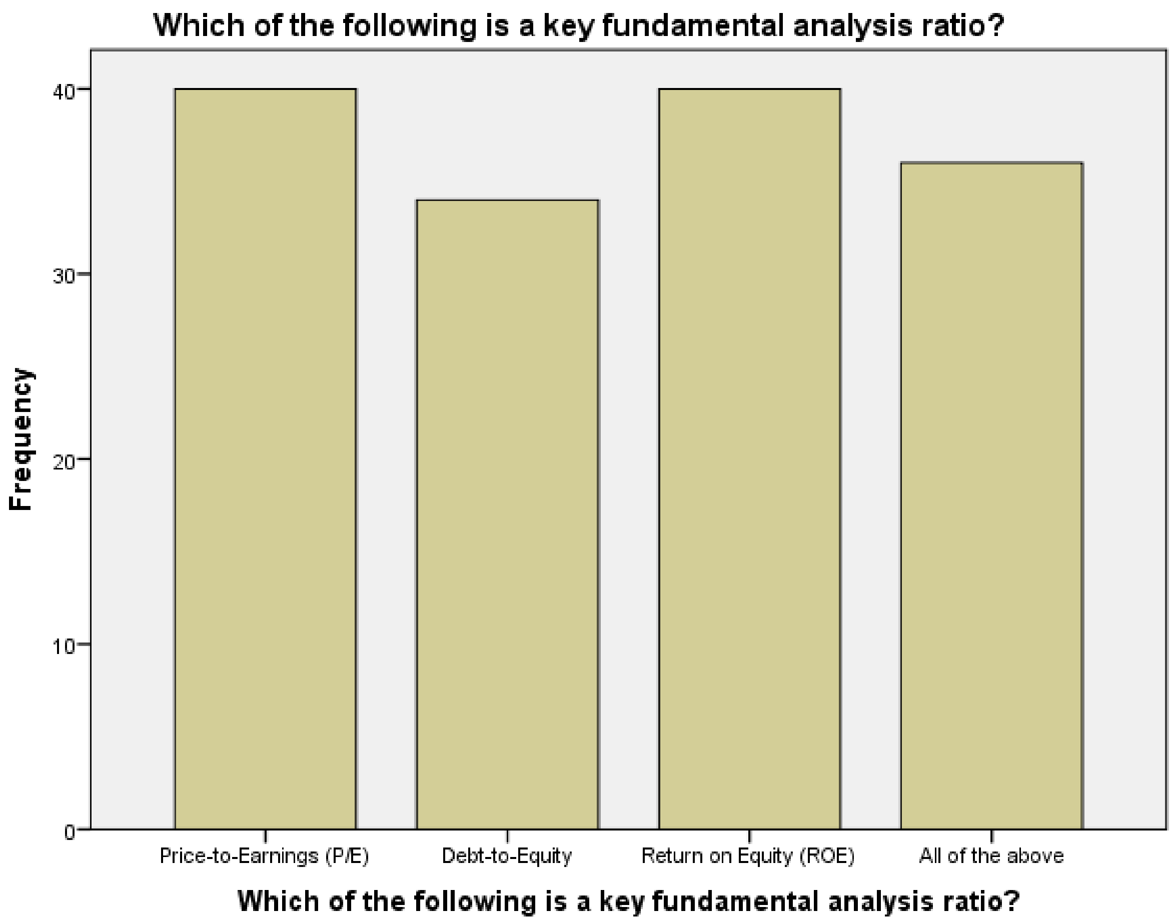


Table 28 : Which fundamental analysis approach focuses on a company's financial statements?

Which fundamental analysis approach focuses on a company's financial statements?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Top-down	38	25.3	25.3	25.3
	Bottom-up	51	34.0	34.0	59.3
	Technical analysis	30	20.0	20.0	79.3
	Quantitative analysis	31	20.7	20.7	100.0
	Total	150	100.0	100.0	

Figure 28 : Which fundamental analysis approach focuses on a company's financial statements?

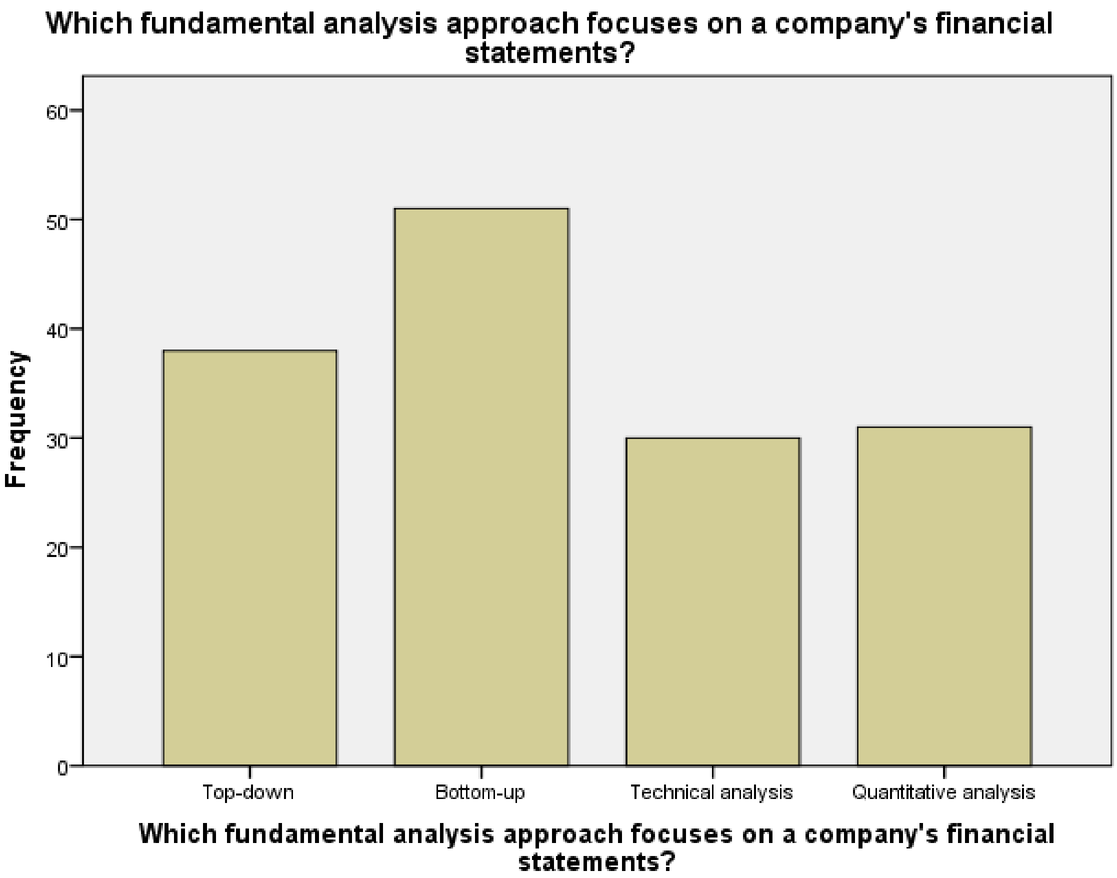


Table 29 :What is the significance of Return on Invested Capital (ROIC) in fundamental analysis?

What is the significance of Return on Invested Capital (ROIC) in fundamental analysis?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Measures profitability	42	28.0	28.0	28.0
	Measures efficiency	26	17.3	17.3	45.3
	Measures growth potential	44	29.3	29.3	74.7
	Measures risk	38	25.3	25.3	100.0
	Total	150	100.0	100.0	

Figure 29 : What is the significance of Return on Invested Capital (ROIC) in fundamental analysis?

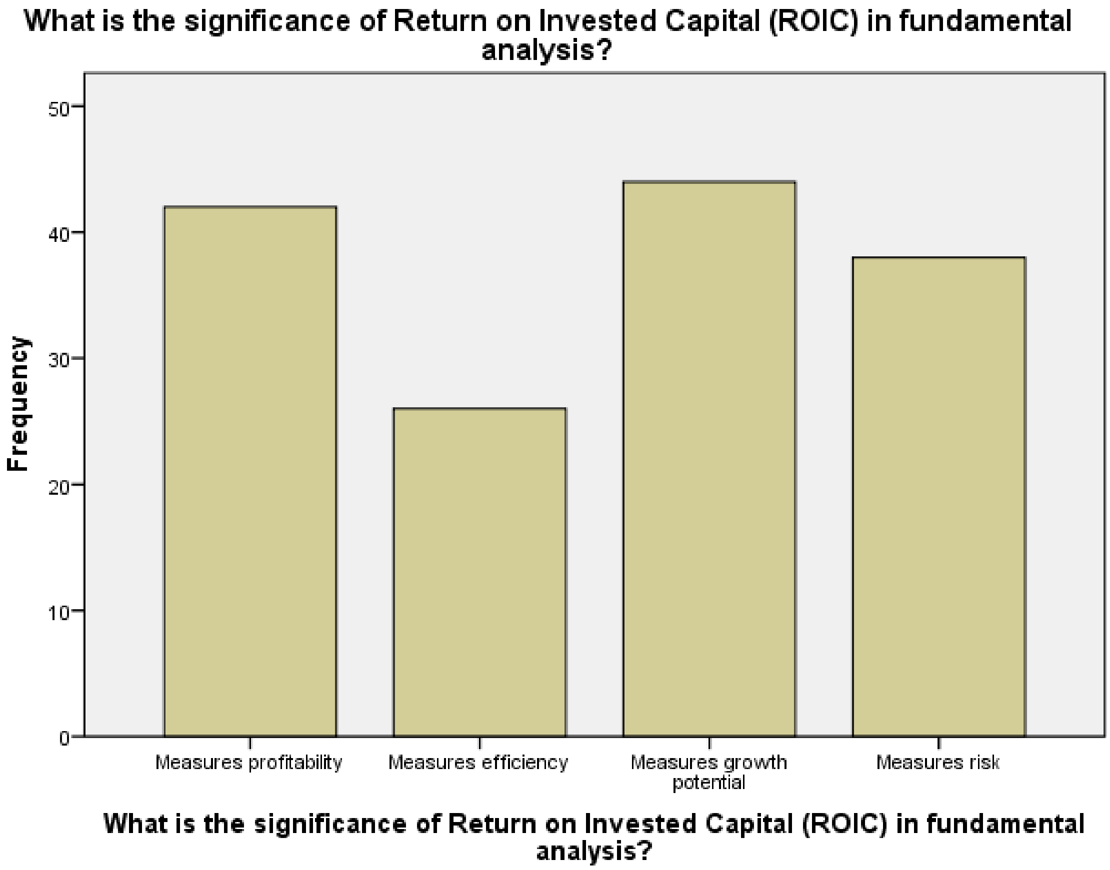


Table 30 :What is the primary goal of fundamental analysis in investment decision-making?

What is the primary goal of fundamental analysis in investment decision-making?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	To predict short-term market trends	35	23.3	23.3	23.3
	To estimate a company's future financial performance	36	24.0	24.0	47.3
	To identify undervalued stocks	37	24.7	24.7	72.0
	To diversify a portfolio	42	28.0	28.0	100.0
	Total	150	100.0	100.0	

Figure 30 :What is the primary goal of fundamental analysis in investment decision-making?

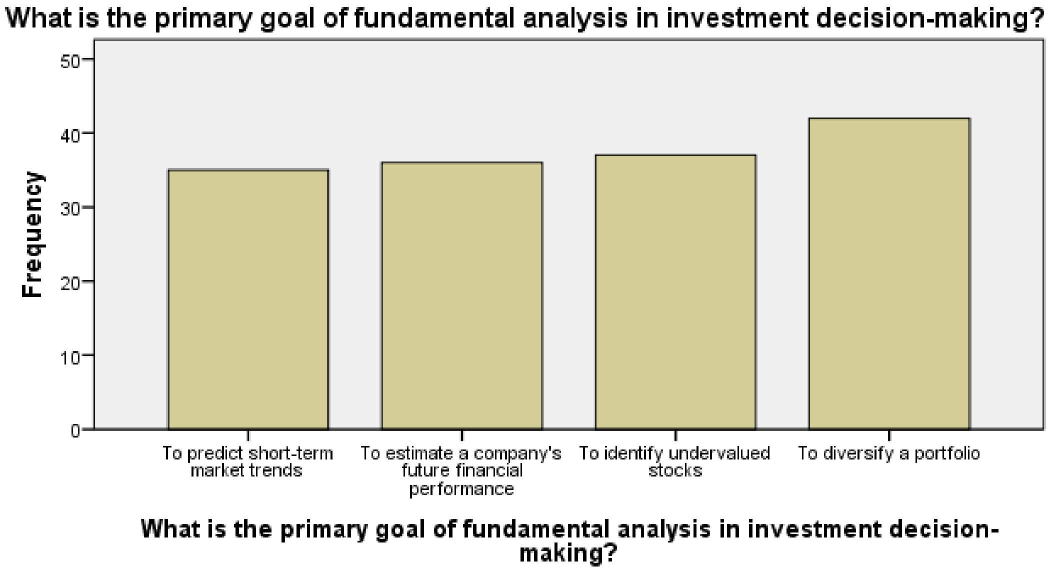


Table 31 : How do you assess the risk associated with an investment?

How do you assess the risk associated with an investment?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Quantitative Measures	34	22.7	22.7	22.7
	Qualitative Assessment	47	31.3	31.3	54.0
	Scenario Analysis	37	24.7	24.7	78.7
	A combination of approaches	32	21.3	21.3	100.0
	Total	150	100.0	100.0	

Figure 31 : How do you assess the risk associated with an investment?

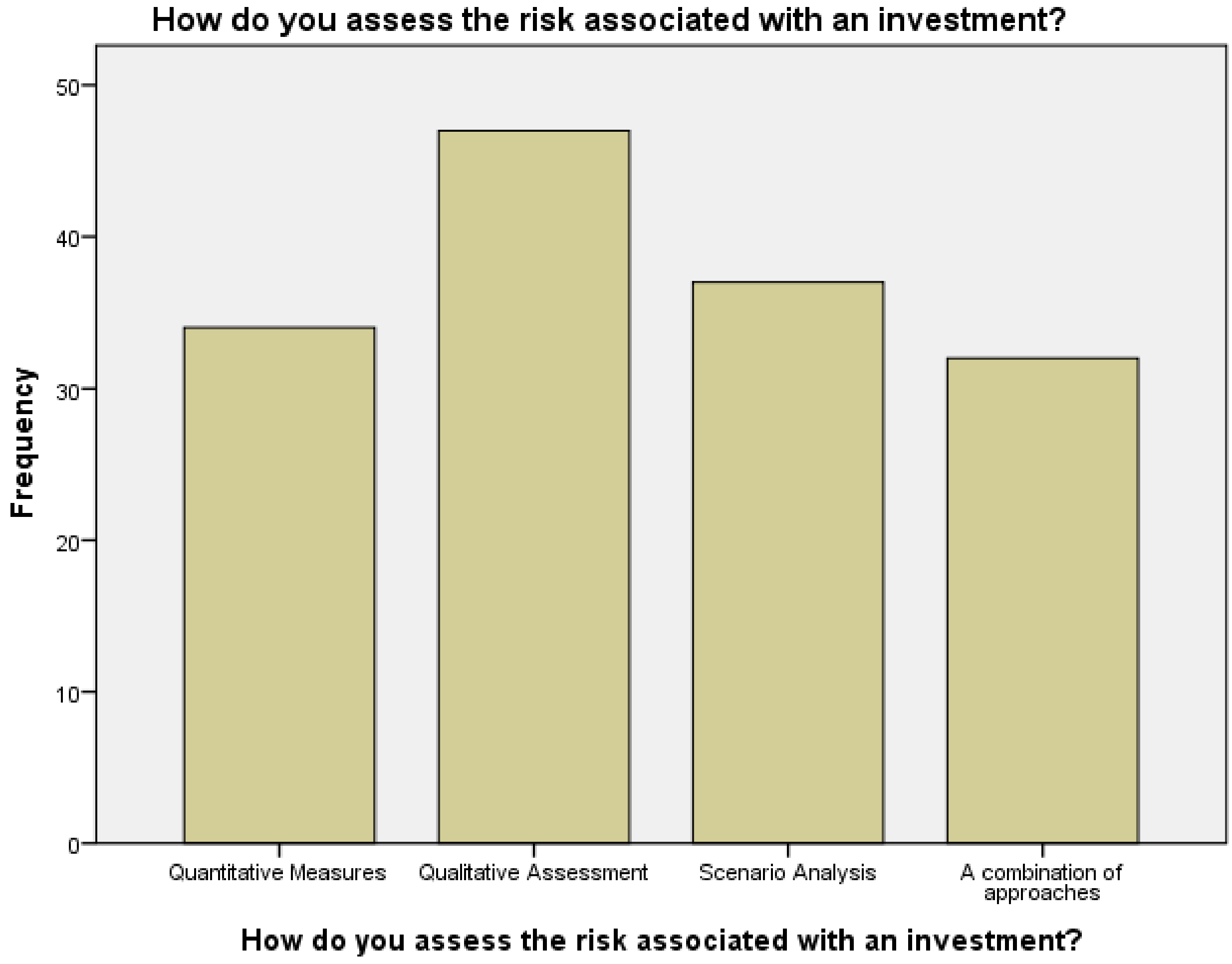


Table 32 : How do you incorporate technology into your investment analysis process?

How do you incorporate technology into your investment analysis process?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Data Analytics & Visualization Tools	46	30.7	30.7	30.7
	AI-Powered Platforms	33	22.0	22.0	52.7
	Algorithmic Trading	37	24.7	24.7	77.3
	I'm still exploring the use of technology in investment analysis.	34	22.7	22.7	100.0
	Total	150	100.0	100.0	

Figure 32 : How do you incorporate technology into your investment analysis process?

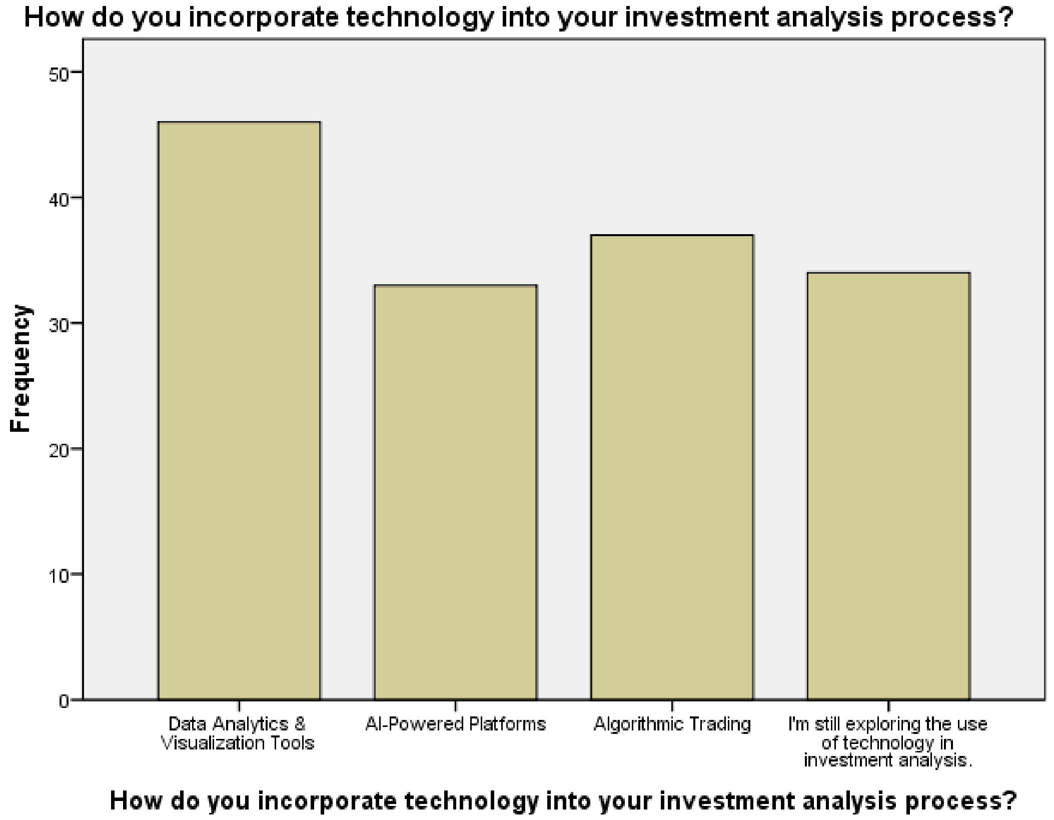


Table 33 : Which emerging trends do you believe will significantly impact investment analysis in the future?

Which emerging trends do you believe will significantly impact investment analysis in the future?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	AI & Machine Learning	41	27.3	27.3	27.3
	Sustainable Investing	43	28.7	28.7	56.0
	Alternative Data	32	21.3	21.3	77.3
	Other	34	22.7	22.7	100.0
	Total	150	100.0	100.0	

Figure 33 :Which emerging trends do you believe will significantly impact investment analysis in the future?

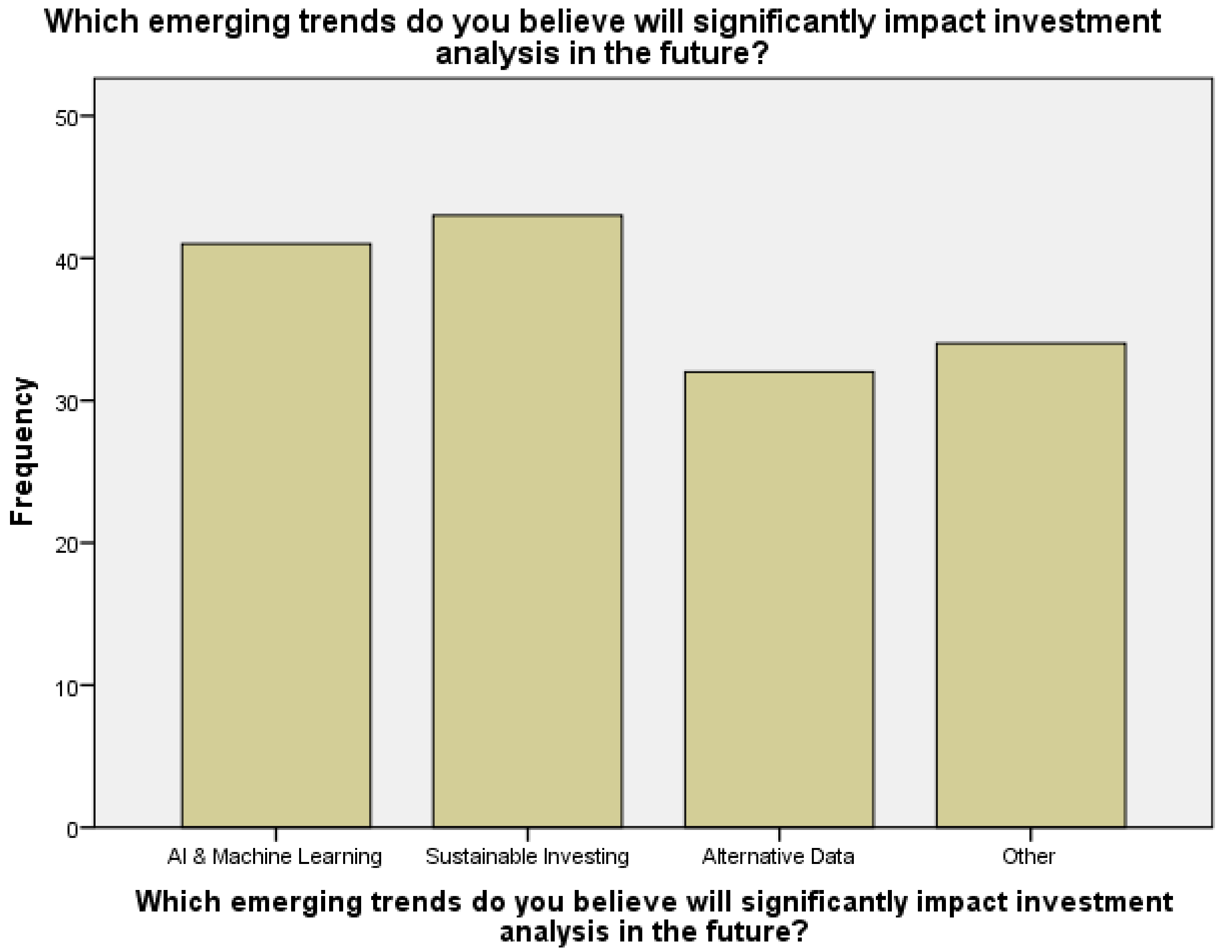


Table 34 : How confident are you in your ability to navigate the complexities of the investment landscape and make informed investment decisions?

How confident are you in your ability to navigate the complexities of the investment landscape and make informed investment decisions?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very confident	36	24.0	24.0	24.0
	Somewhat confident	39	26.0	26.0	50.0
	Not very confident	40	26.7	26.7	76.7
	Not at all confident	35	23.3	23.3	100.0
	Total	150	100.0	100.0	

Figure 34: How confident are you in your ability to navigate the complexities of the investment landscape and make informed investment decisions?

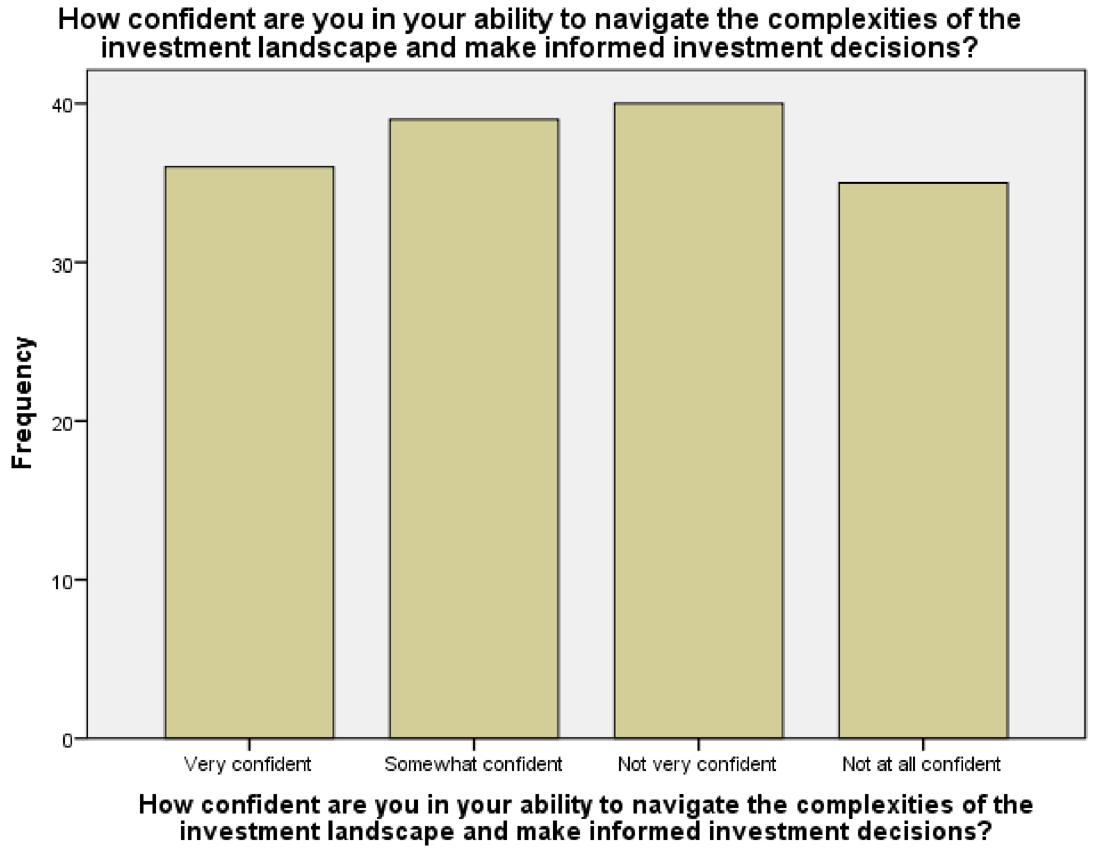


Table 35 : What is the primary goal of risk mitigation in investment management?

What is the primary goal of risk mitigation in investment management?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	To maximize returns	42	28.0	28.0	28.0
	To minimize losses	31	20.7	20.7	48.7
	To optimize portfolio performance	31	20.7	20.7	69.3
	To ensure regulatory compliance	46	30.7	30.7	100.0
	Total	150	100.0	100.0	

Figure 35 :What is the primary goal of risk mitigation in investment management?

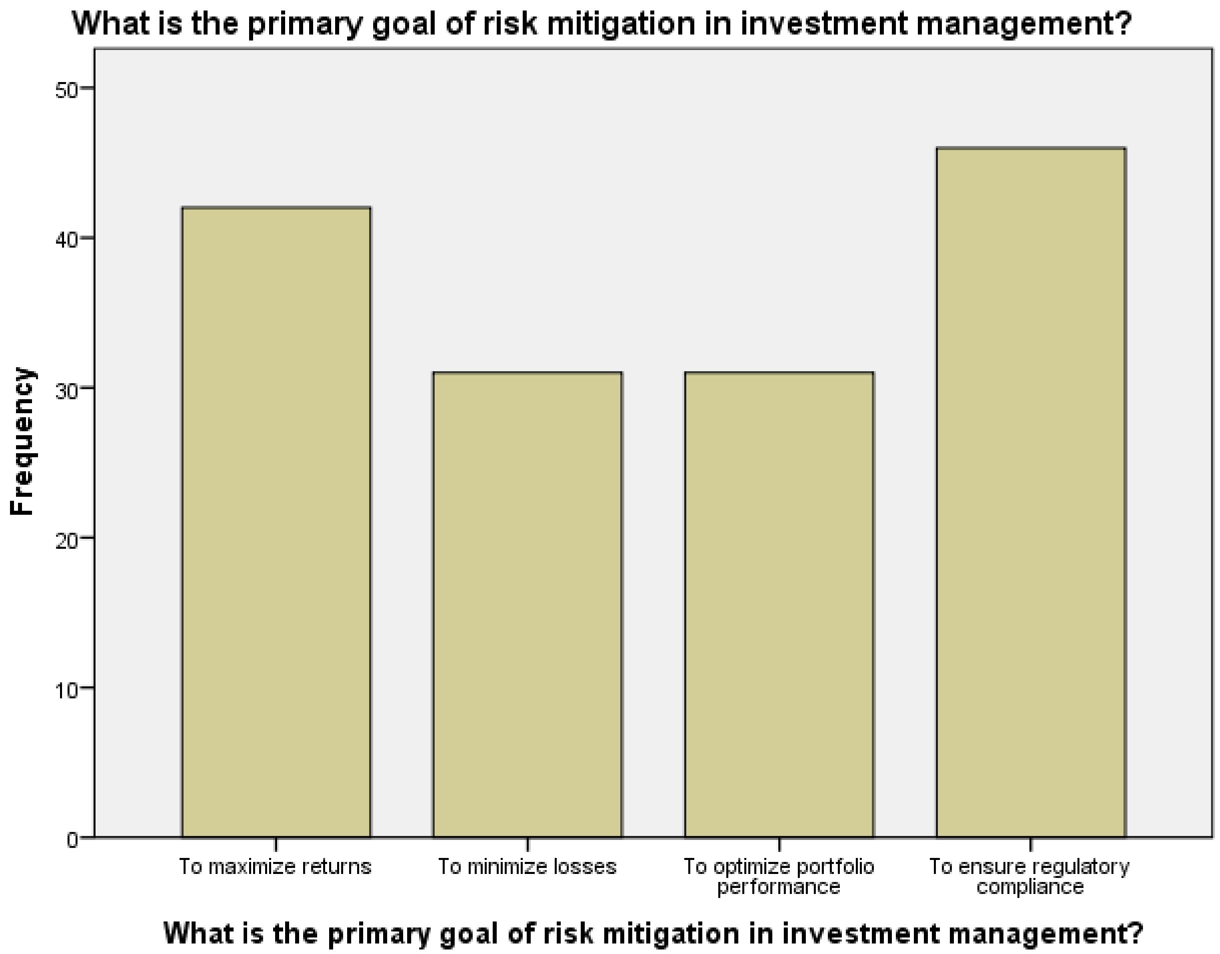


Table 36: Which of the following risk mitigation strategies do you currently use?

Which of the following risk mitigation strategies do you currently use?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Diversification	38	25.3	25.3	25.3
	Hedging	31	20.7	20.7	46.0
	Asset allocation	40	26.7	26.7	72.7
	All of the above	41	27.3	27.3	100.0
	Total	150	100.0	100.0	

Figure 36 : Which of the following risk mitigation strategies do you currently use?

Table 37: What is the most significant risk facing investment managers today?

What is the most significant risk facing investment managers today?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Market risk	45	30.0	30.0	30.0
	Credit risk	35	23.3	23.3	53.3
	Operational risk	33	22.0	22.0	75.3
	Regulatory risk	37	24.7	24.7	100.0
	Total	150	100.0	100.0	

Figure 37: What is the most significant risk facing investment managers today?

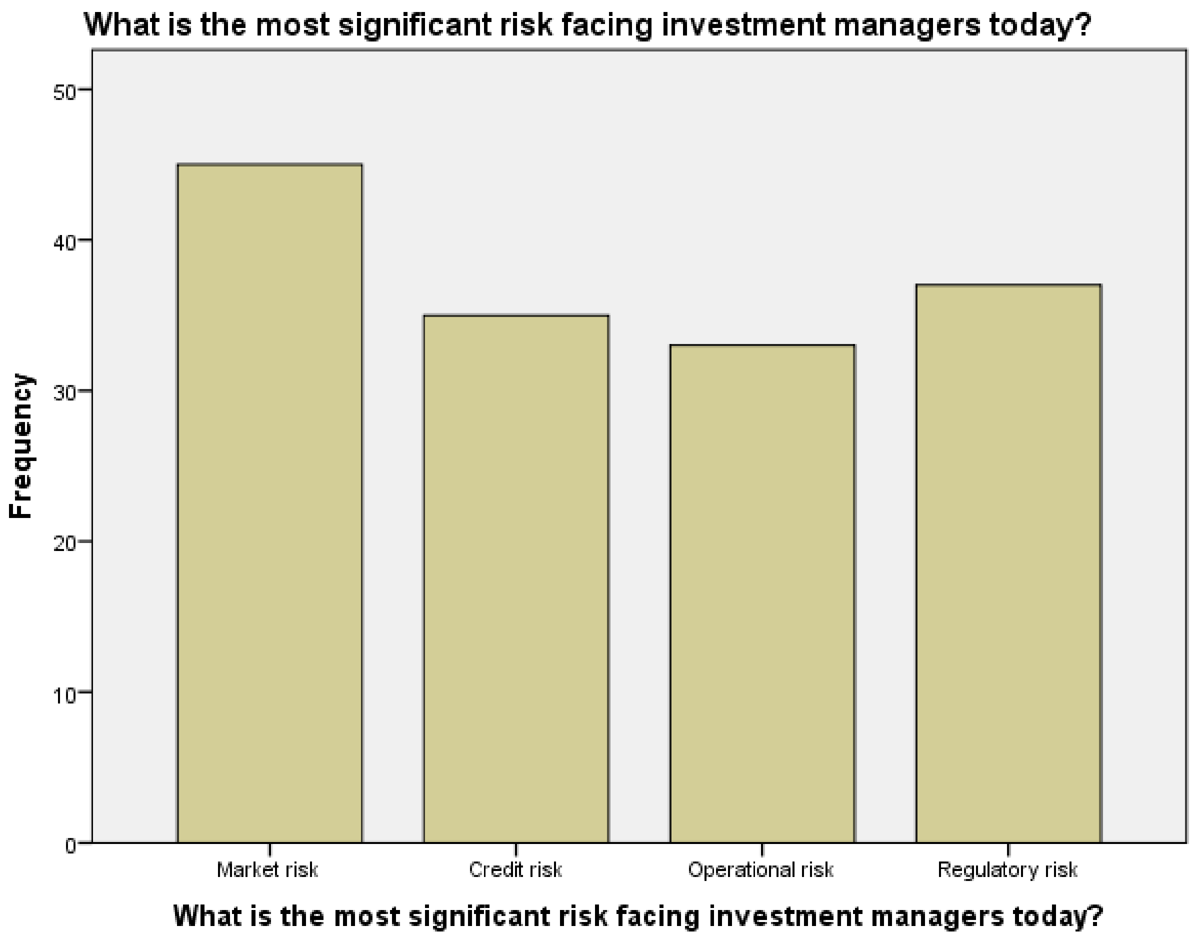


Table 38 : How do you assess and manage potential risks in your investment portfolios?

How do you assess and manage potential risks in your investment portfolios?

	Frequency	Percent	Valid Percent	Cumulative Percent
Qualitative analysis	37	24.7	24.7	50.7
Stress testing	37	24.7	24.7	75.3
All of the above	37	24.7	24.7	100.0
Total	150	100.0	100.0	

Figure 38 : How do you assess and manage potential risks in your investment portfolios?

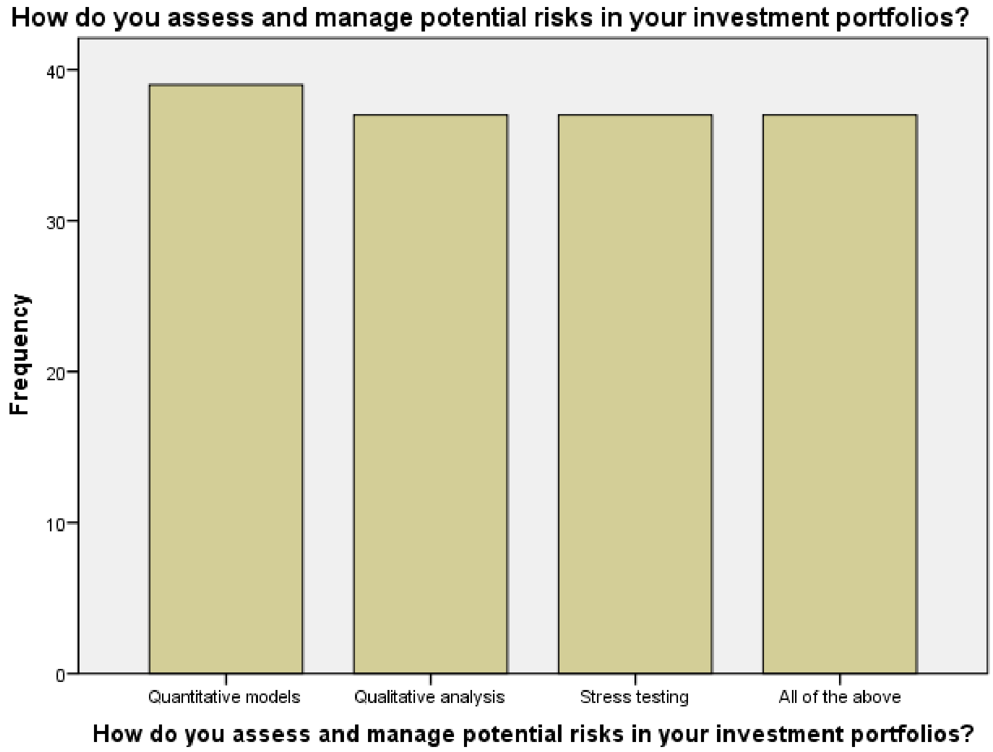
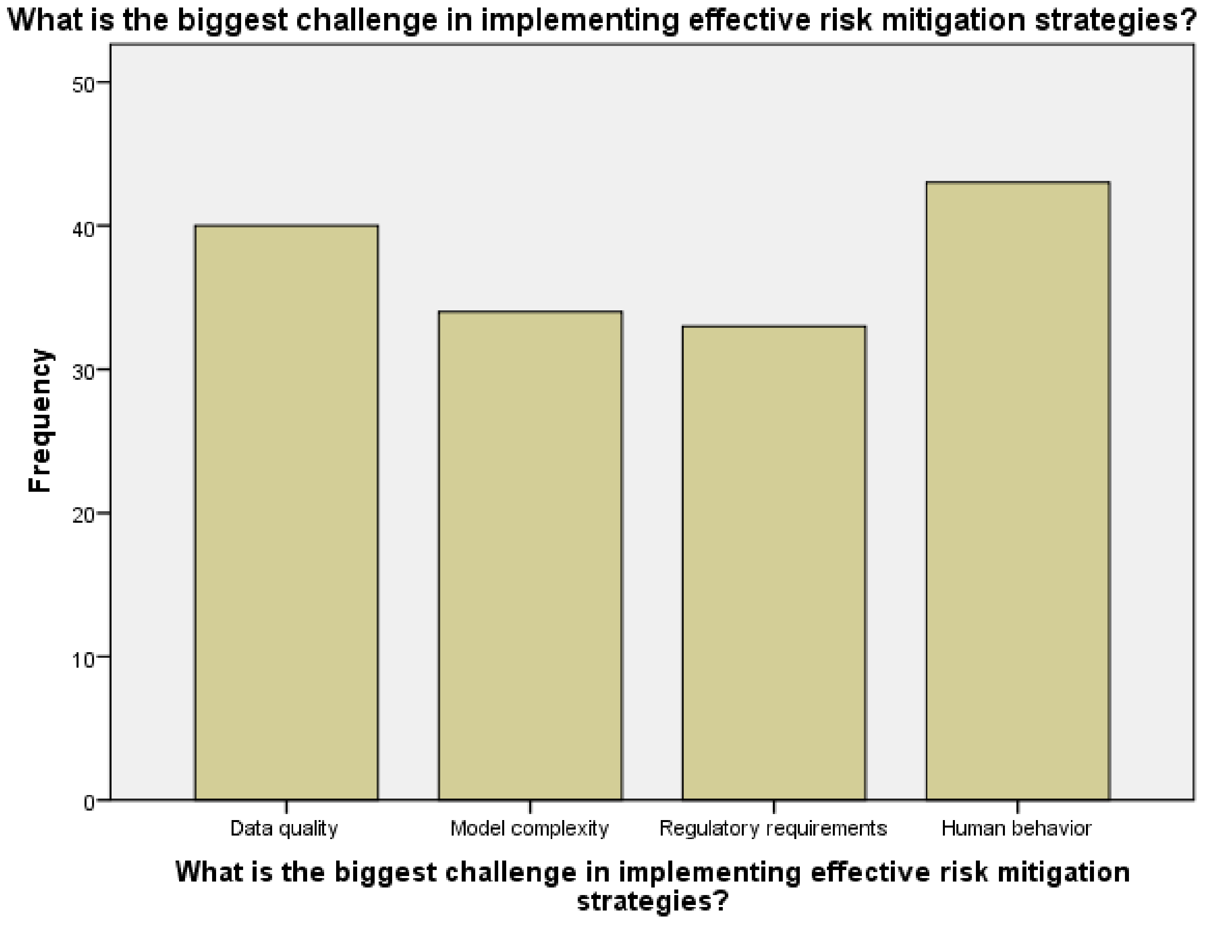


Table 39: What is the biggest challenge in implementing effective risk mitigation strategies?

What is the biggest challenge in implementing effective risk mitigation strategies?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Data quality	40	26.7	26.7	26.7
	Model complexity	34	22.7	22.7	49.3
	Regulatory requirements	33	22.0	22.0	71.3
	Human behaviour	43	28.7	28.7	100.0
	Total	150	100.0	100.0	

Figure 39 : What is the biggest challenge in implementing effective risk mitigation strategies?



The frequency tables reveal a diverse sample with varied professional backgrounds, investment preferences, and levels of familiarity with emerging technologies in investment management. This data highlights the importance of factors such as income size, years of experience, and sector affiliation in shaping investment decisions. The distribution across different levels of satisfaction and familiarity with next-generation technologies like Robotic Process Automation and Artificial Intelligence also provides key insights into the evolving landscape of investment management. These findings will serve as a foundation for further analysis of investment behaviours and emerging trends in financial management practices.

4.2 Regression Analysis

To Investigate AI/ML-driven portfolio performance enhancement.

Table 40 Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.069[a]	.005	-.002	.71820

A. Predictors: (Constant), Investment Edge

The **Model Summary** indicates a weak relationship between **Investment Edge** and **Robotic Automation Architecture for Portfolio Management and Risk Mitigation**, as seen by the low R value (0.069). The R^2 value (0.005) shows that only 0.5% of the variation in the dependent variable is explained by the predictor, suggesting a poor model fit. The adjusted R^2 is negative (-0.002), further indicating that the model is not robust, and the standard error (0.71820) reflects a high level of error in predictions.

Table 41 ANOVA

Anova[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
	Regression	.369	1	.369	.716	.399[b]
1	Residual	76.339	148	.516		
	Total	76.708	149			

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

B. Predictors: (Constant), Investment Edge

The ANOVA Table shows that the model's overall significance is low, as indicated by the F-value (0.716) and the p-value (0.399), which is greater than 0.05. This means that Investment Edge does not significantly explain the variance in Robotic Automation Architecture for Portfolio Management and Risk Mitigation. Most of the variance remains unexplained, as seen by the larger residual sum of squares (76.339) compared to the regression sum (0.369).

Table 42 : Coefficients

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.801	.339		8.272	.000
	Investment Edge	.087	.102	.069	.846	.399

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

The Coefficients Table provides the unstandardized coefficient (0.087) for Investment Edge, indicating that for each unit increase in this variable, the dependent variable increases by 0.087 units. However, with a p-value of 0.399 and a t-value of 0.846, this effect is not statistically significant. The constant (2.801) represents the predicted value of the dependent variable when the independent variable is zero, but the overall lack of significance makes the predictor unimportant.

There is no significant relationship between Investment Edge and Robotic Automation Architecture for Portfolio Management and Risk Mitigation based on the results. The low R^2 value, non-significant F-value, and high p-values indicate that Investment Edge does not meaningfully contribute to the enhancement of portfolio performance in this model. Therefore, the hypothesis that Investment Edge drives AI/ML-driven portfolio performance enhancement is not supported by the data.

To Analyse risk reduction capabilities through AI-powered predictive analytics.

Table 43: Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.013[a]	.000	-.007	.71987

A. Predictors: (Constant), Next Generation Investment Management

The **Model Summary** indicates a near-zero correlation (R = 0.013) between **Next Generation Investment Management** and **Robotic Automation Architecture for Portfolio Management and Risk Mitigation**. The R^2 value (0.000) suggests that the model explains virtually none of the variance in the dependent variable. The adjusted R^2 (-0.007) is negative, further signalling that the model does not fit well. Additionally, the standard error (0.71987) indicates a high level of error in predictions.

Table 44 : ANOVA

Anova[a]

Model		Sum of Squares	DF	Mean Square	F	Sig.
	Regression	.013	1	.013	.025	.874[b]
1	Residual	76.695	148	.518		
	Total	76.708	149			

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

B. Predictors: (Constant), Next Generation Investment Management

The ANOVA Table shows that the model is not statistically significant, as indicated by the F-value (0.025) and the p-value (0.874), which is much greater than the significance threshold of 0.05. This means that Next Generation Investment Management does not explain a meaningful amount of variance in Robotic Automation Architecture for Portfolio Management and Risk Mitigation, as most variance remains unexplained by the model (76.695 residual sum of squares).

Table 45 : Coefficients

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.042	.268		11.349	.000
	Next Generation Investment Management	.017	.104	.013	.159	.874

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

The Coefficients Table shows the unstandardized coefficient (0.017) for Next Generation Investment Management, indicating that for each unit increase in this predictor, the dependent variable increases by only 0.017 units. However, this effect is not statistically significant (p-value = 0.874), and the t-value (0.159) confirms that Next Generation Investment Management has a negligible impact on the dependent variable. The constant (3.042) represents the predicted value of the dependent variable when the independent variable is zero.

There is no significant relationship between Next Generation Investment Management and Robotic Automation Architecture for Portfolio Management and Risk Mitigation. The near-zero R^2 value, non-significant F-value, and high p-value all suggest that Next Generation Investment Management does not contribute meaningfully to risk reduction through AI-powered predictive analytics. Thus, the data does not support the hypothesis that Next Generation Investment Management enhances risk reduction capabilities.

To Evaluate operational efficiency gains from robotic automation.

Table 46 :Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.063[a]	.004	-.010	.72092

A. Predictors: (Constant), Investment Analysis

In Practice, Investment Analysis fundamentals

The Model Summary reveals a weak relationship between Investment Analysis in Practice and Investment Analysis Fundamentals as predictors and Robotic Automation Architecture for Portfolio Management and Risk Mitigation as the dependent variable, with an R value of 0.063. The R^2 value (0.004) indicates that only 0.4% of the variance in the dependent variable is explained by the model. The adjusted R^2 (-0.010) suggests that, after accounting for the number of predictors, the model's fit worsens, and the standard error (0.72092) shows a considerable amount of prediction error.

Table 47: ANOVA

Anova[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
	Regression	.308	2	.154	.296	.744[b]
1	Residual	76.400	147	.520		
	Total	76.708	149			

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

B. Predictors: (Constant), Investment Analysis in Practice, Investment Analysis Fundamentals

The ANOVA Table indicates that the model is not statistically significant, as the F-value (0.296) and p-value (0.744) both suggest that the predictors—Investment Analysis in Practice and Investment Analysis Fundamentals—do not explain a significant amount of variance in Robotic Automation Architecture for Portfolio Management and Risk Mitigation. Most of the variance remains unexplained, as the residual sum of squares (76.400) dominates the total sum.

Table 48 : Coefficients

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.835	.366		7.739	.000
	Investment Analysis Fundamentals	.053	.124	.035	.425	.671
	Investment Analysis in Practice	.048	.074	.054	.651	.516

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

The Coefficients Table shows that the unstandardized coefficients for Investment Analysis Fundamentals (0.053) and Investment Analysis in Practice (0.048) are small, suggesting minimal impact on the dependent variable. The p-values for both predictors are not significant (0.671 for Investment Analysis Fundamentals and 0.516 for Investment Analysis in Practice), indicating that neither predictor contributes significantly to explaining operational efficiency gains through robotic automation. The constant (2.835) represents the predicted value of the dependent variable when both predictors are zero.

The regression analysis shows that Investment Analysis in Practice and Investment Analysis Fundamentals do not significantly predict operational efficiency gains through robotic automation. The low R^2 value and high p-values suggest that these variables explain little to no variance in Robotic Automation Architecture for Portfolio Management and Risk Mitigation. Therefore, the model does not provide evidence to support the hypothesis that these forms of investment analysis drive operational efficiency gains from robotic automation.

To Assess regulatory implications and industry adoption.

Table 49 :Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.017[a]	.000	-.006	.71983

A. Predictors: (Constant), Current Trends & Future Outlook

The Model Summary indicates a very weak relationship between Current Trends & Future Outlook and Robotic Automation Architecture for Portfolio Management and Risk Mitigation, with an R value of 0.017. The R^2 value (0.000) implies that the model does not explain any variance in the dependent variable, while the adjusted R^2 (-0.006) further suggests a poor model fit. The standard error (0.71983) indicates a high level of prediction error, making it difficult to draw reliable conclusions from the model.

Table 50: ANOVA

Anova[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
	Regression	.022	1	.022	.042	.838[b]
1	Residual	76.687	148	.518		
	Total	76.708	149			

A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

B. Predictors: (Constant), Current Trends & Future Outlook

The ANOVA Table shows that the model is not statistically significant, as reflected in the F-value (0.042) and the p-value (0.838), which is well above the typical significance level of 0.05. This means that Current Trends & Future Outlook does not significantly explain variance in Robotic Automation Architecture for Portfolio Management and Risk Mitigation, with the residual sum of squares (76.687) indicating that most variance remains unexplained by the model.

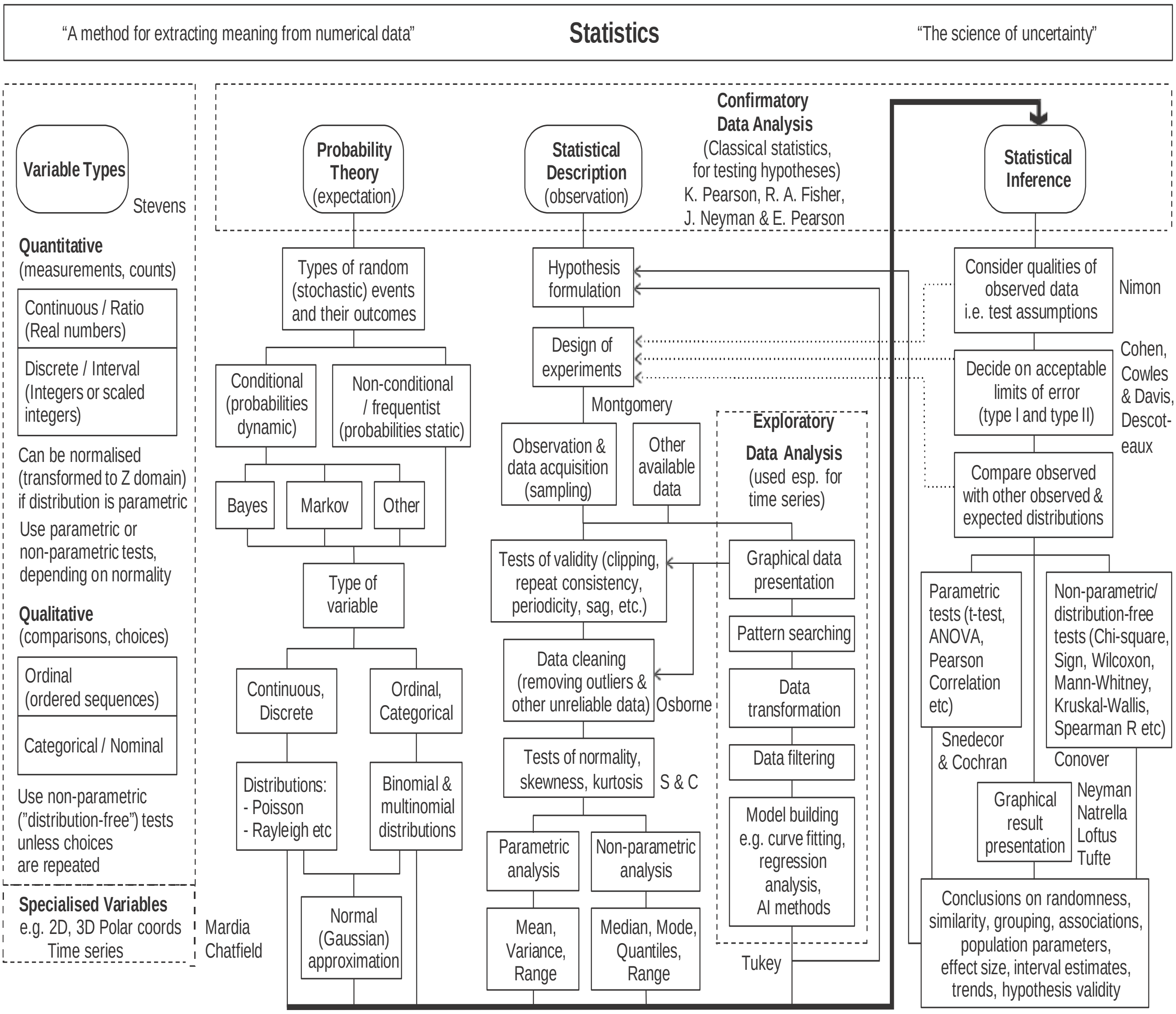
Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.018	.323		9.335	.000
	Current Trends & Future Outlook	.026	.128	.017	.205	.838

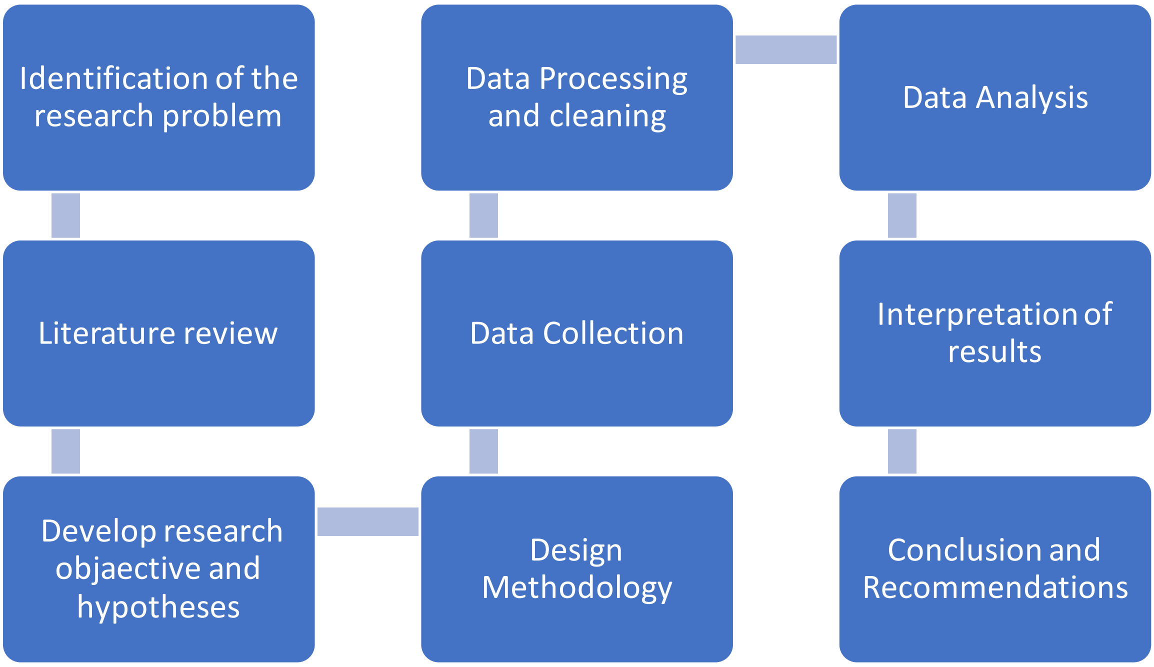
A. Dependent Variable: Robotic Automation Architecture for Portfolio Management and Risk Mitigation

The Coefficients Table presents the unstandardized coefficient (0.026) for Current Trends & Future Outlook, suggesting that for each unit increase in this predictor, the dependent variable would increase by 0.026 units. However, this effect is not statistically significant, as indicated by the p-value (0.838), which implies that Current Trends & Future Outlook does not meaningfully contribute to the model. The constant (3.018) represents the predicted value of the dependent variable when the predictor is zero. The regression analysis reveals that Current Trends & Future Outlook does not significantly impact Robotic Automation Architecture for Portfolio Management and Risk Mitigation. The negligible R^2 value, high p-value, and poor model fit indicate that the predictor does not effectively e explain regulatory implications or industry adoption of robotic automation. Consequently, the data does not support the hypothesis that these trends significantly influence the effectiveness of robotic automation in portfolio management.

Introductory flowchart of statistics for research



Flowchart of the analytical process



CHAPTER 5 : RESULTS AND DISCUSSION

5.1 Introduction

This chapter will provide an analysis of data collected from respondents which has been discussed extensively in the prior chapter. Subsequent sections will discuss the analysis of demographic and other data that has been collected from the respondents. Statistics help in determining whether a measurement tool yields in providing consistent results over time and across different conditions.

5.2 Demographic analysis

The data and information collected for completing the study were obtained through a questionnaire and other sources. It has been identified that the majority of respondents were male i.e. 51.3% and on the other side, the female respondents 48.7%. Considering age as a factor, it has been evaluated that most of the respondents aged between 25-35 years and 55-60 years i.e. 16% respectively. While the least responded age is 60 and above i.e. 12%. Furthermore, considering the highest level of qualification, the majority of respondents, i.e. 24%, have done a PHD and other courses. While the least responses gathered were only done graduation i.e. 14%. The majority of respondents, i.e. 13.3%, have service in the financial sector and the least respondents, 6%, were public sector employees. Furthermore, the income size of respondents is the majority of respondents earning below 4,99,000 i.e. 22%. While the highest-earned respondents were 18.7% 20,00,000 and above. The majority of respondents, i.e. 21.3% were having under five years of experience, 5-10 years, and 15-20 years of experience. Most of the respondents were from Australia i.e. 19.3% and the least respondent were 10% from the USA. It has been analyzed that the majority of respondents, i.e. 14% were from the professional services sector. Most respondents hold commodities and bonds as investments i.e. 14% respectively. The investment horizon considers a majority of the short and medium term i.e. 25.3%.

5.3 Descriptive statistics

A descriptive analysis was carried out to analyze data and information and a five-point Likert scale was used for analyzing the data. Considering the first aspect as, the approximate value of the investment, it has been evaluated that most respondents i.e. 48.7% have investment portfolios valued between 10 lakhs and 25 lakhs, on the other side, a smaller percentage 12.7% have portfolios exceeding 5 crores. Investment portfolio below 1 lakh was only 10.7%. Compared with the literature review, it is determined that portfolio returns are considered a complex issue that can be significantly enhanced with the help of the application of machine learning, deep learning, and reinforcement learning techniques(Manuscript, 2023). It is determined that the traditional method of forecasting mainly depends on linear models (Esenogho, D., & Smith, J. 2022., 2022). This can be further addressed by involving the objective of the study as the integration of next-generation automation architecture into existing investment frameworks. The study therefore seeks to establish how next generation automation architecture with AI & ML could fit into current investment architectures. It is aimed at increasing the value of a portfolio, refining risk handling, and optimizing decisions within such areas of concern as compatibility with technology, the requirements of the legislation, and stakeholders' adjustment.

The expected annual return on investment as a majority of respondents have annual investment is 24.7% i.e. More than 15% and the least annual return on investment i.e. 12.7% is 5-8%. Compared with the literature, it has been analyzed that "machine learning algorithms outperform traditional statistical methods in predicting the prices of stock and the movement of the market" (Bender et al., 2022). Further, considering high return as a factor, it has been evaluated that the majority of respondents, i.e. 32% stated that high returns are not very important for them. While 19.3% said that for them higher returns are not at all important. Compared with literature, it has been identified that predictive analytics helps in guiding investment strategies. Leveraging historical price movements, macroeconomic data, AI and machine learning algorithms helps in uncovering patterns that inform asset allocation decisions (Huang et al. (2024), 2024). Furthermore, the risk related to annual return on investment can be reduced by real-time monitoring. Assessing realism for real-time monitoring entails assessing the dimension of offering timely information, the ability to respond promptly and reducing risks maximally. Real-time also facilitates improvement of decision making by alerting one to abnormalities and avoiding any delays besides compliance. It enhances operational effectiveness and risk identification and fills an organization's capability to handle challenges.

The satisfaction level with the current investment portfolio as the majority of respondents are very satisfied i.e. 27.3%. While 20% of respondents were dissatisfied with the statement and 16.7% stated that they were very dissatisfied. Compared with the literature, it has been analyzed that portfolio adjustment has been supported by predictive analytics to balance risk and return continuously. (Adel, 2023), Highlighted that "algorithms can analyze incoming data in real-time, allowing investment managers to react swiftly to changes in the market and adjust portfolios accordingly". In addition to this, most of the respondents stated that their main goal of investment is capital preservation i.e. 30.7% and 12.7% of respondents stated that retirement savings are considered as their main goal of investing money. Compared with the literature, it has been identified that the process of investment mainly relies on manual labor, resulting in slow decision-making, increasing human error, and higher costs of operations. "The landscape of investment was also reshaped by the integration of AI and ML technologies" (Wang, He and Ouyang, 2024b). It is evaluated that AI and ML in increasing predictive analytics for investment strategies. It is not a secret that AI and ML are the driving force behind improving predictive analytics regarding investment solutions as they analyze big data, patterns, and create precise predictions. These technologies facilitate real-time decision-making, allow efficient management of the portfolio, and minimize risks as they use a more elaborate number-crunching technique with unmatched accuracy and adaptability in volatile financial markets.

Considering investment decisions (Che Hassan *et al.*, 2023)as a factor, it has been evaluated that the majority of respondents i.e. 28.7% make investment decisions on their own and with the help of financial advisors respectively. Compared with the literature, it has been identified that decisions related to investment are supported by the identification of trends and historical data that inform trading strategies enabling firms to make data-driven decisions instead of relying on human intuition (Sarker, 2022b). The statement regarding familiarizing with the concept of next-generation investment management indicated that the majority of respondents, i.e. 32.7% were very familiar with this concept. While 20.7% were somewhat familiar with this concept. Compared with the literature, investment can be managed by involving the evolution of automation and its critical process in optimization, increasing decision-making, and dealing with operational in efficiencies (Pyzer-Knapp *et al.*, 2022).

The majority of respondents, i.e. 26.7%, believed that technologies other than the mentioned have the greatest influence on investment management in the next 5 years. 20% said that big data and alternative data will have a greater influence on investment management in the next 5 years. Compared with literature, it is evaluated that AI and machine learning(Gill *et al.*, 2022a) have gained considerable attention in recent years, and along with this Technologies also help in making predictions and adjusting portfolios (Huang et al. (2024), 2024). It has been identified that the majority of respondents, i.e. 28% stated involving ESG factors in investment decisions is very important. While 21.3% said it's not very important according to them. Moreover, considering personalized investment portfolios most of the respondents stated that 39.3% said maybe personalized investment portfolios(Cocco, 2021) based on individual preferences and risk tolerance will become the norm in the future. While 26.7% stated that they were not in favor of the statement.

The majority of respondents, i.e. 30% stated that they are somewhat familiar with the use of RPA in investment management. On the other side, 18.7% were very familiar with using RPA in managing investment. The studies indicated the “RPA's role in the reduction of time spent on repetitive tasks such as data entry and compliance checks” (Che Hassan *et al.*, 2023). Most respondents, i.e. 19.3%, said that improved efficiency is a benefit that is valuable for portfolio management and managing risk.

Furthermore, the majority of respondents, i.e. 22.7% stated that data security concerns are the main challenge in implementing RPA in managing investment. While at least 17.3% of respondents stated that other than the options provided. The majority of respondents i.e. 24% stated that they are likely considering RPA solutions for managing investment in the next 2 years(Chakraborti *et al.*, 2020b).

27.3% of respondents said that they are familiar with the intrinsic value concept and 22.7% are familiar with this concept. Most respondents, i.e. 28%, discussed that fundamental analysis is the investment analysis methodology on which primarily relies. It has been evaluated that 26.7% of respondents stated that price-to-earnings and return on equity are the key fundamental analysis ratios. It was determined that 34% of respondents stated that the bottom-up approach emphasizes the company's financial statements. Furthermore, it has been identified that 29.3% of respondents discussed that return on invested capital importance is measuring profitability. 28% stated that diversifying portfolios is considered as primary goal in investment decision-making. The majority of respondents i.e. 31.3% stated with the help of qualitative assessment risk associated with an investment.

Can be assessed. 30.7% stated that data analytics and visualization tools help in incorporating technology into the investment analysis process.

Most respondents, i.e. 28.7% stated that sustainable investing is an emerging trend that will significantly affect investment analysis in the future. 26.7% of respondents were not very confident in navigating the complexities of the investment(Che *et al.*, 2024) landscape and making informed investment decisions(Che Hassan *et al.*, 2023). 30.7% of respondents stated that ensuring regulatory compliance is the primary goal in mitigating risk in managing investment. Most of the respondents discussed that 27.3% stated all the above strategies help in dealing with the risk. It has been evaluated that 30% of respondents stated that market risk is the significant risk faced by investment managers. 26% said that through qualitative models they manage potential risk in the investment portfolio. The biggest challenge evaluated in executing an effective risk mitigation strategy is human behavior i.e. 28.7%.

5.4 Regression analysis

The analysis (Saxena *et al.*, 2023) assesses the impact of different factors on the effectiveness of robotic automation architecture for portfolio management and mitigating risk. The findings indicated none of the examined predictors such as investment analysis fundamentals, investment edge, next-generation investment management, and investment analysis in practice or current trends and future outlook contribute towards explaining the dependent variable. The model highlighted consistently weak relationships with R^2 values near zero, depicting the independent variable. The highest recorded R^2 is 0.005 for Investment Edge, meaning that the variable accounts for only 0.5% of the variability. Other variables like Next Generation Investment Management and Current Trends(Gill *et al.*, 2022a) & Future Outlook have an R^2 value of 0.000, meaning that the variables do not explain anything at all. Additionally, the adjusted R^2 values are negative, which suggests that the fit is not good enough, and the high standard errors reflect large prediction errors.

The results of the ANOVA analysis also support this interpretation, since none of the models are statistically significant; the p-value for all is significantly greater than the 0.05 threshold. This would mean that the independent variables do not explain much of the variance in the dependent variable(Saxena *et al.*, 2023). In addition, the residual sums of squares are consistently big in comparison to the regression sums, meaning that the models fail to capture the critical factors influencing robotic automation. The tables presenting coefficients further substantiate these conclusions, as the unstandardized coefficients demonstrate minimal values and the p-values for each variable exceed 0.05, suggesting a lack of significance. In summary, the evidence does not substantiate the hypotheses that any of the variables analyzed significantly influence AI/ML-enhanced portfolio performance, risk mitigation, operational efficiency, or the acceptance of regulatory frameworks through robotic automation.

CHAPTER 6: SUMMARY, CONCLUSION, EXAMPLE, RECOMMENDATION

6.1: Summary:

AI and ML algorithms enhance market predictions by analysing large datasets to identify patterns, enabling more accurate forecasting and proactive investment strategies. Robotic automation improves portfolio efficiency by automating routine tasks, reducing human error, and streamlining workflows. Real-time monitoring allows for dynamic tracking of market conditions, facilitating rapid response to emerging risks and enhancing risk mitigation efforts. Next-generation automation architectures can be integrated into existing frameworks by leveraging modular, scalable technologies that improve data processing, decision-making, and overall operational efficiency.

6.1.1. Research Question 1: "AI-Driven Market Insights: Enhancing Predictions and Investment Strategies"

Leverages artificial intelligence (AI) and machine learning (ML) to revolutionize investment decision-making. By analyzing vast amounts of market data, AI algorithms identify patterns, trends, and correlations that human analysts may miss. These insights enable investors to make informed, data-driven decisions, optimizing portfolio performance and minimizing risk. AI-driven models predict market fluctuations, detect anomalies, and provide real-time recommendations, allowing investors to respond swiftly to changing market conditions. Additionally, AI enhances investment strategies by identifying new opportunities, optimizing asset allocation, and streamlining portfolio rebalancing. By harnessing AI's predictive power, investors gain a competitive edge, making more accurate predictions and achieving better returns in an increasingly complex and dynamic market landscape.

6.1.2. Research Question 2: "Revolutionizing Portfolio Management"

Robotic Automation and AI combines automation's efficiency with AI's cognitive power, transforming investment decision-making. Automation streamlines tedious tasks, such as data processing, rebalancing, and compliance, freeing resources for strategic thinking. AI's cognitive capabilities analyze vast market data, identify patterns, and predict trends, providing actionable insights. This synergy enables portfolio managers to make informed, data-driven decisions, optimizing asset allocation, minimizing risk, and maximizing returns. By automating routine tasks and amplifying human expertise with AI-driven insights, portfolio management becomes more efficient, scalable, and effective, resulting in enhanced performance, reduced costs, and improved investor satisfaction.

6.1.3. Research Question 3: " Real-Time Risk Analytics: Risk mitigation, Return Enhancing."

Real-time risk analytics is vital for enhancing returns and mitigating risks in finance and investment management by continuously monitoring market conditions, enabling dynamic risk assessment, and providing early warning systems for emerging threats. By leveraging big data and machine learning, organizations can optimize investment strategies, implement algorithmic trading, and enhance decision-making, ultimately allowing for more effective portfolio diversification and improved responsiveness to market changes. Despite challenges such as data integration, technology costs, and the need for skilled personnel, the ability to analyse risks in real time empowers firms to make informed decisions that balance risk and return effectively.

6.1.4. Research Question 4: "Automating Success: Integrating Next-Gen Architecture into Investment Management Systems"

Explores how the adoption of advanced automation technologies can revolutionize investment management by streamlining processes, enhancing decision-making, and improving overall efficiency.

This integration involves leveraging artificial intelligence, machine learning, and data analytics to optimize portfolio management, risk assessment, and trade execution. By modernizing legacy systems with next-generation architecture, firms can automate routine tasks, gain real-time insights, and respond swiftly to market changes, ultimately driving better investment outcomes and enhancing competitive advantage. The shift not only boosts operational performance but also positions organizations to adapt to the evolving financial landscape effectively.

6.2 Examples of Successful AL and ML Implementations in Asset Management

1. Blackrock

Blackrock, one of the world's largest investment management firms, has successfully implemented AI and ML techniques in various aspects of asset management. Blackrock's Aladdin Platform utilizes AI-powered algorithms to analyse market data, identify investment opportunities, and optimize portfolio construction. Their use of AI and ML has helped them enhance their investment strategies and deliver better outcomes for their clients.

2. JPMorgan Asset Management

Jpmorgan's LOXM (Liquidity, Optimization, and Execution Management) platform leverages machine learning to optimize trading strategies. It analyses historical data and market conditions to make informed decisions on executing trades. This system has demonstrated improved trading efficiency and cost savings by optimizing trade execution.

The platform's ability to adapt to changing market conditions in real-time contributes to better outcomes for clients thanks to AI and ML techniques to optimize their portfolio construction process. They use sophisticated algorithms that leverage vast amounts of data to identify optimal asset allocations, taking into account factors such as risk, return, and market conditions. Their AI-driven portfolio optimization has allowed them to achieve better diversification and improve investment performance.

3. Vanguard

Vanguard, a prominent investment management company, has integrated AI and ML technologies to enhance its customer experience. They utilize AI-powered chatbots and virtual assistants to provide personalized investment advice and assist clients in managing their portfolios. By leveraging AI and ML, Vanguard has been able to offer efficient and tailored services to its clients, improving overall customer satisfaction.

4. Fidelity Investments

Fidelity Investments has successfully implemented AI and ML in its fraud detection and cybersecurity measures. They utilize machine learning algorithms to continuously monitor transactions, detect anomalies, and identify potentially fraudulent activities. This proactive approach to fraud detection has helped them mitigate risks and safeguard investor assets.

5. AQR Capital Management's Use of Machine Learning

AQR Capital Management, a quantitative investment firm, extensively uses machine learning in its investment strategies. The firm applies ML algorithms to identify patterns and signals in financial markets, helping in the creation of systematic trading strategies. AQR's use of machine learning has contributed to the development of innovative investment strategies. These strategies aim to capture market anomalies and deliver alpha, demonstrating the potential of ML in quantitative finance.

6. State Street Global Advisors' Kensho Technologies

State Street Global Advisors collaborated with Kensho Technologies to develop the "SPYD" ETF, which utilizes natural language processing (NLP) and machine learning to analyse market news and events. The ETF, which tracks the performance of dividend-paying stocks, and uses Kensho's AI to assess the impact of news on stock prices. This implementation demonstrates how AI can be applied to process unstructured data for investment decision-making.

6.3 Conclusion

The first objective of the research is to analyze the role of AI and ML in enhancing predictive analytics for investment strategies. It is observed that AI and ML technologies integration into investment management help in reshaping the landscape. Automation is mainly employed to streamline operations, reduce operational efficiencies and enhance decision-making. It is determined that integrating AI and machine learning technologies into automation framework enhances predictive capabilities, enabling firms to forecast market trends and adjust their strategies proactively. Technologies also empower investment managers to explore new avenues for growth and capitalizing opportunities. The application of AI and machine learning in the financial markets has gained considerable aspects in recent years. AI and ML facilitate the processing of large datasets, enabling investment firms to derive knowledge which is previously unattainable. It is evaluated that AI and ML has the ability to back-test and validate predictive models using historical data allowed for assessing potential strategies. This not only develops confidence in making decisions but also provides structured framework for optimizing performance.

It is determined that studies have shown that machine learning algorithms outperform traditional statistical methods in analyzing the stock prices and movements in market. This can be explained further by taking example as a comparative study demonstrated that ML techniques help in supporting vector machines and neural networks achieving higher rate of accuracy compared with classical approaches such as linear regression. The superior performance encouraged firms to adopt AI/ML driven tools for assessing management, ultimately leading to improved outcomes through investment. Furthermore, AI and ML also have the ability to back -test and validate predictive models using historical data allowing for rigorous assessment of potential strategies. This not only increases confidence in decision-making but also provides structured framework for optimizing portfolio performance. The evolution of AI and ML technologies holds potential to revolutionize investment management practices, enabling firms to deal with the complexities of financial markets with greater precision and agility.

In addition to this, the second objective is to evaluate the importance of real-time monitoring in mitigating risks. It is identified that risk management is considered as an important aspect of investment management, automation technologies are becoming important to deal with the risks. Markets are becoming increasingly volatile and complex, the need to assess risk is more pressing than ever. It is analyzed that traditional risk management methods are falling short in the face of rapid changes in the market and vast volume of data. Automation also emerges vital solutions which increase the efficiency and accuracy of managing risk practices. Automation also facilitates real-time monitoring of market conditions and portfolio performance, allowing investment managers to determine and respond to risks promptly. It is determined that AI-driven systems help in analyzing vast amounts of data to evaluate trends, potential threats and providing firms with critical insights that inform managing risk.

Automation also tends to increase granularity and risk assessing frequency. Automated systems also generated reporting of risk and development of dashboard in real-time. This also allowed portfolio managers to track performance metrics and expose risk continuously. It is determined that cybersecurity is becoming a significant concern in the financial market and automation played a crucial role in safeguarding sensitive information. AI-driven cybersecurity systems help in detecting unusual patterns in transaction data and consider potential breaches, increasing overall security of financial transactions. This capability is important for protecting against the increasing threat of cyberattacks having consequences for investment firms. In addition to this, automated compliance tools also contributed towards mitigating risk by ensuring adherence to ever-evolving regulatory requirements. Automating process of compliance, firms help in reducing the risk of non-compliance and the associated penalties, safeguarding financial standing and reputation. This not only constitutes the reduction of the burden from compliance teams and enhances compliance efforts and minimizes chances of costly missteps.

The third objective of the study is to examine the scalability and efficiency of robotic automation in investment management. It is identified that managing investment significantly affecting how financial institutions operate. Historically, the process of investment relied mainly on manual labor, resulting in slower decision-making, higher cost of operations and increasing human error. Over recent decades, technological advancements have fueled a shift toward automation, starting with the introduction of electronic trading platforms in the late 20th century. These platforms enabled faster trade execution and improved access to market information. The increasing algorithmic trading, in which complex mathematical models executed trades based on predefined criteria, exit points and optimizing market entry. Automation helps in setting groundwork for sophisticated systems, enable firms to process vast amounts of data and executing trades at speeds unachievable by humans.

Investment managers help in focusing on higher-value activities, including strategic planning, and engagement of clients. Automation also fosters scalability, allowing firms to manage increasing workloads without proportional staffing increases, which is important in a competitive market. While financial markets continue to grow in considering speed and complexity, the reliance on manual processes is becoming increasingly untenable. Automation also facilitates the handling of data, allowing firms to leverage advanced analytics for providing real-time insights that drive investment strategies. Automation also reduces framework in enhancing predictive capabilities, enabling firms to forecast trends in the market and adjusting strategies proactively. These technologies also supported empowering investment managers to explore avenues for growth and capitalizing opportunities that have previously gone unnoticed.

The last objective of the study is to investigate the integration of next-generation automation architecture into existing investment frameworks. It is evaluated that from the aspects of managing asset, decision trees can effectively handle categorical variables and making interpretable predictions, which is mainly useful in finance where factors can be both categorical and numerical including rating of company, or classification of sector. In addition to this, deep learning techniques including Recurrent Neural Networks (RNN) and long short-term memory (LSTM) networks excel at capturing temporal dependencies in time-series data, making it particularly effective for forecasting. RNN is designed to process sequential data, making them ideal for financial time series, in which previous values are often predictive of future values. It is identified that LSTM considered as specialized type of RNN, addressing vanishing problem and maintaining long-term dependencies, allowing remember important information over extended periods which is important for modeling market behaviors in which trends help in persist across different time frames.

Integrating ML, DL, and RL techniques paves the way for future research in multi-asset class forecasting, incorporating economic indicators, and development of sophisticated RL algorithms. The involvement of multi-asset class forecasting emphasizes determining different asset types such as bonds, equities and commodities allowed for diversified investment strategies that can adopt to changing dynamics in the market. Leveraging data from different sources, involving macroeconomic indicators, geopolitical events, social media sentiment, and further it supports researcher in developing holistic forecasting models accounting for broader range of factors affecting market movements. Transfer learning is an important promising area for future research, in which knowledge gained from one domain is applied to another. In the finance context, applying insights gained from forecasting asset class to enhance predictions further helps in improving the effectiveness and efficiency of forecasting models. Development of sophisticated RL algorithm involving advanced exploration strategies and hybrid models combining RL with other machine learning approaches holding significant promises for increasing the precision and portfolio effectiveness return forecasting. Innovations lead to adaptive investment strategies that continuously evolve on the basis of real-time data and changes in the market.

6.4 Recommendations

It is recommended that prioritizing AI-driven insights by employing machine learning models continuously analyze vast sets of data for predicting market trends and evaluating emerging risks. Adaptive AI frameworks with reinforcement learning capabilities help in predicting and increasing decision-making processes, enabling accurate portfolio adjustments in real-time. Enhancing data integration and processing helps in leveraging advanced robotic process automation (RPA) systems that aggregate data from different sources including economic indicators and social sentiment. Furthermore, it is suggested that building risk management framework incorporates AI-based stress testing and analyzing scenarios. Development of flexible risk mitigation strategies based on insights provides proactive approach in managing events. Investment managers have better understanding and validating models related to decisions, enhancing trust in AI-driven suggestions and facilitating compliance linked with regulatory requirements.

In addition to this, it is recommended that we invest in human AI-collaboration by training investment teams to working alongside AI tools. The approach helps in leveraging AI's analytical capabilities on the other side, maintaining human oversight for strategic decision making, increasing operational efficiency and reinforcing judgement in complex situations. Ensuring strong cybersecurity measures help in protecting automation architecture from potential cyber threats. Executing advanced encryption, multi-factor authentication and regulating audit systems help in safeguarding financial data which further enhance trust among client and security. It is suggested that prioritizing infrastructure helps support high-frequency trading. It is observed that cloud-based platforms help offer computational power and scalability to deal with complex algorithms used in AI and ML models. Developing centralized repository data within a secure cloud environment helps improve accessibility of data, compliance and developing consistency. Thus, by adopting these strategies, it help in next-generation management robotic automation architecture in managing portfolio and managing risk.

REFERENCE:

1. Adadi, A., & Berrada, M. Doi: (2018) ‘Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence’, IEEE Access 52138-52160, 6, Available at: https://doi.org/10.1109/ACCESS.2018.2870052.
2. Adel, A. (2023) ‘Unlocking the Future: Fostering Human–Machine Collaboration and Driving Intelligent Automation through Industry 5.0 in Smart Cities’, Smart Cities. Multidisciplinary Digital Publishing Institute (MDPI), pp. 2742–2782. Available at: https://doi.org/10.3390/smartcities6050124.
3. Alexander, C. (2009) Market Risk Analysis, Volume IV, Value at Risk Models. ISBN: 978-0- 470-99788-8. Availableat:https://www.wiley.com/enus/Market+Risk+Analysis%2C+Volume+IV%2C+Value+at+Risk+Models-p9780470997888.
4. Allioui, H. and Mourdi, Y. (2023) ‘Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey’, *Sensors*. Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/s23198015
5. Alpaydin, E. (2020) ‘Introduction to machine learning’, MIT press. [Preprint]. Available at: https://doi.org/https://10.7551/mitpress/10607.001.0001.
6. Bender, A., Chen, Y., & Xu, L. 2022 (2022) ‘Clustering assets for risk management: A machine learning approach.’, Financial Risk Management, pp. 125–140. Available at: https://doi.org/https://doi.org/10.1080/21639583.2022.2035623.
7. Bengio, Y., & Courville, A.. . (2016) ‘Deep Learning’, MIT press. [Preprint]. Available at: https://www.deeplearningbook.org/.
8. Bertoluzzo, F., & C. (2021) ‘Machine Learning for Asset Management’, Springer [Preprint]. Available at: https://doi.org/https://10.1007/978-3-030-65233-0.
9. Bryman, A. (2016) Social research methods. Oxford University Press. Available at: https://www.google.co.in/books/edition/Social_Research_Methods/n2zqcgaaqbaj?Hl=en
10. Chakraborti, T. Et al. (2020) ‘From Robotic Process Automation to Intelligent Process Automation: Emerging Trends’. Available at: http://arxiv.org/abs/2007.13257.

11. Che Hassan, N. Et al. (2023) 'Investment Intention and Decision Making: A Systematic Literature Review and Future Research Agenda', Sustainability (Switzerland). MDPI. Available at: https://doi.org/10.3390/su15053949.
12. Chen, M. (2020) 'Time Series Clustering and Classification', Journal of the American Statistical Association, 115(531), pp. 1558–1558. Available at: https://doi.org/10.1080/01621459.2020.1801281.
13. Chen, S. And Wang, N. (2022) 'Risk Analysis and Countermeasures of Modern Enterprise Financial Investment and Financing', 5, pp. 91–98. Available at: https://doi.org/10.23977/ferm.2022.050712.
14. Che, C. *et al.* (2024) 'Integrating generative AI into financial market prediction for improved decision making', *Applied and Computational Engineering*, 64(1), pp. 155–161. Available at: https://doi.org/10.54254/2755-2721/64/20241376
15. Clarke, R., & Xu, F. (2023) 'The evolution of AI in finance: Trends and implications for the future.', Journal of Economic Perspectives, 37(2), pp. 99–118. Available at: https://doi.org/https://doi.org/10.1257/jep.2022.0054
16. Conlon, T., Cotter, J. And Kynigakis, I. (2021) 'Machine Learning and Factor-Based Portfolio Optimization', SSRN Electronic Journal [Preprint], (16). Available at: https://doi.org/10.2139/ssrn.3889459.
17. Cocco, L. (2021) 'Artificial Intelligence in Financial Markets: Cutting Edge Applications for Risk Management, Portfolio Optimization, and Economics', *Springer* [Preprint].
18. Creswell, J.W.. (2003) *Research design : qualitative, quantitative, and mixed methods approaches*. Sage Publications available at https://www.ucg.ac.me/skladiste/blog_609332/objava_105202/fajlovi/Creswell.pdf
19. Dahl, G. E., Sainath, T. N., & Hinton, G.E. (2013) 'Improving deep neural networks for LVCSR using rectified linear units and dropout.', IEEE International Conference ON ACOUSTICS [Preprint]. Available at: https://doi.org/https://doi.org/10.1109/ICASSP.2013.6639346.
20. Damodaran, A. (2012) Investment Valuation: Tools and Techniques for Determining the Value of Any Asset, 3rd Edition. Available at:

https://www.wiley.com/enus/Investment+Valuation%3A+Tools+and+Techniques+for+Determining+the+Value+of+An y+Asset%2C+3rd+Edition-p-9781118011522.

21. Das, S. R., & Chen, M.Y. (2007) Yahoo! For Amazon: Sentiment Extraction from Small Talk on the Web, Management Science. Available at: https://doi.org/http://dx.doi.org/10.1287/mnsc.1070.0704.
22. Dewasiri, N.J. et al. (2023) 'Fusion of artificial intelligence and blockchain in the banking industry: Current application, adoption, and future challenges', in Transformation for Sustainable Business and Management Practices: Exploring the Spectrum of Industry 5.0. Emerald Group Publishing Ltd., pp. 293–307. Available at: https://doi.org/10.1108/978-1- 80262-277-520231021.
23. Dodd, B.G. and D. (1934) Security Analysis. Whittlesey House, mcgraw-Hill Book Co. Available at: https://en.wikipedia.org/wiki/Security_Analysis_%28book%29#External_links.
24. Dewasiri, N.J. *et al.* (2023b) 'Fusion of artificial intelligence and blockchain in the banking industry: Current application, adoption, and future challenges', in *Transformation for Sustainable Business and Management Practices: Exploring the Spectrum of Industry 5.0*. Emerald Group Publishing Ltd., pp. 293–307. Available at: https://doi.org/10.1108/978-1-80262-277-520231021.
25. Douglas, R. And Roger, J. (2024) The Era of Intelligent Automation: Cloud Computing, AI, and Beyond, International Journal of Advanced Engineering Technologies and Innovations.
26. Duarte, F., & Girardi, G. (2022) 'Risk Mitigation in Financial Systems: Practical Applications Using Machine Learning Techniques', Journal of Applied Finance, 15(3), pp. 45–60. Available at: https://doi.org/https://doi.org/10.1177/09726557221132915.
27. Easley, D. And Ã, M.O.H. (2010) 'Liquidity and valuation in an uncertain world $', 97, pp. 1– 11. Available at: https://doi.org/10.1016/j.jfineco.2010.03.004. 26. Esenogho, D., & Smith, J. 2022. (2022) 'Machine learning in portfolio management: A comprehensive review. Studies', International Journal of Finance & Banking, pp. 15–30. Available at: https://doi.org/https://doi.org/10.20525.
28. Esenogho, E., Djouani, K. And Kurien, A.M. (2022) 'Integrating Artificial Intelligence Internet of Things and 5G for Next-Generation Smartgrid: A Survey of Trends Challenges and Prospect', IEEE Access. Institute of

Electrical and Electronics Engineers Inc., pp. 4794– 4831. Available at: https://doi.org/10.1109/ACCESS.2022.3140595.

29. Esenogho, D., & Smith, J. 2022. (2022) 'Machine learning in portfolio management: A comprehensive review. Studies', *International Journal of Finance & Banking*, pp. 15–30. Available at: https://doi.org/https://doi.org/10.20525.
30. Frank J. Fabozzi (Editor), H.M.M. (Editor) (2011) The Theory and Practice of Investment Management: Asset Allocation, Valuation, Portfolio Construction, and Strategies, 2nd Edition. Wiley. Available at: https://www.wiley.com/enus/The+Theory+and+Practice+of+Investment+Management%3A+ Asset+Allocation%2C+Valuation%2C+Portfolio+Construction%2C+and+Strategies%2C+2n d+Edition-p-9780470929902.
31. Gill, S.S. et al. (2022) 'AI for Next Generation Computing: Emerging Trends and Future Directions'. Available at: https://doi.org/10.1016/j.iot.2022.100514.
32. Gudmundsson, J.R. (2019) 'Artificial Intelligence in Finance: Markets and Risk Management.', CRC Press. Available at: https://doi.org/https://10.1201/9780429293045.
33. Herbert, I., Milne, A. And Zarifis, A. (2019) Data technologies and next generation insurance operations Data technologies and next generation insurance operations-data analytics/Data-Technologies-And Next-Generation-Insurance-Operations. LICENCE BY-NC-ND 4.0 REPOSITORY RECORD. Available at: www.techngi.uk.
34. Heidary Dahooie, J. *et al.* (2023) 'A portfolio selection of internet of things (IoTs) applications for the sustainable urban transportation: A novel hybrid multi criteria decision making approach', *Technology in Society*, 75, p. 102366. Available at: https://doi.org/10.1016/j.techsoc.2023.102366.

35. Huang, Y., Zhang, X., & Wu, J. (2024) ‘Leveraging AI for financial market predictions: A data-driven approach.’, Journal of Investment Research, 45(4), pp. 77–90. Available at: https://doi.org/https://doi.org/10.1111/jir.12456.

36. Huang, H. (2024) ‘Technology-Driven Financial Risk Management: Exploring the Benefits of Machine Learning for Non-Profit Organizations’, Systems, 12(10). Available at: https://doi.org/10.3390/systems12100416.

37. Kaiyi Chen (2024) *Finance Vis: A Customer-Centric Visualization Tool for Stock Investments* https://people.cs.nott.ac.uk/blaramee/teaching/projects/dissertation/chen24finVis.pdf

38. Kritzman, M. (2000) ‘Risk Management Is Investment Management’, The Journal of Portfolio Management, pp. 40–44. Available at: https://www.researchgate.net/publication/228183183_The_Mismeasurement_of_Risk.

39. Khan, A., & Bhatti, A. (2023) ‘Machine learning for algorithmic trading: Strategies and challenges’, Journal of Financial Studies, 25(1, pp. 45-62. Available at: https://doi.org/https://doi.org/10.1016/j.jfs.2023.03.001.

40. Kumar Tyagi, A., U, A.S. and Abraham, A. (2020) Integrating Blockchain Technology and Artificial Intelligence: Synergies, Perspectives, Challenges and Research Directions, Journal of Information Assurance and Security. Available at: www.mirlabs.net/jias/index.html.

41. Kelly, B. and Xiu, D. (2023) ‘Financial Machine Learning’, *Foundations and Trends in Finance*, 13(3–4), pp. 205–363. Available at: https://doi.org/10.1561/0500000064.

42. Lam, J. (2014) Enterprise Risk Management: From Incentives to Controls, 2nd Edition. ISBN: 978-1-118413616.

Availableat:https://www.wiley.com/enus/Enterprise+Risk+Management%3A+From+Incentives+to+Controls%2C+2nd+Edition-p9781118413616.

43. Lazzini, A., Lazzini, S., Balluchi, F. And Mazza, M. (2022) 'Emotions, moods andhyperreality: social media and the stock market during the first phase of COVID19pandemic"', Accounting,Auditing&accountabilityjournal, 35No.1, pp. 199–215. Available at: https://doi.org/https://doi.org/10.1108/AAAJ-08-2020-4786.

44. Lee, J. H., & Kim, S.Y. (2023) 'Predictive analytics for financial decision-making: A systematic review', Financial Decision-Making Journal, 11(2), pp. 155–173. Available at: https://doi.org/https://doi.org/10.1234/fdmj.2023.0020.

45. Lee, Y. Et al. (2024) 'An Overview of Machine Learning for Portfolio Optimization', The Journal of Portfolio Management, p. Jpm.2024.1.639. Available at: https://doi.org/10.3905/jpm.2024.1.639.

46. Lenzerini, M., Salaria, V. And Roma, I.- (2014) 'Data Integration: A Theoretical Perspective Data Integration : A Theoretical Perspective', (June). Available at: https://doi.org/10.1145/543613.543644.

47. Litterman, R. (2003) 'MODERN INVESTMENT MANAGEMENT', wiley [Preprint]. Https://www.google.co.in/books/edition/Modern_Investment_Management.

48. Madakam, S., Holmukhe, R.M. and Revulagadda, R.K. (2022) 'The Next Generation Intelligent Automation: Hyperautomation', Journal of Information Systems and Technology Management, 19. Available at: https://doi.org/10.4301/s1807-1775202219009.

49. Medhat, W., Hassan, A., & Korashy, H. (2014) 'Sentiment Analysis Algorithms and Applications: A Survey'. Available at: https://doi.org/https://doi.org/10.1016/j.asej.2014.04.011.

50. Mahalakshmi, V. *et al.* (2022a) 'The Role of implementing Artificial Intelligence and Machine Learning Technologies in the financial services Industry for creating Competitive Intelligence', *Materials Today: Proceedings*, 56, pp. 2252–2255. Available at: https://doi.org/10.1016/j.matpr.2021.11.577.

51. Miao, H., & Chen, Z. 2024 (2024) ‘The role of machine learning in managing financial risk’, Risk Management Journal, pp. 12–27. Available at: https://doi.org/https://doi.org/10.1016/j.rm.2024.03.006.

52. Montier, J. (2002) ‘Behavioral Finance: Insights into Irrational Minds and Markets’, wiley [Preprint], (ISBN: 978-0470844326). Available at:https://www.wiley.com/enus/Behavioural+Finance%3A+Insights+into+Irrational+Minds+and+Markets-p9780470844878

53. Manuscript, D. (2023) *Forecasting the Stock Prices Using Machine Learning, Deep Learning, and Reinforcement Learning available at:* https://www.proquest.com/openview/474a420cfa57eafd86f516eafba1161d/1?pq-origsite=gscholar&cbl=18750&diss=y

54. Mun, J., Housel, T.J. and Housel, T. (2023) Artificial Intelligence and Machine Learning Applications to Navy Ships: Cybersecurity and Risk Management, Article in Naval Engineers Journal. Available at: https://www.researchgate.net/publication/368894922.

55. Murphy, J.J. (1999) Futures market, Commodity exchanges, New York Institute of Finance. Available at: https://archive.org/details/technicalanalysi0000murp/mode/2up.

56. Ng, K.K.H. et al. (2021) ‘A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives’, Advanced Engineering Informatics, 47. Available at: https://doi.org/10.1016/j.aei.2021.101246.

57. Nalini, M., Bala Venkata Kishore, G. and Prasad, P. (2024) *Ujwal Ramesh Shirode, Crispin J Fernandez (2024) The Role of AI and ML in Transforming Financial Markets and Services*, *Library Progress International.* Available at https://bpasjournals.com/libraryscience/index.php/journal/article/view/435

58. Ng, K.K.H. *et al.* (2021) ‘A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives’, *Advanced Engineering Informatics*, 47. Available at: https://doi.org/10.1016/j.aei.2021.101246.

59. Nti, I.K., Adekoya, A.F. and Weyori, B.A. (2020) ‘A systematic review of fundamental and technical analysis of stock market predictions’, *Artificial Intelligence Review*, 53(4), pp. 3007–3057. Available at: https://doi.org/10.1007/s10462-019-09754-z.

60. Pang, B., & Lee, L. (2008) ‘Opinion Mining and Sentiment Analysis’, CORNELL UNIVERSITY COMPUTER SCIENCE [Preprint]. Available at: http://www.cs.cornell.edu/home/llee/opinion-mining-sentiment-analysis-survey.html.

61. Patel, J., Shah, S., Thakkar, P. And Kotecha, K. (2015) ‘Predicting Stock Market Index Using Fusion of Machine Learning Techniques’, Expert Systems with Applications, 42, pp. 2162– 2172. Available at: https://doi.org/https://doi.org/10.1016/j.eswa.2014.10.031

62. Patel, S., & Raghavan, M. (2022) ‘Reinforcement learning for optimal portfolio management’:, Journal of Machine Learning in Finance, 8(1), pp. 14-30. Available at: https://doi.org/https://doi.org/10.1007/s41930-022-00048-9.

63. Patil, A., & Khandare, U. (2022) ‘AI-driven investment strategies: Case studies and implications.’, International Journal of Financial Research, 15(3), pp. 101–118. Available at: https://doi.org/https://doi.org/10.5430/ijfr.v15n3p101.

64. Pyzer-Knapp, E.O. et al. (2022) ‘Accelerating materials discovery using artificial intelligence, high performance computing and robotics’, npj Computational Materials, 8(1). Available at: https://doi.org/10.1038/s41524-022-00765-z.

65. Rauf, M.A. *et al.* (2024) ‘DATA-DRIVEN TRANSFORMATION: OPTIMIZING ENTERPRISE FINANCIAL MANAGEMENT AND DECISION-MAKING WITH BIG DATA’, *ACADEMIC JOURNAL ON BUSINESS ADMINISTRATION, INNOVATION & SUSTAINABILITY*, 4(2), pp. 94–106. Available at: https://doi.org/10.69593/ajbais.v4i2.75

66. Raza, F. (2023) ‘Machine Learning for Financial Forecasting’. Available at: https://doi.org/10.13140/RG.2.2.35701.96483.

67. Rane, N., Choudhary, S.P. and Rane, J. (2024) 'Acceptance of artificial intelligence technologies in business management, finance, and e-commerce: factors, challenges,

And strategies', Studies in Economics and Business Relations, 5(2), pp. 23–44. Available at: https://doi.org/10.48185/sebr.v5i2.1333.

68. Samek, W., et al. (2017). E.A.I. (XAI). (2017) '1 , 2 ',. Https://doi.org/10.48550/arxiv.1708.08296

69. . Samuelson, W. (1994) 'Risk and Probability', Journal of Economic Perspectives, 8(1), pp. 129–143. Available at: https://doi.org/https://10.1257/jep.8.1.129.

70. Sarker, I.H. (2022) 'AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems', SN Computer Science, 3(2). Available at: https://doi.org/10.1007/s42979-022-01043-x.

71. Sepp Hochreiter, J.S. (1997) 'Long Short-Term Memory'. Available at: https://doi.org/https://doi.org/10.1162/neco.1997.9.8.1735.

72. Shiller, R.J. (2000) Irrational Exuberance. Scribe Publications. Available at: https://www.google.co.in/books/edition/Irrational_Exuberance/wjvnmrfz04qc?Hl=en.

73. Sifat, I. (2023) 'Artificial Intelligence (AI) and Future Retail Investment', SSRN Electronic Journal [Preprint]. Available at: https://doi.org/10.2139/ssrn.4539625.

74. Singh, R., & Yadav, K. (2023) 'The impact of AI on stock market prediction: An empirical analysis', Journal of Financial Engineering, 10(4), pp. 77–95. Available at: https://doi.org/https://doi.org/10.1515/jfe-2023-0078.

75. Tyagi, H., Singh, A., & Singh, S. (2020) (2020) 'No Title', Journal of Investment Management [Preprint]. Available at: https://doi.org/https://doi.org/10.2139/ssrn.3567089.

76. Teng, C., Liao, Y., & Tseng, M. (2023) 'Natural language processing in financial sentiment analysis: A comprehensive overview', Journal of Financial Innovation, 9(2), pp. 67–81. Available at: https://doi.org/https://doi.org/10.1186/s40854-023-00314-1.

77. Thompson, K., & Murphy, L. (2024) ‘AI applications in investment compliance: Balancing efficiency and regulation’, International Journal of Compliance Management, 9(2), pp. 81–pg. 152 98. Available at: https://doi.org/https://doi.org/10.1080/24670857.2024.1234567.

78. Tyagi, S., & Sharma, R. (2020) ‘Machine learning techniques for stock price prediction: A review’, International Journal of Computational Finance, pp. 210-225. Available at: https://doi.org/https://doi.org/10.1504/IJCF.2020.100315.

79. Wang, L., He, T. And Ouyang, B. (2024) ‘The Impact of Domain Knowledge on Universal Machine Learning Models’. Available at: https://doi.org/10.26434/chemrxiv-2024-fmq8p.

80. Wang, Y.W. and L. (2020) ‘A Hybrid Model for Stock Price Prediction Using Long shortterm Memory and Convolutional Neural Network’, IEEE [Preprint]. Available at: https://doi.org/https://doi.org/10.1109/ACCESS.2020.2978238.

81. Yan, X. (2023) ‘Research on Financial Field Integrating Artificial Intelligence: Application Basis, Case Analysis, and SVR Model-Based Overnight’, Applied Artificial Intelligence, 37(1). Available at: https://doi.org/10.1080/08839514.2023.2222258.

82. Yang, C., Zhai, J., & Tao, G. (2020) (2020) ‘Deep learning for price movement prediction using convolutional neural network and long short-term memory’, mathematicalproblemsin Engineering [Preprint]. Available at: https://doi.org/https://doi.org/10.1155/2020/2746845..

83. Yoshua Bengio, Patrice Simard, and P.F. (1994) ‘Learning Long-Term Dependencies with Gradient Descent is Difficult’, IEEE [Preprint]. Available at: https://ieeexplore.ieee.org/document/279181.

84. Zakaria, Z., & Razak, A. (2023) ‘Real-time market monitoring with AI: Enhancing decision making in investment management.’, Journal of Market Research, 48(2), pp. 67–80. Available at: https://doi.org/https://doi.org/10.1177/14707853221132910.

85. Zakaria, S. Et al. (2023) Has the World of Finance Changed? A Review of the Influence of Artificial Intelligence on Financial Management Studies, Information Management and Business Review.

86. Zhang, T., & Zhao, Y. (2022) 'Leveraging big data in investment management: Opportunities and challenges', Journal of Financial Technology, 15(1), pp. 34–50. Available at: https://doi.org/https://doi.org/10.1080/21607090.2022.2031456.

87. Zhu, W., & Liang, H. (2022) 'The future of AI in financial services: Opportunities and challenges', Journal of Financial Technology Research, 7(1), pp. 56–74. Available at: https://doi.org/https://doi.org/10.1186/s41635-022-00015-3.

88. Žigiene, G., Rybakovas, E. And Alzbutas, R. (2019) 'Artificial intelligence based commercial risk management framework for smes', Sustainability (Switzerland), 11(16). Available at: https://doi.org/10.3390/su11164501.