Project Dissertation Report on

AI & Big Data in Financial Services

Submitted by

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Under the Guidance

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CERTIFICATE

This is to certify that the work titled **'AI & Big Data in Financial Services'** as part of the final year Major Research Project submitted by Gaurav Kumar Sharma in the 4th Semester of MBA, Delhi School of Management, Delhi Technological University during January-May 2021 is his original work and has not been submitted anywhere else for the award of any credits/ degree whatsoever.

The project is submitted to Delhi School of Management, Delhi Technological University impartial fulfillment of the requirement for the award of the degree of Master of Business Administration.

DECLARATION

I hereby declare that the work titled **'AI & Big Data in Financial Services'** as part of the final year Major Research Project submitted by me in the 4^{th} Semester of MBA, Delhi School of Management, Delhi Technological University, during January-May 2021 under the guidance of Prof. Mohit Beniwal is my original work and has not been submitted anywhere else.

The report has been written by me in my own words and not copied from elsewhere. Anything that appears in this report which is not my original work has been duly and appropriately referred/ cited/acknowledged.

ACKNOWLEDGMENT

It is a great pleasure for me to acknowledge the kind of help and guidance received during the research work. I would like to thank my faculty advisor Prof. Mohit Beniwal, who helped me to take up the topic **'AI & Big Data in Financial Services'** and guided me to complete this project properly. The project provided me with an excellent opportunity to explore the areas of Finance and Artificial Intelligence.

I am highly indebted to Delhi School of Management, Delhi Technological University for giving me an opportunity to work on this project. Lastly, I would like to express my gratitude to all the honorable faculty members for sharing their experience and expertise on this project.

I have put all my efforts to ensure that the project is completed in the best possible manner and also ensured that the project is error-free.

ABSTRACT

Over the past few years, technology has altered the operating psychology of companies. Artificial Intelligence (AI) is becoming increasingly important and in demand, and the financial sector is steadily turning its focus to AI. In a variety of ways, financial institutions are experimenting with and integrating technology. Artificial Intelligence is improving and becoming smarter every day. Investment management companies have embraced Artificial Intelligence at a much faster rate than other industries. This is due to the fact that the financial sector still relies heavily on human involvement in its operations. The Indian banking sector is experimenting with artificial intelligence to improve customer service.

Purpose

As Artificial Intelligence technology reshapes the investment management industry, the aim of this research paper is to define specific use cases so that investment practitioners and firms can take appropriate steps now to navigate the evolving environment and plan for investment success.

Design/methodology/approach

The basis for this research paper is exploratory research. The current analysis is focused on both primary and secondary data. Primary data is gathered from top commercial banks and investment firms' professionals, i.e. ICICI Prudential, BOI AXA, SBI, and Bajaj Finance were asked questions about using Artificial Intelligence to enhance customer service, challenges encountered, and input from customers. Fifty professionals were polled to find out how much they knew about Artificial Intelligence enabled services, how much they used them, and how satisfied they were with them. Secondary data was gathered from a variety of sources, including academic papers, blogs, and documents, in order to ensure a thorough understanding of the topic and the accuracy of the data.

Findings

Big data and Artificial Intelligence have the ability to bring the most dramatic improvement to the investment management industry that current practitioners will ever see. Future successful investment companies will begin strategically planning their incorporation of big data and Artificial Intelligence techniques into their investment processes right now. Collaborative organisational cultures, cognitive diversity, and T-shaped teams will allow successful investment professionals to recognise and leverage the opportunities brought on by these emerging technologies and applications.

Research limitations

This study is restricted to AI in investment management firms only.

Keywords

Artificial Intelligence, investment, machine learning, analytics, management, techniques.

Paper type- Research paper

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Chapter 1

INTRODUCTION

Would human investment managers be replaced by robots?
As the investment industry stands on the cusp of perhaps its biggest technological shift, I set out to show where big data and artificial intelligence (AI) applications in investment management stand right now, as well as how and where such technologies can be used.

Just a small percentage of investment professionals use AI and big data tools in their decision-making processes, according to my research. I attempted to talk with a few experts who are currently implementing these technologies in order to provide a roadmap for investment companies and individuals seeking to enter the next technological frontier.

Their use cases, which are detailed in this article, are instructive. They emphasize, among other things, AI's potential as well as its drawbacks, as well as the continuing importance of human judgement in investment processes.

I believe in the "Artificial Intelligence + HI" model, which notes that Artificial Intelligence techniques can help investment professionals achieve higher levels of performance by freeing them from repetitive works and facilitating better decision-making that utilizes both machines and humans' collective intelligence.

Future investment firms that strategically intend to incorporate Artificial Intelligence and big data techniques into their investment processes will be successful. Those who can comprehend and best leverage the opportunities created by these emerging innovations would be successful investment professionals.
The future is here.

OBJECTIVES OF THE STUDY

The aim of this research is to identify specific use cases as Artificial Intelligence technology reshapes the investment management industry so that investment practitioners and firms can take effective steps now to navigate the changing environment and prepare for investment success.
1. What are the current developments in the investment process?

2. What big data and artificial intelligence technologies were used to make these adjustments?
3. What are the main tasks (and related skills) in a team, and how do they work together to affect change?

SCOPE OF THE STUDY

Artificial Intelligence in investment management firms is the focus of the research.

RESEARCH GAPS

In terms of technical advancement and artificial intelligence application, the financial services industry has advanced by leaps and bounds. However, there is no empirical data on the use of humanoid robots in the industry. More research is needed into the tasks that the robot will perform, as it is currently only focused on answering basic customer questions.

The current study focused solely on the implementation of Artificial Intelligence for different services, but more research on customer satisfaction is needed.

There's a lot of room to talk about the obstacles that fintech companies face while delivering these services, as well as how cost-effective and competitive they've been. The entire scope of Artificial Intelligence has been limited to offering basic information to clients on primary customer services, but what other services it may be able to cover requires further investigation.

CHAPTER 2

LITERATURE REVIEW

Chapter 2

LITERATURE REVIEW

2.1 Machine Learning Improves Trading Strategy and Execution By Anthony Ledford (2019)

This is a difficult task. Nothing works if you buy it off the shelf. It's a common misconception that you can extract useful signals by combining a smart people, fancy computers and lot of data. It is essential to have prior experience. Only a limited amount of information is really "useful." Alternative data opens up new possibilities, but it frequently lacks historical context. The benchmark for determining whether or not to use machine learning should be what you can extract using non-ML methods. Is the extra value you get from machine learning worth the added complexity? As a result, our motto is "Use the simplest method that does the job." Open source should be embraced. Contribute back to stay involved in the long run. Make a circle of goodness. Make a bold move in the process. Have the resolve to determine what ventures are worth pursuing and to kill off those that don't seem to be promising.

2.2 Using Machine Learning to Generate Signals for Quant Models By Poul Kristensen (2018)

As inputs to analytical tools for credit spreads and defaults, we use a wide range of measures of leverage, borrowing, issuance pattern, credit quality, delinquencies, liquidity and so on. We were able to integrate larger volumes of data, increase prediction accuracy, and classify the most appropriate predictors to track in dashboards using machine learning techniques.

The signals produced by machine learning techniques, particularly the value signals and cycle, allow us to concentrate on the most important indicators when making portfolio decisions, allowing us to better assess market opportunities and risks. The cycle system has also allowed us to track a wider range of indicators while gauging a portfolio's outlook, saving time in our preparations for investment committee meetings as well as in portfolio monitoring on a daily basis.

2.3 Using Deep Learning to Improve Equity Trading Volume Prediction By Dajun Wang (2018)

Trading volume prediction project demonstrates that Artificial Intelligence technology can be a valuable addition to State Street's core investment functions in the front office. It sets a benchmark for potential projects aimed at turning AI-assisted models into useful and capable business tools.

Future projects can draw on this knowledge to enhance the company's operations while adhering to architectural data governance, project life cycle management requirements and designs.

2.4 In Sell-Side Study, Using AI and Alternate Data Analysis By Ingrid Tierens, , Dan Duggan (2019)

- Don't overlook the potential of advanced techniques and methods to help investment professionals become more successful, allowing them to devote more time to developing better alpha insights!
- For systematic administrators, alternative data does not always imply a competitive advantage. In reality, we believe that more specialised, sector-specific data sets are best suited to a fundamental analyst or portfolio manager who focuses on a small number of assets rather than an analyst or portfolio manager who covers a large number of assets.
- In our experience, a single data set or methodology has never been the primary driver of a research product. Alternative data contributes to the mosaic's richness, but it isn't a goal in and of itself.
- Good research analysts are always aware of data that is important to the assets they protect, but they do not know how to access and/or analyse the data to the best of their ability.
- Using alternative data does not always imply spending a lot of money. When properly combined with other data sources you might already be looking at, there is a lot of publicly accessible data that can be additive.

2.5 Using AI and Big Data to Analyse Earnings Conference Calls By Tal Sansani (2020)

- First and foremost, concentrate on the investment issue. Our data scientists come from a variety of academic backgrounds, the most important of which are computer science and statistics. It's worth noting that, while these backgrounds provide a solid base, they're difficult to apply in the context of equity investing without domain expertise. Investment teams are most competitive when they collaborate with technologists to develop a solution that is both cost-effective and well-implemented.
- The data from which a computer learns determines its intelligence. Obtaining additional data is often more successful than developing a more complex model. The more detailed the training data, the more generalised the machine's result while processing new events would be, avoiding common pitfalls such as overfitting. Since the information related to valuations

goes beyond conventional financial statements, gaining access to more diverse data is particularly important for equity investing.

- Humans and computers are mutually beneficial. A robo-analyst can systematically apply its objective and specific observations through thousands of companies at once, while human analysts are specialised at scrutinising a limited number of companies. In a highly competitive environment, we believe teams that combine the advantages of each are well placed.

2.6 Debt Portfolio Management Supported by AI and Big Data By Yang Rong, Qu Jing, Fan Siwen, Tian Qiaomei

The standardisation and cleaning of various data sets to the generation of insights from those data sets, developing an integrated framework necessitates a variety of skills. The five tasks must be centralised in one team to work toward a single goal, according to CSCI.

The conventional model of dividing systems, quants and data scientists creation into separate divisions is ineffective.

The CSCI team provides monthly "iterations" to the end users in between major releases that need CLAMC management approval. The CSCI team considers the strategy to be very successful in terms of obtaining client input quickly and reducing the likelihood of miscommunication between technology and investment functions across organisations.

2.7 Filing and processing insurance claims for AI and Big Data technologies, as well as analysing corporate risks By Xiao Jing(2013)

Ping An Technology's artificial intelligence centre is divided into two groups: technology application teams and business application teams.

Two of the teams collaborate to deliver intelligent solutions based on information graphs: One is in charge of big data analysis, data modelling, tool creation in general, and so on, while the other is in charge of information extraction, text analysis, and map building. The former cleans and incorporates structured and unstructured data, while the latter delivers final solutions using its information extraction and graph creation capabilities.

The team now includes over 1,000 artificial intelligence experts, the majority of whom come from top universities in the United States and abroad, including Harvard University, Carnegie Mellon University, Stanford University, Peking University, the University of Oxford, Tsinghua University, and the Chinese University of Science and Technology. The team's key members are technology pioneers in the fields of computer vision, natural language processing, medical image processing, and data analysis, with an average of over 20 years of experience. Prior to joining Ping An, they held key roles at leading high-tech firms such as Microsoft, IBM, Google and Uber.

In terms of the creation process, we get our ideas from a variety of pain points in the massive market, which motivates business experts and Artificial Intelligence scientists to brainstorm technological solutions. Each member will contribute his or her own knowledge and viewpoints, and the group will ultimately reach a consensus and develop implementation plans.

Ping has been using the system for over a year and has successfully processed over 30 thousand claims per day. It not only increases claim processing performance and therefore consumer service, but it also prevents billions of yuan in possible fraud.

2.8 Sentiment Analysis By Gary Kazantsev (2015)

The sentiment analysis product creation phase, as well as the wider text analysis effort that followed, yielded many key takeaways. End-to-end assessment is important, as previously stated. It's crucial to choose the target variable carefully. Starting with clear baselines and performing error analysis at each iteration of the model creation is critical; otherwise, we can easily discover that a particular date is positive or negative on its own—for example, due to inherent bias in the underlying data. Human-in-the-loop and interpretable models are crucial for this and other reasons.

2.9 Putting Together the Data Science Team By Ben Wicks, Mark Ainsworth(2014)

The two most important things I've learned are: (1) having a senior supporter who really believes in this type of creativity and (2) having the right combination of skills on the team. Experts from outside the industry, as well as a domain expert who knows what kind of insights are useful, are needed to develop the team.

Developing a data science capability appears to be both thrilling and fashionable, but it's useless if the results aren't positive and helpful. We were able to demonstrate the importance of the team

early on with a few fast wins. A data science skill can't just be about doing something trendy for the sake of doing something trendy; it has to add value to the company, whether that means bringing in alternative data or developing machine learning algorithms to search for significant changes in a data set's pattern.
The team has always been transparent on what we do and what we can do, and the decision to make the team a centralised function accessible to all investors was made early on. This meant that no one was concerned about the cost of using the data or the team's abilities, or whether they were using a resource that they weren't supposed to. Importantly, this decision enabled the team to identify areas of opportunity that cut through multiple investment teams, allowing them to build items that no single investment team could afford.

Signals from a broad data set are best used to help build an image of an organisation and/or the world in which it works, rather than to start a transaction without taking into account other variables.

2.10 Using Machine Learning to Improve the MPT Efficient Frontier By Marcos López de Prado(2018)

While Markowitz's portfolio optimization method is mathematically right, it has numerical issues in practise. Financial covariance matrices, in particular, have large condition numbers due to noise and signal. Estimation errors are magnified by the inverse of such covariance matrices, resulting in unstable solutions: Changing only a few rows in the observations matrix could result in completely different allocations. Even if the allocations estimator is impartial, the volatility associated with these unpredictable solutions inexorably contributes to high transaction costs, which can wipe out a significant portion of an investment strategy's profitability.

Correlation matrices based on factors, such as those found in BARRA's results only tangentially consider noise-induced instability and ignore signal-induced instability unpredictability. We've spoken about two strategies in this article: de-noising and NCO, both of which reduce the RMSE of estimated optimal portfolios significantly.

CHAPTER 3

RESEARCH METHODOLOGY

Chapter 3

RESEARCH METHODOLOGY

- Analysis is focused on exploratory research. Present analysis is focused on primary as well as secondary data.
- Primary data is gathered from top commercial banks and investment firms' experts, i.e. ICICI Prudential, BOI AXA, SBI, and Bajaj Finance were asked questions about using AI to enhance customer service, challenges encountered, and input from customers.
- A total of 50 professionals were polled to determine their level of awareness, usage, and satisfaction with Artificial Intelligence-enabled services.
- Secondary data was gathered from a variety of sources, including academic papers, blogs, and posts, to ensure a thorough understanding of the topic and the accuracy of the data.

CHAPTER 4

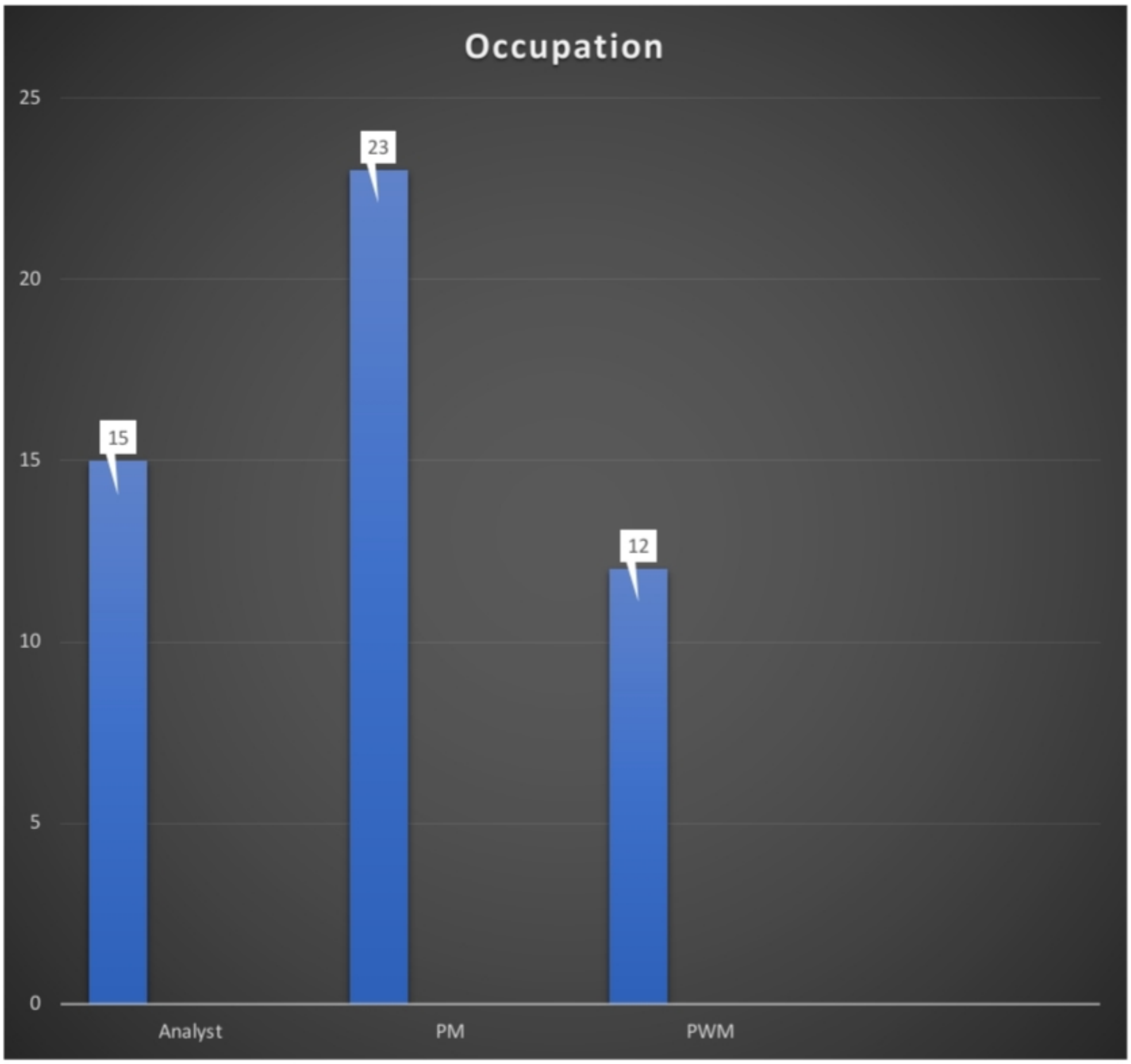
DATA ANALYSIS AND INTERPRETATION

Chapter 4

DATA ANALYSIS AND INTERPRETATION

FIGURE4.1 SURVEY DEMOGRAPHICS

4.1.1 OCCUPATION



4.1.2 YEARS OFEXPERIENCE

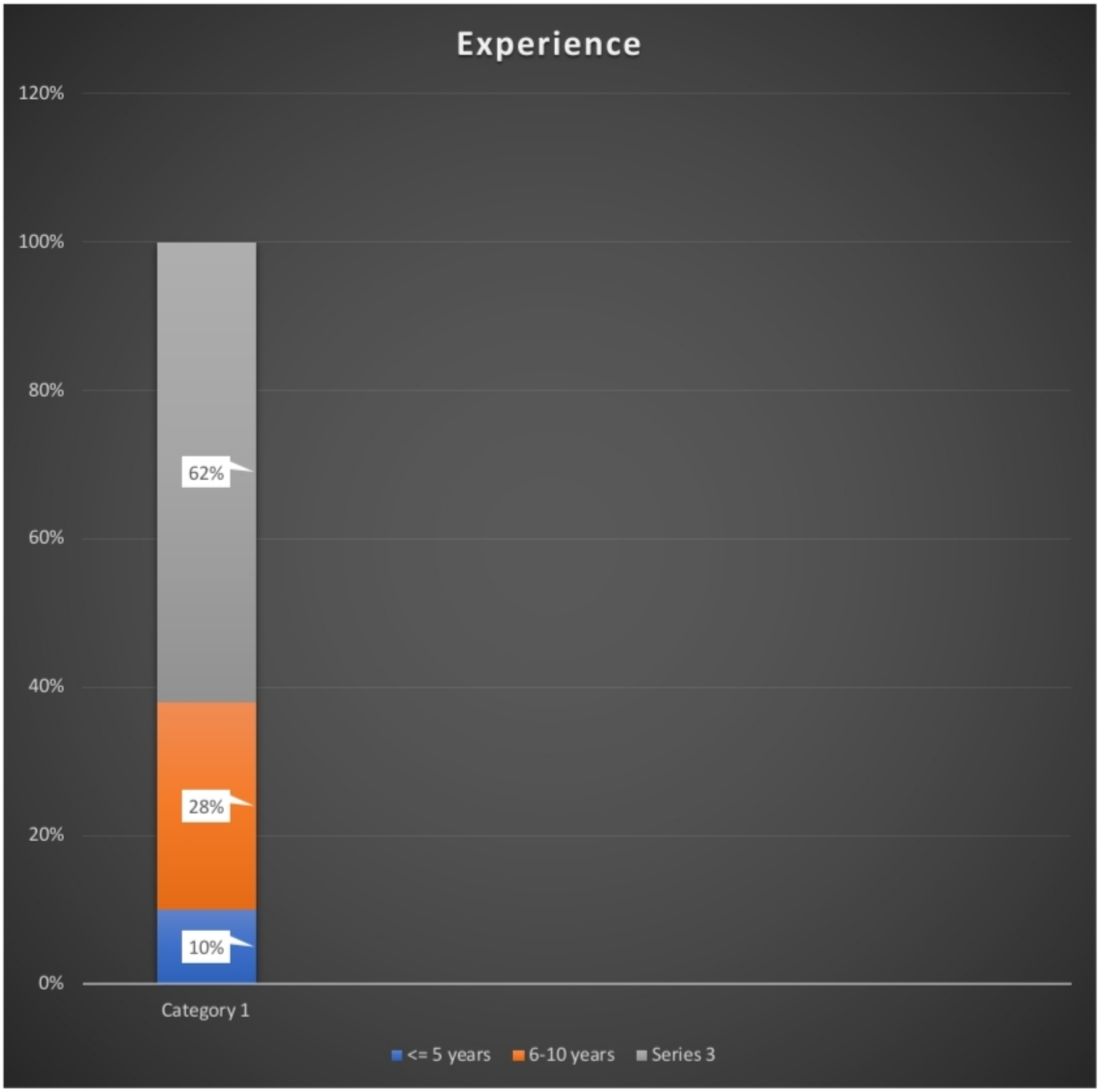


FIGURE 4.2 INVESTMENT STRATEGY AND PROCESS STATISTICAL TECHNIQUES

Portfolio Manager: In the last 12 months, which of these have you used for investment strategy and procedure?

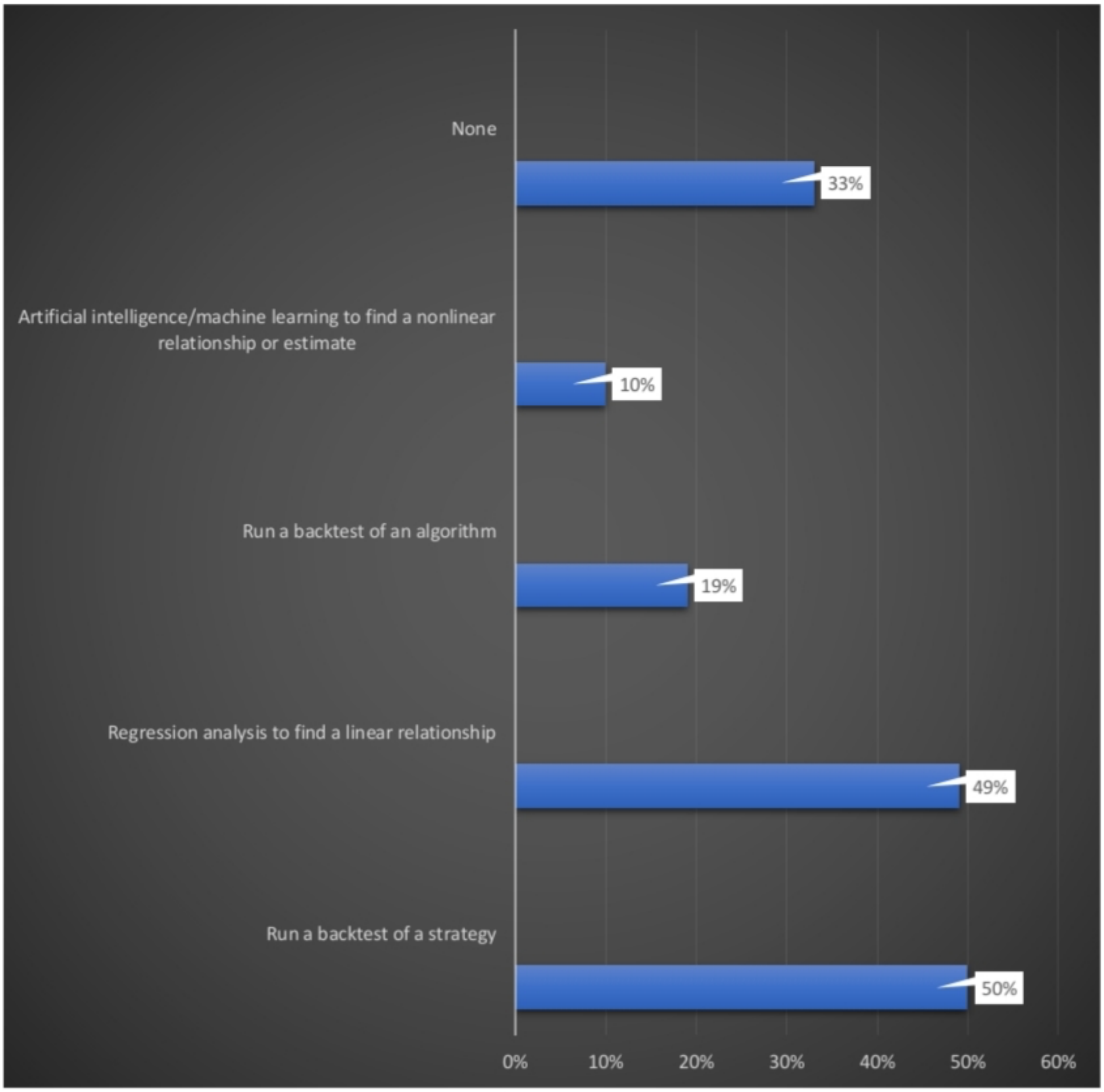


FIGURE 4.3 INVESTMENT STRATEGY AND PROCESS ORGANIZATIONAL RESPONSIBILITIES

Portfolio Manager: Which of the following options best describes your company's investment policy and process?

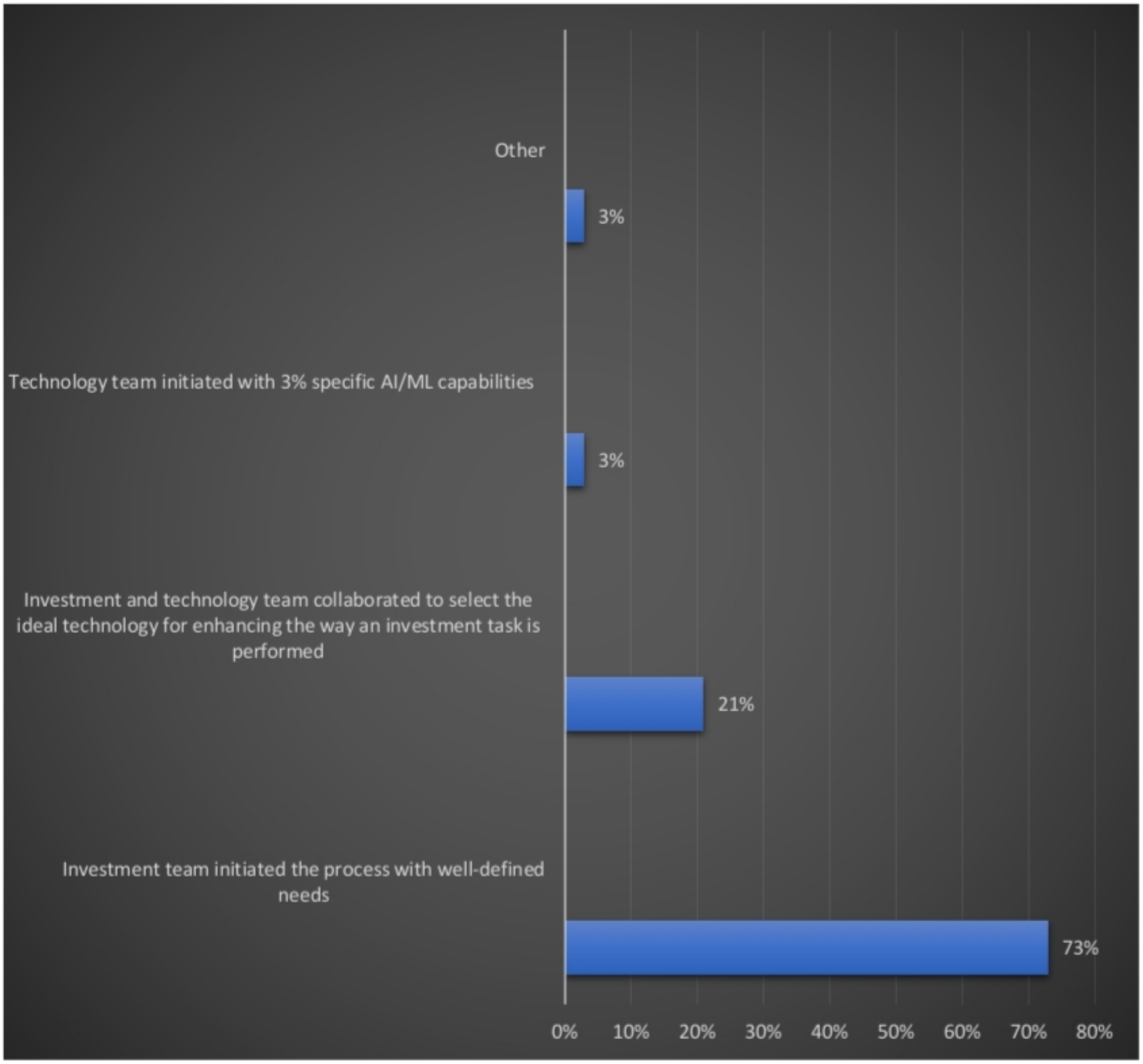


FIGURE 4.4. TRADING ALGORITHMS CREATED USING AI/ML TECHNIQUES

Portfolio Manager: In the last 12 months, which of the following AI/ML techniques have you used to build trading algorithms?

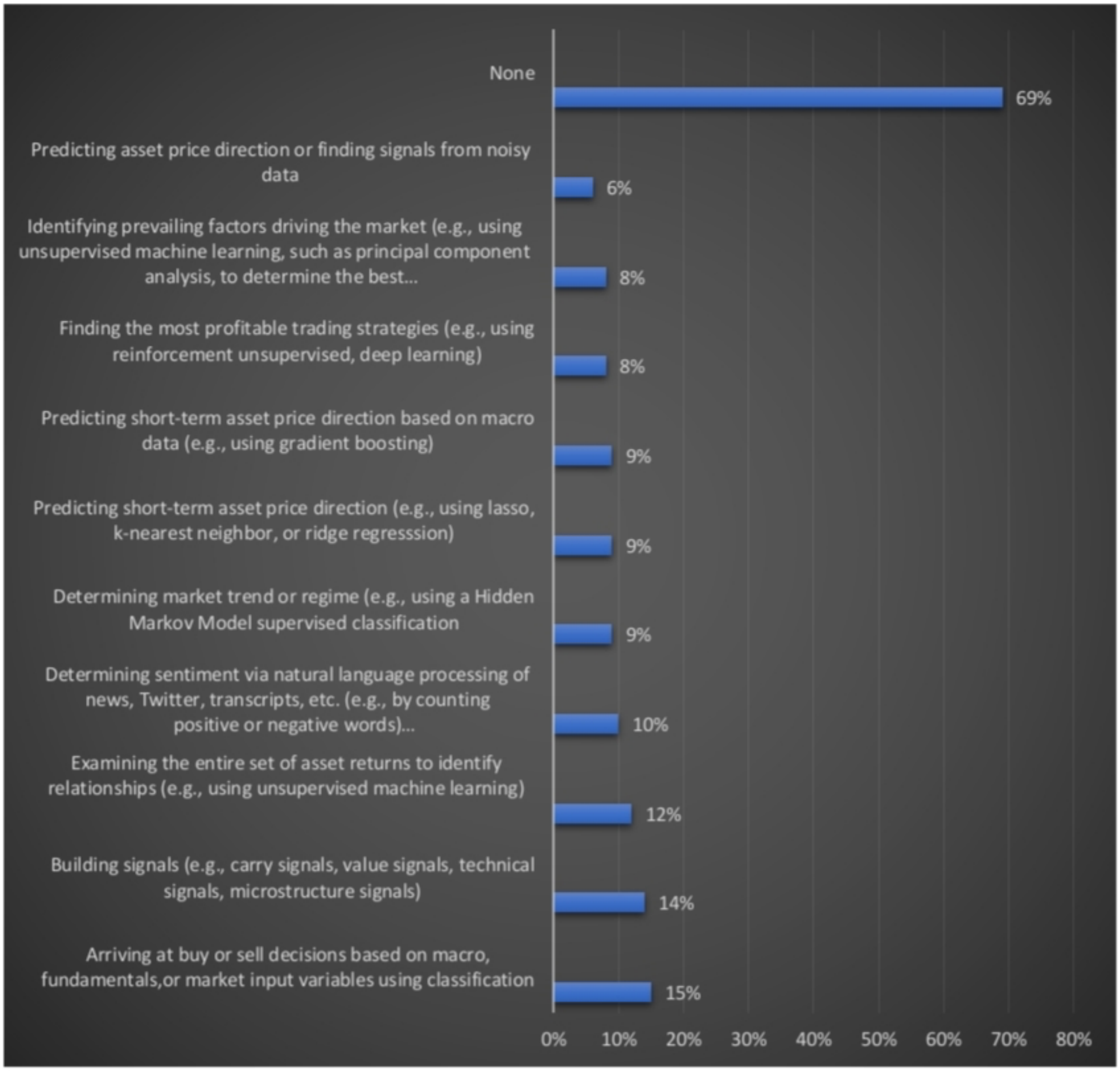
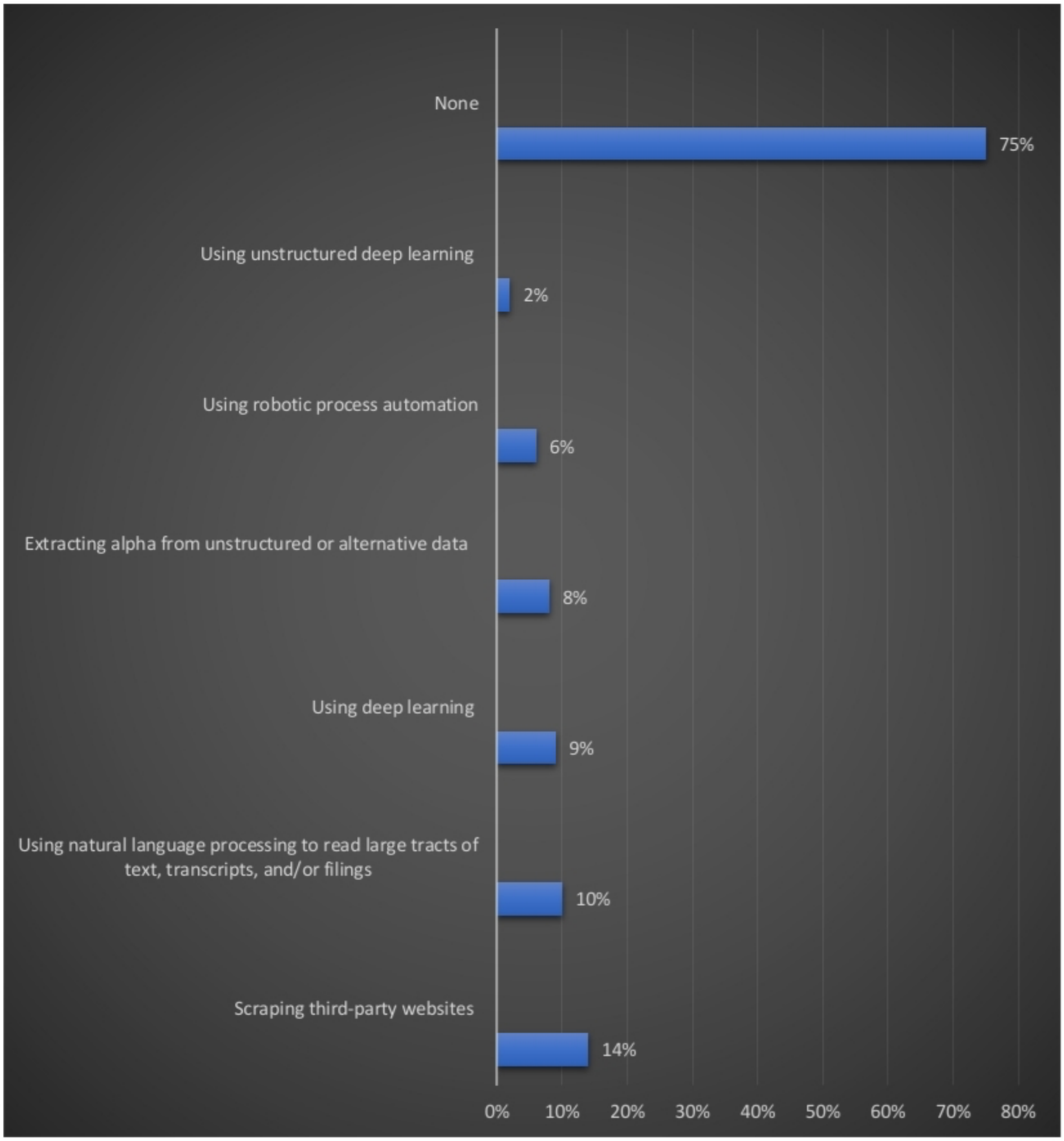


FIGURE 4.5 FOR INDUSTRY AND COMPANY ANALYSIS, AI/ML TECHNIQUES VS. UNSTRUCTRED/ALTERNATIVE DATA

4.5.1Analyst: In the last 12 months, have you done any of the following artificial intelligence/machine learning use cases for business and company analysis?



4.5.2Analyst: In the last 12 months, what type(s) of unstructured and/or alternative data have you used for your business and company analyses?

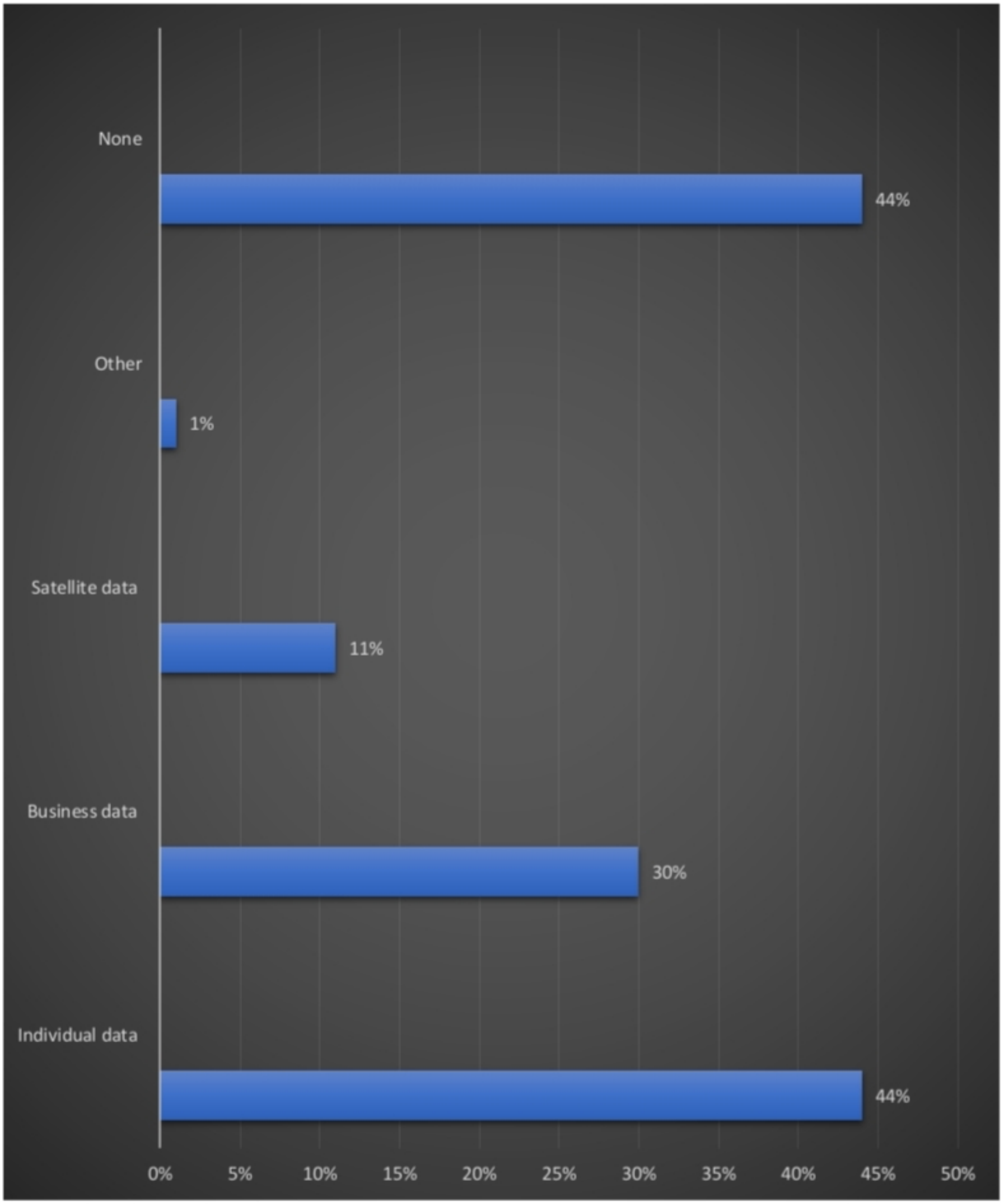
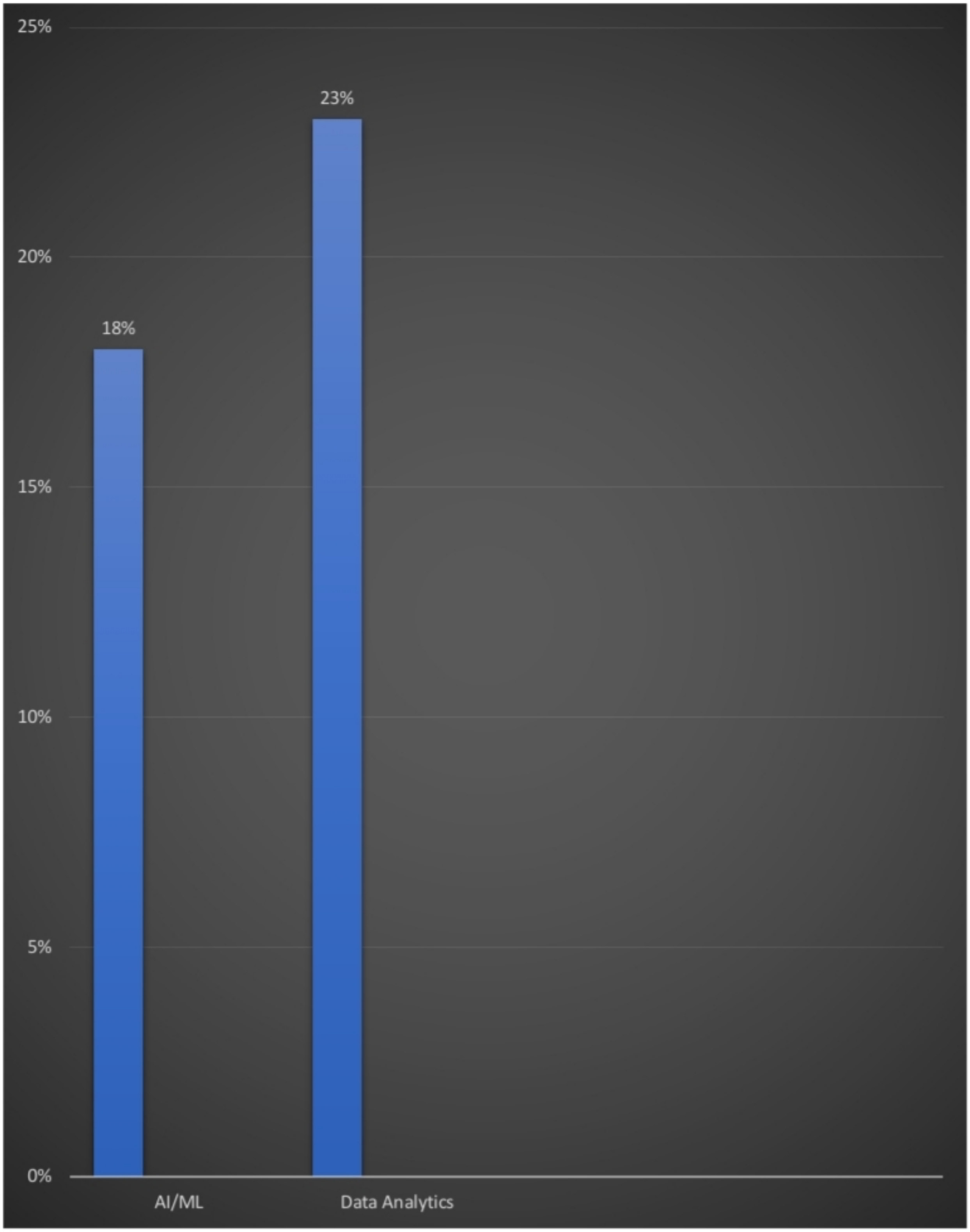


FIGURE 4.6 AI/ML VS. DATA ANALYTICS TRAINING



ANALYSIS

1. According to the survey findings, few investment professionals are currently using programmes commonly used in machine learning techniques, such as R, MATLAB and Python. For their investment strategies and processes, most people still rely on Excel and desktop market data tools.

2. In the previous 12 months, only 10% of those who replied to the survey used Artificial Intelligence/Machine Learning techniques to enhance their investment process.

3. As shown in Figure 3, the level of cooperation between investment and technology teams remains low at the organisational level. As these innovations gain traction, further integration will be needed to realise process efficiencies.

4. According to the study, the use of AI/ML techniques in trading strategies is also uncommon. Figure 4 shows that 69 percent of respondents say they haven't used any Artificial Intelligence/Machine Learning techniques to build trading algorithms in the last 12 months.

5. Professionals who use these techniques say they use them for a variety of reasons, including making buy or sell decisions based on multiple input variables (15 percent), building signals (14 percent), and assessing emotion using natural language processing (10 percent), among others.

6. Panel A of Figure 5 shows a similar result, with three-quarters of analyst respondents not using Artificial Intelligence/Machine Learning techniques for industry and business research. Scraping third-party websites (cited by 14 percent of respondents) and using natural language processing (NLP) are the two most common strategies among those who are (cited by 10 percent of respondents). In contrast, 40% of respondents said they used linear regression to analyse their industry and business (not shown).Investment practitioners prefer to analyse industries and companies using unstructured and alternative data rather than Artificial Intelligence/Machine Learning techniques. In the past 12 months, 44 percent of analyst respondents have used individual data, such as social media, product reviews, and

web search patterns, while only 11 percent have used satellite imagery, as shown in Panel B of Figure 5.However, one limitation of these findings is that they do not enable us to determine how often or extensively these data sources are used in business and company research. A large percentage of professionals, 44%, say they don't use this information.

7. In conclusion, these findings indicate that the investment industry is only in the early stages of adopting Artificial Intelligence and related technologies, with only a few professionals using big data/Artificial Intelligence techniques in their everyday investment processes. However, as shown in Figure 6, about a fifth of respondents claim to have participated in Artificial Intelligence/big data training. Overall, the industry appears poised to expand significantly in the coming years, given the low current utilisation of big data and Artificial Intelligence techniques and the large number of practitioners undergoing training in these fields.

CHAPTER 5

CHALLENGES

Chapter 5

CHALLENGES

5.1 The Difficulties of Using AI and Big Data

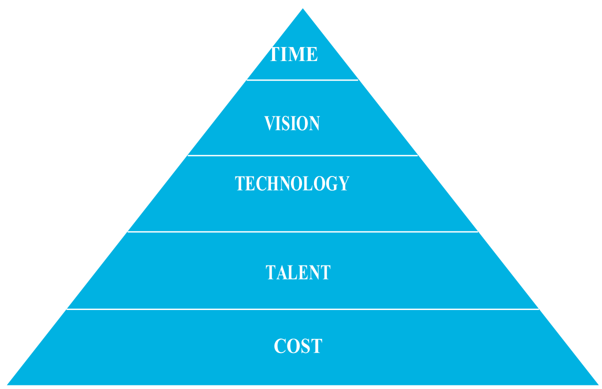


Figure 5.1: The Financial Technology Pyramid

So, what is preventing investment practitioners and companies from harnessing the full potential of Artificial Intelligence and big data?
I've found five major roadblocks, which are listed below in order of the difficulty.

5.1.1 Cost

Financial organisations are no strangers to large IT budgets, but launching big data and Artificial Intelligence capabilities can be costly both upfront and on a long-term basis.
The high cost can be due in part to the new data sets that allow these technologies and have piqued the industry's interest. It takes a lot of work to locate, clean, and make sense of these data sets, which is why one influential economist argues that small businesses will struggle to survive in the era of big data and Artificial Intelligence.

5.1.2 Talent

In the age of AI, college graduates with basic programming and statistics experience, as well as those with advanced degrees in Artificial Intelligence or related fields, are still in high demand by employers. This, however, is just part of the tale.

Working for one of the world's leading technology firms, which hires and invests heavily in AI, has a number of distinct advantages. Any of the names that come to mind are Microsoft, Alibaba, Baidu and Google. These businesses are home to many of the most cutting-edge AI technologies, and the limited number of workers involved in these ventures have become a special breed of access to experience and expertise not yet taught in the world's top universities. What makes it even more complicated is that it seems that only a small percentage of the top AI talent is interested in working in the investment industry.

5.1.3 Technology

The AI revolution is just getting started, and technology is still rapidly evolving. This poses major challenges for those investing in Artificial Intelligence applications, as there is a significant risk of being overtaken by a latecomer. With the exception of a select few, keeping up with the latest trends is a real challenge for most investment professionals and organisations. Similarly, in the alternative data room, new data source discovery is still in its infancy. Many new data vendors are joining the market, and extracting useful signals from the avalanche of data continues to be difficult.

5.1.4 Vision

In the coming decades, developments in big data and Artificial Intelligence technology are expected to cause significant changes in the investment industry. To completely enter the market while effectively deploying capital, these technological advances must be handled from the top of organisations. Investment firms' IT implementation has been largely reactive to date, as noted in Investment Firm of the Future, with firms attempting to marshal technology to capture efficiencies in the face of legacy issues. For businesses to thrive in the future, they will need a strategic strategy, leadership engagement, and mutual control of IT deployment.

5.1.5 Time

Any advancement, no matter how minor, always necessitates a considerable time commitment, among other items. When you're on the cutting edge of creation, this is simply a fact of life. Every company wants to be the first to turn over a rock and find something useful, but figuring out how to boost alpha and incorporating new methods into established investment processes takes time. Except in the most advanced markets and at companies that have been using the most sophisticated technology for many years, most big data ventures take a significant amount of time and effort to plan the data and make it fit for purpose. Perseverance and patience are required, and even so, many projects will fail. Time is still one of the most difficult obstacles to conquer, and performance does not happen overnight.

5.2 The Present Situation and a Road Map to the Top of the Pyramid

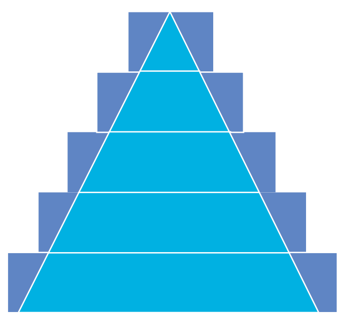


Figure 5.2: Where Finance and Technology Collide

To enter the top of the pyramid, Where Finance and Technology collide, investment firms would need to significantly surpass the five obstacles (i.e., use cutting-edge AI and big data technology to solve core investment problems). However, reaching the top requires a team effort; overcoming each obstacle necessitates consideration of both the financial and technological dimensions.

It depicts this in terms of concept. Investment solutions in the Fin corner are typically guided by quants with a finance history. These types of solutions, for the most part, rely on existing data sets rather than relying heavily on saving effort, time and alternative data in determining validity (separating signal from noise) as well as testing and cleaning data. At the same time, they could miss out on new knowledge derived from alternative data and recent technological advances in NLP, computer vision, and voice recognition, to name a few.

Some discretionary administrators are also playing with new data sources they come across in the Fin corner. The overall strategy of consistently using emerging technology to collect and process new knowledge that will feed into the investment process and provide an edge is often lacking.
Solutions are usually driven by technologists from outside the investment environment in the Engineering corner. Their teams and architects usually have in-depth knowledge of the most recent big data and Artificial Intelligence developments and can produce the most opulent wizardry that takes advantage of the most cutting-edge technology. They are often not designed with a clear business purpose or end user profile in mind, and they are difficult to integrate into an existing investment firm's investment process.

The introduction of big data and Artificial Intelligence into the investment process could be the single most important shift that investment professionals will face in their careers. Given the FinTech pyramid's complexity, doing all right and reaching the top of the pyramid will take several iterations. The most critical takeaway is the need to work together and plan to gradually climb the pyramid. There is no way around it.

5.3 Making It Happen: T-Shaped Teams

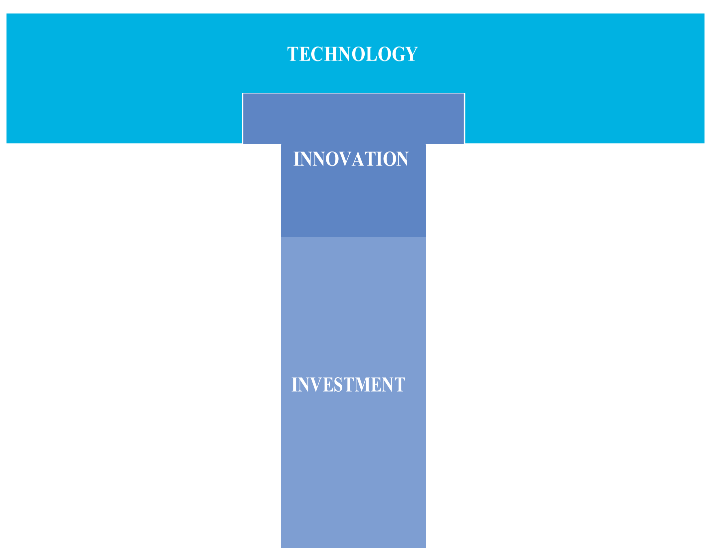


Figure 5.3: T-Shaped Team

The Financial Technology Pyramid emphasises the strategic importance of incorporating big data and Artificial Intelligence into investment strategies. This segment introduces the T-shaped team model, which offers an organisational and operational approach to make it happen.

We may use the idea of T-shaped teams in the sense of big data and Artificial Intelligence in investments. A T-shaped group in this field is defined by the combination of collective knowledge and skills gathered through investment experience and technology implementation through investment strategies or processes. In this context, I also highlight a third aspect of T-shaped teams: the role of innovators in linking technology and investment teams, which necessitates such professionals to be especially strong in T-shaped skills. This is shown in Figure 9 by the small T in the overall T-shape.

Roles in the investment function are not significantly different under this system from what we see today in the market, although this might not be the case in the technology function. Future investment teams' technology functions would almost certainly require different skill sets than those needed today. In addition to computer engineers, data scientists will become increasingly important.

The third feature, creativity, is important because its primary goal is to promote cooperation between the investment and technology functions, which the industry has struggled with in the past. Researchers, strategists, product managers, and company developers are all examples of innovators. The fact that professionals who perform these functions often work in various divisions at different companies demonstrates a lack of respect for their work. Some work in the investment or technology divisions, but to be successful partners, they must have a thorough understanding of their counterparts' businesses. For example, product managers and strategists may take on the role because they have a better view of the big picture than investment and technology specialists.

T-shaped teams are usually minimal in size and operate only on an informal, project-specific basis in the early stages of collaboration. T-shaped teams become more permanent and prevalent elements of the organisational structure as operations develop. The magnitude of the issues at hand necessitates organisational commitment, which can be measured by how many (and how effective) T-shaped teams a corporation sponsors.

5.4 Predictions and a Word of Caution

5.4.1 Humans vs. Machines in IM: Different Points of View

Will AI and robots become so intelligent that they will be able to take our place?
The apprehension has lingered long enough in the human mind to pervade current Finance Technology debates.

We believe in the "Artificial Intelligence + HI" model, which states that most tasks are and will continue to be best done by combining Artificial Intelligence and human intelligence, and that the combined power of the two is superior to either aspect alone. The road to adoption starts with simple, repetitive tasks like extracting data from texts and generating reports, populating spreadsheet models, and photographs where Artificial Intelligence has an advantage over humans in terms of the amount of data they can process at higher speed. Analysts will then devote their time to higher-value activities that require more judgement and experience.

Humans and computers are not in a competition. In the end, the rivalry will be between "Artificial Intelligence + HI" teams, with the stronger teams able to successfully harness and merge both elements outlasting the weaker ones. Via cognitive diversity (artificial and human) and T-shaped abilities, future investment teams will succeed in collective intelligence.

5.4.2 Viewpoints on Using Artificial Intelligence and Big Data in Investment Management

Despite the significant role that big data and Artificial Intelligence can play in the investment sector, they are not a panacea. In some cases, more data (big data) can boost alpha, while in others, improved algorithms (Machine Learning) can uncover previously unknown patterns. Nonetheless, big data and Artificial Intelligence cannot include all of the answers that investors need or want.
One of the difficulties with ML techniques is that they perform best in the test setting (i.e., using the training data set) and do not always react adequately in real-world scenarios. This is the overfitting problem, where algorithms perform well in a sample but not so well outside of it. For AlphaGo, where all the rules are laid out, AI may be useful. The ever-changing investment climate, on the other hand, poses further challenges. Furthermore, at least some company ML systems are more like a black box, with users having little insight to the reasoning behind Machine Learning behaviour. As a result, some of the characteristics captured by the programmes have no causal relationship with the variables that the models are attempting to predict.

These challenges can be resolved as technology and understanding advance, but for the time being, we should keep the power of big data and Artificial Intelligence in perspective when embarking on a journey to discover the unknown.

CHAPTER 6

CONCLUSION

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CONCLUSION

Based on my analysis, I've come to the conclusion that

1. Big data and Artificial Intelligence have the ability to bring the most dramatic improvement to the investment management industry that current practitioners will ever see.
2. Future-ready investment companies will begin strategically planning their incorporation of big data and Artificial Intelligence techniques into their investment processes right now.
3.Collaborative organisational cultures, cognitive diversity, and T-shaped teams will allow successful investment professionals to recognise and leverage the opportunities brought on by these emerging technologies and applications..

CHAPTER 7

STOCK SCREENER AND STOCK SCREENER OUTPUT

Chapter 7

STOCK SCREENER

Mark Minervini's eight principles for successfully selecting a stock.

1. The current price of the security must be greater than the 150 and 200-day simple MA.
2. The 150-day simple MA must be greater than the 200-day simple MA.
3. The 200-day simple MA must be trending up for at least 1 month.
4. The 50-day simple MA must be greater than the 150 simple MA and the 200 simple MA.
5. The current price must be greater than the 50-day simple moving average.
6. The current price must be at least 30% above the 52 week low.
7. The current price must be within 25% of the 52 week high.
8. The IBD RS-Rating must be greater than 70 (the higher, the better). The RS rating is a metric of a stock's price performance over the last year compared to all other stocks and the overall market.

```
From pandas_datareader
Import dataaspdrfromyahoo_fin
Import stock_infoassifrompandas
Import ExcelWriter
Import yfinance as yf import pandas as pd import requests
Import datetime
Import time
yf.pdr_override()
stocklist=si.tickers_sp500()
index_name='^GSPC'# S&P 500
final= []
index= []
n=-1
exportList=pd.DataFrame(columns=['Stock', "RS_Rating", "50 Day MA", "150 Day Ma", "200
Day MA", "52 Week Low", "52 week High"])
```

First, I import the dependencies we will use in the program such as yahoo_fin (to get the list of tickers) and pandas_datareader.data (to get historical stock data).

Next, we must set up the parameters for the rest of the program. As you can see, the stock list variable is set equal to the tickers in the S&P 500 using the "yahoo_fin" module. Index_name is set to the Yahoo Finance symbol for the S&P 500 so that we can calculate the RS_Rating later on. Final and index are two empty lists which will help keep the place in the for-loop later on in case it fails because of too many requests to Yahoo Finance. The variable n is equal to -1 to keep the index of each ticker as you will see later on. The "exportList" is set equal to a panda DataFrame of the metrics we will keep track of. Now we are ready to start the screener.

```
for stock in stocklist:
    n += 1
time.sleep(1)

    print ("\npulling {} with index {}". format (stock, n))

    # RS_Rating
start_date = datetime.datetime.now() - datetime.timedelta(days=365)
end_date = datetime.date.today()

    df = pdr.get_data_yahoo(stock, start=start_date, end=end_date)
df ['Percent Change'] = df ['Adj Close'].pct_change()
stock_return = df['Percent Change'].sum() * 100

index_df = pdr.get_data_yahoo(index_name, start=start_date, end=end_date)
index_df['Percent Change'] = index_df['Adj Close'].pct_change()
index_return = index_df['Percent Change'].sum() * 100

RS_Rating = round ((stock_return / index_return) * 10, 2)
```

Note the time.sleep(1) will hold the code back 1 second each iteration of the loop just to slow the number of requests to Yahoo Finance and curb a potential error. In case the code stops due to an error, the code prints out the name and its index in the list for every stock in the S&P 500 so you can easily just start where you left off. For example, if the code stopped at index 177 (Facebook's stock) then you can exchange them for loop with the code below and then start it again.

for stock in stock list.

The RS_Rating is calculated by dividing the percent change of the stock from the past year to the percent change of the overall market. It essentially shows whether the stock is performing at, above, or below the standard.

```
try:
sma = [50, 150, 200]
    for x in sma:
        df["SMA_"+str(x)] = round(df.iloc[:,4].rolling(window=x).mean(), 2)

currentClose = df["Adj Close"][-1]
    moving_average_50 = df["SMA_50"][-1]
    moving_average_150 = df["SMA_150"][-1]
    moving_average_200 = df["SMA_200"][-1]
    low_of_52week = min(df["Adj Close"][-260:])
    high_of_52week = max(df["Adj Close"][-260:])

    try:
        moving_average_200_20 = df["SMA_200"][-20]

    except Exception:
        moving_average_200_20 = 0

    # Condition 1: Current Price > 150 SMA and > 200 SMA
    if(currentClose> moving_average_150 > moving_average_200):
        condition_1 = True
    else:
        condition_1 = False
    # Condition 2: 150 SMA and > 200 SMA
    if(moving_average_150 > moving_average_200):
        condition_2 = True
    else:
```

```
        condition_2 = False
    # Condition 3: 200 SMA trending up for at least 1 month (ideally 4-5 months)
    if(moving_average_200 > moving_average_200_20):
        condition_3 = True
    else:
        condition_3 = False
    # Condition 4: 50 SMA> 150 SMA and 50 SMA> 200 SMA
    if(moving_average_50 > moving_average_150 > moving_average_200):
        #print("Condition 4 met")
        condition_4 = True
    else:
        #print("Condition 4 not met")
        condition_4 = False
    # Condition 5: Current Price > 50 SMA
    if(currentClose> moving_average_50):
        condition_5 = True
    else:
        condition_5 = False
    # Condition 6: Current Price is at least 30% above 52 week low (Many of the best are up 100-
300% before coming out of consolidation)
    if(currentClose>= (1.3*low_of_52week)):
        condition_6 = True
    else:
        condition_6 = False
    # Condition 7: Current Price is within 25% of 52 week high
    if(currentClose>= (.75*high_of_52week)):
        condition_7 = True
    else:
        condition_7 = False

    # Condition 8: IBD RS_Rating greater than 70
    if(RS_Rating>= 70):
        condition_8 = True
    else:
```

```
            condition_8 = False

        if(condition_1 and condition_2 and condition_3 and condition_4 and condition_5 and condition_6 and condition_7 and condition_8):
final.append(stock)
index.append(n)

dataframe = pd.DataFrame(list(zip(final, index)), columns =['Company', 'Index'])

dataframe.to_csv('stocks.csv')

exportList = exportList.append({'Stock': stock, "RS_Rating": RS_Rating ,"50 Day MA": moving_average_50, "150 Day Ma": moving_average_150, "200 Day MA": moving_average_200, "52 Week Low": low_of_52week, "52 week High": high_of_52week}, ignore_index=True)
            print (stock + " made the requirements")
    except Exception as e:
        print (e)
        print("No data on "+stock)

print(exportList)

writer = ExcelWriter("ScreenOutput.xlsx")
exportList.to_excel(writer, "Sheet1")
writer.save()
```

The first 11 lines of code calculate the rest of the metrics needed for the screener. The current close price is used by taking the adjusted close price for the last day. The high and lows of the past year are taken by finding the maximum and minimum values in the DataFrame for the past 260 trading days (about a year). The moving averages are used by calculating the rolling averages over the respective amount of days. The rest of the code actually executes the screener with the principles that were mentioned earlier. In case the code fails in the middle of execution, any stocks that made the requirements will be stored in a DataFrame downloaded onto your machine. The DataFrame will be both updated and downloaded every time a stock makes the requirements and will include all their names and the indexes in the list.

Lastly, this code will print out a DataFrame of all the stocks that made the requirements and download the stocks to an excel file for your convenience. In addition, there may be a very small number of stocks that make the requirements and if you want to see more, you can tweak the conditions to your preference.

STOCK SCREENER OUTPUT

	Stock	RS_Rating	50 Day MA	150 Day Ma	200 Day MA	52 Week Low	52 Week High
0	ENPH	99	101.29	72.94	64.73	18.12000084	134.4299927
1	SEDG	98	248.28	191.02	168.81	69.48000336	309.7999878

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