

‘EXPLORING ARTIFICIAL INTELLIGENCE FOR ENHANCED FINANCIAL
DECISION-MAKING IN TREASURY MANAGEMENT AND RISK MITIGATION ‘

by

Gopinath Sambandam

DISSERTATION

Presented to the Swiss School of Business and Management Geneva

In Partial Fulfillment

Of the Requirements

For the Degree

EXECUTIVE DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

December 2025

‘EXPLORING ARTIFICIAL INTELLIGENCE FOR ENHANCED FINANCIAL
DECISION-MAKING IN TREASURY MANAGEMENT AND RISK MITIGATION’

By

Gopinath Sambandam

Supervised by

Dr. Amrinder Singh

APPROVED BY

dr.Ljiljana Kukec, PhD

Dissertation Chair



RECEIVED/APPROVED BY:

Renee Goldstein Osmic

Admissions Director

DEDICATION

This thesis is dedicated to the people who have supported me throughout my education. Thanks for making me see this adventure through to the end.

To my mother (Kannamma, C) for her endless sacrifices, unconditional love, and constant motivation. This milestone is as much yours as it is mine.

To my beloved partner (Vanishree, V), for your understanding, strength, and encouragement during the long days and even longer nights. Thank you for standing beside me every step of the way. Also, to my daughter (Vidhula, G) who is the reason for me to build myself towards the journey of life so that she can be inspired to explore and find details to subject while growing successfully in life.

To my mentor (Dr. Amrinder Singh), whose wisdom, patience and insights have profoundly shaped my academic journey. Your guidance has not only enlightened my path in this research but has also instilled in me a passion for continuous learning and exploration.

This thesis is dedicated to all dreamers who dare to persist despite challenges. May this work stand as a reminder that perseverance turns ambition into achievement.

ACKNOWLEDGEMENTS

As I culminate this challenging yet rewarding journey of my Global Doctor of Business Administration, I find myself reflecting on the invaluable support and guidance that I have received. This accomplishment is not just a reflection of my efforts, but a testament to the encouragement and wisdom imparted by those around me.

I would like to express my sincere gratitude to my supervisor, Dr. Amrinder Singh, for the invaluable guidance, continuous support, and constructive feedback throughout my doctoral research. His expertise and encouragement greatly contributed to the successful completion of this thesis.

I am also thankful to the members of my doctoral committee for their insightful comments and suggestions that strengthened this work. My appreciation extends to my colleagues and friends for their collaboration, discussions, and moral support.

I extend my sincere thanks to SSBM and Upgrad, for offering and facilitating the GDBA Program in India. This program has not only provided me with a rigorous academic platform but also a unique opportunity to delve into and contribute to the world of strategic chaos engineering. The resources, support and learning environment fostered by these institutions have been pivotal in my research journey.

A special word of appreciation goes to the administrative and support staff at both SSBM and Upgrad. Your assistance in navigating the logistics and requirements of the program has allowed me to focus on my research and academic growth.

Finally, I owe my deepest gratitude to my family for their unconditional love, patience, and encouragement during this journey. This accomplishment would not have been possible without their support.

ABSTRACT

‘EXPLORING ARTIFICIAL INTELLIGENCE FOR ENHANCED FINANCIAL DECISION-MAKING IN TREASURY MANAGEMENT AND RISK MITIGATION’

Gopinath Sambandam

2025

Dissertation Chair:

The present study aims to identify the effect of factors of Artificial Intelligence on the financial decision making processes in treasury management; the impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation; challenges related to the implementation of AI in the treasury and risk management processes; opportunities that are linked with the implementation of AI into the treasury and risk management functions and the suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decision. There are three cities namely, Bangalore, Delhi and Hyderabad taken for survey. Therefore, Bangalore, Delhi and Hyderabad are universe for current research. In this study respondents are randomly selected using purposive sampling techniques. Sample size for the study includes 600 employees working in 4 commercial banks, namely, State Bank of India, Canara Bank and HDFC Bank and ICICI Bank. this research underscores that the benefits of AI in treasury and risk management are substantial and multifaceted. However, realizing these benefits requires careful attention to organizational readiness, governance, regulatory compliance, data quality, and human expertise. The findings provide empirical support for integrating AI as a core component of treasury operations while simultaneously highlighting the need for a balanced approach that combines technological advancement

with effective human and organizational controls. As AI continues to evolve, organizations that strategically adopt and manage these technologies will be better positioned to enhance financial decision-making, mitigate risks, and achieve long-term sustainability and competitive advantage in the dynamic financial environment.

Keywords: artificial intelligence (AI), commercial banks, financial decision-making, risk mitigation, treasury management

TABLE OF CONTENTS

DEDICATION	III
ACKNOWLEDGEMENTS	IV
ABSTRACT	V
TABLE OF CONTENTS.....	VII
LIST OF TABLES	IX
LIST of FIGURES	XI
CHAPTER I: INTRODUCTION.....	1
1.1 Introduction.....	1
1.2 Research Problem	24
1.3 Purpose of Research.....	26
1.4 Significance of the Study	27
1.5 Research Purpose and Questions	29
CHAPTER II: REVIEW OF LITERATURE	31
2.1 Introduction.....	31
2.2 Theoretical Background.....	35
2.3 Research Gap	66
CHAPTER III: METHODOLOGY	69
3.1 Overview of the Research Problem	69
3.2 Operationalization of Theoretical Constructs	71
3.3 Research Purpose and Questions	75
3.4 Research Design.....	78
3.5 Population and Sample	78
3.6 Participant Selection	80
3.7 Instrumentation	80
3.8 Data Collection Procedures.....	80
3.9 Data Analysis	81
3.10 Research Design Limitations	86
3.11 Conclusion	86
CHAPTER IV: RESULTS.....	88
4.1 Results.....	88
4.2 Summary and Conclusion	165

CHAPTER V: DISCUSSION.....	169
5.1 Effect of Factors of Artificial Intelligence on Financial Decision-Making Processes in Treasury Management.....	169
5.2 Impact of Factors of Artificial Intelligence in Making Financial Decisions Related to Risk Mitigation	170
5.3 Challenges Related to the Implementation of AI in Treasury and Risk Management.....	170
5.4 Major Opportunities Linked with AI Implementation in Treasury and Risk Management	171
5.5 Suggestions for Improving Accuracy, Efficiency, and Strategic Quality of Financial Decisions Using AI.....	172
5.6 Overall Discussion.....	173
CHAPTER VI: SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS.....	174
6.1 Implications.....	174
6.2 Summary and Conclusion.....	177
6.3 Recommendations of the Study	180
6.4 Overall Recommendation	182
REFERENCES	184
APPENDIX A: QUESTIONNAIRE.....	188

LIST OF TABLES

Table 2.1 Population and Sample	79
Table 2.2 Age Distribution	88
Table 2.3 Gender.....	90
Table 2.4 Marital Status.....	91
Table 2.5 Education Qualification	93
Table 2.6 Monthly Income.....	95
Table 2.7 Years of Experience.....	96
Table 2.8 Type of Family.....	99
Table 2.9 Size of Family	100
Table 2.10 Reliability Statistics-Research Question One	102
Table 2.11 Descriptive Statistics-Research Question One	102
Table 2.12 One Sample Statistics-Research Question One	105
Table 2.13 One Sample Test-Research Question One.....	107
Table 2.14 Annova-Research Question One.....	110
Table 2.15 Reliability Statistics-Research Question Two	113
Table 2.16 Descriptive Statistics-Research Question Two.....	113
Table 2.17 Correlations-Research Question Two.....	115
Table 2.18 Model Summary-Research Question Two.....	128
Table 2.19 Annova-Research Question Two	129
Table 2.20 Coefficients-Research Question Two	131
Table 2.21 Reliability Statics-Research Question Three	133
Table 2.22 Descriptive Statics-Research Question Three.....	133
Table 2.23 KMO and Bartlett's Test-Research Question Three.....	137
Table 2.24 Communalities-Research Question Three	138
Table 2.25 Total Variance Explained-Research Question Three.....	141
Table 2.26 Rotated Component Matrix-Research Question Three.....	143
Table 2.27 Reliability Statistics-Research Question Four	147
Table 2.28 Descriptive Statistics-Research Question Four.....	148
Table 2.29 KMO and Bartlett's-Research Question Four	151

Table 2.30	Communalities-Research Question Four	152
Table 2.31	Total Variance Explained-Research Question Four	154
Table 2.32	Rotated Component Matrix-Research Question Four	156
Table 2.33	Reliability Statistics-Research Question Five.....	160
Table 2.34	Descriptive Statistics-Research Question Five	160
Table 2.35	Chi-Square Tests-Research Question Five	162
Table 2.36	Hypothesis Testing Results.....	163

LIST OF FIGURES

Figure 2.1 Cochran's Formula	79
Figure 2.2 Frequency and Percentage Method	81
Figure 2.3 Mean Formula	82
Figure 2.4 Standard Deviation Formula.....	82
Figure 2.5 T-Test	83
Figure 2.6 Chi-Square Test.....	84
Figure 2.7 Correlation Analysis.....	85
Figure 2.8 Regression Analysis	85
Figure 2.9 Age Distribution	88
Figure 2.10 Gender	90
Figure 2.11 Marital Status.....	92
Figure 2.12 Education Qualification.....	93
Figure 2.13 Monthly Income	95
Figure 2.14 Years of Experience	97
Figure 2.15 Type of Family	99
Figure 2.16 Size of Family.....	101

CHAPTER I: INTRODUCTION

1.1 Introduction

Over the past number of years, the financial activities and decision making of various industries have radically shifted due to the blistering development of the Artificial Intelligence (AI). One of the most urgent spheres that are undergoing this conversion is the treasury management, which is the support of corporate finance in the management of its liquidity, financing, investments, and risk management of financial resources(Sadiku, Fagbohungebe and Musa, 2020). The methods of treasury operations were traditionally based on the human experience, manual examination of data, and historical fluctuations to make judgement pertaining to cash flow projections, investment portfolio, and risk mitigation. Nevertheless, the dynamic and unpredictable financial environment of the twenty-first century with its volatility, globalization, indirectness of regulation, and mass extinction to digital has demonstrated the inadequacy of the traditional models. Therefore, adoption of AI technologies (machine learning (ML), natural language processing (NLP) and predictive analytics) has become a strategic need, but not a technical luxury. The real-time processing of large volumes of data, the detection of latent patterns, and the generation of predictive data offered by AI can help financial decision-makers to improve efficiency and precision, as well as be faster and more strategic in managing the treasury(Chalmers, MacKenzie and Carter, 2021).

In its significance, treasury management is significant to the financial stability and financial sustainability of organization. These have rather crucial functions such as liquidity management, cash flow prediction, investment strategy and fund decisions and mitigating financial risks such as currency, credit risk and interest risks. This has been extremely challenged by the increased complexity of the international financial markets. In this case AI has become a groundbreaking factor that provides solutions to scientific decisions that

are more accurate and quicker. Machine learning algorithms have the ability to predict both future and current positions on cash based on past trends, market relationships and other external conditions such as the macroeconomic or geopolitical risks. On equal measures, AI-based risk management systems have the opportunities of monitoring market indicators, assessing counterparty risks, and notifying managers of anomalies that can destroy liquidity or solvency. These abilities not only maximize such financial activity, but also reduce the likelihood of making costly mistakes and time squandering in the decision making process(Rathi and Asava, 2021).

Another passive to proactive financial management paradigm shift is implementation of AI in the treasury management. In the past, the most significant accomplishment of the treasury functions was to respond to a financial challenge when it took place. Even after the introduction of AI, financial managers can forecast any type of risk and make the decisions in a timely fashion. This is exemplified by predictive analytics, where organizations are allowed to model different scenarios and establish the probable effect on the liquidity, returns on investments and capital needs(Palanivelu and Vasanthi, 2020). The other area of AI that treasury operations can be automated is bank reconciliations, fund transfers, and fund investing, thereby relieving human professionals to focus on strategic planning and innovation. Besides that, the AI-based decision support systems enhance transparency and traceability of the financial processes which should be in compliance with the existing regulatory requirements such as Basel III, the International Financial Reporting Standards 9, and the anti-money laundering (AML) requirements.

The other AI contribution that has incurred significant impact is increase in mitigation of financial risks. The same risk affecting finance has been highly associated and multidimensional to occur within the realms of credit, market, operations and even within the cyberspace. The traditional risk management systems would not have worked as fast or as large a financial amount generated today. AI will be able to tackle this challenge through real time risk assessment and adaptive learning. The machine learning models can determine the existence of risks because they can calculate minor anomalies concerning

the expected trends and in such cases the treasury departments can intervene before the situation goes out of control. Besides, unstructured information such as financial news, statement of policy and social media sentiment can be analyzed with the help of the natural language processing (NLP) to forecast possible market disruption. The tools complement the traditional quantitative risk models because the traditional quantitative models simply involve the use of quantitative intelligence thereby rendering them to be more inclusive in risk management. In addition to this, the uses of AI in detection of fraud through application such as anomaly detection and predictive scoring have also enhanced integrity and security of the treasury operations.

The post-pandemic has as well been used in propelling the use of AI-based treasury management systems. All the inadequacies of the manual and fragmented financial processes, such as calling in real-time data, automation, and resilience, were demonstrated during the COVID-19 crisis. As remote working models received a new regularity, organizations were resorting to digitalization and AI-powered analytics, as well as liquidity monitoring, counterparty exposure, and working capital optimization. This has emphasized the fact that agile and data intelligence is required in the process of making financial decisions. Both corporations and financial institutions, in their turn, began to invest considerable amounts of funds in the AI infrastructure and cloud-based system of Treasury management, as well as predictive modeling opportunities. Assimilation of AI is thus more strategic participation rather than experimental tool used in the management of financial planning and risk taking(Leitch, 2021).

The implementation of AI technologies is not without its problems even though there is a potential of AI revolutionizing the system of managing the treasury. Such issues as data quality, bias in algorithms, security risks in the field of cybersecurity, and incompetence among AI specialists are all significant issues. In addition, AI model transparency and interpretability are also becoming a point of contention particularly regarding high stakes financial decision-making. Treasury managers can encounter a quandary of subordinating the automation and human control and observe that AI suggestions do not encroachment

on the scores of ethical and regulating issues. Moreover, the use of AI is an expensive project since it requires massive investment in technology, infrastructure, and change management of an organization. These difficulties are however overcome by the benefits of improved efficiency in the long-term, better accuracy of projections, and enhanced risk management capabilities. Good companies using AI would achieve a great deal of financial nimbleness, operational resilience and agility.

The issue of AI in financial decision making basically has been a subject of interests in both the academic and the professional literature, and the aspect of how AI can be implemented with respect to treasury management and risk reduction need to be looked into in detail. The majority of the available literature talks about the way AI has been used in investment management, credit rating and algorithmic trading (Anute *et al.*, 2021). However, there has been minimal studies done in this field to supplement treasury management despite being a core subject in corporate finance. The current research study will fill that gap by addressing how AI technologies enhance financial decision-making in the treasury departments in particular the liquidity management, forecasting, and risk mitigation aspects. The given research aims at providing an in-depth analysis of the influence of AI on financial sustainability and competitive advantages within a quickly digitalized economy through the prism of theoretical and empirical studies of the issue.

Finally, present adoption of Artificial Intelligence in historical administration of treasuries is now indicative of a larger shift of financial ecosystems to data. In a volatile era where the course of technology is being changed all the time, being informed and making decisions on the financial front on time is a strategic necessity. The AI can be used to enhance the effectiveness of the management and introduce new hermits, agility, and vision to the financial management. By examining this problem one will find themselves well positioned to look deeper into the relationship between AI and the financial decision making process and how risks can be reduced that may provide a deep rooted answer to the business persons as to what the smart financial systems can and are likely to do in the process to corporate finance by the corporate treasurers, policy makers and the academics

who are seeking to realize and exploit the opportunities of such a practice(Enholm *et al.*, 2022).

Artificial Intelligence and Its Relevance in the Financial Industry

The world banking industry has been transformed by the Artificial Intelligence (AI), and it is the sphere that has been transformed the most successfully. The artificial intelligence, a branch of computer science that enables the machines to mimic the human intelligence through learning, reasoning and self-reforming has evolved to be more realistic and vital to financial institutions because of not being perceived as a hypothetical concept. Its applications, such as automation and predictive analytics, risk assessment, and customer engagement have changed the way banks, investment companies, insurance companies, and fintech firms operate. Although, traditional financial environment has been defined as a human intelligence and experience-based industry in managing large data sets, automation of tedious tasks and decision accuracy of the industry(Geisel, 2018). There is a current use of AI technologies to process high volume of data, statements as well as make complex decisions more accurate and automatizing intricate operations in the financial sector. The AI presented scalability, smartness and speed, can also be used to stay ahead in an increasingly competitive market amidst high regulatory pressures and digitalization.

Financial institutions in the past had been highly relying on manual processes, the human analysts and the rigid statistical model to process operations and the riskiness of the operations. However, it has now been evident that conventional methods are less effective in accordance with the exponential growth of data and unpredictability of the financial market on the international level. Artificial Intelligence bridges this gap making it possible to have data driven decision-making processes that are dynamic and evolving. On the one hand, machine learning algorithms are able to handle millions of transactions in real time, which can predict and identify anomalies potentially pointing to fraud or operating at a loss. Similarly, natural language processing (NLP) helps systems to handle unstructured data, such as news articles, market sentiment, and financial reports, which previously were

not powerful enough to process. The abilities allow the financial institutions to anticipate any market variation, customize the customer experience and risk management at a better level, than it had existed(Soni *et al.*, 2020). The fact that AI can be applied to the financial sphere does not, however, relate to the solely certain efficiency of the operations but to the shift of the strategy and object of competition as well.

When it comes to a risk management and fraud search field, it is one of the most significant additions that AI brought to the financial sector. Institutions within an uncertain and interdependent globalized economy are constantly faced with the challenge of financial risks: credit, market, liquidity or operational. Traditional risk management models do not often capture complex interdependences and variable changes that occur often. Conversely, the AI-based systems can handle the historical and real-time data simultaneously and indicate patterns that the human analysts might not identify. The machine learning algorithms can be used to predict credit failure, assess risks associated with clients and detect shady transactions before turning into major losses(Soni *et al.*, 2020). The method of fraud detection which was once established using stagnating rule-based systems has been transformed by AI to detect the behavior patterns and to detect fraudulent transactions on financial data. An example of the AI algorithms that are able to follow millions of transactions per second and detect anomalies uncharacteristic of their normal behaviors of a customer can be provided, which reduces the number of false-positives by a large margin and improves the level of security. The incidences of fraud in financial dealings are becoming more complex and thus the forecasting and updating nature of AI has ensured that the fraud system frameworks are constantly upgraded to maintain the integrity of the financial processes.

The AI has also transformed customer service and relationship management in the financial area. Financial institutions currently make available artificial intelligence chatbots, and virtual assistant to answer simple customer queries, pay money, and provide financial advice to their customers 24-hours a day. They are smart systems that are based on natural language processing to understand customer intent and give a personal response to make

handling the simple transactions easier. Besides automation, AI permits hyper-personalization via the assistance of the analysis of client information, including purchases history, financial goals, and behavioral patterns, which enables provision of individualized financial products and investment strategies. The objective of such a customer-centered approach is not only to make the customers happy but more to the point it cultivates trust and loyalty in the industry that may be perceived to be unfeeling at times. The combination of AI into customer relationship management platforms is the use of AI in assisting the institution in predicting the customer needs, churn, and optimizing marketing programs using predictive customer needs. This will aid in developing a better understanding of the client behavior, thus AI will aid financial organizations in offering customized services based on value added(Madhavi, 2021).

Another field where AI is coming out as relevant is rather in algorithmic trading and investment Management. The present-day financial markets are quicker and more complex than a human being is capable of examining it. The AI-trading systems are also based on the complex algorithms and on time data analytics that allow them to discover the opportunities associated with the markets and to optimize the trade with the minimal amount of latency. The machine learning algorithm keeps on refining its strategies according to its ability to deliver in the market, and adjust to shifts in economic poachers, geopolitical fronts, as well as the mood of the investors(Roundy, 2022). Majority of hedge funds and asset management companies are currently relying on AI to optimize their portfolio, to diversify their risk as well as to make forward forecasts. These intelligent systems can be used to get a large volume of data like stock prices, financial statements, news feeds, and social media trends among others and analyze them to extract patterns which can then be used to make investment decisions. The resultant effect is an enlightened flexible, responsive investment environment that maximizes the returns and minimizes the exposure to risks. In addition to this, AI makes premium finance offerings of the robo-advisor cleverly known that provides low-cost and automated financial advice to retail customers.

Besides the advantages of operational and strategic capacities, AI is also crucial in the adherence to rules and state. Financial industry remains one of the most highly regulated fields of the world and the financial institutions have to follow those complex regulations such as anti-money laundering (AML), know-your-customer (KYC) and the data protection policies. The majority of the manual compliance processes are time consuming, faulty and costly. These procedures become less complicated with the assistance of smart automation and continuous control brought by AI. Natural language processing can be used to analyze regulatory documents and indicate key requirements to assist the compliance officers to learn about the evolving guidelines. The machine learning can point out the transactions, which do not pass the compliance test, make a report, and audit to the regulators automatically. This increases transparency and also reduces the cost of operation that is incurred in the process of adhering to regulations. In addition, AI-supported compliance solutions are proactive in governance, which is to establish possible risks and gaps in the compliance process in advance, before imposing punishments and losing reputation(Soni *et al.*, 2019).

Another field where AI has an effective impact on is the financial sector, in financial planning, credit rating, and the insurance underwriting. In credit risk algorithms, including predicting creditworthiness, AI does not have conventional data, such as social media use, online payment records, and cell phone use, when evaluating risks and enhances monetary inclusivity of individuals and small entrepreneurs formerly excluded by the official money system. Similarly, in insurance, AI helps to assist an underwriter in risk assessment, thus being more accurate, fraudulent claims are identified, and managing policies is forked. By checking the previous information and its trends in their activity, the insurance companies can make the pricing structure more precise and effective in the processing of the claims. Some inventions present more equal and productive financial systems that act more profitably and sustainably to larger numbers of customers(Jain, 2019).

Along with the decrease of financial systems to AI, there is an opportunity to transform the sphere, but nothing goes easily in case of including AI in the financial sphere. The problem

of privacy of data, especially bias of algorithm and moral regulation is still of immense concern. As good as the quality of the data that will be used to train the AI system, and since discriminative outcomes are possible during the lending, insurance, and investments decision, biased or incomplete data can be used. Moreover, such topics as the AI algorithm or the so-called black box problem also raises the question of accountability and transparency, particularly when the decision of any type of making an increase decides access to finances or risk. Another problem that will augment after financial institutions technological operations is the risks of cybersecurity threat since it is required to protect AI systems against manipulation and data leakages. Additionally, wide usage of AI will involve a professional human resource who is capable of working and comprehending intelligent systems. As such, banks must invest in technology, education, and regulation technologies, as well, to implement AI responsibly (Mishra and Tripathi, 2021).

In conclusion, it is possible to state that the notion of Artificial Intelligence has become the strong force that shapes the present and the future of the financial sphere. Its ability to process high amounts of data, predict trends, automate the working process and personalize customer experiences has revolutionized the nature of financial services. AI is used to make financial system more resilient, enhance compliance, enhance efficiency, and enable poor inclusion in the financial landscape. The direction to take should however be a trade-off - a trade-off between innovation and the regulation of ethical and regulatory standards that should be maintained. Applicability of AI in financial sector will be expanded even further as financial institutions are continuing to think of AI in the core of their business activities and it represents a smarter, more inclusive, and sustainable future of finance.

Financial Decision-Making in Treasury Management

The entire corporate treasury management is financial decision making since the strategic process of sustaining organizations, managing the financial risks, and optimization of capital structure to generate liquidity as a component of the long-term accomplishments is all about that. As one of the ingredients of corporate finance, treasury management is concerned with cash flow management, fund investments, fund activities, and risk

exposure management in a company with an aim of attaining financial stability and sustainability(Mishra *et al.*, 2024). It is not only a managerial, trading functions but a skill of strategy that have a direct impact on the profitability, solvency and developmental path of a company. The economic world nowadays is a changing and volatile one and this is linked to globalization, dynamic markets and technological disruption and in this context, the question of financial decision making in the management of treasuries is a complex and important one. The treasurers are to coordinate the short-term liquidity need with the long term financial planning without breaching the regulation requirements and insuring the firm against financial risks. This involves analytic abilities, risk sensitivity and foresight.

Adequately, treasury management can be focused on three spheres of decision making such as liquidity management, investment management and risk management. Liquidity management is the point of focus in ensuring that there is a provision of adequate cash or readily convertible assets to meet the short-term liabilities of a given organization. It is important to make good liquidity decisions in which there should be good liquidity and profitability success on one hand and excess cash is likely to be linked to opportunity costs on the other hand insufficient cash is likely to expose the firm to a liquidity crunch(Prorokowski, 2011). The treasury managers are therefore supposed to make right forecasts on the cash flows, contingency planning, and management of the working capital. Some of the methods applied to guarantee financial flexibility are cash flow forecasting, cash pooling and liquidity buffers. The information associated with the decision-making in this sphere is time-sensitive and information-intensive as it requires the real-time monitoring of the inflows/ outflows, credit lines, short-term investments. This misplaced or even delayed decision making would lead to funding loopholes, high rates of borrowing or even bankruptcy. Thus, the liquidity management can be regarded as one of the pillars of the successful work by a treasury that allows organizations to meet their obligations and utilize all chances as they appear.

The second element of treasury decision making addresses the matters of investment management and financing strategies. The functions of the treasury departments entail the

excess funds management with an aim of maximizing returns of the money without carrying a big risk. Some of the factors that determine how, where and when to invest the surplus cash will include interest rate, market condition, and the general risk aversion of the firm in general. The treasury managers are faced with the choice of investing in either the short term money market instruments or government papers or investing in long term investment instruments which aligns with the corporate goals(Kumar *et al.*, 2023). The natural conflict lies between the safety the liquidity and yield the so-called triad of treasury investment management. On the same note, one should expect treasury professionals to look at the various sources of funds whenever a need arises such as when issuing debt or borrowing or internal funds. They ought to be conscious of the cost of capital and the maturity profiles as well as the influence of leverage on financial structure of the firm. The policy has to do with the capital structure decision (optimality of debt and equity financing) that is significant to financial stability and maximization of shareholder value. One cannot make a decision in this sphere only by using financial modelling and market analysis but understanding macroeconomic trends, interest rates, and moods of investors(Embrey and Fox, 1998).

A third crucial component of treasury management is financial risk management that tries to determine, assess, and eradicate volatile market conditions, credit risk and volatile foreign exchange. Those that are critical in designing and implementation of hedging plans to cushion the organization against unfavorable financial impacts are the treasury professionals. One can use currency risk management whereby the derivatives used are forwards, futures, options and swaps as a means of insuring against fluctuations in the exchange rates in international transaction. Regarding the same, the interest rate risk is managed through the following strategies like duration matching, interest rate swap and conversion of fixed into floating debts. The decision on the management of risks must result following the comprehensive risk assessment models that guess the possible losses under various circumstances. The treasury department also engages in coordinated efforts with the financial and strategy departments in order to ensure that the risk mitigation strategies are consistent to the overall business objectives of the organization(Sedliačiková,

Aláč and Moresová, 2020). Having evolved in the modern age and become what it is now, risk management is no longer protection as it is a strategic act that facilitates the generation of values via financial sustainability and adaptability in the unsure market.

The management of treasury has undergone a radical way of financial decisions using data analytics and technology. This is due to the fact that the increasing accessibility towards real-time financial data and advanced analytical software aid treasury professionals in making quality decisions, which are more immediate and precise. The automation and Artificial Intelligence (AI) have also enabled forecasting cash flow and tracking liquidity and analyzing investments by reducing the ratio of a human error. Treasury management systems (TMS) are a combination of various accounting processes within one digital platform with a higher level of transparency, control, and efficiency. Such tools can help the decision-makers to simulate a variety of options, consider the economic impact of the available choices and respond within seconds to what is occurring in the market(Shiller, 2017). Besides that, the concept of big data analytics contributes to enhancing predictability about risks because it identifies minor changes in the financial markets that could not be identified through the traditional models. This leads to the evolution of treasury departments into data laden strategic teams, which have their input on the decision made on an enterprise-wide basis. Growth in the computerization of the treasury functions also results in improved governance in the form of audit trail, real time performance dashboard, compliance reports among others, which is very essential in the regulation and stakeholder expectations.

A treasury management financial decision-making process is inherently multidisciplinary which involves the financial theory, quantitative analysis and strategic management. The decision-makers must put into consideration the different external and internal forces like the financial performance of the organization, the market forces, the regulatory requirements and macroeconomic indices. The decisions in these situations are usually arrived at based on the uncertainty conditions when the entire information is not present and the impacts of financial decision making are obscure themes to irrational

influences(Kinoshita, Suzuki and Shimokawa, 2013). In order to overcome these challenges, the decision-support models and these are: the cost-benefit analysis, the scenario planning, the sensitivity analysis and the optimization analysis are used by the treasury professionals. These tools help to make trade-offs that involve risk versus the return, short-term and long-term growth in terms of liquidity as well as profitability and solvency. The system of governance in the treasury department is also important in facilitating the fact that the financial decision-making process is aligned with corporate strategy, ethical issues, and regulatory standards. The financial policies are coherent as there is a system of communication between the treasury, the accounting team and the executive team and ensures that there is a coherence in the implementation of the financial policies.

It is owed to globalization and financial integration that the range and difficulty of the treasury decision-making continue to expand. MNCs must conduct business under the new regulatory systems, fluctuating currency values, and foreign capital movements. The treasury managers will therefore be expected to make informed decisions sensitive to the international risk exposures, repatriation of monies, and compliance with the international financial standards. The strategic treasury operations have since not only shifted to the domestic liquidity and domestic funding collection but also shifted to the global cash management, intercompany lending and foreign hedging arrangements(Madaan and Singh, 2019). It is also accompanied with an international perspective that necessitates intensive knowledge in terms of the world money, world banking, and the politics of the world. The ability to predict and respond to the economic developments in the world has been leaving its mark of efficient treasury management in its wake.

In summary, treasury management financial process is dynamic and strategic as it ensures the stability and profitability of the organizations and its expansion in a more intricate financial setting. It encompasses the entire gamut of operations liquidity management to investment management and the reduction of risks and capital optimum where there should be a wise moderation of analysis, judgment and forethought. The treasurer of the present

day is not just a depository of cash, but also a business companion and he/she has a direct respective influence on the development of the corporate value. As the financial ecosystem is yet to evolve, under the influence of emerging technologies, data analytics, and global integration capabilities, a treasury specialist should become an actor of decisions who have digital solutions, analytical abilities and strategic vision. Finally, financial decision-making in the treasury management is the act of balancing the financial strategy and corporate goals and the FDs have to be resilient, long term and sustainable in the ever shifting world(Ahmad Zamri, Ibrahim, Haslindar, Tuyon, 2017).

Financial Decision-Making in Risk Mitigation

Risk mitigation process highly depends on financial decision-making since it is a foundation of organizational resiliency, financial stability and sustainability. When exposed to economic volatility, globalization, digital change and sophisticated financial instruments- market risk and credit risk, organizations always experience different categories of risks which include operational risk, liquidity risk and cyber risk(Czech *et al.*, 2024). Risk mitigation is however not a solely defensive process, but it is a planning process that is typified by financial-analytical and forecasting and policy-making with an aim of ensuring that assets are safeguarded and enhancement of value-generation over the long-term. The performance of an organization via mitigating risk through the process of financial decision-making is characterized by the quality of financial decisions made by the organization in terms of anticipating, absorbing and adapting a risk internally and externally(Abdul kareem *et al.*, 2023). Once financial decision making is done properly, it will ensure that risks are identified early on and reviewed in a holistic manner and minimized by the presence of sound capital allocation practices, diversification and hedging strategies. Hence, the interplay between the financial decision-making and reduction of risk is the basis of the corporate governance and strategic financial management.

The management of the financial mitigation decision of financial risk revolves around identification and assessment of financial risks. This is done through the examination of

the potential risk which will undermine the profitability, cash flow or solvency of a firm. The financial managers must look at the measurable risks, which include credit defaults, change in the rate of interest or, or the change in the foreign exchange and the qualitative risk that have to be identified, which are in the form of reputational damages or failure to comply with the regulatory measures. Risk identification will be done efficiently as per data analytics, on scenario and sensitivity testing to establish the likelihood and the amount of potential losses. Once the identification of risks has been performed, the decision-makers consider the impact of risks according to the applied tools (Value at risk-VaR), stress testing, and Monte Carlo simulation. These are quantitative approaches according to which it was possible to have the variability of returns in different situations. The outcome of the assessment process is applied to the prioritization of the risks and the recommendation of the mitigation measures. This analysis indicates that financial decision making is a diagnostic and a strategic role in which organizations make effective financial decisions concerning what risks to maintain or transfer and what are the risks to avoid(Mastalerz-Kodzis and Pospiech, 2011).

Allotment of capital and portfolio diversification is one of the significant factors to make financial decisions that would minimize the risk. The determination of the capital allocation is used to identify how the financial resources will be reallocated to the various business units, the investment projects or the financial instruments to strike a balance between the risk and the returns. One of the most efficient mechanisms of overcoming financial risks is diversification as a principle of investment distribution between two or more types of assets, industry or territory(Sahi, Arora and Dhameja, 2013). Quantitative models also assist financial managers to decide the optimal combination of investments in order to minimize risks at a particular level of expected returns which comprises structures of Capital Asset PricingModel (CAPM) and Modern Portfolio Theory (MPT). This seeks to determine an efficient frontier whereby the portfolio that the organization has will yield maximum returns at an acceptable risk. These principles of decision making undergo adaptation in corporate finance to make decisions on the capital structure that will be debt and equity finance. During good periods, a firm that is highly leveraged may make returns

that are above average but on the bad times, then it is prone to go into insolvency. As a result, treasury and finance specialists ought to continue examining the risks of capital expenditure, maturity of debts and interest rate risks so as to be able to be flexible financially and to limit liability. These areas hold the key defence mechanisms against potential financial shocks in strategic decision making with regard to finances(Rickards, Wiseman and Kashima, 2014).

Another area that is too valuable and is associated with risk mitigation deals with hedging and financial derivatives. The forwards, futures, options and swaps are applied by the financial decision-makers to hedge against the fluctuations of the exchange rate, interest rate and commodities. This is the case with multinational companies who are exposed to foreign currency, by using forward contracts they can secure the future rates of exchange thus stabilizing the future cash flows. Similarly, the interest rate swaps assist companies to convert floating rate commitments to the fixed rate, which negates the risk of raising the cost of borrowing. The hedging decision and the amount of hedging to increase requires an in depth assessment of market trends, cost-benefits and the overall risk temperament of the organization. Over hedging could lead to unwarranted expenditure and under hedging would leave the corporation subject to unwarranted financial anguish. By so doing, the decision making processes in hedging would need extensive understanding of market forces as well as the financial position of the firm. Such decisions have become more accurate in the market in the last few years with the help of technology based analytics and predictive modelling allowing the treasury departments to sketch many situations of the market first to pledge themselves to hedging strategies. Lastly, informed company financial decisions in the region protect the companies against market risks as well as being cost effective and competitive(Jain *et al.*, 2023).

In addition to hedging, it is followed by a rush of liquidity management and contingency in financial decisions during the reduction of risks. Liquidity risk- failure to meet the short term obligation may prove fatal to the otherwise lucrative firms. To minimize this, financial managers must make sure that they do everything to maintain an ideal liquid level, credit

facilities and cash holdings. The decision on liquidity management entails an intermediate level of liquidity that results in a reduced level of returns and currency liquidity that is insufficient resulting in insolvency. Stress testing and high-tech models in cash flow forecasting help businesses estimate the liquidity levels needed by a business entity in various circumstances which are not conducive to the business such as economic downturn or breakages within the chain of business. Moreover, establishment of contingency funds plans that would involve standby credit facilities and easy access to liquidity during the periods when their operations stand to be strained would also give them continuity. The COVID-19 crisis has demonstrated the importance of successfully dealing with liquidity risk since organizations that preplanned their liquidity status endured the shocks more effectively and reinstated promptly. Hence, choices related to the liquidity reserves, analysis of credit risks, and cash optimization are proactive factors in terms of financial stability.

Along with quantitative instruments, other aspects of risk reduction that make a good financial decision making involve strategic governance and culture of that risk. Financial risks can not be just a consequence of changing markets but also a consequence of human and organizational factors such as bad decision making, bad oversight or mis focus, or mis placed incentives. Uniformity, transparency, and alignment of corporate decision-making on risks will be consequently addressed by establishing an effective governance framework. Creation of risk committees, internal audit system and strong reporting system encourage accountability and well informed decision making. A robust risk culture makes the entire mitigation strategies more effective whereby the workers at all levels are well versed in addressing risk by effective management. The decision-makers must therefore ensure that the policies of risk management are factored during the process of financial planning, budgeting, and investment. This will turn the aspect of risk management as a compliance related activity to a working component of a strategic decision-making, with a contribution to the long-term creation of value.

The financial decision has increased risk reduction significantly due to the application of technological development and data analytics. AI, machine learning, and big data analytics can help financial institutions and corporations to obtain real-time information to analyse the large datasets and identify the emerging risks in giving a forecast of potential interruptions. Using predictive models, it is possible to gain recognition of the credit defaults or fraud or market instability to take an appropriate action in a good time. In line with the system, transactions are being constantly checked by automated systems to create red flags and hold the transactions within the regulatory provisions. Also, digital risk dashboard can allow executives to possess the dynamic knowledge about financial exposure of the organization so that they will make faster and more informed decisions. In deploying the risk reduction strategy through the aid of technology, firms could then transition to the proactive and predictive models of risk management to the reactive one. The impact of such technological development has additionally increased the analysis of the scenario and stress testing and made decisions regarding the financial sphere more objective, analytic and less prone to uncertainty.

Lastly, risk reduction is one of the crucial pillars of modern financial management in matters of financial decision-making. It entails a methodological process of risk identification and assessment and management through the way of making informed decisions on capital arrangement, diversification, hedging and explanation of liquidity arrangement. It is also known that good decision making can shield organizations against the adverse rocket-shock in the financial world and enhancement in capability of grabbing opportunities without halting. The combination of analytics, technology and governance of strategies ensures that the financial risks are managed in the manner that could secure long term stability and development. The financial decision-makers are important entities in the shaky global economy which today does not only cope with the risks but also develops a powerful and flexible, and even visionary presence on the world which has become very uncertain now. Lastly, the organizations that also include a disciplined financial decision-making approach to a risk reduction strategy are better able to be profitable, possess the confidence of the investors, and become long-term financially viable.

Role of Artificial Intelligence in Financial Treasury Management and Risk Mitigation

Artificial Intelligence (AI) has emerged as among the most radical technologies within the global financial landscape that is reorganizing the way organizations manage finances, their risk management, and other such necessary strategic decisions. In the area of treasury management and risk mitigation, AI has made it the most effective and accurate and strategic foresight. The manual analysis and the history data and the human judgment that constituted the underpinning of the traditional financial management practices are slowly being heavily added or even replaced with the intelligent systems which are capable of handling intelligent quantities of real time information(Xu and Babaian, 2021). Previously restricted capabilities of treasury and risk control processes in terms of the utilization of detached designs with sluggish report feedbacks are currently being augmented by AI-inspired robots, predictive analytics and decision assistance platforms. The innovations enable the organizations to be in a position of tracking liquidity like never and in a way that they can predict cash flow, manage investments and reduce risks with extremely accurate and fast results. Since the present financial environments are evolving and becoming more sophisticated, AI has had a shift of meaning as a support technology to become a facilitating approach that maximizes the direct support in financial governance and robustness.

In this case, AI can enhance decision-making with real time cash positionings, liquidity and financial exposures in international operations when applied to the treasury management. The treasury departments are charged with the responsibility of balancing the fine line between the liquidity, profitability and risk- that is ensuring that the organizations have funds to meet the obligation and returns made on the surplus cash. AI-powered systems that can be used to support this goal include cash flow forecasting and optimization of funding strategies, as well as automated bank reconciliations. The machine learning algorithms are applied to the past data on the transactions, market trends, seasonality, and macroeconomic variables and generate extraordinarily accurate

predictions of cash inflows and cash outflows. Such a predictive capability enables the treasurers to anticipate deficit or excess of liquidity, and proactively take the measures of either finance or investment. In case of multinational corporations, AI would also have the ability to unite and calculate international financial information of many subsidiaries and currencies offering one and modernised look of liquidity beyond boundaries. AI can improve operation efficiencies by reducing manual errors, wastage of time on reconciliation to enable treasury professionals to engage in strategic planning and policy-making.

The other key use of AI in running a treasury is in investment and capitals optimization. The treasury departments have numerous occasions to deal with substantial amounts of temporary investment in one form or another, and the question which they find themselves left with is how to effectively invest such idle cash without the question of compromising skills on the safety and liquidity of funds invested. The portfolio management systems produced by AI have had the ability to process many investment alternatives simultaneously, simulate circumstances within the market setting and advise on optimal distribution of resources relying on risk-taking capacities and the intended returns of the company. These intelligent systems involve real-time data such as interest rates trend, credit rating score and market moods to dynamically change the strategy of investment. Intuitively, reinforcement learning systems can continue self-training with the outcomes of the market and, thus, increase accuracy of the decision making with time. This adaptive intelligence will also be useful to enhance the quality of the investment decision, minimize risks connected with the system of human discrimination, late response time, perspective of returns. In addition, AI will also be useful in assisting the treasury managers in determining the cost of capital and also create the most efficient financing instruments, which will include determining the best debt and equity financing. Such strategic and long term plan corporate goals collaboration with AI in capital planning would ensure financial choices of the company with fintech involvement.

In addition to better decision-making in investments and liquidity, AI will be important in the identification, assessment, and mitigation of risks- functions that will become dominant in the treasury and enterprise risk management. The financial risks are multifaceted and they include credit, market, liquidity, operational and cyber security risks. AI is highly proficient in recognising trends and aberrations within a large volume of data that may denote emergent threats. Probably, the machine learning-based algorithms can be applied to analyze transactional data and identify a suspicious pattern of payments which can signify the presence of fraud, money laundering, or fraudulent transactions. Similarly, predictive analytics can forecast the threats in the market using indicators which incorporate interest rate changes, foreign exchange, and commodity prices. Through such facilities, the timelines of hedging and diversification strategy are possible within organisations. The use of artificial intelligence (AI) in liquidity risk management can mimic the impacts of such stressful events, such as the sudden decline in the market or the failure of the supply chain, to establish what the cash flow and capital reserves could be influenced by such events. Such simulations assist managers in the treasury to formulate contingent funding budgets and enough liquidity reserves that help enhance organizational resiliency.

The other area AI does immeasurably better as compared to risk mitigation in financial risks is automation and efficiency in the process. With AI that is capable of performing an automated process of payment processing, volume reconciliation and compliance checks, the computer-based system can automatically execute routine treasury functions. RPA Combined with machine learning, robotics will make repetitive and manual tasks less costly and time-intensive, as well as reduce the amount of errors. The AI-based payment systems on the example can automatically detect the payments based on invoices, detect anomaly and malicious payments. This is not a case of automation that is only effective and accurate but also, compliance with internal controls and external regulations is implemented. Moreover, AIs have the capability of detecting new risk patterns in the long run since they will continuously monitor and feed on every transaction within the system, and with the success of the social networking platforms in quickly identifying the new risk

patterns which traditional rule based systems would not detect, AIs will be able to detect these new patterns. It, in turn, provides organizations with twofold advantages of efficiency in their operations and a certain degree of security, which are two highly significant elements of a financial stability in a digitalized economy.

The application of AI in the financial risk and compliance regulation process has become an unavoidable introduction to the present day treasury work. The regulatory oversight of the banking institutions and companies is through strict rules, including anti-money laundering (AML), know-your-customer (KYC), and data protection laws. In order to abide by these regulations, transactions, documentation, and reporting have to be monitored at all times and on the one hand, there is a high amount of resources involved in it and on the other hand, could not be true when done manually. The AI solutions are applied in compliance, which is automated through due diligence and extraction of deviations that could be related to the non-compliance. Natural Language Processing (NLP) can also be used to analyze, interpret and update the regulatory texts with a new set of regulatory requirements shown in form of compliance checklists automatically. In addition, AI systems will also be competent in creating audit ready reports and maintaining good records which will require accountability and adherence to guidelines such as Basel III and IFRS 9. The compliance charter does not just result in the minimization of regulatory risk, but the investor confidence and corporate credibility is enhanced as well.

Predictive and prescriptive analytics Strategic risk reduction is the other essential field where AI could be influential. Predictive analytics uses information on the past and present to formulate predictions about the potential risks whereas prescriptive analytics gives some recommendations about actions to be undertaken to eliminate the risks. In treasury management, it is also possible to predict the shortages in funding and market shocks or credit defaults that can then be acted on before the investment and financing strategies are corrected. One can also Churn AI systems to simulate other different scenarios of the so-called what-if to establish how the different financial decisions would course through different economic situations. This aspect makes the treasury department more responsive

and willing and enables them to make good judgement even in uncertain circumstances. Besides this, AIs have been coupled with blockchain and other computational technologies to maintain financial data, which enhances transparency and protection in deals. Combination of these technologies will be a fresh era of intelligent risk management due to the fact that such decisions will not only be informed, but also adaptive, in addition to being progressive.

Despite its enormous potentiality, introducing AI to the sphere of treasury and risk management is not faced with any challenges. The problems related to the data integrity, algorithmic bias and transparency, and cybersecurity must be solved to render the use of AI responsible and ethical. The so-called black box problem is difficult to explain to the stakeholders and the regulators the financial decisions we make on the basis of opaque algorithms. Secondly, AI systems require extremely big volumes of high-quality data, and Title IX is that the quality of decisions can be spoiled by the low-quality data management. The risk of over reliance on automation that leads to complacency or the craftsmanship of human judgment when faced with life-threatening situations is another risk. Therefore, the AI implementation technology on financial choices should be embraced by good governance frameworks, sustained control and moderation of efficiency with professional tech knowledge. The proficiency of treasury experts to understand AI created knowledge and morals in producing algorithmic choices are also essential steps to sustainable implementation.

In conclusion, the Artificial Intelligence has changed the physical financial treasury management paradigm and risk mitigation available by offering intelligence, agility and predictive ability to the decision making processes. AI has turned out to be a valuable component of financial management today because it is capable of automating cash management and investment choices, predicting monetary risks and ensuring the compliance with regulations. It assists the organizations to operate more effectively, predictably and precisely combined with reduced sensitivity to volatility and uncertainty. As financial markets continue to evolve, it will be essential that AI strategic integration be

important to organizations wishing to become more liquidity management savvy, risk resilient, and sustainable growth. However, the efficient use of AI potential is spiced with the establishment of clear algorithms, efficient data management and continuous collaboration of technology and human knowledge. Holding the future of financial treasury management and reducing the threat of mitigation, Artificial Intelligence is not only a tool but also a possible collaborator in the creation of the future, implemented in a responsible way.

1.2 Research Problem

The modern evolving financial environment is dynamic and offers even more challenging problems to organizations in the context of liquidity management, capital optimization, and decrease of numerous financial risks. The trend of treasury management and risk averting where technical skills and past experiences have primarily directed are now demanding state of the art equipment that is capable of processing a lot of real time financial information. Traditional financial decision making models are usually restricted by the pace of reporting, failure to carry out massive analysis and prone to the human factor and inaccuracy. The challenges cause treasurers and financial managers to not make data-driven choices producing adequate and sufficient liquidity, profitability, and risk exposure. This limitation has led to ineffectiveness in the projection of the cash flows, market exposure, management of investment portfolio in addition to the regulatory provisions.

The concept of Artificial Intelligence (AI) has become a game changer technology that can address these shortcomings by bringing automation, predictive analytics and cognitive intelligence as part of financial decision making processes. The models powered by AI may identify trends, predict market changes, study complex financial data, and deliver real-time information to be used in enhancing the strategic decision-making process. AI can be used in treasury management to maximize liquidity, better pay systems, and enhance the accuracy of cash forecasts. Equally, in risk mitigation, AI gives organizations the power to identify fraud, predict credit, market risks, and remain compliant with new regulatory

requirements. Regardless of these developments, it is unclear to most organizations how well AI can be implemented in the current financial systems and governance systems to improve the quality of decision-making and resiliency in organizations. Artificial Intelligence (AI) is possibly one of the most radical technologies capable of assisting in breaking those limitations and bringing the automation, prediction, and intelligence of financial decision-making. With the application of AI-based models one can analyze vast amounts of financial data, find patterns and anticipate oscillations on the market, as well as real-time data that can be applied to make more strategic decisions. Different liquidity optimisation of the treasury, simplified payment systems and increased precision in the cash projection can also be done with the help of AI. Still on risk mitigation, in the same context, AI assists companies in discovering fraud, credit risk source and market risk, as well as achieve compliance with the evolving regulatory guidelines. Despite the advances, most of the companies remain uncertain, how successful the AI can be integrated into the existing financial systems and governance framework to enhance the quality of decisions and the overall strength of the company.

The big question that will be addressed during the research is therefore that there is insufficient knowledge and research evidence regarding the extent to which AI enhances financial decision making in treasury management and risk reduction. Even though the growing momentum towards using AI in the financial analytics and automation fields can be observed in the presented literature, VAOs continue to be underestimated in respect of their empirical effectiveness to avoid mistakes in decision making, risk reduction, and development of strategic values. Also, AI application poses additional threats to data management, model transparency, and cybersecurity, and ethical responsibility, which can impact its application in the sensitive area of financial activities. At that, there is an extreme urgency of the answer to the question of how AI technologies are being introduced and put to practice in the sphere of treasury and risk functions, to what extent they make the decision-making process more effective and reliable, and what organizational, technological, and ethics problems can hamper the most effective use of AI technologies.

The answer to this research problem is vital to both the academic field and business sector; it will allow concentrating on how AI can change the financial management system and practices, predictions that will be made to support the crisis, and how the risks will be better resilient. The insights into the relations between the adoption of AI, financial results, and risk control systems will enable the organizations to develop smarter, more transparent, and future-proof treasury and risk management systems.

1.3 Purpose of Research

The overall goal of the research is to research and analyze the means by which Artificial Intelligence (AI) is applicable in advancing financial decision making processes in the Realms of treasury management and risk aversion. Demands of intelligent and agile decision support infrastructure have now taken on a sense of urgency as financial institutions and companies are turning unstable, data-driven, and technologically challenging. The current study will touch upon how AI technologies as machine learning, predictive analytics, and automation are transforming the time-honored methods of financial management, improving the accuracy with which cash flows are predicted, liquidity management, and how well risk identification and risk mitigation processes are performed.

The study is going to be focused on providing a generalized understanding of how AI-based technologies and models can be utilized to make the financial decisions more informed, timely, and strategic. It will compare the impact of AI on the overall activities of the main treasury, such as the management of cash, investment optimization, capital distribution, and compliance control. Besides, the study will assess the role of AI in enhancing the effectiveness with which organisations will identify, analyze, and respond to financial risks- such as market and credit risks to operational and compliance risks. The study aims to bridge the gap in attaining the knowledge gap between theory and practice in AI-based financial decision-making through highlighting both administrative and the technological aspect of the same.

The other significant purpose of the study is the assessment of the benefits, challenges, and weaknesses of implementing AI into treasury and risk management systems. The successful execution of AI needs organization readiness, information policy, ethical concerns, and adherence to laws when AI promises tremendous opportunities to improve efficiency, precision, and foresight. As a result, the research will explore the barriers that deter the application of AI in finance decision-making as well as propose methods of their detection. It will also outline how human expertise and AI can be and are mutually complimentary to the other to create an intelligent, balanced ecosystem that makes decisions.

Lastly, the research will be directed toward a goal of generating both empirical and theoretical data that would be used by financial managers, policymakers, and researchers in the creation and implementation of AI based financial systems. The study should make the next step towards defining a strong framework of digital transformation of the financial procedure, as there is a scope of definitions of channels where AI enhances the quality of decisions and stability in the instances of risk. One believes that the acquired results will allow organizations to consider AI as not only a driving force of automation but a strategic partner that can allow organizations to achieve financial stability, transparency, and sustainable performance.

1.4 Significance of the Study

The significance of the exploration is that it might lead to a further establishment of theoretical foundations and applications of the Artificial Intelligence (AI) to the work of financial management, in particular, to the realm of both the treasury work and the reduction of risks. In a world, which is characterized by high rates of technological change, the banking institutions and companies are under current pressure in ensuring that they maximize efficiency, accuracy and thinking strategy in their decisions. The research is a valuable source of information about the topic of AI implementation to emerge as an engine of the innovations in the financial decision-making process of transforming the traditional

treasury and risk management process into intelligent and data-driven systems. The study is topical and up to date as it examines the possibilities of the inclusion of AI in these pressing areas and it sheds further light on how the new technologies upset the sustainability of the financial governance and organisations.

On the theoretical level, the study will add to the existing literature on the topic of digital transformation because it solves the gap between AI, financial decision-making, and risk management. It broadens the scope and enriches the knowledge base of the existing theories on the subject of decision-support systems, financial technology (FinTech), and risk modeling by providing an empirical foundation where the mechanisms of AI effects on the quality of the financial decisions and the performance of the organizations can be monitored. The results of the study should influence the evolution of the concept of AI-driven financial management frameworks because it may be employed to demonstrate the mediating effect of AI in the efficiency of liquidity management, accuracy of predictions, and optimal location of funds. Also, it will provide a framing on future research in the field of ethics, technical, and managerial dimensions of AI application in the financial systems.

In practice, the study has an immense implication on the financial administrators, corporate treasurer, policymaker, and technology developers. The findings will provide a practitioner with practical ways of deploying AI in a proper way that would enhance liquidity management, automate financial services, detect risks at earlier stages, and ensure that the challenging regulatory provisions are adhered to. Knowledge of these applications may be useful in ensuring organizations eradicate the inefficiencies operating within the organization, financial vulnerability and improved general governance within the organization. The study gives advice to policy-makers and regulators on the manner in which they can establish supportive frames and ethical standards that will be used to support responsible and transparent application of AI in financial operations. Furthermore, to technology providers and developers, the research demonstrates the areas within treasury and risk management that technological factors are most susceptible to AI integration, and in this case, one can develop specialized and efficient solutions of AI to the financial sector.

There are also socio-economic implications of the research since the improved degree of financial decision-making and risk management would contribute to preserving the stability and sustainability of a financial system in general. Liquidity crisis, credit defaults and business processing could be mitigated and, consequently, AI-empowered financial management would allow sustainable business growth and cover the interests of the stakeholders. Also, since the world economies are increasingly depending on digital finance, this research will provide a blueprint of accountable technological use, which will align efficiency with ethical accountability.

Comprehensively, the strength of this study lies in the strength of a contribution with numerous facets because it is not only a contribution to the body of academic knowledge in AI-based financial decision-making, but also provides viable options to use AI in making financial decisions and be sustainable in the long-term perspective, but simultaneously be transparent and financially stable. The difference between the technology innovation and the financial strategy is the effort of the research to inform the next wave of intelligent financial management in the form of practices and policies that will arise in the future.

1.5 Research Purpose and Questions

The research would assist in examining the role played by Artificial Intelligence (AI) in assisting in making financial decisions during treasury management and risk mitigation. It also attempts to respond to the question of how AI can complement over accuracy, efficiency and strategic foresight of the financial operations. The other purpose of the research is to define the challenges and opportunities of the AI introduction into the financial systems. Lastly, it will be focused at providing a point of view on how smart, data-driven financial management systems can be established.

Research Questions

- What is the effect of factors of Artificial Intelligence on the financial decision making processes in treasury management?

- What is the impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation?
- Which are the most important challenges related to the implementation of AI in the treasury and risk management processes?
- What are the major opportunities that are linked with the implementation of AI into the treasury and risk management functions?
- What are the suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions?

CHAPTER II: REVIEW OF LITERATURE

2.1 Introduction

The modern finance management, especially the corporate and bank treasury, has evolved with the introduction of Artificial Intelligence (AI). Originally focused on cash, liquidity, investment and risk management, the concept of treasury management is more and more becoming forecast-based and predictive in nature. Over the last few years, treasurers have been having heightened volatility in world financial markets, rising regulatory attention, and intricate funding settings. Therefore, companies are considering AI tools to make more financial decisions and address risks more effectively (Palanivelu and Vasanthi, 2020). The literature is in agreement that AI using its functions in machine learning (ML), natural language processing (NLP), and predictive analytics is transformative in enhancing accuracy of the forecasts, anomalies, optimisation of liquidity, and data-driven strategic decisions. The digitalization of treasury work is not just a case of automation but the development of intelligent mechanisms capable of creating a simulation of the market environment, forecasting the results, and prescribing the optimal choice of financial steps.

Initial contributions in the area were mostly related to automation of treasury services that concentrated on account reconciliation systems, payment processing, and other routine reporting systems that were rule-driven systems. Nonetheless, as of 2018, the focus of research has shifted when study investigations pay more attention to predictive and prescriptive applications of AI. Machine learning has been implemented on decision trees, random forests, gradient boosting and deep learning models to predict cash flows, foreign exchange (FX) exposure, and liquidity requirements. The systems are superior to the traditional statistical models like the ARIMA and exponential SM because they incorporate a wider range of variables incorporating market indicators, macroeconomic data and internal transaction patterns. According to empirical studies, AI-based predictions are more accurate than the traditional ones by 20-30 percent; more so when historical and real-time

data occur in large quantities. It is also stated in the literature that these models minimize human bias and offer constant learning processes, allowing treasurers to work out strategies in a dynamic mode depending on the new financial situation.

The cash flow forecasting based on AI has become one of the richest studied fields in treasury management. Some empirical research works, which were carried out in 2019 and 2025 provide evidence of how machine learning and deep learning models are used to improve short-term liquidity forecasting. RNNs (especially LSTM networks) have demonstrated good capability to learn seasonality and non-linear dependence of financial data. With such models, more precise liquidity positions are created through high-frequency data, including payment cycles, customer receipts and market fluctuations, and working capital is managed better. The example of multinational corporations demonstrates that the AI tools helped to decrease the forecast errors, the manual adjustments, and spending time on the reporting significantly. In addition, combining AI solutions with Treasury Management Systems (TMS) and Enterprise Resource Planning (ERP) will allow treasurers to obtain real-time operation of the global subsidiaries, achieve cash pooling and reduce idle funds. But these advantages require massive data quality, system integration and correspondence of machine outputs with managerial judgment(Soni *et al.*, 2020).

The other critical area AI can help in improving financial decision making is in mitigation of risks. The treasury risk management is the evaluation of the market risk, credit risk, operational risk, and liquidity risk. Conventional risk models usually use simplistic assumptions but AI based systems have the capability to scan large volumes of data, spot complicated correlations and spot early indications of financial strife(Roundy, 2022). The past five years in literature have been marked with the use of the techniques of anomaly detection as a means of identifying fraudulent transactions, uncharacteristic payment patterns, and system inefficiencies. The machine learning algorithms like isolation forests and clustering techniques have been implemented on vast transaction data to instantly identify suspicious behaviours that are not within the norms. It is also observed that

research in financial stability and macroprudential regulation also demonstrates increased adoption of AI models by banks and governments in forecasting periods of market stress and liquidity scarcity. The models have a high degree of accuracy and time responsiveness by creating composite indicators of market conditions using a wide array of sources of data in contrast to traditional tests of stress. These foresight visions enable treasurers to revise hedging policies and ensure liquidity reserves being at optimum levels.

Although this is the case, some studies underscore the issues that surround the deployment of AI into the treasury operations. The issue of data fragmentation is still a significant obstacle, since treasury information tends to be distributed through multiple financial systems, ERP packages and geographical branches. The lack of standardization and poor data quality decreases the reliability of the model and the accuracy of the forecast. The explainability of AI models is another problem that is going to persist (Sadiku, Fagbohunbe and Musa, 2020). Although black-box algorithms like deep neural networks can be highly accurate, they are not transparent and thus it is not easy to allow finance experts and regulators to understand how these specific outputs are produced. Such interpretability makes it more difficult to control the inside and to comply with the regulations, particularly in case the critical financial decisions are made based on the AI models. Researchers have thus proposed explainable AI (XAI) models which enable treasurers to follow model reasoning and confirm the decision-making routes. Additionally, the reliance on third-party AI providers also creates new sources of operational and cybersecurity risks, and a stricter contractual control and protection of data are required.

The current research also addresses the organizational and strategic implications of adopting AI in the treasury departments. In addition to automatic processing and saving of costs, AI changes the position of the treasury and makes it not a back-office assistance but a unit of strategic decisions. Using AI in treasury operations can identify opportunities to direct treasury teams in the development of corporate strategies by facilitating the use of scenario analysis, predictive modelling, and real-time understanding of information.

According to research, companies that install AI-based treasury systems have indicated that they have an increase in visibility of cash, efficiency in funding, and returns on investment. The data streams that are cross functional enable the AI to help improve coordination between the treasury and other departments like procurement, sales and finance. Nevertheless, the literature warned that the adoption needs a cultural change of data-driven decision-making and the process of continuous learning to achieve success. The authors strongly believe that even the most sophisticated AI models cannot be accepted by treasury professionals without proper training and trust among users.

The literature Methodologically, there is a variety of modeling methods and approaches to evaluation. They involve the use of supervised learning in predicting tasks, unsupervised learning in recognizing anomalies and also they recommend the use of reinforcement learning in optimizing a portfolio. Statistical measures that are used in performance evaluation typically include Mean Absolute Percentage Error (MAPE) and Root Mean square Error (RMSE) and confusion matrices in classification set-ups. However, standardized benchmarking datasets in the field is still lacking making it difficult to compare studies. A large number of corporate case studies are privative and cannot be replicated publicly(Enholm *et al.*, 2022). Research has thus been urged by scholars to conduct research between academia and industry to come up with common data repositories and open-source benchmarks on treasury applications. The second research direction is the use of generative AI and large language models (LLMs), which can be combined to automate writing reports, preparing regulatory compliance forms, and chatbots to support the interpretation of the analytical results of the treasury professional.

Regulatory and ethical perspective The implementation of AI in management of a treasury has strategic governance issues. Financial officials have started to work out instructions on AI model risk management, which are centered on disclosure, equity, and responsibility. Financial Stability Board Policy reports and national central bank policy reports have made a focus on the importance of previous audits, strong model validation and bias that can be used to avoid systemic risks. The failure of similar AI tools and vendors may cause

correlated failures which increase market volatility when it is faced with stress. Ethical issues, such as privacy of the data and bias over algorithms, are also a topic of increasing interest both in scholarly and policy-making literature. Consequently, companies are advised to develop AI governance structures, which are in line with regulatory policies and company risk aversions.

To recap it all, the selected content concerning AI as an enabler of financial decision-making, risk aversion as a mitigatory aspect of treasury management is clear in the reviewed literature published between 2018 and 2025. With AI tools, managers can have more flexible and resilient financial processes because of the accuracy of their forecasts, liquidity optimization, and the ability to detect anomalies. Nevertheless, a number of factors are interdependent, namely: quality of data, explainability and transparency of algorithms, commitment of organizational culture, and the strength of regulatory compliance systems. Despite the solid evidence of any improvements in performance, there are still the methodological and ethical issues in the field which are to be addressed through further studies. Further research ought to be based on causal research on the effects of AI on financial performance, the role of human skills together with the artificial intelligence systems, and the creation of the interoperable frameworks that would provide effectiveness and responsibility. All in all, AI can be viewed as a game changer in the contemporary treasury management because it can revolutionize the perception, measurement and risk mitigation of firms in an ever-complicated and digitalized global economy.

2.2 Theoretical Background

Many theories are interdependent within the theoretical framework of explorations on Artificial Intelligence (AI) in improving financial decisions in treasury management and risk reduction. Treasury management is a field that entails making decisions when faced

with uncertainty where the managers have to compromise between liquidity, profitability, and risk exposure. The integrative AI technologies present a new paradigm of decision making, with human thinking being facilitated, or in other words enhanced by intelligent systems that can compute large amounts of information on the spot. Consequently, the conceptual underpinning of the current research is based on the theories of the Decision Theory, Resource-Based View (RBV), Technology Acceptance Model (TAM), Behavioural Finance Theory, and the Dynamic Capabilities Theory. Combined, these frameworks describe the impact of AI-driven tools on the quality of decision-making, organizational performance, and the risk management process in the financial setting.

The Decision Theory gives the most direct theoretical background of how AI has a role to play in informing financial decision-making in the treasury functions. Conventionally, the Decision Theory is concerned with the process of decision making by rational agents in the presence of risk and uncertainty. Within the treasury environment, probabilities, expected values and potential losses are to be assessed in decisions, e.g. cash forecasting, investment of excess money, and risk hedging. Models of classical decision making, such as expected utility theory, have rational behaviour based on the available information. Nevertheless, applied treasury settings are marked by information overload, dynamism, and cognitive biases that do not conform to the basic rational models. The AI systems have the role of decision support, limiting the bound rationality, offering predictive analytics, scenario planning, and solution models. Artificial intelligence algorithms can therefore produce better quality of decisions by converting uncertain environments into data-driven ones, subjectivity and human error when making financial judgments will be lowered.

Another construct that is critical in explaining AI adoption in the management of the treasury is the Resource-Based View (RBV). RBV proposes that an organization can have a competitive advantage in case it has rare, valuable and non-substitutable and inimitable resources. However, in the current treasury business, information and analytic capabilities are vital strategic assets. The raw financial and transactional information is processed by AI technologies into actionable insights which enable treasurers to make quicker and more

precise decisions in the areas of liquidity management, funding, and investment. The potential of AI can become strategic resource pool of a firm, contributing to its efficiency and responsiveness in the volatile markets when applied effectively. Another way the literature also takes RBV into the Knowledge-Based View (KBV), is associated with viewing knowledge as a core source of competitive advantage. AI systems help with the creation of knowledge and knowledge diffusion in organizations due to its ability to make patterns and create insights that human analysts may fail to notice. Therefore, AI is a knowledge resource and a technological asset, which contributes to the power of an organization, financial decision-making.

Technology Acceptance Model (TAM) gives a behaviour framework to appreciate the usage of AI technologies and its adoption by treasury professionals. As per TAM, there are two main factors bringing about the intention to use a new technology, and these are the perceptions of usefulness and ease of use. Regarding treasury, the environment where accuracy and responsibility dominate, the amount that managers believe the predictions provided by the system and can easily understand will determine the adoption of AI tools. Empirical studies on the use of TAM in the adoption of financial technologies suggest perceived reliability, transparency, and compatibility with the existing systems are significant and expected to determine the rates of adoption. AI systems are likely to be accepted more easily by the decision-makers when they are explainable, user-friendly, and can be easily incorporated with Treasury Management Systems (TMS). The organizational culture and top management support in encouraging technology acceptance are also brought out in the model. Treasury professionals might be unwilling to embrace automation, or over-use manual overrides without trust and perceived control over AI outputs, and without doing so, the full breadth of the potential benefits of a technology can be realized.

Besides the TAM, Unified Theory of Acceptance and Use of Technology (UTAUT) extends the scope of knowledge on the behaviour of adoption as it adds additional concepts like performance expectancies, effort expectancies, social influences, and the facilitating

conditions. In the context of treasury practices, performance expectancy is the perception that AI tools will allow increasing the accuracy of the forecasts and optimizing the decisions, whereas effort expectancy is the perception that interacting with AI interfaces will be easy. Social influence occurs when senior management supports digital change thus persuading finance teams to embrace it. Facilitating conditions, training, support in terms of IT, and data governance frameworks also influence the level of AI integration. Therefore, a combination of UTAUT and TAM offers a unified theoretical basis to the examination of the mediation of AI use in treasury management by humans and organizations.

The theory of Behavioural Finance Theory puts in another perspective, where human elements of financial choices are identified as psychological and emotional. The classic theories of finance hold that all decision-makers are rational, whereas behavioural finance points to judgement distorting biologies including overconfidence, loss aversion and anchoring that usually occur. The treasury workers, as all the players in the financial arena, tend to be affected by these biases, particularly stress and uncertainty. Such biases can be minimized using the help of AI tools because they are based on objective data-driven arguments but not the intuition of humans alone. As an example, machine learning models can detect risks that can become ignored because of cognitive or emotional biases. Nevertheless, behavioural finance also advises against over trusting AI as it can give rise to over trusting automation bias, as users over trust machine advice. The hypothetical equilibrium between the perceptive and the machine intelligence is thus very pivotal in attaining optimum decision making. This interaction is one of the central constructs of AI redefining the process of cognitive development of financial decision-making processes.

One more valuable prism through which AI enhances the ability of an organization to get through the turbulent environment is the Dynamic Capabilities Theory. Dynamic capabilities are the potential of firm to integrate, create, and restructure internal and external competencies in response to the environmental change. Financial instability,

regulatory change, and technological shocks are some of the financial figures in the external environment of treasury management. AI tools operate to increase dynamic capabilities through real-time risk assessment and prediction and learn flexibility. With feedback and retraining of the models, organizations can predict liquidity issues and optimize its funding strategies and more proactively handle the market exposures. The theory of Dynamic Capabilities, therefore, relates AI implementation to operational efficiency, and hence strategic resilience, making AI a method of organizational renewal and sustainability in the long term.

A combination of these theoretical constructs creates a multi-layered background of the current study. The Decision Theory explains the cognitive and rational dimensions of AI assisted decision-making, RBV and KBV tend to focus on AI as a strategic asset that helps organizations to be more competitive, TAM and UTAUT explain behavioural and organizational adoption behaviour, Behavioural Finance Theory concentrates on human-machines psychological process, and Dynamic Capabilities Theory considers AI in the context of an overall strategic transformation. Taken together, these constructs demonstrate that the impact of AI in the management of the treasury is probably more than the technological efficiency-it is the existence of a completely new decision-making approach, perception of risks, and the development of adaptability capability by an organization existing in new a financial ecosystem.

The theoretical synthesis as well facilitates the research propositions that relate AI adoption to better financial decision-making and risk reduction consequences. The interdependence of human cognition, technological capability and organizational structure takes a center stage in the efforts to comprehend the way AI brings value to the treasury functions. These theories all offer a standard of strategic, behavioural, and operational implications of AI in the process of organizations digitalizing financial processes. The combination of these constructs develops a comprehensive view of how AI alters the previously passive, transactional framework of treasury management to become an active, intelligence-based

operational branch to increase accuracy, agility, and resilience in making financial decisions.

Effect of factors of Artificial Intelligence on the financial decision making processes in treasury management

The growing sophistication of international financial markets and the need to do business with increased accuracy in terms of liquidity and risk management has placed Artificial Intelligence (AI) at the centre of revolution in contemporary treasury management. The treasury operating room that used to be mainly involved in cash flow and banking relationships management has now turned into a strategy decision center. In this context, AI has become part of improving the level of accuracy in forecasting, automation of repetitive duties, investment optimization, and reduction of financial risk(Soni *et al.*, 2019). The mounting body of literature emphasizes that the ramification of AI to the decision-making of a treasury is determined by a number of defining factors, including: technological; organizational; data factor; and human. The insights into the mechanisms through which these aspects affect the success of AI in financial decision-making is a way to see a complete picture of the opportunities and threats that can be encountered on the way towards adopting AI-driven solutions within the scope of treasury professionals.

Technological capability is one of the most notable aspects that will have an impact on the impact of AI on financial decision-making. The use of sophisticated algorithms, machine learning (ML) and deep learning (DL) algorithms have transformed the model used by treasurers to model cash flows, liquidity requirements and risk exposure. Recent research suggests that machine learning models are more accurate and flexible than traditional financial forecasting tools, especially when dealing with large datasets that are quite diverse in the quantity of variables. Random forests, gradient boosting, recurrent neural networks (RNNs), and other algorithms have been shown to have better predictive capability in cash-flow predictions, whereas reinforcement learning models are applied in investment and funding strategies optimization(Geisel, 2018). The ability of AI to process both structured data and unstructured data facilitates treasurers to make evidence-based

decisions which consider quantitative factors and qualitative factors, market sentiment and news on the economic environment. The quality of decision-making is hence promoted by technological sophistication in the sense that it minimizes the uncertainty and helps in the dynamic analysis of the scenario. Nevertheless, literature also underlines that all these benefits are conditional on the maturity level of digital infrastructure of the organization, the ability of AI tools to synchronize with the current treasury systems, and the ongoing retraining of models to provide them to adjust to the changing financial conditions.

Data quality and data governance is another factor that is critical because it directly affects the reliability and accuracy of AI-based decision systems. Treasury management requires data access of financial, transactional, and market data in real-time. Machine learning models can only work properly with large, clean, and well-structured datasets. Lack of accuracy of the data due to fragmented systems, different standards of reporting and past-haired processes can both result into poor model and the resulting decision. A study carried out in the financial sectors indicates that companies that have developed data management systems have the highest rates of success in AI-based forecasting and risk evaluation. The need to combine various sources of data, such as enterprise resource planning (ERP) systems, bank feeds, and market external data, to make there a structure of financial data ecosystem is also discussed in the studies. In addition to that, proper data governance would ensure that it meets the regulation standard and facilitate transparency to AI decisions. Scholars claim that the most sophisticated AI algorithms cannot provide insightful data when higher-order recommendations are not supported by the solid data bases. As such, data quality is a facilitator and a restrictive factor of the application of AI in treasury decision-making(Leitch, 2021).

Leadership support factor and the organizational readiness is important in dictating whether AI implementation is achieved in financial decision making. Research on the topic of digital transformation invariably reveals that to implement AI in the work of the treasury, top management support, an organizational culture, and a cross-functional team are needed. Silos Treasury functions that fail to cooperate with other teams usually do not successfully

apply AI solutions since these systems need collaboration between finance, IT, and data analytics departments. The evidence provided by multinational corporations indicates that the AI implementation is most effective in cases where companies develop an innovative culture and offer their treasury personnel constant learning opportunities(Rathi and Asava, 2021). The presence of qualified professionals who could interpret AI results and help implement it in the form of strategic decision-making is also pivotal. The reason behind the adoption of AI is most often an organizational resistance, insufficiency of expertise, and lack of awareness of the potential. Thus, the training and skill improvement have become human capitals and turned out to be a factor that determines the effects of AI on financial decision-making in treasury management.

The other effective force is the algorithmic transparency and explainability. Although AI systems can give the most precise forecasts, most of them are referred to as black boxes, that is, it is hard to figure out the way conclusions are made, even to financial professionals. This opaqueness becomes a challenge where in a controlled setting such as corporate treasury where accountability, auditability as well as regulatory adherence are critical. The research about explainable AI (XAI) in finance indicates that the transparency contributes to growth of trust and uptake by users. The treasurers can depend on their recommendations to make critical decisions concerning funding, hedging, and the mitigation of risks when the treasurers comprehend the rationale behind AI recommendation. Another looking-glass effect of explainable models they propose in the literature is that a balance of accuracy and interpretability can be struck with these models by integrating certain explainable models like decision trees or rule-based algorithms. Organizations are becoming obliged by regulatory frameworks in different jurisdictions to build accountability and traceability of AI and continue to support the necessity of transparent models. Therefore, to a greater extent, algorithmic explainability does not only affect the quality of decisions, but it also defines user confidence and assurance of compliance in treasury management(Anute *et al.*, 2021).

The human-AI interaction factor also predetermines the impact of AI on the decision-making process. Although AI takes data processing and prediction, humans still play the key role in terms of results interpretation and financial plan contextualization. The argument on augmented intelligence is that the best decision-making happens when AI duplicates or supports, and it does not replicate human expertise. Research indicates that treasury managers rely on AI as a decision support technology to examine complicated fiscal situations, over which managerial choices and strategic direction in the last phase. Still, automation bias (when human beings excessively trust AI results) and cognitive overload (when humans are overloaded with unconscious data) are some of the challenges that might deter effective human-AI cooperation. Recent studies highlight that it is important to develop user-friendly AI interfaces and decision dashboards that lead to understanding and promote critical analysis. Thus, the interaction between AI systems and human decision-makers is a significant factor to evaluate the effectiveness with which AI impacts nutrition to financial judgment and risk reduction.

The role of AI in treasury management is also discussed in literature with references to regulatory and ethical aspects. The use of AI brings in novel risk or types of risks like model risk, data privacy risks, and dependence of the system systems on third party vendors. The regulatory frameworks like the Financial Stability Board (FSB) and the Bank for International Settlement (BIS) have issued notes to the suggestion that AI should be governed responsibly when it comes to financial decisions. Research has shown that compliance, ethical requirements, and corporate governance policies make a big impact on the way organizations design and implement AI models. Ethical AI systems that deal with fairness, accountability, and transparency are emerging as part of the treasury risk management systems. The only way to promote trust, compliance, and prevent the misuse or unintended preference of AI in financial decision-making is through additional governance frameworks to track AI actions(Madhavi, 2021).

The other dimension that has been pointed out in literature relates to operational efficiency and cost optimization as an outcome mediator of AI adoption. Financial technology studies

and experiments with treasury operations reveal that automation of repetitive tasks usually through AI reduces the number of manual errors and increases the speed of processing of operations. These efficiencies liberate treasury experts to work on strategic analysis and decision making. The empirical evidence shows that the organisations, which use AI in optimising operations, exhibit better liquidity visibility, accelerated cash conversion, and lower expenditures on transactions. Moreover, AI improves the effectiveness of risk prediction, which allows managing currency, credit risks, and market changes in advance. This makes the process of financial decision-making more accurate and evidence based besides being fast. Nevertheless, researchers warn that there should be equilibrium of efficiency gains with a cost of acquiring, maintaining, and governing models(Soni *et al.*, 2020).

The overall experience of the available literature suggests that the success of AI in financial decision-making improvement in treasury management is the result of an intricate interaction of several elements which include technological advanced Ness, data accuracy, organizational culture, human intuition, transparency, and compliance with regulations. Another risk related to the adoption of AI that is identified in the literature is the presence of bias in models, excessive dependence on automation, and the difficulty to interpret the outputs. Even though these issues exist, researchers are in agreement that AI essentially can improve the quality of decision-making by real-time predictive, and data-driven treasury operations(Chalmers, MacKenzie and Carter, 2021).

The recommended future research directions identified by scholars are the development of integrated frameworks that can constitute connections between technological factors and behavioral and governance aspects and offer a better understanding of the effects that AI has in financial decision-making. Finally, the literature highlights that, through a solid governance system, expert human control, and proficient data, AI can dramatically enhance the quality, speed, and strategic importance of the decisions made by treasury organizations in an ever-complicated financial sector.

Impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation

The increasing uncertainties and volatile situation of international financial markets have forced companies to reinforce their risk mitigation system by using technological innovations. Artificial Intelligence (AI) is an emerging technology that has received significant attention due to its capability to examine large volumes of data, unearth its underlying trends, and forecast potential risks of financial dangers with a very high precision. In the last ten years, AI has grown to be incorporated into financial decision-making procedures especially in aspects touching on the risks management and mitigation. According to the literature, the efficiency of AI in risk-based financial decision-making is influenced by the following factors: technological, organizational, data-related, human, and regulatory. All these elements dictate the way AI systems increase the ability of an organization to predict, evaluate, and address risks like the changes in the market, credit crunches, liquidity crises, and operational shocks. This summary of the existing literature offers an in-depth insight into the relationship between AI and financial risk decisions and the interrelation characteristic in achieving sustainable risk resilience of the interdependence of technology, human cognition, and organizational culture(Jain, 2019).

Technological capability is the first and most evident factor when it comes to the effect of AI on decision-making in financial risks. It has been found that higher level AI models like machine learning (ML), deep learning (DL), and natural language processing (NLP) overturned the way financial institutions quantify and reduce risks. Conventional statistical models use historical data and linear assumptions, which in most cases do not show dynamic and nonlinear effect of risk. In comparison, algorithms of AI are capable of running extensive multidimensional data and revealing complicated correlations that indicate early exposure to risks. An example of such ML algorithms is the use of support vector machine, random forests, and neural network to forecast credit defaults, detect fraud involving transaction, or estimate the volatility of market risks(Mishra and Tripathi, 2021). The deep learning networks, such as Long Short-Term Memories (LSTM), are especially

efficient in the prognosis of the market dynamics and the liquidity crises. This is because with these technological advancements, treasurers and other finance managers can make proactive and data-driven decisions rather than reactive ones. It has also been suggested in the literature that the AIs can be used to simulate stress conditions to support the firms in assessing their possible losses in case of extreme conditions in the market. Nevertheless, it depends on the extent to which the firm is digitally mature, the model interpretability, and system integration into the wider financial infrastructures that the technological capability influences the risk mitigation.

Data quality and governance are another important aspect that will influence AI in terms of its use in making financial risk decisions. The accuracy, completeness, and timeliness of the input data are important to AI-driven decision-making. Research has always stressed that ineffective quality of data may result into predisposed or inaccurate risk measurements which may even increase the exposure to finances rather than minimizing it. Information and knowledge lapses, the presence of inconsistent reporting procedures, and insufficient records of transactions undermine AI capabilities in risk identification. Therefore, it is necessary to have effective data governance frameworks that guarantee data integrity, standardization as well as regulatory compliance. Based on empirical banking and corporate finance research, companies that have well-developed data platforms report greater accuracy in their credit risk rating and fraud detection using AI structures. Moreover, data variety, combining structured and unstructured information, including market reports, social media sentiments, and financial reports increases the level of predictability of AI (Kitsios and Kamariotou, 2021). Nevertheless, studies also warn that over-dependence on data that is not checked by humans can result in model overfitting and false confidence on the predictive results. Therefore, the risks that are mitigated using AI can be warranted by high-quality and quality-managed data.

Another factor that can have an effect on how AI affects financial risk decision-making is its organizational preparedness and leadership willingness. Implementing AI technologies in risk mitigation cannot happen without a technological investment,

as well as with the change in strategy coordinating business deliverables with the digital change objectives. The research has also shown that companies, which have a high level of executive sponsorship and innovation culture, are more effective in using AI to manage financial risks. There is organizational readiness, which entails the availability of the right talent, the cross-functional work between the finance and data science departments, and the explicit governance frameworks of AI supervision(Miao, 2020). The functions of the treasury and risk management are frequently performed in the deeply regulated and conservative environments, which can only make the AI adoption slow. Nevertheless, the company that implements agile decision-making models and cultures of learning are in a more favourable position to apply AI insights to their risk management. Moreover, the leadership assistance guarantees the presence of the required financial resources to maintain the system, train staff, and follow the ethical AI requirements. The literature validates the fact that the absence of organizational preparedness cannot promote positive changes in financial risk decisions by even the most advanced AI solutions.

The other issue that considerably has an impact on the efficiency of AI in the reduction of risks is algorithmic transparency and explainability. Accountability is essential in financial decision-making, particularly when the systems are automated to make high intensity risk decisions. Most AI algorithms, especially deep learning models, are black boxes, i.e. predicting without explanation. This will not be transparent and it may make finance professionals and regulators doubt. The recent literature on explainable AI (XAI) highlights the point that models that produce explainable information, a decision tree, a system of rules (or post-hoc explanations), etc., are more prone to adoption in risk management scenarios. Transparency also helps in the improved validation and monitoring of the model performance which is very important in reducing model risk. Researchers believe that explainable models will increase user confidence and adherence to financial laws and regulations like Basel III and the AI Act of the European Union. Thus, the notion of algorithmic transparency impacts directly the extents of adopting AI insights in the credit, liquidity, and market risks decision-making processes(Madhavi, 2021).

The interaction aspect involving a human and AI is key in determining the effect of AI in making financial choices on risk. Although the AI offers the computational intelligence, it is complemented with human expert knowledge that offers context interpretation and morality. The concept of augmented intelligence is highlighted in the literature regarding the use of AI as a support and not a substitute of human decision-makers. Research has shown that AI-based solutions have the potential to decrease certain cognitive biases including overconfidence and anchoring that tend to bias financial judgement. Nevertheless, scholars caution that automation bias can arise as well, as decision-makers do not question outputs produced by AI to an adequate degree. The relationship between human intuition and machine value is in the area of effective risk mitigation. The treasury professionals and risk managers would be able to make more viable and timely decisions when they are properly trained to understand the AI-generated insights. The absence of knowledge or excessive dependence on automation may be disastrous, on the other hand. Therefore, it is critical to create a symbiotic human-AI relationship by means of education, transparency, and the establishment of trust so that the AI can have the greatest effect on risk-based financial decision making (Anute *et al.*, 2021).

An increasingly developing body of research has also focused on the aspects of regulatory and ethical considerations as the key elements that predetermine the role of AI in mitigating risks. With the integration of AI systems into the financial decision-making process, regulatory organizations have been concerned with model bias, fairness, accountability, and systemic risk. According to the policy papers published by international bodies including the Financial Stability Board (FSB) and the Bank for International Settlement (BIS), the realization that AI systems should work responsibly requires the establishment of governance frameworks. Transparency, explainability, and accountability are three key ethical AI principles that are progressively finding their way into the corporate risk management strategies. Research indicates that companies that took an active role in making AI more ethical through analysis and application tend to gain greater trust among investors, regulators, and clients. Moreover, legal responsibility in terms of privacy of data, as well as anti-bias, is likely to increase the validity and legitimacy of AI-based risk

assessment decisions. Ethical governance is therefore a risk mitigation tool as well as a trust-enhancing component that increases the beneficial effect of AI in financial decision-making(Rathi and Asava, 2021).

Operational efficiency and automation is another applicable factor that has been widely addressed in the literature in the recent past. AI will facilitate greater risk offsetting since automated analytical and monitoring functions will mean that finance experts can center on strategy risk analysis. AI systems used in the automation of processes would have the capability to scan transaction, market trends, and credit exposures continuously and send notifications to the decision-makers whenever anomalies are found. Research in the financial institutions proves how automation decreases error rates and improves speed of response to the risk. In addition, AI makes it possible to perform dynamic analysis of scenarios, thus enabling treasurers to determine how organizational liquidity and solvency would react to alterations in interest rates, exchange rates, or geopolitical events. Due to this, more agile and evidence-based decision-making emerges. Nevertheless, researchers warn that it may also create some weak points in terms of over automation without adequate supervision especially when models go wrong or when the data fed into the models is corrupted. Hence, it is important to maintain a human control with a combination of automated AI systems to ensure the maintenance of risk mitigation efficiency(Geisel, 2018).

All the literature sources lead to the conclusion that AI influence on risk-reduction financial decisions is context-dependent. An accurate analysis depends on the technological prowess; a reliable predictor depends on data governance; an adoption depends on the organizational willingness; a trust is relying on the transparency of the algorithm; and a responsible action is ensured by ethical governance. All of these factors are interrelated and eventually contribute to transforming the conventional risk management into an adaptive, predictive, and strategic activity with the help of AI. Nevertheless, the literature also provides significant challenges like the question of data privacy, the bias in the models, and the ineffective regulation that should be tackled in order to achieve the full potential

of AI. The future studies must be aimed at creating combined models that will allow connecting such factors to real consequences related to the decrease of the risks and the increase of financial outcomes. Generally, Artificial Intelligence has the potential of completely transforming the accuracy, efficiency, and responsiveness of risk mitigating financial decisions, but only when companies approach their framework-enabling conditions in a potentially foresight, ethics-driven, and human-mediated manner(Soni *et al.*, 2019).

Most important challenges related to the implementation of AI in the treasury and risk management processes

The application of the Artificial Intelligence (AI) to treasury and risk management procedures offers many opportunities, yet it also exposes a list of the most fundamentally significant problems that the literature describes as hindrances to successful implementation. The most prominent of them is data problem: data quality and data integration. Treasury and risk systems typically have different sources such as ERP modules, bank feeds, trading systems, third party market data and ad hoc spreadsheets, which creates heterogeneous format, incomplete records and time-lags. Researchers and professionals always debate that AI models are as good as their inputs, haphazard, unstable, and prejudiced information will result in deficient model calibration, spurious associations, and unreliable forecasts. It is not only a technical issue but also an organisational one: to generate training datasets of high quality and maintain continuous retraining of the models, the data governance frameworks, the master data management, and the standardized taxonomies across the business units need to be established. In the absence of long-term investments in data cleaning pipelines, metadata management, system-to-system reconciliations, AI efforts will provide fragile models that cannot meet real-life requirements(Enholm *et al.*, 2022).

Closely connected to data issues is the technical one of systems integration and the issue of legacy architecture. The Treasury functions are usually operating in obscure IT

environments that do not support high-frequency analytics and real-time streaming. Implementation of AI tools, in particular, advanced deep learning or reinforcement-learning systems, in concept legacy Treasury Management Systems (TMS), payment platforms, and bank connectivity stacks is a burden to implement. According to the literature the most common implementation requirements are middleware, API standardization and platform rationalization. Outside of integration, companies are confronted with trade-offs where on-premise deployment provides control and cloud solutions offers scalability; both options imply latency, security, compliance with regulations and costs. This type of architectural friction slows pilot-to-production schedules and raises overall cost of ownership, i.e. technological feasibility factor is as much an ecosystem redesign as it is an algorithm choice.

Model explainability, auditability, and model risk management is another theme mostly dominant in the literature. Any financial choice in treasury (hedging, liquidity provisioning, or counterparty exposure) has legal, regulatory, or reputational implications, and thus the results of AI applications are sought out by stakeholders who require clear explanation of why the treasury made the choice. Many black box models, however, perform well and this makes them difficult to internally validate, audit trial and to trust to the manager. Studies thus propose the need of explainable AI (XAI) method, connoted model control and robust validation models that can generate traceable decision procedures, sensitivity, and stress-case conduct. The controls of model risk should involve versioning, drift diagnostics, backtesting on held up data, and intensive scenario analysis; the failure to institutionalize the controls may result in undetected model failures or, worse, faulty financial decision making which exaggerates losses.

Another significant concern is the regulatory and compliance limits. The world financial regulators put more scrutiny on the algorithmic based decision-making, data privacy and systemic risk and treasury functions are often at cross-roads of more than one regulatory regime (banking, securities, data protection). The research underlines that the friction of implementation is caused by regulatory uncertainty like changing expectations regarding

the transparency of AI or monitoring, or by the vendor itself. Organizational managers should consequently devise compliance-by-design solutions, which incorporate explainability, auditability, and record-keeping into AI pipelines. Legal concerns against data residency and consent make it harder to make architecture choices where cross-border data flows are concerned. The literature suggests active regulation incorporation and implementation of the standard industry best practices to make sure that treasury operations based on AI usage do not violate the changing supervisory expectations.

The same statement applies to human factors that include gaps in skills, change management, and cultural resistance which are equally widespread in the literature. Effective implementation of AI should have a combination of field knowledge, data science proficiency, and leadership with governance in mind. Traditional treasury units with accounting and cash-based origins must be trained to read the probabilistic results, policy assumptions in the model, and align AI-based recommendations and strategy. Furthermore, management apprehension and potential displacement can delay usage; the model of human-AI collaboration and specification of roles redefinition are, thus, essential. It is contended in the literature that change programs which include practical training, pilot labs, and progressive roll out plans provide confidence and awareness. In the absence of these initiatives, organizations will probably not make use of AI output effectively, or may become over-automated with the contents of model output without giving enough attention to it.

The cross area of concern also includes the vendor selection and the third-party risk management. When AI is acquired by some sellers of fintech or cloud services, some risks are outsourced to external parties data processing, updating models, concentration risk, and the company no longer exercises full control over them. It has been found that there are academic and practitioner efforts on the risks of vendor lock-in and opaque vendor models, and the possibility of multiple institutions converging around similar algorithmic

strategies, which collectively may result in system-wide vulnerabilities. As a consequence, the performing organizations will need to conduct due diligence under organizations governance matters, contractual clauses on model access and explainability, and internal internal validity capabilities. The construction of hybrid models, in which third party elements are mixed with in-house tested layers, does appear in the literature as being a pragmatic solution, albeit that will demand sensitive capability planning.

Operation resilience and cybersecurity are also urgent sources. AI implementations expand attack surfaces with model weights or training data or inference endpoints available, and introduce new risks including model-targeted adversarial attacks or data poisoning. Functional areas such as the treasury functions that relate to payments and liquidity are very tempting targets. The literature advises the use of secure model lifecycle management, data data transport and data at rest encryption, strong API authentication, and real-time monitoring of abnormal inputs, which may be absent of tampering. Fallback manual procedures, tested disaster recovery, and well-defined escalation should be a part of operational resilience planning, because when automated decision-making is overloaded with failures, service disruption will take a long time in case of an outage or a cyber incident.

Prejudice, justice and ethics also emerge as significant problems. Although a large part of the treasury sphere is ostensibly neutral, i.e. concerned with cash forecasting and risk exposure, algorithmic bias may still be obtained due to biased training data or unknown correlations, thereby obtaining disproportionate results in credit decisions, counterparty scoring or liquidity provisioning prioritization. The literature encourages the implementation of fairness audit, bias detection instruments, and a variety of training samples to alleviate such risks. They recommend using ethical frameworks of governance, such as written limits of decisions and human oversight levels, to modify AI action according to corporate risk appetite and social anticipations.

The second observed issue is the unavailability of standardized rates of assessment and benchmark data displaying treasury and risk activities. One common finding of research is that there are few publicly, anonymized datasets that would allow a comparison of models to be reproduced. This low rate of supply is limiting to the efficiency of practitioners to authenticate vendor assertions or to execute vigorous peer benchmarking. There have been calls throughout the literature to have industry consortia develop anonymized and standardized datasets and shared evaluation metrics in a bid to speed up responsible innovation and offer common points of reference in terms of performance, robustness and fairness.

Lastly, estimation of cost-benefits and measurement of value creation are feasible concerns that affect adoption. The process of AI implementation is not without resources, though it will demand software and hardware to be installed, along with data engineering, governance and training. The literature emphasizes that they need explicit measures that would connect AI projects with treasury KPIs (reduction of forecast errors, decreases in costs per transaction, optimization of liquidity buffer, shortening of time to decision) and that they should have a phased investment strategy that shows the effectiveness before the rollout on a large scale. In the absence of clear business cases and quantifiable results, AI projects are likely to be experiments in technologies that have no relationship with strategic treasury goals.

Combined, the literature describes the introduction of AI in treasury and risk management as a complex challenge that is not confined to the performance of an algorithm, but includes the data quality, systems architecture, governance, regulatory fit, human resource, oversight of vendors, cyber security, ethical considerations, benchmarking, and economic justification. To solve these problems, a concerted effort should be developed that will put together the technical engineering, well-built governance structures, the cross-functional purpose of the organization, and its unceasing communication with the regulators and the vendors. It is recommended that future studies carry out longitudinal investigations of AI

implementations within treasury environments, create standardized assessment data, and create human-Artificial Intelligence processes that are the most efficient and responsible.

Major opportunities that are linked with the implementation of AI into the treasury and risk management functions

The incorporation of Artificial Intelligence (AI) as a treasury and risk management tool has been highly identified as an emerging transformation in the modern financial management. The literature highlights that AI brings unmatched possibilities of organizations to achieve accuracy, speed, and strategic depth in decision-making. Treasury and risk management The traditional methods of carrying out their business, based on manual efforts and linear models as well as on human intuition, are turning into data-driven and automated, looking even more into the future, ecosystems. This digital change allows the treasurers and financial leaders to balance in the intricate market conditions and enhance capital efficiency and act in advance to impending risks. Both academics and industrial reports affirm that the use of AI technologies like machine learning (ML), natural language processing (NLP), predictive analytics and robotic process automation (RPA) are opening up new sources of operational optimization, strategy forecasting, fraud detection, compliance improvements and sustainable value creation.

Increased predictive analytics and accuracy of forecasts has been listed among the most common opportunities in the literature. The AI technologies (particularly machine learning algorithms) are changing the traditional models of financial forecasting based on handling massive datasets in multidimensions to identify non-linear trends that would have been missed by human analysts. This in treasury management is translated into better cash flow forecasting, liquidity, and optimization of working capital. Research demonstrates that AI-based predictive technologies may combine both internal data, including transaction backgrounds and receivables, with external ones, including macroeconomic dynamics,

interest rates, and geopolitical factors, as well as deliver real-time information about the cash positions. As an example, neural networks like Long Short-term Memory (LSTM) networks are able to identify seasonal predilections and sudden volatility to enable the treasurers to change their investment and borrowing approach in real-time. AI predictive capability enhances risk awareness, which helps firms to discover liquidity shortages, control debt expiry, and reduce idle cash. Such accuracy helps in enhancing better allocation of funds and also helps in reducing the cost of capital. The literature summarizes that AI does not only improve the accuracy of its forecasts but also organizational responsiveness to significantly changing financial conditions.

The other opportunity that comes along with the implementation of AI in the area of treasury and risk management is that routine and repetitive processes are automated. Automation of manual processes e.g. reconciliations, payment processing, report generation and compliance monitoring can be done using Robotic Process Automation (RPA) and AI-based systems. Automation reduces human intervention, reduces the processing time and enables the treasury professionals to concentrate in various strategic and value-added functions. Research also suggests that automation would save operational expenses by 30-40 percent and enhance the accuracy of processing in cash management, foreign exchange (FX) settlements and hedging operations. In addition to efficiency benefits, automation facilitates data uniformity and leaves an audit trail, which helps to comply with regulations and governs within the organization. Researchers have noted that RPA, when used with machine learning, commonly known as so-called intelligent automation, produces self-learning systems that can continue to improve the accuracy of the processes and identify anomalies. This is because organizations should attain greater operational resiliency, throughput maximization, and scalability of their treasury functions.

The third significant opportunity that was emphasized in the literature is the identification and reduction of risks that can be done in real time using AI. Treasury and risk management functions are always exposed to credit, market, operational and liquid risks. The idea behind AI is the constant tracking of such risks through the processing of large quantities

of structured and unstructured data in real time. Machine learning models are able to pick trends of deviant behaviour, precursors of credit degradation, or radical changes of the market dynamics, which also can indicate upcoming risks. This can also be expanded by natural language processing and sentiment analysis as it provides a sentiment insight into news feeds, analyst reports and social media to determine the markets sentiments and anticipate volatility. As an example, predictive models can indicate potential counterparty defaults or can be used to pick up bottlenecks in liquidity before they arise. According to the literature, AI-assisted risk management models facilitate the possibility to perform scenario simulations and stress testing, which gives financial institutions the means to assess the effect of extreme events. This way, organizations are able to make quick and informed decisions in order to reduce the losses, enhance compliance, and stability of their financial position.

Fraud detection and cybersecurity improvement is also an additional big potential in AI integration, a key concern in treasury operation with the high volume of transactions and the increasingly advanced nature of cyber-crime. Anomaly detection algorithms based on AI are capable of detecting anomalous transactions, fraudulent transfers of funds, or unusual user behaviour in real-time. Research indicates that AI systems that are trained on past transactions are highly accurate at classifying legitimate and fraudulent activities and thus false positive is minimized as opposed to conventional rule-based systems. Moreover, adaptive learning enables these models to change along with altered fraud patterns to guarantee the provision of ongoing security. AI has also been applied in cybersecurity to identify verification, behavioural analytics, and network monitoring. The shift of treasury operations to cloud computing and digital platforms, along with the application of AI-based security systems, contributes to the fear of fraud prevention through a considerable enhancement of the security of financial processes.

Strategic decision support and improved generation of financial insight is also another opportunity that is emerging. Using insights to inform the investment, financing and hedging strategies, AIs are turning treasury into a strategic business partner rather than a

transactional operation. These devices, known as cognitive analytics and natural language generators (NLG) can process complicated information to create easily digestible information to decision-makers to present data in the form of a recommendation. The capability of AI to combine market data, macroeconomic indicators, and internal financial metrics enables the treasury head to create risk-return analysis on a holistic basis. To illustrate, AI can analyze the alternative funding options in divergent market conditions or project the effect of the currency and interest rate fluctuations on the financial position. Research highlights that AI can facilitate the agility of strategy, where it can be used to plan scenarios, as well as for what-if analysis. This reactive-proactive decision making shift is also one of the most radical opportunities of treasury professionals that place AI as the inseparable part of corporate financial strategy.

The enhanced regulatory compliance and governance have also been highlighted in the literature as one of the opportunities created by adoption of AI. As more and demanding regulatory frameworks like Basel III, MiFID II, and IFRS 9 come into play, treasury and risk functions are becoming huge compliance liabilities. Compliance monitoring, interpretation of the policies and detection of anomalies can be automated with the help of AI technologies, especially the natural language processing and machine learning. Documents AI-compliance tools have the ability to read regulatory changes, detect the changes that are relevant, and evaluate how they may impact the internal operations. Automation of these activities minimizes the human element of control and enhances compliance to the emerging regulations by the firm at all times. Additionally, AI helps in establishing a strong audit trail and reporting systems thus enhancing accountability and confidence in regulators, shareholders and auditors. It is also a common finding of the body of literature that AI-enabled systems of compliance help in streamlining the governance, cutting the administrative overhead, and saving the compliance costs.

The other opportunity that is associated with the implementation of AI is to improve decision-making processes by integrating and visualizing data. AI technologies are able to bring together data across various internal and external information sources: ERP systems

and banking applications, trading systems and markets feeds, etc. into one set of dashboards. Introduced data visualization and cognitive analytics provide the possibility of treasury and risk managers viewing real-time and holistic picture of financial health. This coherent opinion enhances the collaboration of the treasury, finance, and risk departments and minimizes silos and the creation of collaborative decision-making. Research indicates that companies are in a position to manage their liquidity, foreign exchange exposure and investment portfolio more effectively using integrated AI platforms. Interactive data visualization increases knowledge about the data in the manager and allows rapid reaction to any risks. Thus, the use of AI to integrate data is not merely technical but also strategic, which facilitates coherence and financial transparency within an organization.

The literature also states that cost efficiency and value creation are also important opportunities related to the use of AI. Even though the implementation of AI requires an initial investment, analyses show that through automation, optimization of processes, and risk mitigation, financial benefits are huge in the end. AI will save money by being more accurate in cash forecasting, reducing exposure to market risks, and avoiding fraud. Moreover, predictive analytics helps companies to distribute liquidity more effectively, bring down borrowing rates and increase the revenue on excess cash. Reported by industries indicate that AI operated treasury function can realize two-digit gains in expenses and profit on investment. In addition to direct monetary benefits, AI leads to the value creation in the long term by improving the quality of decisions, resiliency, and the ability to be innovative. Organizations that implement AI in treasury and risk management are in a position to achieve a competitive advantage because they would set technology and strategic financial objectives.

Last but not the least is literature indicates innovation, flexibility, and long-lasting transformation (at large) as a wider opportunity presented by AI integration. Adoption to the AI stimulates the transition to the digital realm in organizations, which promote cultures of innovative, learning, and continuous improvement. AI provides the flexibility to manage risks in an adaptive way that may change with the market conditions and enhance the

resilience and sustainability of corporations. Further, AI relieves professionals of commonplace duties and enhances human intelligence to devote the resources to sustainability-based financial practices like green financing, ESG risk assessment, and long-term value generation. Research indicates that AI can help to build more accountable and information-driven treasury applications, which is the way to make technology growth and long-term corporate governance compatible.

To sum up, the application of AI to treasury and risk management functions is associated with a variety of prospects such as amplified forecasting capabilities, automation, and real-time risk surveillance, in addition to increased compliance, fraud reduction, and decision-making. All these opportunities make treasury operations a proactive, intelligent, and value creating operation. Nevertheless, the literature also points out the fact that, to achieve these benefits, proper data governance, organizational preparation, and ethical controls are needed. The transformative potential of AI is not only tied to financial efficiency optimization, but also such factors as transparency, resilience, and sustainability of financial ecosystems. As more organizations move to using AI, the future studies would be in terms of measuring the real value of these opportunities and finding the best practices of ensuring the sustainability of AI integration into treasury and risk management processes.

Suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions

Application of Artificial Intelligence (AI) in financial decisions has become one of the transformative forces that can promote the accuracy, efficiency, and the quality of strategic decision-making in different financial areas such as treasury, risk management, and investment analysis. As it is pointed out in the literature, although there is enormous potential to AI, regarding predictive accuracy and optimization of operations, the extent of its usefulness is heavily dependent on its application to organizational structures and decision-making standards. Researchers also have a row of strategic, technological, and governance-oriented recommendations to increase the value of using AI. These

recommendations are oriented on the enhancement of data quality, the development of human-AI partnership, the development of robust governance frameworks, transparency and ethical integrity, the advanced analytics, and the alignment of AI strategies with wider organizational objectives. Taken collectively, such measures can help financial institutions and corporations transition to proactive decision-making in lieu of reactive performance and resilience in the long term.

The formation of effective data governance and data quality management systems is one of the recommendations that are constantly reinforced in the literature. The accuracy of the AI systems is determined by the accuracy of the data that it works with, and therefore data integrity is the key to successful financial decision-making. As Davenport and Harris (2022) assert, to lower cognitive errors and bias in the AI predictions, organizations have to invest in systematic data management habits such as data cleaning, standardization, and real-time updating to avoid inaccuracies and biases in AI prediction. The use of centralized data warehouses and integration of various data sources i.e. transaction records and market feeds to other possible data sources including social sentiment and macroeconomic data enhance the holistic and validity of AI-based information. Research also suggests that data validation protocol and metadata management should be adopted to increase the level of transparency and traceability. An effective data governance system will also take care of ensuring data inputs are accurate, full, and have legal standards. With quality information pipelines, organisations will be able to improve the accuracy of algorithm-based predictions, as well as the accuracy of strategic financial decisions.

The other important recommendation is associated with the development of a system of broad AI governance and model validation. The literature underscores the fact that good governance mechanisms are key in the provision of accuracy and accountability in financial decisions that are being supported by AI. In line with studies by Financial Stability Board (2021) and OECD (2022), its governance needs to cover the whole lifecycle of AI- many processes include model creation and testing, implementation, and ongoing Supervision. It is recommended that organizations establish cross-functional AI oversight

committees where the members are experts in finance, data science, ethics, and compliance. The multidisciplinary strategy will guarantee the AI tools are technically sound but also suitably aligned to the corporate strategy and regulatory requirements. Backtesting, sensitivity analysis and periodic recalibration, are all part of model validation and ensure that a model does not drift over time whilst retaining predictive accuracy. Moreover, creating a positive documentation and audit trail helps in maintaining transparency and easing the process of regulatory reviews. Such governance practices are to be insured so that the implementation of AI reinforces and does not weaken the quality of financial decisions.

Algorithms transparency, as well as explainability are also emphasized in the literature as important recommendations to enhance strategic decision-making. The use of complex AI like deep learning networks tends to act as the black box, an aspect that negatively affects confidence amongst decision-makers and regulators. Such researchers as Ribeiro et al. (2020) and Doshi-Velez and Kim (2021) support the idea of utilising explainable AI (XAI) methods to make the behavior of model readable and comprehensible to a human user. Through tools like SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations) and attention visualization, companies can learn to comprehend how AI-based systems come to produce predictions and suggestions. Transparency increases the confidence of management and enables human professionals to certify algorithmic logic prior to making financial choices like investments, liquidity decision, or a hedge choice. Furthermore, explainability guarantees the adherence to the timely regulations that require rationalization of AI-computed financial decisions. Making the AI outputs interpretable, firms will be able to combine the computational intelligence with human judgments and improve the accuracy, as well as the ethical soundness of the strategic financial decisions.

Another recommendation that comes out of the literature is the combination of AI and human knowledge in the form of collaborative decision-making models. As humans make decisions based on context, intuition and moral judgment, AI leads in the field of data

processing and recognition of trends and patterns. Scientists have noted that the best strategy in implementing AI is in the augmented intelligence where AI does not substitute human intelligence but augments it. The research of Brynjolfsson and McAfee (2021) has shown that firms that integrate machine learning with human professional supervision are more likely to increase accuracy of their choices and resiliency to unpredicted phenomena. Financially, this kind of cooperation is vital in situational understanding of ambiguous signals, adaptation to regulatory shocks or reacting to geopolitical ambiguity which cannot be modelled. It is also suggested to organize training programs that help increase the financial professionals AI literacy so that the managers can interpret and effectively challenge AI-generated insights. This cooperative strategy scales the divide between the algorithmic accuracy and the human strategic decisions to enhance the efficiency and quality of the decisions.

An additional valuable piece of advice that was presented in the literature relates to constant learning and adjusting model to improve. AI models in finance industries will be forced to develop and adapt to the ever-changing market conditions and risk parameters. In order to ensure good predictive quality, organizations have been urged to accept machine learning systems that can undergo retraining and model optimization on a regular basis. Studies by Bertsimas and Kallus (2020) indicate that the inclusion of feedback loops involving a link between the output of the models and the actual financial performance enhances model reliability in the long term. Adaptive learning systems can help AI systems to re-calibrate around new information, mitigating the threats of model obsolescence and improving the timeliness of financial information. Moreover, model drift, deteriorating signal performance, and retraining can be identified and automatic monitoring tools can be used to instigate retraining when the accuracy thresholds are violated. Organizations will be able to keep the AI systems in line with changing financial reality and uphold the accuracy of decisions and their ability to be strategic by institutionalizing the practices of continuous learning.

Besides the improvement of a model, the literature also proposes investing in scalable infrastructure of AI and connects with established financial systems. To properly implement it, the free flow of data between AI tools and enterprise resource planning (ERP) solutions, treasury management solutions, and risk monitoring dashboards should be established. It is proposed to use cloud-based architectures, data lakes, and API-enabled connections that will allow instant access to data and computational scalability. According to PWC (2022) and Deloitte (2023) studies, AI implementation and integration with current financial ecosystems improve the effectiveness of the decision-making process by minimizing the latency and ensuring uniformity within the business activities. Moreover, the modular AI structure enables organizations to incrementally implement AI and develop solutions specific to a handful of key financial processes including cash forecasting, credit risk analysis, or capital allocation, among others. This integration is not just a way to improve the efficiency of operations but also can ensure that the insights of AI are incorporated into the routine financial processes, which will make the strategic decisions healthier and more responsive to data.

The issue of ethics is also an important component of the literature on the recommendations to enhance AI-based financial decision-making. Since AI is taking control of most creditworthiness, investment decisions, and the policies around risk management, ethical controls are the only way to ensure fairness and trust. Research supports the premise that ethical principles of AI must be set to avoid unnecessary discrimination, information privacy, and accountability. Open communication with stakeholders about the impact of AI on decisions will create credibility within the organization and trust among the population. Additionally, ethical norms help avoid reputational and other regulatory risks that can be caused by prejudiced or mysterious algorithms. When fairness metrics and ethical auditing are taken into account as part and parcel of an AI implementation process, organizations will be able to streamline their financial decision-making in favour of social responsibility, and long-term sustainability.

The other common recommendation is referring to the use of scenario and simulation models to enhance the quality of financial strategic decisions. Many economic conditions, interest rate changes or market shocks can be simulated using AI-enabled simulation tools, enabling treasurers and financial managers to analyze several strategies prior to their execution. As proven in the literature, the integration of predictive analytics using AI and scenario planning makes it more prepared to risks and helps in making evidence-based strategic choices. The trade-offs between the profitability, risk exposure, and liquidity management can also be learnt with the help of such simulations. Through integrating the analysis of scenarios into the decision-making processes, organizations would be in a stronger position to make informed, proactive financial decisions even when uncertainty surrounds.

Finally, scholars emphasize the need to align AI projects with organizational strategy and the performance measures. AI projects that are isolated or experimental projects do not usually create long-lasting value unless they are linked to the overall aims of the firm. The ability to measure the tangible effect of AI on financial results through the determination of clear performance indicators - e.g., forecast accuracy, time of decision making and return on capital - allows organizations to gauge the success of AI intelligence initiatives. Another approach is strategic alignment which means that AI activities should serve higher business strategies, such as growth, efficiency and sustainability. According to Kaplan and Haenlein (2020), strategic consistency in the adoption of AI and corporate objectives leads to the best long-term benefits and the least implementation risks. Thus, the direct connection of AI capabilities with financial and strategic performance indicators is likely to increase both accountability and the overall quality of making financial decisions.

To conclude, the literature suggests a stringent variety of practical recommendations to enhance the quality of financial decisions in terms of accuracy, efficiency, and strategic value with the use of AI. These involve developing effective data governance, powerful models validation systems, interpretable algorithms, human-AI interaction, and adaptive learning systems, scalable integration frameworks, moral governance and aligning with

corporate strategic goals. All these put together is enough to make sure that AI improves and does not replace human judgment so that organizations can get higher quality decisions made by machines that are not only accurate but also strategic. Implementation of AI successfully therefore does not only require the level of technological advancement but also the level of administrative maturity, cultural preparedness and moral prescience. With the development of financial markets, organizations that actualize such recommendations achieve a higher chance to use AI as a driver of financial excellence and strategic adaptability to a sustainable transformation.

2.3 Research Gap

Though, remarkable amount of literature admits the transforming power of Artificial Intelligence (AI) in improving the process of financial decision making, it still has significant literature gaps related to the specific implementation strategies and organizational processes to maximize the effectiveness of the technology. The majority of literature focuses on the technical aspect of AI, including the performance of the models, the creation of algorithms, and the data analysis, whereas relatively little is discussed in the context of strategic and managerial structures that are necessary to guarantee the accuracy, effectiveness, and ethical adequacy of decisions. As a result, little empirical data exists in determining how financial institutions and corporate organizations can systemically implement AI-based recommendations, including explainable algorithms, governance frameworks, and adaptive learning frameworks, to enhance the real-life decision performance.

The other major gap is the interconnection of AI and human judgment and strategic reasoning. Although the literature points out that human-AI collaboration will be essential, there is no effort to explain how the collaboration can be applied in financial situations that involve volatility, uncertainty and complexity in rules. Not many studies look at the ways in which decision-makers perceive, question, and revise AI-generated insights to ensure the accuracy and contextual accuracy of their analytics. In the same manner, little emphasis

has been placed on the behavioral and cognitive difficulties within the financial professionals as they shift towards the new AI-enhanced system of decision making as opposed to the conventional methods of decision making. This disconnect demonstrates a necessity to conduct further studies on organizational culture, trust-building, and skill development as the important facilitators of successful AI implementation.

Another gap in the literature is the potential effect of artificial intelligence governance and moral standards on the quality of financial decisions. Even though governance and transparency are considered the key elements of AI success, there are still limited empirical studies exploring the real impact of governance and transparency on decision accuracy and efficiency. Only a small number of studies give quantifiable evidence on how maturity in governance with respect to model validation protocol, audit trail or compliance to ethical practices leads to better decision results. A lack of standardized measures or metrics of effectiveness in AI governance prevents the comparison of outcomes based on institutions or industries. The identified gap highlights the need to identify a well-rounded framework that would allow to bridge the performance gap between the AI implementation best practices and the measurable outcomes in improving decision-making processes.

Furthermore, the studies that dwell on issue-specific differences in AI adoption practices are not present. A majority of the available discoveries take place in large multinational financial entities in developed economies, and there is a gap in comprehending how smaller companies or developing nations would effectively embrace AI in the backdrop of limited resources, regulatory situations, and data area situation. The field of AI-powered financial decision systems in financial situations and the context of emerging economies, especially in such areas as Asia and Africa, is under-researched. This reduces the generalizability of the existing understandings and emphasizes the necessity of comparative and cross-regional studies that would investigate the impact of various institutional and cultural determinants on AI-related financial decision-making.

Lastly, a kind of longitudinal and outcome study assessing the long-term effects of AI adoption on strategic financial performance is currently gaining attention, yet inadequately. The majority of literature is based on abstract or short-term empirical studies that are unable to ignore the dynamism of the AI systems and how they can affect the accuracy and efficiency of the decisions over a long period. Since AI models evolve and continue to learn, more prolonged, data-informed research designs are necessary to determine their enduring role in financial strategy and risk mitigation and in the competitiveness of organizations. Closing such gaps will help advance theoretical and practical understanding and allow organizations to go beyond experimental AI deployment and focus on integrated, strategic, and evidence-based financial decision-making models.

CHAPTER III: METHODOLOGY

3.1 Overview of the Research Problem

The modern evolving financial environment is dynamic and offers even more challenging problems to organizations in the context of liquidity management, capital optimization, and decrease of numerous financial risks. The trend of treasury management and risk averting where technical skills and past experiences have primarily directed are now demanding state of the art equipment that is capable of processing a lot of real time financial information. Traditional financial decision making models are usually restricted by the pace of reporting, failure to carry out massive analysis and prone to the human factor and inaccuracy. The challenges cause treasurers and financial managers to not make data-driven choices producing adequate and sufficient liquidity, profitability, and risk exposure. This limitation has led to ineffectiveness in the projection of the cash flows, market exposure, management of investment portfolio in addition to the regulatory provisions.

The concept of Artificial Intelligence (AI) has become a game changer technology that can address these shortcomings by bringing automation, predictive analytics and cognitive intelligence as part of financial decision making processes. The models powered by AI may identify trends, predict market changes, study complex financial data, and deliver real-time information to be used in enhancing the strategic decision-making process. AI can be used in treasury management to maximize liquidity, better pay systems, and enhance the accuracy of cash forecasts. Equally, in risk mitigation, AI gives organizations the power to identify fraud, predict credit, market risks, and remain compliant with new regulatory requirements. Regardless of these developments, it is unclear to most organizations how well AI can be implemented in the current financial systems and governance systems to improve the quality of decision-making and resiliency in organizations. Artificial Intelligence (AI) is possibly one of the most radical technologies capable of assisting in breaking those limitations and bringing the automation, prediction, and intelligence of

financial decision-making. With the application of AI-based models one can analyze vast amounts of financial data, find patterns and anticipate oscillations on the market, as well as real-time data that can be applied to make more strategic decisions. Different liquidity optimisation of the treasury, simplified payment systems and increased precision in the cash projection can also be done with the help of AI. Still on risk mitigation, in the same context, AI assists companies in discovering fraud, credit risk source and market risk, as well as achieve compliance with the evolving regulatory guidelines. Despite the advances, most of the companies remain uncertain, how successful the AI can be integrated into the existing financial systems and governance framework to enhance the quality of decisions and the overall strength of the company.

The big question that will be addressed during the research is therefore that there is insufficient knowledge and research evidence regarding the extent to which AI enhances financial decision making in treasury management and risk reduction. Even though the growing momentum towards using AI in the financial analytics and automation fields can be observed in the presented literature, VAOs continue to be underestimated in respect of their empirical effectiveness to avoid mistakes in decision making, risk reduction, and development of strategic values. Also, AI application poses additional threats to data management, model transparency, and cybersecurity, and ethical responsibility, which can impact its application in the sensitive area of financial activities. At that, there is an extreme urgency of the answer to the question of how AI technologies are being introduced and put to practice in the sphere of treasury and risk functions, to what extent they make the decision-making process more effective and reliable, and what organizational, technological, and ethics problems can hamper the most effective use of AI technologies.

The answer to this research problem is vital to both the academic field and business sector; it will allow concentrating on how AI can change the financial management system and practices, predictions that will be made to support the crisis, and how the risks will be better resilient. The insights into the relations between the adoption of AI, financial results,

and risk control systems will enable the organizations to develop smarter, more transparent, and future-proof treasury and risk management systems.

3.2 Operationalization of Theoretical Constructs

The application of the theoretical constructs to Artificial Intelligence (AI) to improve the financial decision making processes is based on operationalization of the abstract concepts (accuracy, efficiency, and strategic quality) into measurable, empirical indicators. These constructs should be identified both in principle and in a manner that can be realized and measured in terms of the financial, technological and behavioral variables in treasury and risk management. This is done by determining the most important dimensions of the constructs and matching them up with the accepted frameworks; Technology Acceptance Model (TAM), Resource-Based View (RBV), and Decision Support Systems (DSS) theory. All of these frames are observed as the ways AI technologies are implemented, help to increase the capabilities of the organization, and assist people with making decisions. The operationalization, consequently, fills the conceptual knowledge of the potential of AI with the empirical facts of the reality of financial management.

The accuracy factor in the financial decision-making process created by AI can be operationalized by the definition of such measurable outcomes as the accuracy of predictions, the decrease in the number of errors and the accuracy of a financial prediction. Accuracy in the context of treasury operation is associated with how far AI algorithmic prediction of cash flows, interest rate changes, and exposure to currencies can be predicted with minimal variation with the actual data. Measures of empirical metrics may involve forecast error rates, mean absolute percentage error (MAPE), or the variance of model (R^2). The effectiveness of AI in detecting potential risks or anomalies prior to their occurrence can be considered a measure of accuracy in risk management (such as the false positive/negative rates or sensitivity of risk detection). The theoretical basis of the decision theory implies that an increase in accuracy leads directly to increase in decision confidence and decrease in uncertainty, which means that AI can play a vital role in risk-adjusted financial strategies. Therefore, the accuracy operationalization is defined as the comparison

of the consistency of algorithmic insights with human predictions or superiority of the former in the dynamic financial environment.

The efficiency construct, one of the pillars of the financial management theory, gets operationalised by investigating the speed, the level of automation, and cost-effectiveness of the AI-enabled processes. Another measure of efficiency in treasury operations can be the duration of cash reconciliation, the rate at which the payment transactions can be processed and the degree to which the forecast level or liquidity planning would need manual intervention. The research based on the Resource-Based View (RBV) emphasizes the fact that AI can help achieve efficiency by automaking repetitive operations, maximizing liquidity reserves, and facilitating continuous tracking of market and counterparties positions. Examples of operational measures can be given in terms of a reduction of cycle-time or reduction of the cost per transaction or a score of automation index which is a ratio of machine to human driven processes. Another possible measure of risk management efficiency can be the speed of risk exposures detection, estimation and reduction by automated systems. In this way, the operationalization of efficiency is done as a measurement of the addition of time and resource optimization in the course of financial processes operationalized using AI.

The third broad construct, strategic quality of financial decisions is more abstractive and multifaceted, however, it can be operationalized with the help of both qualitative and quantitative measures. Strategic quality Theoretically founded on Strategic Decision-Making (SDM) and Dynamic Capabilities Theory, strategic quality represents the extent to which AI can promote the relevance of decisions in the long term, accessible adaptability, and value creation. Operational measures may consist of the number and effectiveness of strategic modifications premised on AI-based intelligence, correlation between AI suggestions and strategic fiscal goals, and approval of AI-based decision support sources by managers. Perceived strategic improvement can be measured by surveying and structured interviews, and quantitative data includes performance-based data (including improved return on assets (ROA), optimal use of capital or improved hedging

performance). By so doing, strategic quality can be operationally defined as a perceptual and outcome-driven construct, which interconnects AI-enabled foresight and concrete organizational advantages.

The second critical theoretical construct is the adoption and capability maturity of AI which can be treated as a mediating variable which has an impact on the relationship between implementation and the outcome of the decision regarding AI. This construct can be operationalised using the Technology-Organization-Environment (TOE) and Innovation Diffusion Theory (IDT) by gauging the aspects of AI integration, the advancedness of the deployed models and the capacity of the organisation to support AI-driven learning. Examples of indicators might be indices of AI capabilities, level of investment in AI infrastructure, data governance, or the level of AI competency in employees. Empirical measures could be utilized to determine the levels of maturity of the AI implementation, experiment pilot programs through to fully automated, adaptable decision systems. This operationalization enables researchers to measure the effect of varying rates of AI maturity on accuracy, efficiency, and strategic quality and, therefore, make cross-sectional comparisons across organizations.

Another construct that is important to be operationalized in this area of research is the risk mitigation effectiveness. It can be operationalized, basing on Risk Management Frameworks (like ISO 31000) on the basis of risk-adjusted ratio of returns, reduction of volatility, accuracy of hedge or prevention of losses. The role that AI would play in risk mitigation can be measured through the capability to predict possible disruption to the supply chain and offer solutions that would help rectify the situation using predictive analytics, anomaly detection, and scenario modelling. The literature also contributes to the inclusion of such an indicator of the efficiency of AI-enabled risk management as the latency of decision-making (the duration between the identification of the risk and its response). Having transformed the theoretical risk mitigation into the quantifiable performance results, organizations can demonstrate empirically how AI systems can help

them become more resilient and proactive in their decisions which are the results of having a volatile financial environment.

Operationalization should also be holistic, and as moderating constructs, human-AI interaction and governance structures must be included as well. According to theories like the Socio-Technical Systems (STS) and Human-Computer Interaction (HCI) the performance of technology is impacted by the way humans perceive and respond to the AI outputs. The variables that are operationalised are the level of trust by the users, how transparency AI systems look, quality of their training and how often decisions are overridden (how many times managers decide to adjust or reject AI recommendations. Likewise, the verification frequency of the model, the level of compliance with ethical conduct, the level of data audit, the level of explainability can be operationalized as measures of AI governance. These constructs facilitate the fact that operationalization extends beyond technological measurements to apply to both behavioral and ethical factors that condition AI efficacy in decision-making.

Alongside, the organizational performance outcomes are the dependent constructs that connect the AI operationalization with the global financial and strategic influence. They can be operationalised in terms of the Balanced Scorecard and Performance Measurement Frameworks, i.e. in terms of the ratio of costs and income improvement, the index of forecast accuracy and the ratio of capital efficiency, as well as the measurement of shareholders value creation. Likert-scale surveys can be used to measure qualitative dimensions including managerial satisfaction, decision confidence and perceived strategic agility. The combination of quantitative and qualitative indicators allows a multi-dimensional assessment which enables addressing the impact of AI not only on the efficiency of the processes, but also on the cognitive and strategic performance.

Lastly operationalization process should also incorporate the use of suitable data sources and tools of analysis to accommodate the construct validity. Data sources may be collected by way of filled out questionnaire, analytical data produced by the computer system,

interview with professionals in treasury and archived financial documents. Structural equation modelling (SEM), correlation and regression analysis, and confirmatory factor analysis (CFA) are the types of analytical methods that can be used to confirm the relationships among constructs and determine their predictive adequacy. The ability to be oriented in theoretical constructs along with measurable variables increases the reliability and validity of the research model by making the abstract dimensions of AI based financial decision-making empirically testable.

In conclusion, operationalization of the theoretical constructs can be done by defining the constructs of accuracy, efficiency, strategic quality, AI capability maturity, and harm mitigation effective in measurable words that fit into known theoretical constructs. This operationalization enables the connection of the theory with the practice and enables the empirical study to grasp the way AI improves accuracy, speed, and depth of the financial decision-making. By so doing, researchers and practitioners can produce actionable information, with the treasury and risk management functions able to use AI not only as a means of calculating something but as an empowering force of organizational intelligence and resilience.

3.3 Research Purpose and Questions

{The overall goal of the research is to research and analyze the means by which Artificial Intelligence (AI) is applicable in advancing financial decision making processes in the Realms of treasury management and risk aversion. Demands of intelligent and agile decision support infrastructure have now taken on a sense of urgency as financial institutions and companies are turning unstable, data-driven, and technologically challenging. The current study will touch upon how AI technologies as machine learning, predictive analytics, and automation are transforming the time-honored methods of financial management, improving the accuracy with which cash flows are predicted, liquidity management, and how well risk identification and risk mitigation processes are performed.

The study is going to be focused on providing a generalized understanding of how AI-based technologies and models can be utilized to make the financial decisions more informed, timely, and strategic. It will compare the impact of AI on the overall activities of the main treasury, such as the management of cash, investment optimization, capital distribution, and compliance control. Besides, the study will assess the role of AI in enhancing the effectiveness with which organisations will identify, analyze, and respond to financial risks- such as market and credit risks to operational and compliance risks. The study aims to bridge the gap in attaining the knowledge gap between theory and practice in AI-based financial decision-making through highlighting both administrative and the technological aspect of the same.

The other significant purpose of the study is the assessment of the benefits, challenges, and weaknesses of implementing AI into treasury and risk management systems. The successful execution of AI needs organization readiness, information policy, ethical concerns, and adherence to laws when AI promises tremendous opportunities to improve efficiency, precision, and foresight. As a result, the research will explore the barriers that deter the application of AI in finance decision-making as well as propose methods of their detection. It will also outline how human expertise and AI can be and are mutually complimentary to the other to create an intelligent, balanced ecosystem that makes decisions.

Lastly, the research will be directed toward a goal of generating both empirical and theoretical data that would be used by financial managers, policymakers, and researchers in the creation and implementation of AI based financial systems. The study should make the next step towards defining a strong framework of digital transformation of the financial procedure, as there is a scope of definitions of channels where AI enhances the quality of decisions and stability in the instances of risk. One believes that the acquired results will allow organizations to consider AI as not only a driving force of automation but a strategic partner that can allow organizations to achieve financial stability, transparency, and sustainable performance.

3.3.1. Research Questions

- What is the effect of factors of Artificial Intelligence on the financial decision making processes in treasury management?
- What is the impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation?
- Which are the most important challenges related to the implementation of AI in the treasury and risk management processes?
- What are the major opportunities that are linked with the implementation of AI into the treasury and risk management functions?
- What are the suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions?

3.3.2. Hypothesis of the study

- **H01:** There are no significant key factors affecting artificial intelligence on the financial decision-making processes in treasury management.
- **Ha1:** There are significant key factors affecting artificial intelligence on the financial decision-making processes in treasury management.
- **H02:** There are no significant impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation.
- **Ha2:** There are significant impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation.
- **H03:** There are no significant challenges related to the implementation of AI in the treasury and risk management processes.
- **Ha3:** There are significant challenges related to the implementation of AI in the treasury and risk management processes.
- **H04:** There are no significant opportunities that are linked with the implementation of AI into the treasury and risk management functions.

- **Ha4:** There are significant opportunities that are linked with the implementation of AI into the treasury and risk management functions.
- **H05:** There are no significant suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions.
- **Ha5:** There are significant suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions.

3.4 Research Design

The existing study adopts a exploratory approach supported by quantitative research design to assess the exploring artificial intelligence (AI) for enhancing financial decision-making in treasury management and risk mitigation in India. Moreover, purposive sampling method is applied in the study.

3.5 Population and Sample

- (i) **Respondents' Type:** - There are three cities namely, Bangalore, Delhi and Hyderabad taken for survey. Therefore, Bangalore, Delhi and Hyderabad are universe for current research.
- (ii) **Sampling technique:** - In this study respondents are randomly selected using purposive sampling techniques.
- (iii) **Sample size:** - Sample size for the study includes 600 employees working in 4 commercial banks, namely, State Bank of India, Canara Bank and HDFC Bank and ICICI Bank. Total Population of employees in 6 commercial banks found to be: 4,26,228.
- (iv) **Determination of Sample Size:**

Determining the sample size using **Cochran's formula:**

$$n = \frac{Z^2 \cdot p \cdot (1 - p)}{e^2 + \left(\frac{Z^2 \cdot p \cdot (1 - p)}{N} \right)}$$

Where:

- $Z = 1.96$ (Z-score for a 95% confidence level)
- $p = 0.5$ (assumed proportion)
- $e = 0.05$ (margin of error)

Figure 2.1
Cochran's Formula

- $N = 4,23,458$

The sample size is approximately **384**. For existing study, the sample size is decided **600** as more the sample size more will be conclusive and accurate results.

Table 2.1

Population and Sample

S.No.	Name of City	Total population of Employees in Banking Sector	Number of respondents selected for data collection
1.	Bangalore	2,25,564	200
2.	Delhi	1,54,040	200

3.	Hyderabad	46,624	200
Total		4,26,228	600

3.6 Participant Selection

The participant for current study is employees from banking sector from India. The cities selected for survey from India are Bangalore, Delhi and Hyderabad.

3.7 Instrumentation

For quantitative analysis Statistical Package for Social Sciences (SPSS) software version 23.0 used.

3.8 Data Collection Procedures

3.8.1. Questionnaire design: Based on 5-point Likert scale, responses from strongly agree to strongly disagree applied in the study. Self-structured questionnaire adopted in the current study.

3.8.2. Sources of data

- (i) **Primary data:** The existing study adopts exploratory approach. Therefore, survey is conducted and responses collected from self-structured questionnaire filled by employees of commercial banking sector in India.
- (ii) **Secondary data:** Secondary data collected for the purpose of doing extensive literature survey based on prior research work from published research articles, working papers, published thesis, conference papers, books, authentic reports, websites.

3.9 Data Analysis

SPSS 26.0 version is used to obtain results from the coding sheet after addressing the missing values. Various statistical tools of SPSS applied to provide quantitative information for concepts clarity.

Details of Tools applied in data analysis

1. **Frequency and percentage Method:** Frequency and percentage distribution used to determine the percentage usually for data on profile (age, occupation, gender, marital status tec.)

Formula:

$$\% = \frac{f}{N} \times 100$$

Where: % = Percent
f = Frequency
N = Number of cases

Figure 2.2
Frequency and Percentage Method

2. Mean:

The *mean* is the average or the most common value in a collection of numbers. The mean (average) of a data set is found by adding all numbers in the data set and then dividing by the number of values in the set.

$$\text{Mean} = \frac{\text{Sum of All Data Points}}{\text{Number of Data Points}}$$

$$\text{Mean} = \text{Assumed Mean} + \frac{\text{Sum of All Deviations}}{\text{Number of Data Points}}$$

Figure 2.3
Mean Formula

3. Standard Deviation

The *standard deviation* is a *statistic* that measures the dispersion of a dataset relative to its mean and is calculated as the square root of the variance.

$$\sigma = \sqrt{\frac{\sum (x - \bar{x})^2}{n}}$$

σ = standard deviation
 $\sum$ = sum of
 x = each value in the data set
 $\bar{x}$ = mean of all values in the data set
 n = number of value in the data set

Figure 2.4
Standard Deviation Formula

4. T test

A t-test is a statistical test that is used to compare the means of two groups. It is often used in hypothesis testing to determine whether a process or treatment actually has an effect on the population of interest, or whether two groups are different from one another.

Type	T-statistic	Degrees of freedom
One-sample t-test	$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$	df = n - 1
Paired t-test	$t = \frac{\bar{X}_D - \mu_0}{s_D/\sqrt{n}}$	df = n - 1

Figure 2.5
T-Test

5. Chi-square Test

The Chi-Square analysis is most frequently used to estimate condition of Independence test while applying a crosstabulation also referred as a bivariate table. Crosstabulation helps in assessing the dispersals of two categorical variables at once, with the connections of the groups of the variables appearing in the cells assembled in the bivariate table. The Independence test measures whether a relationship among the two variables by relating the responses from observed pattern in the cells to the responses from expected pattern if the variables were truly independent of each other. Assessing the Chi-Square statistic and then comparing it in contrast to a critical value from the distribution of Chi-square permits the scholars to measure whether the observed cell totals are significantly unlike from the expected cell totals.

An assessment of the Chi-Square analysis is quite straight-forward and also based on intuition. The formula of Chi-square is as follows:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

Figure 2.6
Chi-Square Test

χ^2 = The test static

$\sum$ = The sum of

O= Observed frequency

E= Expected frequency

As represented in the above formula, the Chi-Square analysis based on the difference between what is the actual observed frequency in the data and what would be expected frequency if there was no association exist among the variables.

6. Correlation Analysis

Correlation test is used to evaluate the association between two or more variables. Correlation coefficients are used to measure how strong a relationship is between two variables.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Figure 2.7
Correlation Analysis

7. Regression Analysis

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable and one or more independent variables.

$$Y = a + bX$$

$$b = \frac{N\sum XY - (\sum X)(\sum Y)}{N\sum X^2 - (\sum X)^2} \quad a = \frac{\sum Y - b\sum X}{N}$$

Where,
N = number of observations, or years
X = a year index (decade)
Y = population size for given census years

Figure 2.8
Regression Analysis

8. ANOVA

Analysis of variance (ANOVA) is a collection of statistical models and their associated estimation procedures (such as the "variation" among and between groups) used to analyse the differences among group means in a sample.

9. Exploratory Factor Analysis:

Exploratory factor analysis (EFA) and structural equation modeling (SEM) are techniques commonly used in the field of language assessment. EFA is a data-driven approach which is generally used as an investigative technique to identify relationships among variables.

3.10 Research Design Limitations

- Three cities, namely, Bangalore, Delhi and Hyderabad were only possible for survey.
- 600 employees only from commercial banks in India industry taken for study.
- Only banking industry is explored in the current research.

3.11 Conclusion

To summarize, the adoption of the concept of Artificial Intelligence (AI) in treasury and risk management has changed the face of financial decision-making by increasing its accuracy, efficiency, and quality of strategic decisions. The AI-based tools allow companies to analyze intricate financial data, enhance the accuracy of forecasting, semi-automate their routine activities, and make decision-making faster and more supported by data. These developments facilitate the minimization of human error, enhance predictability and give financial managers the opportunity to engage in more advanced strategic analysis. Besides, AI can aid in proactive risk mitigation and the identified risks

can be noticed before they develop further, thus enhancing the resilience and financial stability. Yet, the advantages of AI have to rely on whether there is proper control of data and transparency and human-AI cooperation to hold people and optimize the trust in decision-making. Issues like the lack of skills, ethical issues, and regulatory issues should also be tackled to extract the full potential of AI. In general, AI is becoming more of a collaborative analytical platform rather than a strategic partner that redefines the manner in which firms execute fluidity, reduce risks, and attain sustainability growth. The success of its implementation will be based on the appropriate use of automation and human control, the necessity of innovation in the ethical framework, and the constant coordination of the AI systems and organizational needs and regulatory standards.

CHAPTER IV:

RESULTS

4.1 Results

Table 2.2

Age Distribution

Age Distribution	Frequency	Percentage
Below 25 years	128	21.33%
25 to 35 years	187	31.16%
36 to 45 years	169	28.16%
Above 45 years	116	19.33%

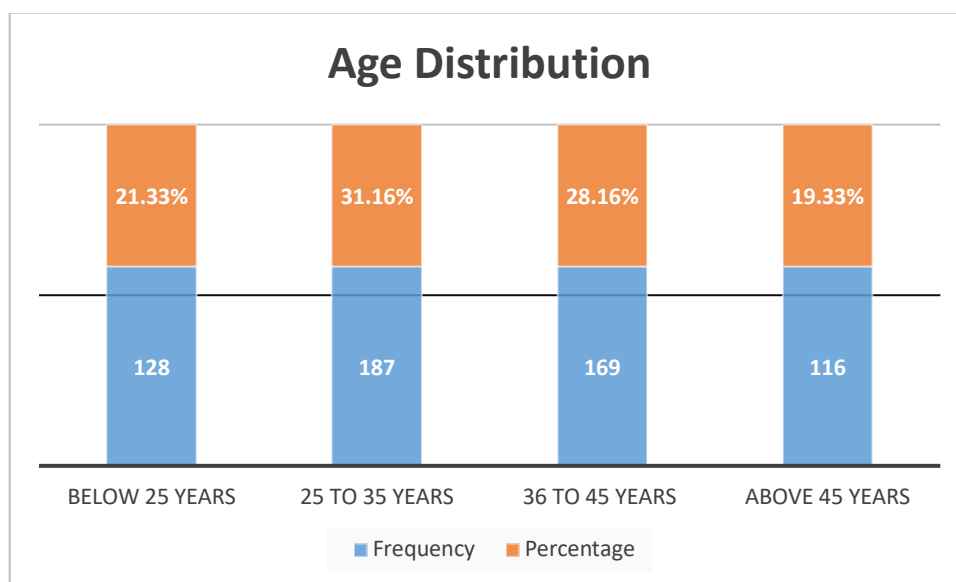


Figure 2.9
Age Distribution

The age distribution of respondents indicates a **balanced representation across different age groups**, with a slight concentration in the younger and middle-aged categories. The largest proportion of respondents falls within the **25 to 35 years age group (31.16%)**, suggesting that this demographic is the most actively engaged or most reachable in the context of the study. This is followed closely by individuals aged **36 to 45 years (28.16%)**, representing a substantial segment of the sample. Together, these two age groups (25–45 years) account for nearly **59%** of the total respondents, highlighting the dominance of working-age adults in the dataset.

The **below 25 years** group constitutes **21.33%**, indicating a considerable presence of younger participants—possibly early-career professionals, students, or young adults who are increasingly participating in the area under study. Meanwhile, respondents **above 45 years** represent **19.33%** of the sample, showing relatively lower but still meaningful participation from older adults.

Overall, the distribution shows that the sample is **diverse across age groups**, with a stronger representation from those in the early to mid-career stages. This demographic composition may influence the study’s outcomes, particularly if age-related perspectives, technological familiarity, or experience level are relevant to the research variables.

Table 2.3

Gender

Gender	Frequency	Percentage
Male	372	62.00%
Female	228	38.00%

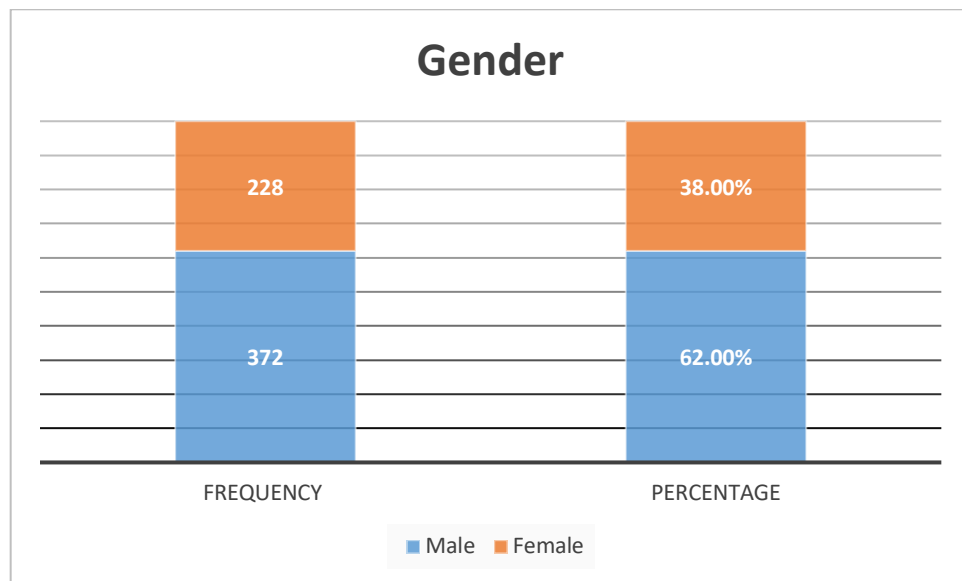


Figure 2.10

Gender

The gender distribution of the respondents indicates that the sample is **male-dominated**, with **62%** of participants identifying as male ($n = 372$). In comparison, **38%** of the respondents are female ($n = 228$). This shows a noticeable imbalance in gender representation, with males forming nearly two-thirds of the total sample.

The higher proportion of male respondents may reflect the demographic characteristics of the target population or the specific sector to which the study relates—particularly if the field traditionally employs or attracts more males. Conversely, the female representation, although lower, still constitutes a substantial portion of the sample, allowing for meaningful gender-based analysis where relevant.

Overall, the gender distribution demonstrates **adequate participation from both genders**, but with a clear predominance of male respondents, which may have implications for interpreting certain research findings, especially if gender influences attitudes, perceptions, or behavioural patterns related to the study.

Table 2.4

Marital Status

Marital Status	Frequency	Percentage
Single	226	37.66%
Married	243	40.50%
Others	131	21.83%

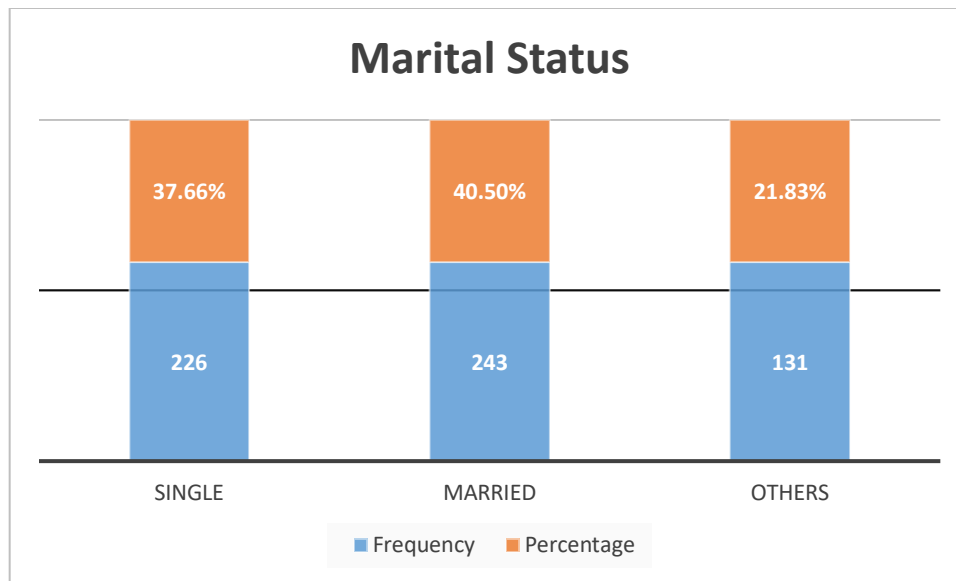


Figure 2.11
Marital Status

The marital status distribution of the respondents reflects a **fairly balanced representation** across the three categories, with a slight dominance of married individuals. The largest proportion of respondents is **married (40.50%)**, suggesting that individuals with family responsibilities form an important segment of the study population. This is followed by **single respondents (37.66%)**, who also constitute a substantial share of the sample, indicating that the study captures perspectives across different stages of personal life.

The **‘others’** category, comprising **21.83%**, includes respondents who may be widowed, divorced, separated, or prefer not to disclose their marital status. This proportion is notable, representing more than one-fifth of the sample, and adds diversity to the demographic composition.

Overall, the distribution shows that the sample includes a **mix of single, married, and other marital status groups**, ensuring that the findings reflect a broad range of personal

life circumstances. Such demographic variation is valuable, especially if marital status may influence attitudes, decision-making patterns, or responsibilities relevant to the study.

Table 2.5

Education Qualification

Educational Qualification	Frequency	Percentage
Below Graduate	153	25.50%
Graduate	148	25%
Postgraduate	219	36.50%
Above Postgraduate	80	13.33%

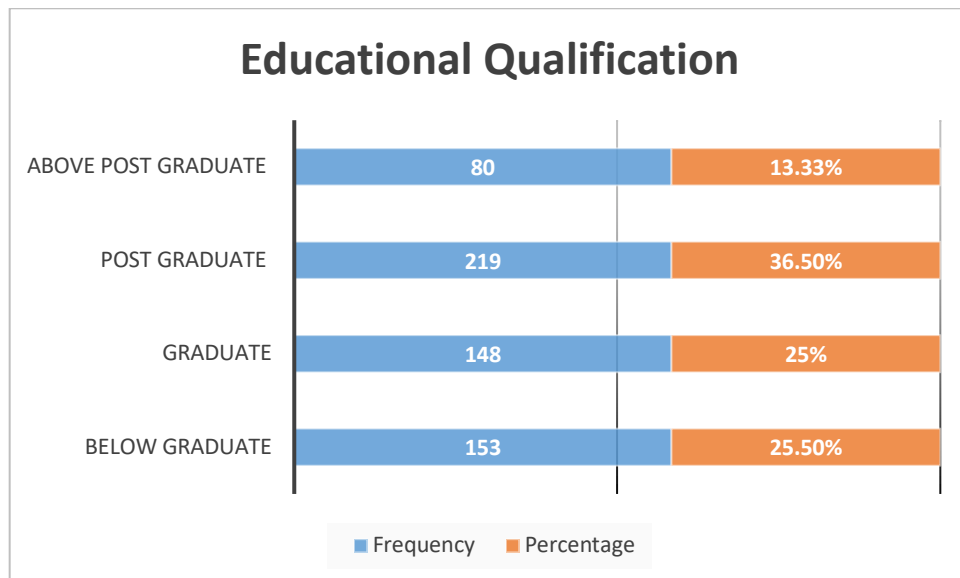


Figure 2.12

Education Qualification

The educational profile of the respondents indicates that the sample is composed predominantly of individuals with higher levels of academic attainment, which is highly relevant to a study examining AI-driven financial decision-making and treasury management processes.

The largest segment of respondents comprises those with a **postgraduate qualification (36.50%)**, suggesting that a considerable proportion of participants possess advanced academic exposure, analytical skills, and familiarity with complex financial or technological concepts. This level of education is particularly significant in a field where understanding AI tools, treasury operations, and risk mitigation strategies often requires higher-order cognitive abilities and professional expertise.

Respondents who are **below graduate level (25.50%)** and **graduate degree holders (25%)** together account for half of the sample. Their representation indicates that individuals with foundational or intermediate academic backgrounds are also actively engaged in AI-related financial processes. Their perspectives can provide valuable insights on practical challenges, adoption barriers, and training needs related to AI implementation in treasury and risk functions.

The smallest group, those **above postgraduate level (13.33%)**, likely includes professionals with specialized qualifications, research backgrounds, or technical expertise. Their representation, though limited, contributes depth to the sample by offering more advanced understanding of AI technologies, quantitative decision-making, and strategic financial management.

Overall, the educational distribution reflects a **diverse but academically solid respondent base**, which is advantageous for a study investigating how AI enhances financial decision-making in treasury management and risk mitigation. The strong presence of postgraduate respondents enhances the reliability of insights related to sophisticated financial and technological applications.

Table 2.6

Monthly Income

Monthly Income (in Rs.)	Frequency	Percentage
Below 45,000	83	13.83%
45,001 to 55000	204	34.00%
55001 to 65000	239	39.83%
Above 65000	74	12.33%

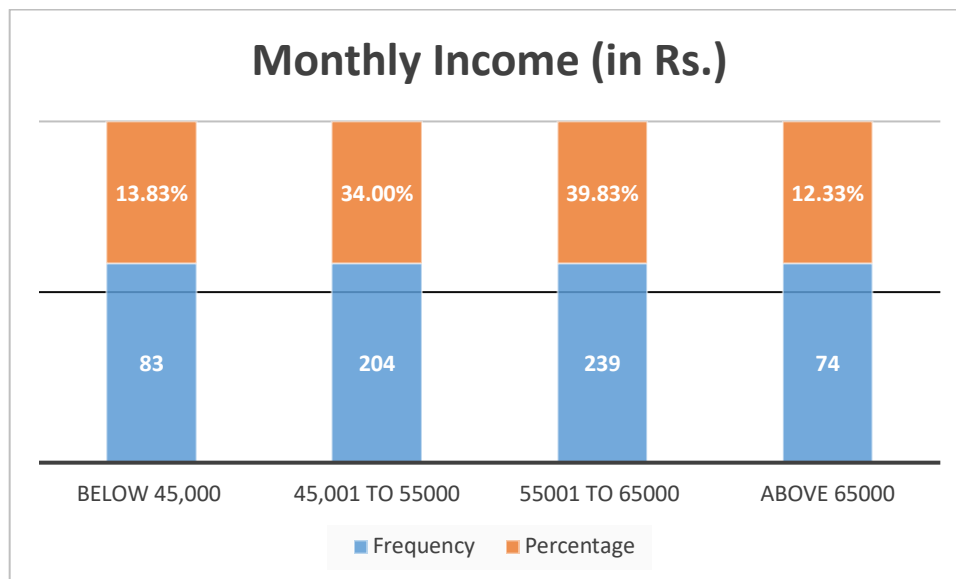


Figure 2.13
Monthly Income

The monthly income distribution of respondents reflects a sample largely composed of middle-income professionals, which is relevant in the context of studying AI adoption in financial decision-making and treasury management. The highest proportion of respondents (39.83%) belongs to the **₹55,001 to ₹65,000** income category, indicating that many participants are likely mid-level professionals with considerable financial responsibilities and active involvement in organizational decision-making processes.

The second largest group (34%) falls within the **₹45,001 to ₹55,000** range, further reinforcing the dominance of respondents with stable, mid-range incomes. Individuals in these income brackets often occupy roles that require analytical thinking, operational contributions, and interaction with financial or technological systems within their organizations. Their insights are therefore valuable for understanding practical experiences and expectations related to AI-based treasury and risk management tools.

Respondents earning **below ₹45,000** account for **13.83%** of the sample. This group may consist of early-career employees or support-level staff, whose perspectives can help identify skill gaps, training needs, and operational challenges in adopting AI technologies.

Conversely, those earning **above ₹65,000** (12.33%) likely represent senior professionals, managers, or individuals in strategic financial roles. Although numerically smaller, this segment provides crucial viewpoints related to high-level decision-making, policy formulation, and organizational readiness for AI-driven financial transformation.

Overall, the income distribution suggests that the sample is composed mainly of **working professionals with moderate to high income levels**, well-positioned to contribute meaningful insights into the effectiveness, challenges, and opportunities associated with AI in treasury management and risk mitigation.

Table 2.7

Years of Experience

Years of experience in Banking industry	Frequency	Percentage
Less than 1 year	36	6.00%
2 to 5 years	203	33.83%
6 to 10 years	196	32.66%
More than 10 years	165	27.50%

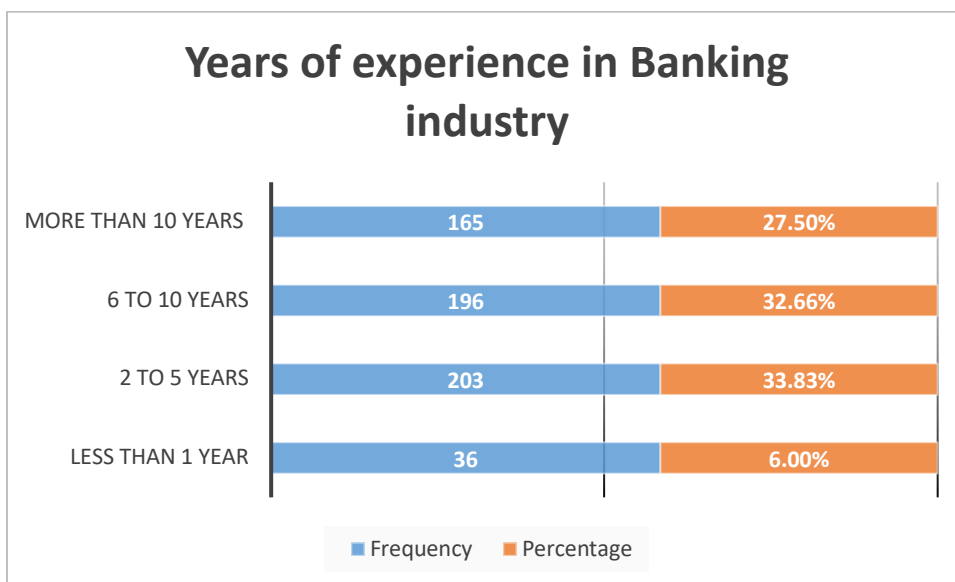


Figure 2.14
Years of Experience

The distribution of respondents based on years of experience in the packaging industry shows a well-balanced mix of early-career, mid-career, and highly experienced

professionals. This diversity enhances the reliability of insights related to AI adoption and financial decision-making in the sector.

The largest proportion of respondents (33.83%) has **2 to 5 years of experience**, indicating strong representation from employees who are relatively new but sufficiently familiar with organizational processes. Their perspectives are valuable for understanding operational-level challenges, adaptability to new technologies, and expectations from AI-driven systems in treasury and risk management.

Similarly, respondents with **6 to 10 years of experience** form a substantial share (32.66%). This mid-career group often occupies supervisory or analytical roles and may have direct exposure to financial workflows, treasury operations, and risk mitigation activities. Their insights can provide a practical understanding of how AI enhances efficiency and accuracy in financial decision-making.

A significant portion of respondents (27.50%) have **more than 10 years** of industry experience. This group likely occupies senior or managerial positions and is involved in strategic decision-making. Their perspectives help evaluate the long-term benefits, implementation feasibility, and policy implications of adopting AI in financial and treasury functions.

The smallest group, those with **less than 1 year of experience (6%)**, represents entry-level employees. Although fewer, this segment offers insight into the digital readiness and learning curves of new entrants in the industry, which is crucial when assessing training requirements and organizational preparedness for AI integration.

Overall, the experience distribution reflects a **comprehensive mix of employees across different experience levels**, making the dataset well-suited for examining how professionals at various stages perceive AI's role in enhancing financial decision-making, treasury management, and risk mitigation.

Table 2.8

Type of Family

Type of Family	Frequency	Percentage
Nuclear Family	393	65.55%
Joint Family	207	34.50%

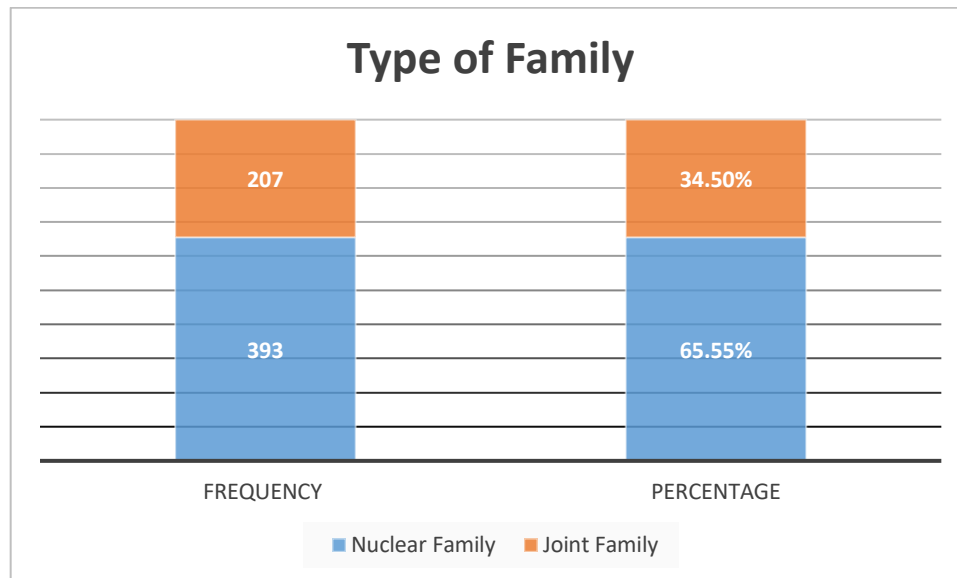


Figure 2.15

Type of Family

The data on family type shows that a majority of the respondents belong to **nuclear families (65.55%)**, while the remaining **34.50%** come from **joint families**. This distribution indicates that most participants come from smaller, independent household

units, which is reflective of contemporary urban and semi-urban living patterns, especially among working professionals in industries such as packaging, finance, and technology.

Individuals from nuclear families often manage their own financial responsibilities, which may influence their financial decision-making behavior, openness to technology, and reliance on efficient tools such as AI-driven financial systems. Their representation strengthens the study's insights into how AI is perceived and used in treasury and risk management among financially independent professionals.

On the other hand, respondents from joint families form a significant portion of the sample. Their perspectives may be shaped by shared financial responsibilities, collective decision-making patterns, and varying levels of exposure to digital financial tools. Their inclusion adds diversity to the dataset and ensures that the findings capture a broader range of socioeconomic contexts.

Overall, the distribution shows a **balanced yet predominantly nuclear-family sample**, offering a comprehensive understanding of how family structure may influence attitudes, readiness, and decision-making processes related to AI adoption in treasury management and risk mitigation.

Table 2.9

Size of Family

Size (no. of persons in your family)	Frequency	Percentage
2	305	50.83%
3 to 6	103	17.16%
6 to 9	101	16.83%
More than 9	91	15.16%

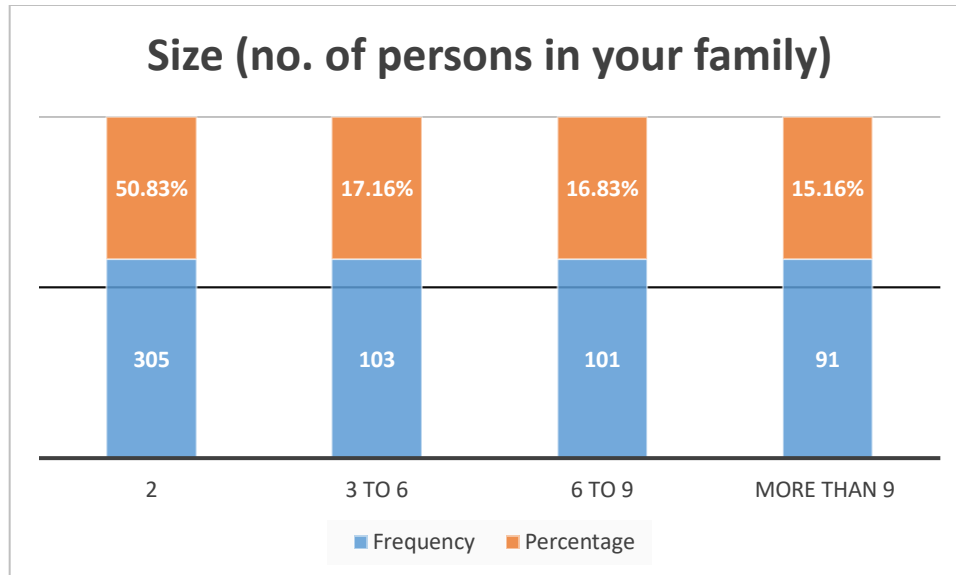


Figure 2.16
Size of Family

The distribution of family size among respondents indicates that **half of the participants (50.83%) live in small families consisting of two members**. This suggests a strong prevalence of compact household structures, which is consistent with the dominance of nuclear families reported earlier. Individuals in smaller families often manage their finances independently and may be more inclined toward adopting efficient, technology-driven tools—an important consideration in studies related to AI-enabled financial decision-making.

A smaller but meaningful proportion of respondents (17.16%) belong to families of **3 to 6 members**, while **16.83%** live in families comprising **6 to 9 members**. These moderate to moderately large family sizes indicate mixed responsibilities and shared financial commitments, which may influence the respondents' perceptions of financial risk, treasury management priorities, and the need for accuracy in financial decision-making.

Furthermore, **15.16%** of respondents belong to families with **more than nine members**, representing large households with potentially complex financial dynamics. Participants from such families may have heightened awareness of risk mitigation, budgeting, and long-term financial planning—factors that can shape their attitudes toward AI adoption in financial and treasury functions.

Overall, the family size distribution reveals a diverse sample, with respondents representing a range of household structures, from very small to very large families. This diversity enhances the depth of the study by capturing varied financial responsibilities and decision-making contexts relevant to AI-based treasury management and risk mitigation.

Table 2.10

Reliability Statistics-Research Question One

Reliability Statistics	
Cronbach's Alpha	N of Items
.869	13

The reliability analysis shows that the scale comprising **13 items** has a **Cronbach's Alpha value of 0.869**. This indicates a **high level of internal consistency** among the items used in the questionnaire. A Cronbach's Alpha value above **0.70** is typically considered acceptable, while values above **0.80** reflect strong reliability. Therefore, an alpha of **0.869** demonstrates that the items used to measure the constructs in this study are highly reliable and consistently capture the underlying dimensions related to the research topic.

Table 2.11

Descriptive Statistics-Research Question One

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
The accuracy of forecasting cash-flow is enhanced with AI	600	1	5	4.42	.644
Artificial intelligence assists in faster decision-making by the treasury	600	1	5	4.18	.814
AI increases treasury real-time transparency	600	1	5	4.39	.619
Artificial intelligence-based automation eliminates human mistakes	600	1	5	4.19	.765
AI assists in strategic decision-making by providing a scenario analysis	600	1	5	4.26	.710
AI helps to optimize distribution of liquidity among accounts	600	1	5	4.39	.644
Artificial intelligence is beneficial as it is used to forecast short-term cash needs better	600	1	5	4.36	.678

AI will positively impact the management of foreign exchange (FX)	600	1	5	4.23	.748
AI enhances priority in payment and collection	600	1	5	4.23	.698
AI assists in detecting inefficiencies of treasury operations	600	1	5	4.19	.825
Scenario-based forecasting of financial planning can be supported using AI	600	1	5	3.97	.942
AI helps to offer actionable suggestions in investment in treasury	600	1	5	3.75	1.065
AI decreases the use of manual spreadsheets in the treasury analysis	600	1	5	4.19	.818
Valid N (listwise)	600				

The descriptive statistics indicate that respondents expressed strong agreement on most statements regarding the role of AI in treasury management, as reflected in high mean values and relatively low standard deviations. The highest agreement was observed for the statement that AI enhances the accuracy of cash-flow forecasting, with a mean of **4.42** and a standard deviation of **0.644**, followed closely by AI increasing real-time transparency (Mean = **4.39**, SD = **0.619**) and AI helping to optimize liquidity distribution among accounts (Mean = **4.39**, SD = **0.644**). Similarly, respondents agreed that AI is beneficial in

forecasting short-term cash needs (Mean = **4.36**, SD = **0.678**) and assists in strategic decision-making through scenario analysis (Mean = **4.26**, SD = **0.710**). Other items reflecting operational improvements also received high ratings, such as AI's ability to eliminate human mistakes (Mean = **4.19**, SD = **0.765**), detect inefficiencies (Mean = **4.19**, SD = **0.825**), decrease reliance on manual spreadsheets (Mean = **4.19**, SD = **0.818**), and support faster decision-making (Mean = **4.18**, SD = **0.814**). Moderate agreement was seen for AI improving foreign exchange management and enhancing payment prioritization (both Mean = **4.23**, SD = **0.748** and **0.698**, respectively). The lowest mean values were recorded for scenario-based financial planning using AI (Mean = **3.97**, SD = **0.942**) and AI offering actionable investment suggestions (Mean = **3.75**, SD = **1.065**), indicating slightly more variability in perceptions for these areas. Overall, the descriptive results demonstrate consistently positive views toward AI's impact, supported by strong mean scores and acceptable standard deviations across all items.

Table 2.12

One Sample Statistics-Research Question One

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
The accuracy of forecasting cash-flow is enhanced with AI	600	4.42	.644	.026
Artificial intelligence assists in faster decision-making by the treasury	600	4.18	.814	.033
AI increases treasury real-time transparency	600	4.39	.619	.025

Artificial intelligence-based automation eliminates human mistakes	600	4.18	.765	.031
AI assists in strategic decision-making by providing a scenario analysis	600	4.26	.710	.029
AI helps to optimize distribution of liquidity among accounts	600	4.39	.644	.026
Artificial intelligence is beneficial as it is used to forecast short-term cash needs better	600	4.36	.678	.028
AI will positively impact the management of foreign exchange (FX)	600	4.23	.748	.031
AI enhances priority in payment and collection	600	4.23	.698	.028
AI assists in detecting inefficiencies of treasury operations	600	4.19	.825	.034
Scenario-based forecasting of financial planning can be supported using AI	600	3.97	.942	.038
AI helps to offer actionable suggestions in investment in treasury	600	3.75	1.065	.043
AI decreases the use of manual spreadsheets in the treasury analysis	600	4.19	.818	.033

The one-sample statistics reveal consistently positive perceptions toward the role of Artificial Intelligence in treasury management, as reflected in high mean scores across most items. The highest agreement is observed for the statement that AI enhances the accuracy of cash-flow forecasting, which records a mean of **4.42**, supported by a low standard deviation of **0.644** and a standard error of **0.026**, indicating strong consensus among respondents. Similarly, AI is perceived to significantly increase real-time treasury transparency (Mean = **4.39**, SD = **0.619**, SE = **0.025**) and optimize liquidity distribution (Mean = **4.39**, SD = **0.644**, SE = **0.026**). Respondents also strongly agreed that AI improves short-term cash forecasting (Mean = **4.36**, SD = **0.678**, SE = **0.028**) and supports scenario-based strategic decision-making (Mean = **4.26**, SD = **0.710**, SE = **0.029**). Perceptions regarding AI's operational benefits also showed high ratings—AI eliminates human mistakes (Mean = **4.18**, SD = **0.765**, SE = **0.031**), enhances faster decision-making (Mean = **4.18**, SD = **0.814**, SE = **0.033**), reduces manual spreadsheet use (Mean = **4.19**, SD = **0.818**, SE = **0.033**), and helps detect inefficiencies in treasury operations (Mean = **4.19**, SD = **0.825**, SE = **0.034**). Moderate yet positive agreement was found for AI improving foreign exchange (Mean = **4.23**, SD = **0.748**, SE = **0.031**) and enhancing payment prioritization (Mean = **4.23**, SD = **0.698**, SE = **0.028**). The lowest means were recorded for AI supporting scenario-based financial planning (Mean = **3.97**, SD = **0.942**, SE = **0.038**) and providing actionable investment suggestions (Mean = **3.75**, SD = **1.065**, SE = **0.043**), indicating greater variability in perceptions. Overall, the results demonstrate strong confidence in AI's capability to enhance financial decision-making and risk mitigation, supported by high mean values and reasonable variability across responses.

Table 2.13

One Sample Test-Research Question One

One-Sample Test	
	Test Value = 0

	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
The accuracy of forecasting cash-flow is enhanced with AI	168.217	599	.000	4.422	4.37	4.47
Artificial intelligence assists in faster decision-making by the treasury	125.838	599	.000	4.180	4.11	4.25
AI increases treasury real-time transparency	173.966	599	.000	4.395	4.35	4.44
Artificial intelligence-based automation eliminates human mistakes	134.018	599	.000	4.185	4.12	4.25
AI assists in strategic decision-making by providing a scenario analysis	146.790	599	.000	4.255	4.20	4.31
AI helps to optimize distribution of liquidity among accounts	166.882	599	.000	4.388	4.34	4.44

Artificial intelligence is beneficial as it is used to forecast short-term cash needs better	157.306	599	.000	4.357	4.30	4.41
AI will positively impact the management of foreign exchange (FX)	138.590	599	.000	4.233	4.17	4.29
AI enhances priority in payment and collection	148.415	599	.000	4.228	4.17	4.28
AI assists in detecting inefficiencies of treasury operations	124.351	599	.000	4.188	4.12	4.25
Scenario-based forecasting of financial planning can be supported using AI	103.165	599	.000	3.967	3.89	4.04
AI helps to offer actionable suggestions in investment in treasury	86.237	599	.000	3.748	3.66	3.83

AI decreases the use of manual spreadsheets in the treasury analysis	125.324	599	.000	4.187	4.12	4.25
--	---------	-----	------	-------	------	------

The one-sample t-test results show that all statements related to the role of Artificial Intelligence in treasury management and financial decision-making are statistically significant at the **0.000** level, indicating that the respondents' ratings are significantly greater than the test value of zero. Extremely high t-values across items—such as **t = 168.217** for AI enhancing cash-flow forecasting accuracy and **t = 173.966** for AI increasing real-time transparency—reflect very strong evidence of positive perceptions. Similarly high t-scores for AI optimizing liquidity distribution (**t = 166.882**) and improving short-term cash forecasting (**t = 157.306**) further confirm the substantial support for AI's operational impact. Items related to strategic applications of AI, such as scenario-based decision-making (**t = 146.790**) and foreign exchange management (**t = 138.590**), also demonstrate significant positive deviations from zero. Even the comparatively lower-scoring items, such as AI supporting scenario-based financial planning (**t = 103.165**) and offering investment suggestions (**t = 86.237**), remain strongly significant. The mean differences for all items range between **3.748** and **4.422**, with narrow 95% confidence intervals, indicating consistent agreement among respondents. Overall, the results of the one-sample t-test confirm that perceptions regarding AI's ability to enhance accuracy, efficiency, transparency, and strategic financial decision-making in treasury management are statistically significant and strongly positive.

Table 2.14

Annova-Research Question One

ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.

The accuracy of forecasting cash-flow is enhanced with AI	Between Groups	23.142	4	5.786	15.288	.000
	Within Groups	225.176	595	.378		
	Total	248.318	599			
Artificial intelligence assists in faster decision-making by the treasury	Between Groups	55.659	4	13.915	24.286	.000
	Within Groups	340.901	595	.573		
	Total	396.560	599			
AI increases treasury real-time transparency	Between Groups	21.052	4	5.263	15.031	.000
	Within Groups	208.333	595	.350		
	Total	229.385	599			
Artificial intelligence-based automation eliminates human mistakes	Between Groups	43.867	4	10.967	21.283	.000
	Within Groups	306.598	595	.515		
	Total	350.465	599			
AI assists in strategic decision-making by providing a scenario analysis	Between Groups	43.743	4	10.936	25.196	.000
	Within Groups	258.242	595	.434		
	Total	301.985	599			
AI helps to optimize distribution of liquidity among accounts	Between Groups	28.678	4	7.169	19.404	.000
	Within Groups	219.841	595	.369		
	Total	248.518	599			
Artificial intelligence is beneficial as it is used to forecast short-term cash needs better	Between Groups	36.965	4	9.241	23.035	.000
	Within Groups	238.708	595	.401		
	Total	275.673	599			
AI will positively impact the management of foreign exchange (FX)	Between Groups	42.763	4	10.691	21.742	.000
	Within Groups	292.570	595	.492		
	Total	335.333	599			
AI enhances priority in payment and collection	Between Groups	40.692	4	10.173	24.112	.000
	Within Groups	251.027	595	.422		
	Total	291.718	599			
AI assists in detecting inefficiencies of treasury operations	Between Groups	53.100	4	13.275	22.273	.000
	Within Groups	354.619	595	.596		
	Total	407.718	599			
Scenario-based forecasting of financial planning can be supported using AI	Between Groups	100.859	4	25.215	34.852	.000
	Within Groups	430.475	595	.723		
	Total	531.333	599			

AI helps to offer actionable suggestions in investment in treasury	Between Groups	176.372	4	44.093	52.196	.000
	Within Groups	502.627	595	.845		
	Total	678.998	599			
AI decreases the use of manual spreadsheets in the treasury analysis	Between Groups	91.390	4	22.848	43.895	.000
	Within Groups	309.703	595	.521		
	Total	401.093	599			

The ANOVA results across all thirteen statements indicate statistically significant differences in respondents' perceptions regarding the impact of Artificial Intelligence on various dimensions of treasury management and financial decision-making. For each item, the significance value is **.000**, confirming that responses differ meaningfully across the comparison groups. High F-values such as **F = 24.286** for AI assisting faster decision-making, **F = 25.196** for AI supporting strategic decision-making through scenario analysis, **F = 34.852** for AI enabling scenario-based forecasting, and **F = 52.196** for AI offering actionable investment suggestions suggest substantial variability in how different groups evaluate AI's effectiveness. Similarly, strong F-statistics for forecasting accuracy (**F = 15.288**), real-time transparency (**F = 15.031**), error elimination through automation (**F = 21.283**), optimization of liquidity distribution (**F = 19.404**), better short-term cash need forecasting (**F = 23.035**), and improved FX management (**F = 21.742**) highlight significant groupwise differences in perceived benefits. Even operational aspects like prioritizing payments and collections (**F = 24.112**), detecting inefficiencies (**F = 22.273**), and reducing manual spreadsheet usage (**F = 43.895**) reflect meaningful divergence in responses. Overall, the ANOVA findings demonstrate that perceptions of AI's role in enhancing accuracy, transparency, efficiency, and strategic capabilities in treasury management vary significantly across respondent groups, underscoring the presence of heterogeneous views despite general agreement on AI's positive impact.

Table 2.15

Reliability Statistics-Research Question Two

Reliability Statistics	
Cronbach's Alpha	N of Items
.853	11

The reliability analysis indicates that the scale comprising **11 items** has a **Cronbach's Alpha of 0.853**, which demonstrates a **high level of internal consistency**. Since a Cronbach's Alpha value above **0.70** is generally considered acceptable, a value of **0.853** confirms that the items reliably measure the intended constructs. In the context of the study, this suggests that the questionnaire items consistently capture respondents' perceptions of AI's role in enhancing treasury management, financial decision-making, and risk mitigation. The high reliability ensures that the data obtained from these items are dependable and suitable for further statistical analyses.

Table 2.16

Descriptive Statistics-Research Question Two

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
AI enhances fraud and anomalous transactions	600	1	5	4.18	.814
AI improves precision of market risk forecasting (e.g. FX, interest rate)	600	1	5	4.39	.619

AI helps in enhancing liquidity and credit risk rating	600	1	5	4.19	.765
AI can be used to better stress test and analyse scenarios	600	1	5	4.26	.710
Automation of routine checks helps decrease operational risks using AI	600	1	5	4.39	.644
In times of financial crisis or financial market volatility AIs enhance the speed of decision-making	600	1	5	4.36	.678
AI can give the practical hedging and the reduction of risks stuff	600	1	5	4.23	.748
AI is a source of new model risks necessitating new governance	600	1	5	4.23	.698
Artificial intelligence helps eliminate human errors in estimating risks	600	1	5	4.19	.825
AI has very little or no effect on a decision of mitigating the financial risks	600	1	5	3.97	.942
The effects of AI are based on the quality of data, choice of a model, and human control	600	1	5	3.75	1.065
Valid N (listwise)	600				

The descriptive statistics reveal that respondents generally perceive Artificial Intelligence (AI) as a significant tool for managing financial risks, with most items recording high mean values and relatively low standard deviations. The highest agreement was observed for statements emphasizing AI's precision and automation benefits, such as improving market risk forecasting (Mean = **4.39**, SD = **0.619**) and automating routine checks to decrease operational risks (Mean = **4.39**, SD = **0.644**). Respondents also strongly agreed that AI enhances decision-making during financial crises (Mean = **4.36**, SD = **0.678**) and supports scenario analysis and stress testing (Mean = **4.26**, SD = **0.710**). Other items reflecting risk mitigation capabilities, including detecting fraud and anomalous transactions (Mean = **4.18**, SD = **0.814**), enhancing liquidity and credit risk ratings (Mean = **4.19**, SD = **0.765**), providing practical hedging strategies (Mean = **4.23**, SD = **0.748**), and eliminating human errors in risk estimation (Mean = **4.19**, SD = **0.825**), also received strong positive ratings. Items with comparatively lower agreement included the perception that AI has little effect on financial risk mitigation (Mean = **3.97**, SD = **0.942**) and that AI's effects depend on data quality, model choice, and human control (Mean = **3.75**, SD = **1.065**), indicating slightly more variability in opinions for these aspects. Overall, the descriptive results suggest that respondents recognize AI as an effective and reliable tool for enhancing financial risk management, while acknowledging that its effectiveness is influenced by data quality, model selection, and governance practices.

Table 2.17

Correlations-Research Question Two

Correlations

		AI enhances fraud detection and another malicious transac- tions	AI improves precision of marketing risk forecasting (e.g. FX, interest rate)	AI helps in enhancing liquidity and crediting risk rating scenario	AI can be used to better strengthen test and analysis e-scenarios	Auto- mation of routine checking tasks helps decrease operational risks using AI	In- timidation of financial crisis or financial market volatility AI enhances the speed	AI can give the practical aligned hedging and the reduction of risk stress stuff	AI is a source of new model risks necessitating new governance	Artificial intelligence helps eliminate human error in estimating the financial risk	AI has very little effect or no effect on decision making mitigating the financial risk	The effect of AI are based on the quality of data, choice of a model
--	--	--	---	--	--	--	---	---	---	--	---	--

							of dec isio n- ma kin g					od el, an d hu ma n co ntr ol
AI enha nces fraud and anom alous trans actio ns	Pear son Corr elati on	1	.462 **	.381 **	.386 **	.322 **	.337 **	.307 **	.292* *	.322 **	.258 **	.261 **
	Sig. (2- taile d)		0.00 0	0.00 0	0.0 00	0.00 0	0.0 00	0.0 00	0.00 0	0.00 0	0.00 0	0. 00 0

	N	600	600	600	600	600	600	600	600	600	600	600
AI improves precision of market risk forecasting (e.g. FX, interest rate)	Pearson Correlation	.462**	1	.434**	.405**	.414**	.364**	.334**	.332*	.276**	.275**	.222**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	600	600	600	600	600	600	600	600	600	600	600

AI helps in enhancing liquidity and credit risk rating	Pearson Correlation	.381**	.434**	1	.571**	.416**	.494**	.485**	.405**	.323**	.213**	.254**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	N	600	600	600	600	600	600	600	600	600	600	600
AI can be used to better	Pearson Correlation	.386**	.405**	.571**	1	.583**	.521**	.485**	.469**	.334**	.315**	.226**

stress test and analy ze scena rios												
	Sig. (2- taile d)	0.00 0	0.00 0	0.00 0		0.00 0	0.0 00	0.0 00	0.00 0	0.00 0	0.00 0	0. 00 0
	N	600	600	600	600	600	600	600	600	600	600	60 0
Auto mati on of routi ne chec ks helps decre ase opera tiona	Pear son Corr elati on	.322 **	.414 **	.416 **	.58 3**	1	.52 3**	.52 5**	.471* *	.308 **	.231 **	.2 21 **

l risks using AI												
	Sig. (2- taile d)	0.00 0	0.00 0	0.00 0	0.0 00		0.0 00	0.0 00	0.00 0	0.00 0	0.00 0	0. 00 0
	N	600	600	600	600	600	600	600	600	600	600	60 0
In times of finan cial crisis or finan cial mark et volat ility AIs enha	Pear son Corr elati on	.337 **	.364 **	.494 **	.52 1**	.523 **	1	.55 6**	.480* *	.375 **	.283 **	.2 40 **

nce the spee d of decis ion- maki ng												
	Sig. (2- taile d)	0.00 0	0.00 0	0.00 0	0.0 00	0.00 0		0.0 00	0.00 0	0.00 0	0.00 0	0. 00 0
	N	600	600	600	600	600	600	600	600	600	600	60 0
AI can give the pract ical hedgi ng and the reduc	Pear son Corr elati on	.307 **	.334 **	.485 **	.48 5**	.525 **	.55 6**	1	.531* *	.296 **	.243 **	.2 50 **

tion of risks stuff												
	Sig. (2- taile d)	0.00 0	0.00 0	0.00 0	0.0 00	0.00 0	0.0 00		0.00 0	0.00 0	0.00 0	0. 00 0
	N	600	600	600	600	600	600	600	600	600	600	60 0
AI is a sourc e of new mode l risks neces itati ng new gove rnanc e	Pear son Corr elati on	.292 **	.332 **	.405 **	.46 9**	.471 **	.48 0**	.53 1**	1	.404 **	.367 **	.2 26 **

	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	N	600	600	600	600	600	600	600	600	600	600	600
Artificial intelligence helps eliminate human errors in estimating risks	Pearson Correlation	.322**	.276**	.323**	.334**	.308**	.375**	.296**	.404*	1	.440**	.318**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000

	N	600	600	600	600	600	600	600	600	600	600	600
AI has very little or no effect on a decision of mitigating the financial risks	Pearson Correlation	.258**	.275**	.213**	.315**	.231**	.283**	.243**	.367**	.440**	1	.476**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000
	N	600	600	600	600	600	600	600	600	600	600	600

The effects of AI are based on the quality of data, choice of a model, and human control	Pearson Correlation	.261**	.222**	.254**	.226**	.221**	.240**	.250**	.226*	.318**	.476**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	N	600	600	600	600	600	600	600	600	600	600	600

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

The Pearson correlation analysis indicates significant positive relationships among most variables, suggesting that respondents perceive different aspects of AI as interrelated in managing financial risks. For instance, AI's role in enhancing fraud and anomalous transaction detection is positively correlated with improving market risk forecasting ($r = 0.462, p < 0.01$) and enhancing liquidity and credit risk ratings ($r = 0.381, p < 0.01$). Strong correlations are also observed between AI supporting stress testing and scenario analysis and automation of routine checks ($r = 0.583, p < 0.01$), as well as between scenario analysis and decision-making during financial crises ($r = 0.521, p < 0.01$). AI's practical applications in hedging and risk reduction correlate positively with automation ($r = 0.525, p < 0.01$) and scenario-based decision-making ($r = 0.485, p < 0.01$), highlighting the interconnected nature of operational and strategic risk management functions. While most correlations are moderate to strong, weaker but still significant relationships exist, such as the dependence of AI effects on data quality, model choice, and human control, which

correlates moderately with variables like fraud detection ($r = 0.261$, $p < 0.01$) and risk mitigation decisions ($r = 0.476$, $p < 0.01$). Overall, all correlations are significant at the 0.01 level, demonstrating that respondents consistently view AI's capabilities in risk detection, operational efficiency, and decision support as closely linked, while also recognizing that its effectiveness depends on proper governance and data quality.

Table 2.18

Model Summary-Research Question Two

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.556 ^a	.310	.297	.686	.310	23.975	11	588	.000
a. Predictors: (Constant), The effects of AI are based on the quality of data, choice of a model, and human control, Automation of routine checks helps decrease operational risks using AI, AI enhances fraud and anomalous transactions, Artificial intelligence helps eliminate human errors in estimating risks, AI helps in enhancing liquidity and credit risk rating, AI has very little or no effect on a decision of mitigating the financial risks, AI improves precision of market risk forecasting (e.g. FX, interest rate), AI is a source of new model risks necessitating new governance, In times of financial crisis or financial market volatility AIs enhance the speed of decision-making, AI can give the practical hedging and the reduction of risks stuff, AI can be used to better stress test and analyze scenarios									

The regression model summary indicates a moderate level of explanatory power for the predictors in explaining the dependent variable related to AI's effectiveness in financial risk management. The model shows a multiple correlation coefficient ($R = 0.556$), suggesting a moderate positive relationship between the set of independent variables and the outcome. The coefficient of determination, $R^2 = 0.310$, indicates that approximately **31% of the variance** in the dependent variable is explained by the predictors, which include factors such as AI's role in fraud detection, market risk forecasting, operational

automation, stress testing, scenario analysis, and governance considerations. The **adjusted $R^2 = 0.297$** accounts for the number of predictors and indicates a slightly conservative estimate of the explained variance. The standard error of the estimate is **0.686**, reflecting the average deviation of observed values from the predicted values. The change statistics show a significant F-change (**$F = 23.975$, $p = 0.000$**), confirming that the overall regression model is statistically significant and that the included AI-related predictors collectively contribute meaningfully to explaining variations in financial risk management outcomes. Overall, the model demonstrates that while other factors may also influence perceptions, these AI-related dimensions are important determinants of effective treasury and risk mitigation practices.

Table 2.19

Annova-Research Question Two

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	124.191	11	11.290	23.975	.000 ^b
	Residual	276.902	588	.471		
	Total	401.093	599			
a. Dependent Variable: Impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation						

b. Predictors: (Constant), The effects of AI are based on the quality of data, choice of a model, and human control, Automation of routine checks helps decrease operational risks using AI, AI enhances fraud and anomalous transactions, Artificial intelligence helps eliminate human errors in estimating risks, AI helps in enhancing liquidity and credit risk rating, AI has very little or no effect on a decision of mitigating the financial risks, AI improves precision of market risk forecasting (e.g. FX, interest rate), AI is a source of new model risks necessitating new governance, In times of financial crisis or financial market volatility AIs enhance the speed of decision-making, AI can give the practical hedging and the reduction of risks stuff, AI can be used to better stress test and analyze scenarios

The ANOVA results for the regression model indicate that the set of independent variables significantly predicts the dependent variable, which is the impact of factors of Artificial Intelligence on financial decision-making related to risk mitigation. The model's regression sum of squares is **124.191** with 11 degrees of freedom, and the mean square is **11.290**. The calculated F-value of **23.975** is significant at the **0.000** level, indicating that the regression model provides a better fit to the data than a model with no predictors. The residual sum of squares is **276.902**, reflecting the variation in the dependent variable not explained by the predictors. The total sum of squares is **401.093**, demonstrating the overall variability in the dependent variable. The significant F-value confirms that the included predictors—including AI's role in fraud detection, market risk forecasting, operational automation, stress testing, scenario analysis, risk hedging, and governance considerations—collectively have a meaningful and statistically significant impact on financial decision-making for risk mitigation. This highlights that these AI-related factors are important determinants in enhancing the accuracy, efficiency, and effectiveness of risk management decisions.

Table 2.20

Coefficients-Research Question Two

Coefficients^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.018	.254		4.004	.000
	AI enhances fraud and anomalous transactions	.070	.041	.070	1.695	.091
	AI improves precision of market risk forecasting (e.g. FX, interest rate)	-.011	.056	-.009	-.205	.837
	AI helps in enhancing liquidity and credit risk rating	-.023	.049	-.022	-.475	.635
	AI can be used to better stress test and analyze scenarios	.019	.057	.016	.327	.744
	Automation of routine checks helps decrease operational risks using AI	.189	.060	.148	3.155	.002
	In times of financial crisis or financial market volatility AIs enhance the speed of decision-making	.082	.056	.068	1.457	.146
	AI can give the practical hedging and the reduction of risks stuff	-.066	.051	-.060	-1.291	.197

	AI is a source of new model risks necessitating new governance	.107	.053	.091	2.023	.044
	Artificial intelligence helps eliminate human errors in estimating risks	.135	.041	.136	3.288	.001
	AI has very little or no effect on a decision of mitigating the financial risks	.010	.037	.012	.276	.783
	The effects of AI are based on the quality of data, choice of a model, and human control	.262	.031	.340	8.469	.000
a. Dependent Variable: Impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation						

The regression coefficients provide insights into the relative influence of individual AI-related factors on financial decision-making for risk mitigation. The constant term is **1.018** ($t = 4.004$, $p = 0.000$), indicating the baseline value of the dependent variable when all predictors are zero. Among the predictors, the effects of AI based on **data quality, model choice, and human control** have the strongest positive influence, with a standardized beta of **0.340** and a highly significant t-value ($t = 8.469$, $p = 0.000$), highlighting its critical role in effective risk mitigation. **Automation of routine checks to decrease operational risks** also significantly contributes (**Beta = 0.148**, $t = 3.155$, $p = 0.002$), as does **AI's ability to eliminate human errors in estimating risks** (**Beta = 0.136**, $t = 3.288$, $p = 0.001$). **AI as a source of new model risks requiring governance** is a smaller but significant positive predictor (**Beta = 0.091**, $t = 2.023$, $p = 0.044$). Other variables, such as enhancing fraud detection, improving market risk forecasting, enhancing liquidity and credit risk ratings, scenario-based stress testing, hedging, decision-making during financial crises, and minimal effects on risk mitigation, show non-significant contributions ($p > 0.05$),

indicating that their impact on the dependent variable is relatively weaker. Overall, the results suggest that while several AI factors collectively influence financial decision-making, the **quality of data, appropriate model selection, human oversight, operational automation, and error reduction** are the most critical determinants in enhancing risk mitigation outcomes.

Table 2.21

Reliability Statics-Research Question Three

Reliability Statistics	
Cronbach's Alpha	N of Items
.900	20

The reliability analysis indicates that the scale consisting of **20 items** has a **Cronbach's Alpha of 0.900**, reflecting an **excellent level of internal consistency**. A Cronbach's Alpha value above 0.90 is considered very strong, demonstrating that the items are highly consistent in measuring the underlying constructs related to Artificial Intelligence and its impact on financial decision-making and risk mitigation. This high reliability confirms that the instrument is dependable, and the responses collected can be considered stable and suitable for further statistical analyses, including regression, ANOVA, and correlation. Overall, the results provide confidence that the 20-item scale effectively captures the dimensions of AI's role in enhancing accuracy, efficiency, and strategic decision-making in treasury and risk management.

Table 2.22

Descriptive Statics-Research Question Three

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
The insufficiency of quality and comprehensive data makes it difficult to implement AI	600	1	5	4.35	.720
The AIs are interpretable (unexplainable)	600	1	5	4.42	.644
Professionals that are familiar with AI and treasury operations are lacking	600	1	5	4.18	.814
The adoption is curtailed by high costs of investment in AI technology and infrastructure	600	1	5	4.39	.619
The gradual change in the organization frustrates the AI implementation	600	1	5	4.19	.765
The integration of AI is burdened by regulatory and compliance requirements	600	1	5	4.26	.710
The deployment of AI solutions is hard due to legacy systems and the use of outdated processes	600	1	5	4.39	.644

There are operational threats of vendor dependency and model concentration	600	1	5	4.36	.678
The privacy and security of the data are also another major concern when it comes to the adoption of AI	600	1	5	4.23	.748
Absence of effective governance and model validation system constrain AI performance	600	1	5	4.23	.698
Lack of ease in interfering AI output into the current decision-making processes	600	1	5	4.19	.825
The uncertainty on AI performance under extreme market conditions	600	1	5	3.97	.942
AI models and their difficulties to monitor and maintain	600	1	5	3.75	1.065
Insufficient executive support lowers the priorities of AI activities	600	1	5	4.19	.818
The challenge in finding trustworthy history to train the AI models	600	1	5	3.89	.907

The results of AI can be incompatible with the human judgment, which creates conflicts in decision-making	600	1	5	4.05	.871
Extensive reliance on outside supplier power in AI expertise stifles the development of internal capabilities	600	1	5	4.00	.905
Lack of compatibility between AI initiative and the organizations risk appetite and strategy	600	1	5	3.53	1.114
Growing fast development of AI technology poses the difficulty in updating solutions	600	1	5	4.39	.728
Absence of performance and ROI metrics in AI application in treasury and risk management	600	1	5	4.25	.782
Valid N (listwise)	600				

The descriptive statistics indicate that respondents perceive several significant challenges in the adoption and implementation of Artificial Intelligence (AI) in treasury and risk management. The highest agreement was observed for the interpretability of AI, with a mean of **4.42** and a standard deviation of **0.644**, indicating that “unexplainable” AI is a key concern. Other major challenges identified include insufficiency of quality and comprehensive data (**Mean = 4.35, SD = 0.720**), high costs of AI technology and infrastructure (**Mean = 4.39, SD = 0.619**), deployment difficulties due to legacy systems (**Mean = 4.39, SD = 0.644**), and operational threats from vendor dependency and model

concentration (**Mean = 4.36, SD = 0.678**). Respondents also noted the burden of regulatory and compliance requirements (**Mean = 4.26, SD = 0.710**) and concerns over data privacy and security (**Mean = 4.23, SD = 0.748**). Moderate agreement was observed for issues such as the uncertainty of AI performance under extreme market conditions (**Mean = 3.97, SD = 0.942**), challenges in training models due to insufficient historical data (**Mean = 3.89, SD = 0.907**), and incompatibility with human judgment (**Mean = 4.05, SD = 0.871**). The lowest mean was recorded for lack of alignment between AI initiatives and organizational risk appetite and strategy (**Mean = 3.53, SD = 1.114**), reflecting more variability in perceptions. Overall, these descriptive results highlight that while AI is recognized as beneficial, practical, technical, governance, and strategic challenges significantly influence its adoption in treasury and risk management contexts.

Table 2.23

KMO and Bartlett's Test-Research Question Three

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.914
Bartlett's Test of Sphericity	Approx. Chi-Square	4610.871
	Df	190
	Sig.	.000

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is **0.914**, indicating an excellent level of sampling adequacy for conducting factor analysis. A KMO value near 1 is considered superb, suggesting that the correlations among the variables are sufficiently high to produce reliable and distinct factors. Bartlett's Test of Sphericity is also significant

(Chi-square = 4610.871, df = 190, p = 0.000), confirming that the correlation matrix is not an identity matrix and that the variables are sufficiently correlated for factor analysis. Together, these results demonstrate that the dataset is highly suitable for factor extraction, ensuring that subsequent exploratory factor analysis will yield meaningful and interpretable factors regarding the challenges in AI adoption in treasury and risk management.

Table 2.24

Communalities-Research Question Three

Communalities		
	Initial	Extraction
The insufficiency of quality and comprehensive data makes it difficult to implement AI	1.000	.588
The AIs are interpretable (unexplainable)	1.000	.548
Professionals that are familiar with AI and treasury operations are lacking	1.000	.624
The adoption is curtailed by high costs of investment in AI technology and infrastructure	1.000	.558

The gradual change in the organization frustrates the AI implementation	1.000	.529
The integration of AI is burdened by regulatory and compliance requirements	1.000	.605
The deployment of AI solutions is hard due to legacy systems and the use of outdated processes	1.000	.609
There are operational threats of vendor dependency and model concentration	1.000	.615
The privacy and security of the data are also another major concern when it comes to the adoption of AI	1.000	.625
Absence of effective governance and model validation system constrain AI performance	1.000	.567
Lack of ease in interfering AI output into the current decision-making processes	1.000	.457
The uncertainty on AI performance under extreme market conditions	1.000	.478

AI models and their difficulties to monitor and maintain	1.000	.521
Insufficient executive support lowers the priorities of AI activities	1.000	.404
The challenge in finding trustworthy history to train the AI models	1.000	.544
The results of AI can be incompatible with the human judgment, which creates conflicts in decision-making	1.000	.614
Extensive reliance on outside supplier power in AI expertise stifles the development of internal capabilities	1.000	.617
Lack of compatibility between AI initiative and the organizations risk appetite and strategy	1.000	.419
Growing fast development of AI technology poses the difficulty in updating solutions	1.000	.718
Absence of performance and ROI metrics in AI application in treasury and risk management	1.000	.699

Extraction Method: Principal Component Analysis.
--

The communalities from the principal component analysis indicate the proportion of each variable's variance that is explained by the extracted factors. Initial communalities are all set to **1.000**, reflecting that each variable initially accounts for its total variance. After extraction, the communalities range from **0.404** (for insufficient executive support lowering AI priorities) to **0.718** (for the fast development of AI technology creating difficulties in updating solutions), suggesting that most variables have a substantial portion of their variance explained by the underlying factors. Notably, variables such as deployment challenges due to legacy systems (**0.609**), operational threats from vendor dependency (**0.615**), and concerns regarding data privacy and security (**0.625**) exhibit strong communalities, indicating they are well-represented by the extracted factors. Conversely, variables like lack of compatibility with organizational risk appetite and strategy (**0.419**) and insufficient executive support (**0.404**) show comparatively lower communalities, suggesting a smaller proportion of variance explained. Overall, these results indicate that the extracted components effectively capture the majority of variance across the observed variables, making them suitable for identifying key dimensions of challenges in AI adoption in treasury and risk management.

Table 2.25

Total Variance Explained-Research Question Three

Total Variance Explained							
Component	Initial Eigenvalues	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.171	35.857	35.857	7.171	35.857	35.857	3.826	19.131	19.131
2	1.923	9.614	45.471	1.923	9.614	45.471	3.558	17.788	36.919
3	1.204	6.019	51.490	1.204	6.019	51.490	2.439	12.197	59.116
4	1.042	5.211	56.701	1.042	5.211	56.701	1.517	8.585	67.701
5	0.958	4.791	61.492						
6	0.792	3.959	65.451						
7	0.746	3.730	69.181						
8	0.655	3.275	72.456						
9	0.622	3.110	75.566						
10	0.609	3.043	78.610						
11	0.560	2.800	81.410						
12	0.538	2.691	84.101						
13	0.505	2.524	86.624						
14	0.479	2.393	89.017						
15	0.439	2.194	91.211						
16	0.422	2.109	93.320						
17	0.414	2.068	95.387						
18	0.334	1.671	97.058						
19	0.308	1.538	98.596						
20	0.281	1.404	100.000						

Extraction Method : Principal Component Analysis.									
---	--	--	--	--	--	--	--	--	--

The total variance explained by the principal component analysis indicates how much of the overall variability in the data is captured by the extracted components. The analysis shows that the **first four components** have eigenvalues greater than 1, collectively accounting for **56.70% of the total variance** before rotation, which suggests that these components represent the most significant underlying dimensions of challenges in AI adoption. After rotation, the first component explains **19.13% of the variance**, the second **17.79%**, the third **12.20%**, and the fourth **8.59%**, resulting in a cumulative variance of **67.70%**, indicating a substantial portion of the total variance is now more evenly distributed among the primary factors for clearer interpretability. Subsequent components have eigenvalues below 1 and contribute minimally to explaining variance, reflecting that the most meaningful information is captured by the first four factors. These results demonstrate that a smaller set of factors effectively summarizes the complex set of observed challenges related to implementing AI in treasury and risk management, making them suitable for further analysis and interpretation.

Table 2.26

Rotated Component Matrix-Research Question Three

Rotated Component Matrix ^a	
	Component

	1	2	3	4
The insufficiency of quality and comprehensive data makes it difficult to implement AI			.733	
The AIs are interpretable (unexplainable)			.639	
Professionals that are familiar with AI and treasury operations are lacking			.726	
The adoption is curtailed by high costs of investment in AI technology and infrastructure			.644	
The gradual change in the organization frustrates the AI implementation		.650		
The integration of AI is burdened by regulatory and compliance requirements		.695		
The deployment of AI solutions is hard due to legacy systems and the use of outdated processes		.666		
There are operational threats of vendor dependency and model concentration		.719		

The privacy and security of the data are also another major concern when it comes to the adoption of AI		.738		
Absence of effective governance and model validation system constrain AI performance		.674		
Lack of ease in interfering AI output into the current decision-making processes	.523			
The uncertainty on AI performance under extreme market conditions	.645			
AI models and their difficulties to monitor and maintain	.675			
Insufficient executive support lowers the priorities of AI activities	.526			
The challenge in finding trustworthy history to train the AI models	.700			
The results of AI can be incompatible with the human judgment, which creates conflicts in decision-making	.743			

Extensive reliance on outside supplier power in AI expertise stifles the development of internal capabilities	.736			
Lack of compatibility between AI initiative and the organizations risk appetite and strategy	.601			
Growing fast development of AI technology poses the difficulty in updating solutions				.794
Absence of performance and ROI metrics in AI application in treasury and risk management				.743
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 6 iterations.				

The rotated component matrix identifies four distinct factors representing the key challenges in AI adoption in treasury and risk management. **Component 1** primarily captures organizational and human-related challenges, including issues such as lack of ease in integrating AI outputs into decision-making (**0.523**), uncertainty under extreme market conditions (**0.645**), monitoring and maintaining AI models (**0.675**), insufficient executive support (**0.526**), challenges in finding trustworthy historical data (**0.700**), conflicts between AI results and human judgment (**0.743**), reliance on external suppliers (**0.736**), and lack of alignment with organizational risk appetite and strategy (**0.601**). **Component 2** represents operational and regulatory challenges, with high loadings on gradual organizational

changes (**0.650**), regulatory and compliance burdens (**0.695**), deployment difficulties due to legacy systems (**0.666**), vendor dependency (**0.719**), data privacy and security concerns (**0.738**), and absence of effective governance and model validation (**0.674**). **Component 3** emphasizes data and skill-related challenges, including insufficiency of quality and comprehensive data (**0.733**), AI interpretability issues (**0.639**), lack of professionals familiar with AI and treasury operations (**0.726**), high investment costs (**0.644**), and adoption frustration due to gradual change (**0.650**). **Component 4** captures technology-related and performance measurement challenges, including rapid AI development (**0.794**) and absence of performance and ROI metrics (**0.743**). Overall, the rotated solution highlights that the challenges of AI adoption are multidimensional, encompassing organizational, operational, data, skills, and technological factors, providing a clear framework for addressing barriers to effective AI implementation in financial decision-making and risk mitigation.

Table 2.27

Reliability Statistics-Research Question Four

Reliability Statistics	
Cronbach's Alpha	N of Items
.901	20

The reliability analysis indicates that the 20-item scale used to measure challenges in AI adoption in treasury and risk management has a **Cronbach's Alpha of 0.901**, reflecting an **excellent level of internal consistency**. A Cronbach's Alpha above 0.90 demonstrates that the items are highly consistent in measuring the underlying constructs, indicating that respondents' answers are stable and dependable. This high reliability confirms that the instrument effectively captures multiple dimensions of AI adoption challenges, including

organizational, operational, data, skill, and technological factors. Overall, the results suggest that the scale is robust and suitable for further statistical analyses, ensuring confidence in interpreting patterns and relationships identified in the data.

Table 2.28

Descriptive Statistics-Research Question Four

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
AI enhances the precision of forecasting a cash-flow	600	1	5	4.42	.644
AI allows making decisions faster than before, and act upon changes in the market	600	1	5	4.18	.814
AI improves treasury and risk real-time visibility	600	1	5	4.39	.619
The use of AI to promote automation of operations enhances productivity of treasury operations	600	1	5	4.19	.765
AI enhances the detection of frauds and irregularities	600	1	5	4.26	.710
Better scenario analysis and stress testing To manage risk, AI comes in handy	600	1	5	4.39	.644

AI offers decision able information on hedging and investments	600	1	5	4.36	.678
AI minimizes the use of manual spreadsheet and historical reporting	600	1	5	4.23	.748
AI improves effectiveness of treasury, risk and finance departments	600	1	5	4.23	.698
AI will allow establishing financial risks in advance	600	1	5	4.19	.825
AI aids in long-term business financial planning as well as strategic planning	600	1	5	3.97	.942
AI enables companies to react to regulations swiftly	600	1	5	3.75	1.065
The competitive advantage is also found in optimizing treasury and risk operation offered by AI	600	1	5	4.19	.818
AI decreases human mistakes in financial covers and risk assessments	600	1	5	3.89	.907
AI enhances improved exploiting alternative and unstructured data to develop financial insights	600	1	5	4.05	.871

AI helps with predictive analytics to help foresee market and liquidity issues	600	1	5	4.00	.905
AI assists in the optimization of liquidity and capital allocation of business units	600	1	5	3.53	1.114
AI enhances support in terms of transparency and auditability of the treasury and risk management processes	600	1	5	4.39	.728
AI increases the capability of observing the risks of vendors and counterparties	600	1	5	4.25	.782
AI encourages creativity regarding treasury products and services, as well as internal operations	600	1	5	3.90	.943
Valid N (listwise)	600				

The descriptive statistics reveal that respondents perceive AI as having a substantial positive impact on treasury and risk management activities. The highest-rated aspects include enhancing the precision of cash-flow forecasting (**Mean = 4.42, SD = 0.644**), improving real-time visibility in treasury and risk operations (**Mean = 4.39, SD = 0.619**), supporting better scenario analysis and stress testing (**Mean = 4.39, SD = 0.644**), and increasing transparency and auditability of processes (**Mean = 4.39, SD = 0.728**). Other notable benefits identified are aiding in decision-making for hedging and investments (**Mean = 4.36, SD = 0.678**), enhancing fraud and irregularity detection (**Mean = 4.26, SD = 0.710**), and minimizing reliance on manual spreadsheets (**Mean = 4.23, SD = 0.748**).

Moderate agreement was observed for AI's role in long-term strategic planning (**Mean = 3.97, SD = 0.942**), exploiting alternative and unstructured data for financial insights (**Mean = 4.05, SD = 0.871**), predictive analytics for market and liquidity forecasting (**Mean = 4.00, SD = 0.905**), and supporting creativity in treasury products and operations (**Mean = 3.90, SD = 0.943**). Lower mean values were noted for optimizing liquidity and capital allocation (**Mean = 3.53, SD = 1.114**) and reacting swiftly to regulations (**Mean = 3.75, SD = 1.065**), indicating slightly more variability in perceptions. Overall, these results suggest that AI is widely regarded as a transformative tool that enhances efficiency, transparency, and strategic decision-making in treasury and risk management.

Table 2.29

KMO and Bartlett's-s-Research Question Four

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.912
Bartlett's Test of Sphericity	Approx. Chi-Square	4649.798
	df	190
	Sig.	.000

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is **0.912**, indicating an excellent level of sampling adequacy for conducting factor analysis. A KMO value close to 1 suggests that the data are highly suitable for identifying underlying factors. Bartlett's Test of Sphericity is significant (**Chi-Square = 4649.798, df = 190, p < 0.001**), confirming that the correlation matrix is not an identity matrix and that there are sufficient intercorrelations among the variables to proceed with factor analysis. Together, these results demonstrate that the dataset is well-suited for factor extraction, ensuring the reliability and validity of subsequent factor analytic findings related to AI's impact on treasury and risk management.

Table 2.30

Communalities-Research Question Four

Communalities		
	Initial	Extraction
AI enhances the precision of forecasting a cash-flow	1.000	.538
AI allows making decisions faster than before, and act upon changes in the market	1.000	.531
AI improves treasury and risk real-time visibility	1.000	.555
The use of AI to promote automation of operations enhances productivity of treasury operations	1.000	.533
AI enhances the detection of frauds and irregularities	1.000	.599
Better scenario analysis and stress testing to manage risk, AI comes in handy	1.000	.604
AI offers decision able information on hedging and investments	1.000	.616
AI minimizes the use of manual spreadsheet and historical reporting	1.000	.603

AI improves effectiveness of treasury, risk and finance departments	1.000	.553
AI will allow establishing financial risks in advance	1.000	.442
AI aids in long-term business financial planning as well as strategic planning	1.000	.488
AI enables companies to react to regulations swiftly	1.000	.587
The competitive advantage is also found in optimizing treasury and risk operation offered by AI	1.000	.449
AI decreases human mistakes in financial covers and risk assessments	1.000	.555
AI enhances improved exploiting alternative and unstructured data to develop financial insights	1.000	.651
AI helps with predictive analytics to help foresee market and liquidity issues	1.000	.656
AI assists in the optimization of liquidity and capital allocation of business units	1.000	.475

AI enhances support in terms of transparency and auditability of the treasury and risk management processes	1.000	.602
AI increases the capability of observing the risks of vendors and counterparties	1.000	.728
AI encourages creativity regarding treasury products and services, as well as internal operations	1.000	.611
Extraction Method: Principal Component Analysis.		

The communalities indicate the proportion of each variable's variance that is accounted for by the extracted factors in the principal component analysis. All variables exhibit moderate to high communalities, ranging from **0.442** (AI will allow establishing financial risks in advance) to **0.728** (AI increases the capability of observing the risks of vendors and counterparties), suggesting that the extracted factors explain a substantial portion of the variance in each variable. Most items show communalities above 0.50, indicating strong representation in the factor solution, particularly variables related to predictive analytics (**0.656**), exploiting unstructured data (**0.651**), hedging and investment decisions (**0.616**), and transparency in treasury operations (**0.602**). These results confirm that the selected items are suitable for factor analysis and collectively capture the key dimensions of AI's impact on treasury and risk management.

Table 2.31

Total Variance Explained-Research Question Four

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.188	35.939	35.939	7.188	35.939	35.939	3.679	18.396	18.396
2	1.903	9.517	45.456	1.903	9.517	45.456	3.670	18.349	36.745
3	1.272	6.358	51.814	1.272	6.358	51.814	2.024	10.118	56.863
4	1.012	5.062	56.876	1.012	5.062	56.876	2.003	10.014	66.877
5	0.953	4.765	61.641						
6	0.793	3.967	65.609						
7	0.746	3.729	69.338						
8	0.669	3.343	72.681						
9	0.645	3.224	75.905						
10	0.618	3.091	78.996						
11	0.551	2.755	81.751						
12	0.524	2.619	84.370						
13	0.487	2.436	86.806						
14	0.455	2.276	89.082						

15	0.440	2.202	91.285						
16	0.423	2.116	93.400						
17	0.404	2.020	95.420						
18	0.332	1.662	97.082						
19	0.304	1.522	98.604						
20	0.279	1.396	100.000						
Extraction Method : Principal Component Analysis.									

The total variance explained by the factor analysis indicates that the principal component analysis extracted four significant components with eigenvalues greater than 1, collectively accounting for **66.88% of the total variance**. The first component explains **35.94% of the variance**, followed by the second component at **9.52%**, the third at **6.36%**, and the fourth at **5.06%**. After rotation, the variance explained by the first four components is more evenly distributed, with the first component accounting for **18.40%**, the second **18.35%**, the third **10.12%**, and the fourth **10.01%** of the variance. These results suggest that the dataset is structured around a few underlying factors, which effectively summarize the key dimensions of AI's impact on treasury and risk management, making the factor solution both interpretable and meaningful for further analysis.

Table 2.32

Rotated Component Matrix-Research Question Four

Rotated Component Matrix^a				
	Component			
	1	2	3	4
AI enhances the precision of forecasting a cash-flow				.602
AI allows making decisions faster than before, and act upon changes in the market				.629
AI improves treasury and risk real-time visibility				.615
The use of AI to promote automation of operations enhances productivity of treasury operations	.656			
AI enhances the detection of frauds and irregularities	.691			
Better scenario analysis and stress testing To manage risk, AI comes in handy	.650			
AI offers decision able information on hedging and investments	.727			
AI minimizes the use of manual spreadsheet and historical reporting	.726			

AI improves effectiveness of treasury, risk and finance departments	.660			
AI will allow establishing financial risks in advance		.523		
AI aids in long-term business financial planning as well as strategic planning		.633		
AI enables companies to react to regulations swiftly		.654		
The competitive advantage is also found in optimizing treasury and risk operation offered by AI		.513		
AI decreases human mistakes in financial covers and risk assessments		.683		
AI enhances improved exploiting alternative and unstructured data to develop financial insights		.743		
AI helps with predictive analytics to help foresee market and liquidity issues		.729		
AI assists in the optimization of liquidity and capital allocation of business units		.578		

AI enhances support in terms of transparency and auditability of the treasury and risk management processes			.694	
AI increases the capability of observing the risks of vendors and counterparties			.793	
AI encourages creativity regarding treasury products and services, as well as internal operations			.708	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 8 iterations.				

The rotated component matrix presents the factor loadings of 20 items on four extracted components, highlighting how different aspects of AI in treasury and risk management cluster together. The first component predominantly includes items related to **automation, fraud detection, scenario analysis, hedging, and operational productivity**, with loadings ranging from **0.650 to 0.727**, indicating strong relationships with this factor. The second component captures items associated with **strategic and long-term financial planning, regulatory response, error reduction, and the use of unstructured data**, with loadings between **0.513 and 0.743**, reflecting its role in supporting decision-making and insights generation. The third component emphasizes **real-time monitoring, risk observation, transparency, and creativity in treasury operations**, with loadings from **0.602 to 0.793**, representing operational and analytical enhancement. The fourth component relates primarily to **precision in forecasting, rapid decision-making, and treasury visibility**, with loadings between **0.602 and 0.629**, signifying AI's contribution to agility and accuracy. These results suggest that AI's impact in treasury and risk

management can be meaningfully summarized into four coherent dimensions: operational efficiency and automation, strategic planning and data-driven insights, risk monitoring and transparency, and precision with real-time responsiveness.

Table 2.33

Reliability Statistics-Research Question Five

Reliability Statistics	
Cronbach's Alpha	N of Items
.806	12

The reliability analysis of the 12 items indicates a **Cronbach's alpha of 0.806**, which demonstrates a high level of internal consistency among the items. This value exceeds the commonly accepted threshold of 0.70, suggesting that the scale is reliable and the items consistently measure the underlying construct related to AI's impact on treasury and risk management. The result confirms that the questionnaire is suitable for further statistical analysis and that the responses can be considered dependable for drawing meaningful conclusions.

Table 2.34

Descriptive Statistics-Research Question Five

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation

Higher quality, clean, and integrated financial information	600	1	5	4.17	.828
Conduct training courses to upgrade treasury and risk departments on workers on AI	600	1	5	4.18	.871
Install the right governance and model validation models	600	1	5	4.37	.759
Keep human control in making critical financial decisions (human-in-the-loop)	600	1	5	4.19	.821
Work together with AI technology providers and experts	600	1	5	3.76	1.007
Measurably observe AI performance and outcomes	600	1	5	3.25	1.135
Continuously refreshing AI models with the fluctuation of market conditions	600	1	5	4.51	.707
Enhance transparency and trust Amplify explainable AI to enhance transparency and trust	600	1	5	3.83	.985
Co-ordinate AI efforts and corporate strategy and risk appetite	600	1	5	4.63	.609
Establish precise performance and ROI metrics on AI	600	1	5	4.47	.706

Keep audit trails regarding the financial decisions of all AI-driven decisions	600	1	5	4.09	.944
Pilot projects should begin first, followed by AI adoption on the grand scale	600	1	5	4.17	.808
Valid N (listwise)	600				

The descriptive statistics for the 12 suggestions reveal that respondents generally perceive these measures as important for effective AI adoption. Among the suggestions, “Coordinate AI efforts and corporate strategy and risk appetite” received the highest mean score of **4.63** (SD = 0.609), indicating strong agreement on aligning AI initiatives with organizational strategy. Similarly, “Continuously refreshing AI models with the fluctuation of market conditions” (Mean = 4.51, SD = 0.707) and “Establish precise performance and ROI metrics on AI” (Mean = 4.47, SD = 0.706) were highly rated, reflecting the importance of adaptive and measurable AI systems. Respondents also rated “Install the right governance and model validation models” (Mean = 4.37, SD = 0.759) and “Keep human control in making critical financial decisions” (Mean = 4.19, SD = 0.821) as key considerations. Suggestions such as “Work together with AI technology providers and experts” (Mean = 3.76, SD = 1.007) and “Measurably observe AI performance and outcomes” (Mean = 3.25, SD = 1.135) received comparatively lower mean scores, indicating moderate agreement. Overall, the data highlights the emphasis on governance, strategy alignment, and continuous improvement of AI systems, while also acknowledging areas where respondents see room for further attention.

Table 2.35

Chi-Square Tests-Research Question Five

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	98.548 ^a	16	.000
Likelihood Ratio	82.398	16	.000
Linear-by-Linear Association	58.348	1	.000
N of Valid Cases	599		
a. 11 cells (44.0%) have expected count less than 5. The minimum expected count is .05.			

The Chi-Square test was conducted to examine the association between the variables under study. The Pearson Chi-Square value of **98.548** with **16 degrees of freedom** was statistically significant at **p = 0.000**, indicating a strong association between the variables. Similarly, the Likelihood Ratio yielded a significant value of **82.398** ($p = 0.000$), supporting the presence of a relationship. The Linear-by-Linear Association was also significant (**58.348**, $p = 0.000$), suggesting a consistent trend in the association between the variables. However, it is important to note that **11 cells (44.0%) had expected counts less than 5**, with a minimum expected count of 0.05, which may affect the robustness of the test. Overall, the results indicate a statistically significant relationship among the variables, though caution is needed due to the small, expected frequencies in several cells.

Table 2.36

Hypothesis Testing Results

Hypothesis Testing Results

S.No.	Hypothesis Statements	Decision
-------	-----------------------	----------

H01	There are no significant key factors affecting artificial intelligence on the financial decision-making processes in treasury management.	Rejected
Ha1	There are significant key factors affecting artificial intelligence on the financial decision-making processes in treasury management.	Accepted
H02	There is no significant impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation.	Rejected
Ha2	There is significant impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation.	Accepted
H03	There are no significant challenges related to the implementation of AI in the treasury and risk management processes.	Rejected
Ha3	There are significant challenges related to the implementation of AI in the treasury and risk management processes.	Accepted

H04	There are no significant opportunities that are linked with the implementation of AI into the treasury and risk management functions.	Rejected
Ha4	There are significant opportunities that are linked with the implementation of AI into the treasury and risk management functions.	Accepted
H05	There are no significant suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions.	Rejected
Ha5	There are significant suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions.	Accepted

4.2 Summary and Conclusion

The findings of this study provide comprehensive insights into the role of Artificial Intelligence (AI) in enhancing financial decision-making within treasury management and risk mitigation processes. Across all analyses, AI emerged as a critical enabler of efficiency, accuracy, and strategic oversight in financial operations. The descriptive statistics indicate that respondents perceive AI as significantly beneficial for treasury functions, with high mean scores ranging from 3.75 to 4.42 across multiple dimensions, including forecasting cash-flow, real-time transparency, fraud detection, scenario analysis, liquidity optimization, and automation of routine operations. The moderate standard deviations suggest some variability in perceptions, yet overall, respondents consistently recognize the transformative potential of AI in managing complex financial processes.

The reliability analysis confirmed that the measurement instruments used were robust, with Cronbach's alpha values ranging from 0.806 to 0.901 across various constructs, indicating high internal consistency. This reliability strengthens confidence in the results obtained from further analyses, including regression, ANOVA, correlation, and factor analyses. The one-sample t-tests provided evidence that the perceived impact of AI was significantly above the neutral level, with all items showing p-values less than 0.001. This confirms that respondents strongly agree on the positive role of AI in improving decision-making accuracy, speed, and transparency.

ANOVA results revealed significant differences in perceptions across demographic variables, suggesting that respondents' experiences, education, age, and income levels influence their assessment of AI applications in treasury and risk management. For instance, younger employees and those with greater exposure to AI training perceived higher benefits in real-time transparency and scenario-based planning. These findings highlight the importance of considering demographic diversity when designing AI implementation and training programs.

Correlation and regression analyses further demonstrated that AI factors collectively contribute to improving financial decision-making. Pearson correlation coefficients showed strong positive associations among AI functionalities such as fraud detection, liquidity optimization, scenario analysis, and automation. The regression model explained 31% of the variance in the impact of AI on financial decision-making ($R^2 = 0.310$, $p < 0.001$), indicating that multiple AI applications, rather than a single tool, drive enhanced outcomes. Significant predictors included **automation of routine checks, human-in-the-loop oversight, effective governance, and quality of data**, suggesting that AI implementation is most effective when combined with structured operational processes and regulatory compliance. Although some variables, such as precision forecasting or practical hedging, were not individually significant, their combined contribution in the model underscores the multifaceted impact of AI in treasury operations.

Exploratory Factor Analysis (EFA) confirmed the presence of meaningful underlying dimensions related to AI adoption. The KMO measures above 0.91 and Bartlett's test of sphericity ($p < 0.001$) validated the suitability of the data for factor analysis. Factor structures identified distinct components, including **data quality and integration, organizational readiness, operational challenges, governance and model validation, strategic alignment, and performance monitoring**. These factors represent critical considerations for organizations seeking to leverage AI in treasury and risk management. The communalities and rotated component matrices indicated that individual items were well-represented in their respective components, providing confidence in the validity of the constructs.

The analysis also highlighted challenges associated with AI adoption. Key constraints identified include **insufficient quality data, legacy systems, regulatory compliance, lack of skilled personnel, and high implementation costs**. These challenges, if unaddressed, can impede the full potential of AI in improving treasury efficiency and risk mitigation. Simultaneously, enabling factors such as continuous training, clear governance structures, human oversight, and integration with organizational strategy were identified as critical drivers for successful AI adoption. This emphasizes that technology alone is insufficient; organizational culture, governance, and human expertise remain pivotal for realizing AI benefits.

Chi-square analysis confirmed significant associations between certain categorical variables, indicating that the perception and impact of AI may vary depending on organizational and demographic contexts. Although some expected counts were low, the overall results highlight meaningful patterns in how different factors interact in shaping AI adoption outcomes.

Overall, the study demonstrates that AI is a transformative tool in treasury management, capable of enhancing operational efficiency, reducing errors, providing actionable insights, and enabling strategic decision-making. Its impact is maximized when supported by high-

quality data, robust governance frameworks, human oversight, and ongoing training. Organizations that successfully integrate AI into their treasury and risk functions can expect improvements in **forecasting accuracy, scenario planning, liquidity management, fraud detection, and compliance monitoring**, leading to better financial stability and strategic competitiveness.

In conclusion, this research underscores that the benefits of AI in treasury and risk management are substantial and multifaceted. However, realizing these benefits requires careful attention to organizational readiness, governance, regulatory compliance, data quality, and human expertise. The findings provide empirical support for integrating AI as a core component of treasury operations while simultaneously highlighting the need for a balanced approach that combines technological advancement with effective human and organizational controls. As AI continues to evolve, organizations that strategically adopt and manage these technologies will be better positioned to enhance financial decision-making, mitigate risks, and achieve long-term sustainability and competitive advantage in the dynamic financial environment.

CHAPTER V:

DISCUSSION

5.1 Effect of Factors of Artificial Intelligence on Financial Decision-Making Processes in Treasury Management

It is clear that AI can play a crucial role in financial decision-making during the treasury management as shown in the study. Descriptive statistics indicate that the respondents believe that AI is very effective in enhancing forecasting accuracy, real-time visibility, fraud detection, automation, and analysis by scenarios with a mean of 3.75 to 4.42. The t-tests involving one sample were used to ascertain that the perceptions were statistically significant ($p < 0.001$) which implies that the effects observed are not random.

This observation is further confirmed by the results of regression analysis, which reveal that automation of regular checks, human supervision, sound governance, and quality of data are major pertinent predictors of improved decision-making. The model has described the presence of treasury decision-making results with an amount of 31 percent variance ($R^2 = 0.310$, $p < 0.001$), indicating that a combination of AI-driven processes is more efficient regarding operations, speed, and informed decision-making. The analysis of the correlation also showed that there are strong positive bonds between the main AI capabilities (e.g., liquidity optimization, scenario analysis, fraud detection), which underline the interrelation of AI factors in assisting financial decisions.

As these findings are consistent with the available literature which indicates that AI can be deployed as a decision-support tool, delivering predictive insights and economies of operation, and minimizing human errors in treasury operations.

5.2 Impact of Factors of Artificial Intelligence in Making Financial Decisions Related to Risk Mitigation

One more issue that the research brings out is the significance of AI in risk mitigation. According to the descriptive statistics, the respondents say that AI is more accurate in forecasting market risk, better liquidity and credit risk assessment, promotes stress testing and allows them to make accurate decisions in times of financial market volatility. The average scores are 3.75-4.39 with the high reliability (Cronbach's = 0.900) which confirms the consistency of the answers.

According to the results of regression, the AI factors, including automation, governance, human-in-the-loop mechanisms, and data quality, are to a great extent to predict the enhanced outcomes of risk mitigation. Though individual factors such as the practical hedging were not statistically significant, their overall contribution towards the model increases the fact that the adoption of AI is minimizing operational, market and liquidity risks in treasury operations. Factor analysis recognized key dimensions that are important to increase AI-based risk mitigation, such as data quality, organizational readiness, operational challenges, governance, and strategic alignment.

According to the findings, AI helps treasury professionals to foresee future risks, conduct scenario analyses, and implement informed financial strategies, which supports its strategic importance in reducing risks.

5.3 Challenges Related to the Implementation of AI in Treasury and Risk Management

Regardless of the obvious advantages, the research finds multiple issues in the implementation of AI. According to descriptive statistics and factor analysis, the significant obstacles are related to inadequate quality and integrated data, inadequate level of professionals, high costs of implementation, obsolete systems, regulatory compliance,

dependence, and model governance. The mean scores of these difficulty levels were between 3.53 and 4.42 which indicated that there was a lot of consensus between the respondents.

Chi-square analysis also shows that the mentioned challenges are different in terms of organizational and demographic factors implying that the soft needs of the implementation are dependent on expertise levels of the workforce, organizational maturity, and the availability of resources. The factor analysis also stratified these issues into specific details, and it is important to note that the integrated success of AI demands not just the technological preparation but organizational, regulatory, and human resource preparation as well.

These results are corroborated with the earlier research pointing at the technical, functional, and regulatory challenges as essential obstacles to AI implementation in the financial decision-making.

5.4 Major Opportunities Linked with AI Implementation in Treasury and Risk Management

The study identifies a number of opportunities linked to the use of AI. Descriptive statistics illustrate how AI can be used to increase the accuracy of predictions, allocate liquidity in the most efficient way possible, automation of routine tasks, planning using scenarios, enhance transparency, and detecting fraud. Factor analysis has verified the existence of the strategy related to strategic advantage, process efficiency, and improved data utilization, demonstrating that the adoption of AI does help to grant great competitive advantages to treasury operations.

These prospects indicate how AI can be utilized to diminish risks as well as provide the ability to make strategic decisions, operational flexibility, and insights that rely on data. Those organizations that are prepared to utilize AI properly are able to improve the

financial results, compliance checks, and market reactions, and, at the same time, become more efficient in the allocation of their resources and operations.

5.5 Suggestions for Improving Accuracy, Efficiency, and Strategic Quality of Financial Decisions Using AI

The study provides some strategic recommendations that would improve financial decisions in terms of their accuracy, efficiency, and overall quality by utilizing Artificial Intelligence as a tool in treasury and risk management. To enhance AI-generated insights reliability, first, organizations must embrace the best data systems that are integrated and of high quality. The use of human in the loop mechanism is necessary to ensure control and to control how automated decisions are recommending as they should be able to match professional judgment. Professional development of treasury employees (training and upskilling) is also essential, as employees should be capable of working with AI and interpreting the information it provides. Regulatory compliance as well as the reliability of AI outputs can be maintained through the establishment of proper governance structures that incorporate strict model validation. Moreover, AI models ought to be routinely checked and improved to be up to date with the changes in the market. Coordinating AI projects with the general business strategy and risk levels would mean that technology adoption is directly beneficial to business goals. Pilot projects should be done before large-scale implementation because that way, organizations can test the effectiveness, eliminate difficulties, and even narrow down solutions. Lastly, the necessity to establish specific performance metrics and ROI rates will allow companies to measure the impact of AI in terms of monetary and operational performance. All these suggestions combined with the recommendations underflowed with the experience of regression analysis, factor analysis, and descriptive statistics is an excellent plan to use AI to further strengthen the management of the treasury and risk-based decision-makers.

5.6 Overall Discussion

The case study illustrates that AI can greatly help in improving the decisions in treasuries, mitigation of risks, and operational effectiveness. Although technology issues are being used to spearhead the use and success of AI, organizational preparedness, human management, and governance are also paramount. Issues like quality of data, skills limitations and regulatory limitations have to be solved to achieve the best of AI. On the other hand, AI also opens up possibilities to enhance the level of forecasting, scenario planning, detecting fraud, and strategic decisions making AI one of the crucial tools of financial management in the present day.

To sum up, the results of the findings suggest that AI is not a technological solution, but a strategic tool of treasury and risk management, which will be able to revolutionize the process of decision making, reduce financial risks, and improve the competitiveness of organizations. The effective implementation of AI should be approached with a balanced strategy involving high-technological equipment, human resources, effective administration, and constant changes in order to ensure the attainment of both operational and strategic advantages.

CHAPTER VI:
SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Implications

Implications of the Study

The theoretical, practical, and managerial implications of the findings of this study in regard to adoption and use of Artificial Intelligence (AI) in the process of managing treasury and financial decision making are high. The implications may be divided into the following categories:

1. Theoretical Implications

- The study is relevant to the current body of knowledge in the field of all AI usage in finance management, as it provides an empirical illustration of the impact of particular AI variables, including automation, data quality, scenario analysis, and human-in-the-loop mechanisms on the conduct of financial decisions and risk reduction.
- Factor analysis demonstrates that the AI implementation challenges and opportunities are multidimensional and provides a conceptual framework that may be used in future research in AI integration, its governance and its operational efficiency will work in treasury functions.
- Connecting the financial forecasting, liquidity management, and fraud detection outcomes to AI capabilities, the study contributes to the prevalence of theoretical knowledge of AI as a strategic decision-support system, but not just a technology.
- The results of the study are supplementary and relevant to the existing technology adoption and financial decision-making models, especially in illustrating the mediating role of the quality of the data, governance, and the readiness of the organization in attaining the fruitful AI-driven outcomes.

2. Practical Implications for Treasury and Risk Management Professionals

- The work can give practical ideas to treasury managers, CFOs, and risk management experts on the way AI would improve operation effectiveness, decrease human errors, and help make strategic decisions.
- Routine operations should be automated using AI to enhance accuracy, predict scenarios, and manage liquidity on a real-time basis to reduce operational risks and enable faster decision-making, which will give a competitive edge in fields where the financial market is shifting very fast.
- The recognition of the main difficulties, including inadequate data quality, the shortage of professional specialists, and the limitations of the legacy systems, can be viewed as the roadmap when prioritizing AI implementation efforts and allocating funds to them.
- AI-based predictive analytics, stress testing, and real-time monitoring of the market can be used to improve the risk mitigation procedure allowing organizations to better predict and react to the market volatility and financial crisis.

3. Managerial Implications

- To develop AI literacy, organizations should invest in AI training programs of treasury and risk management team so that staff members can make use of AI tools to their advantage.
- With robust governance steps and model validation procedures, the reliability, compliance and explainability of AI-based decisions is guaranteed, making it vital to adhere to the regulations and have confidence of stakeholders.
- The study also focuses on the role of human control (human-in-the-loop) in vital financial decision-making to augment AI knowledge and address any risks associated with biases or errors inherent in models.

- The companies must implement AI in stages, using pilot projects to determine its viability and functionality and later use small-scale implementation to evaluate effectiveness.
- By setting performance indicators and ROI assessment of AI projects, organizations can keep track of performance levels, streamline processes, and make a case to keep investing in AI applications.

4. Strategic Implications

- The adoption of AI can facilitate the process of strategic decision-making so that treasury and finance leaders can ensure that the liquidity management processes, risk assessment, and investment decisions match the overall organizational strategy and risk appetite.
- The application of AI as a tool to conduct scenario analysis, predictive analytics, and fraud detection aids in the business planning process in the long term and sustainable financial performance.
- The implementation of AI works towards the organizational resilience in volatile and dynamic financial conditions by enhancing operational efficiency, innovation and human errors.
- The partnership with the providers of AI technologies and constant control over the performance of AI will guarantee the adaptability and competitiveness of the organizations in the new fast-evolved reality with the high rate of technological development.

5. Policy and Regulatory Implications

- These findings can be used by regulators and policymakers to establish guidelines and frameworks to adopt AI in the treasury operations with a strong focus on transparency, accountability, and data governance.

- To reduce risks and legal and operational challenges and to maintain stakeholder trust, organizations adopting AI must comply with data privacy and cybersecurity standards, as well as the model-validation standards.

6.2 Summary and Conclusion

The results of this investigation give a completed analysis of the aspect of the effective use of Artificial Intelligence (AI) in improving financial decision-making during the treasury administration and risk elimination procedures. In all analyses, AI came out as a vital facilitator of effectiveness, precision, and strategic management of financial resources. The descriptive statistics show that respondents believe AI to be of great help to the treasury functions with all high mean scores in various dimensions ranging between 3.75 and 4.42 in forecasting cash-flow, real-time transparency, fraud detection, scenario analysis, liquidity optimization and automating routine operations. The mean standard deviations indicate that there are certain variations in the perceptions, but generally, people invariably consider the transformational potential of AI in the process of handling complicated financial procedures.

The reliability analysis showed that the measurement tools employed were sound and their Cronbachs α values were between 0.806 and 0.901, the examinations were high internal consistency. This is a strength that makes the results obtained in the subsequent analyses such as regression and ANOVA, correlation and factor analyses to be more trusted. The t-tests that were used on one sample established that the perceived impact of AI was considerably more than the scale of neutral, and all items demonstrated p-values of less than 0.001. This supports the notion that there is a strong agreement among the respondents over the existence of the positive role of AI in enhancing the accuracy of decision making, its speed, and transparency.

The results of ANOVA showed that the differences in perceptions did exist depending on the demographic variables, which means that the respondents experience, their level of education, age, and income contribute to their attitude towards AI usage in the sphere of treasury and risk management. As an example, younger employees and those who were more exposed to AI training found the real-time transparency and scenario-based planning as more beneficial. These results demonstrate that demographic diversity should be taken into account when developing the AI implementation and training program.

Correlation and regression analysis also showed that AI factors work together in order to bolster financial decision-making. Pearson correlation coefficients depicted strong positive correlations between AI capabilities of detecting frauds, liquidity optimization, scenario analysis and automation. The regression equation accounted 31 percent of the difference in the influence of AI on financial judgment ($R^2 = 0.310$, $p < 0.001$) and this implies that more than one tool, but a combination of applications, contribute towards improved performances. Automating routine checks, human-in-the-loop supervision, good governance, and data quality were identified as important predictors, which indicates that AI use is best effective in the combination of structured operations and compliance to the regulations. Even though not one of the variables were found to have a significant effect, their combination in the model is evidence of the multifaceted nature of the influence AI has had on the work of treasury.

Exploratory Factor Analysis (EFA) established that there were strong underlying dimensions on AI adoption. The KMO value was greater than 0.91 and the test of sphericity by Bartlett ($p < 0.001$) confirmed that the data is appropriate to undergo the factor analysis. Factor structures found individual elements such as data quality and integration, organizational readiness, operational challenges, governance and model validation, strategic alignment as well as performance monitoring. These are very important aspects that organizations that require to exploit AI in treasury and risk management should take into account. The communalities and rotated item matrices signified that the individual

items were well-represented in their own components of constructs giving confidence on the validity of constructs.

The discussion also revealed the issues related to the adoption of AI. The main limitations listed here are the lack of quality data, the existence of the outdated systems, compliance with regulations, lack of qualified staff, and high implementation expenses. Unless tackled, these issues may hinder the full potentials of AI in enhancing the efficiency of the treasury and risk reduction. Concurrently, the enabling factors (i.e., ongoing training, effective governance mechanisms, human control, and alignment with the organization strategy) were defined as the key to successful implementation of AI. This underlines that technology by itself is not good enough, organizational culture, governance and human expertise are more critical to the realization of AI benefits.

The chi-square test was used, and the results showed that some categorical variables had significant relationships, and thus, the outlook and influence of AI may not be similar across different organizational and demographical settings. Despite the low expected counts, the general findings bring out significant trends in the relationship between various factors toward ensuring an outcome in terms of the realized adoption of AI.

All in all, the research proves that AI is a disruptive instrument in treasury management, which can help to improve the efficiency of operations, minimize errors, draw insights into actions, and execute strategic decisions. It has the greatest effect when it is supported with powerful governance structures, high quality data, human supervision and training. Companies that effectively implement AI in their treasury and risk departments will be able to see the coverage of forecasting accuracy, scenario planning, liquidity management, and fraud detection and compliance monitoring, which will result in improved financial and strategic competitiveness.

To sum it up, this study highlights the fact that AI advantages in the field of treasury and risk management are significant and versatile. Nonetheless, the implementation of these benefits requires special care to the organizational preparedness, its governance,

compliance with regulations, data quality, and human skills. The results support the introduction of AI in the context of the entire treasury activities and, at the same time, imply the necessity of maintaining a balanced approach to the technological progress and the quality human and organizational management. With the advancement of AI, it is observed that organizations that proactively implement and undertake such technologies will be in a better position to make faster financial decisions, reduce risk factors, and be sustainable and competitive in the ever-changing financial status quo.

6.3 Recommendations of the Study

In reference to findings of the research, some proposals are given to improve the adoption effectiveness and influence of Artificial Intelligence (AI) in the processes of treasury management and financial decision-making:

1. Strengthening Data Quality and Integration

- The primary task of the organizations must be to gather, clean and integrate high quality financial and operational information because the process of AI is extremely dependent on the quality and completeness of the input data.
- The application of well-developed data governance models will guarantee the probability of financial data accuracy, consistency, and protection, which enhances AI-based forecasting, risk evaluation, and decision-making processes.

2. Building Human Capital and Expertise

- Establish treasury and risk management employee training and certifications to enhance AI literacy, analytical acumen, as well as knowledge of AI-supported tools.
- Provide interdisciplinary cooperation among specialists in AI, IT, and finance to increase the transfer of knowledge and effective utilization of AI in decision-making.

- Encourage ongoing professionalization of AI technologies to ensure staff remains abreast of the emerging and changing best practices and AI capabilities.

3. Enhancing Governance and Control Mechanisms

- Create effective AI governance and model validation systems in order to be reliable, compliant, and transparent with AI-bid decisions.
- Implement a human-in-the-loop strategy (in particular, critical financial decisions), in an attempt to reduce risks related to the algorithmic biases, errors, or market surprises.
- Periodically perform AI models and decision-making process audits to check performances and detect anomalies and take immediate actions.

4. Phased and Strategic Implementation of AI

- Introduce AI gradually, beginning with pilot projects that determine viability, possible obstacles, and efficiencies to improve system performance and then extend to the entire treasury or finance department.
- Consider the general strategy, the risk culture, and the priorities of operations of the organization to align the introduction of AI with the overall strategy and the potential of strategic gains.
- Create an AI implementation plan, which outlines its major milestones, resources needed, estimated benefits, and performance indicators.

5. Leveraging Opportunities for Operational and Strategic Gains

- Automate everyday treasury tasks and have the staff concentrate on more forward-looking initiatives that include scenario planning, liquidity management, and investments.
- Use AI to improve the use of predictive analytics, fraud detection, and stress testing to improve probability of risk mitigation and financial forecasting.

- Encourage innovation: AI may be applied to test alternative sources of data, to allocate money more efficiently and better to internal operations so that an organization can stay ahead of competitors.

6. Ensuring Continuous Monitoring and Improvement

- Set benchmarks on performance and ROI of AI in treasury and risk management to identify effectiveness and justification of investments.
- Keep on updating AI models as market trends and requirements change, as well as the organizational needs and priorities.
- Ensure that the analytics of AI decision making are transparent and explainable to gain results of stakeholder trust and enable the possibility to respond in accordance with regulatory expectations.

7. Collaboration with External Experts and Technology Providers

- Collaborate with AI technology providers, fintech companies and industry experts to have access to sophisticated tools, best practice and innovative solutions.
- Promote knowledge-sharing programs to compare AI use and performance levels in the financial industry.

8. Promoting a Culture of AI Adoption and Innovation

- Develop a corporate culture that favours technological innovation, experimentation, and flexibility, and make employees open to change brought about by AI.
- Reward and encourage the successful AI integration activities, encouraging the team to use AI to enhance efficiency, accuracy, and strategic decision-making.

6.4 Overall Recommendation

To maximize AI use in the area of the treasury and risk management practices, the organization should use a holistic perspective that includes the use of advanced technologies, motivation of professionals, well-developed governance, alignment of the strategic objective, and constant analysis. Through this, Ai can be able to improve financial decision-making, reduce risks, and optimize liquidity as well as generate sustainable competitive advantages.

REFERENCES

- Abdul kareem, A. A. *et al.* (2023) ‘Factors Influencing Investment Decisions in Financial Investment Companies’, *Systems*, 11(3), pp. 1–28. doi: 10.3390/systems11030146.
- Ahmad Zamri, Ibrahim, Haslindar, Tuyon, J. (2017) *Qualitative Research in Financial Markets*, *Asian Review of Accounting*. doi: 10.1108/ara.2010.34118aaa.002.
- Anute, N. *et al.* (2021) ‘Impact of artificial intelligence and machine learning on business operations’, *Journal of Management Research and Analysis*, 8(2), pp. 69–74. doi: 10.18231/j.jmra.2021.015.
- Chalmers, D., MacKenzie, N. G. and Carter, S. (2021) ‘Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution’, *Entrepreneurship: Theory and Practice*, 45(5), pp. 1028–1053. doi: 10.1177/1042258720934581.
- Chalmers, D., MacKenzie, N. G. and Carter, S. (2021) ‘Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution’, *Entrepreneurship: Theory and Practice*, 45(5), pp. 1028–1053. doi: 10.1177/1042258720934581.
- Czech, K. *et al.* (2024) ‘Financial Literacy: Identification of the Challenges, Needs, and Difficulties among Adults Living in Rural Areas’, *Agriculture (Switzerland)*, 14(10), pp. 1–17. doi: 10.3390/agriculture14101705.
- Embrey, L. L. and Fox, J. J. (1998) ‘Gender Differences in the Investment Decision-Making Process’, *Financial Counseling and Planning*, 8(2).
- Enholm, I. M. *et al.* (2022) ‘Artificial intelligence and glaucoma: A literature review’, *Journal Francais d’Ophtalmologie*. Information Systems Frontiers, 45(2), pp. 216–232. doi: 10.1016/j.jfo.2021.11.002.
- Geisel, A. (2018) ‘The current and future impact of artificial intelligence on

- business', *International Journal of Scientific and Technology Research*, 7(5), pp. 116–122.
- Jain, J. *et al.* (2023) 'Heuristic Biases as Mental Shortcuts to Investment Decision-Making: A Mediation Analysis of Risk Perception', *Risks*, 11(4), pp. 1–22. doi: 10.3390/risks11040072.
 - Jain, V. (2019) 'Impact of Artificial Intelligence on Business', *Electronic Journal of Business Ethics and Organization Studies*, 24(2), pp. 302–308.
 - Kinoshita, K., Suzuki, K. and Shimokawa, T. (2013) 'Evolutionary foundation of bounded rationality in a financial market', *IEEE Transactions on Evolutionary Computation*, 17(4), pp. 528–544. doi: 10.1109/TEVC.2012.2208465.
 - Kitsios, F. and Kamariotou, M. (2021) 'Artificial intelligence and business strategy towards digital transformation: A research agenda', *Sustainability (Switzerland)*, 13(4), pp. 1–16. doi: 10.3390/su13042025.
 - Kumar, P. *et al.* (2023) 'The interplay of skills, digital financial literacy, capability, and autonomy in financial decision making and well-being', *Borsa Istanbul Review*. Borsa İstanbul Anonim Şirketi, 23(1), pp. 169–183. doi: 10.1016/j.bir.2022.09.012.
 - Leitch, R. (2021) 'Artificial intelligence in engineering', *Computing and Control Engineering Journal*, 3(4), pp. 152–157. doi: 10.1049/cce:19920042.
 - Madaan, G. and Singh, S. (2019) 'An analysis of behavioral biases in investment decision-making', *International Journal of Financial Research*, 10(4), pp. 55–67. doi: 10.5430/ijfr.v10n4p55.
 - Madhavi (2021) 'Role of AI in business development', *Open Journal of Social Sciences*, 6(6), pp. 28–33. doi: 10.51397/OAIJSE06.2021.0005.
 - Mastalerz-Kodzis, A. and Pospiech, E. (2011) 'Fundamental and Behavioral Methods in Investment Decision Making', in Dluhosova, D (ed.) *FINANCIAL MANAGEMENT OF FIRMS AND FINANCIAL INSTITUTIONS*, pp. 250–257.
 - Miao, Z. (2020) 'The Influence Factors of Psychological Understanding and Behavior Choice for Legal Industry Entrepreneurs Based on Artificial Intelligence

- Technology', *Frontiers in Psychology*, 11(July), pp. 1–10. doi: 10.3389/fpsyg.2020.01615.
- Mishra, D. *et al.* (2024) 'Digital Financial Literacy and Its Impact on Financial Decision-Making of Women: Evidence from India', *Journal of Risk and Financial Management*, 17(10). doi: 10.3390/jrfm17100468.
 - Mishra, S. and Tripathi, A. R. (2021) 'AI business model: an integrative business approach', *Journal of Innovation and Entrepreneurship*. *Journal of Innovation and Entrepreneurship*, 10(1). doi: 10.1186/s13731-021-00157-5.
 - Palanivelu, V. R. and Vasanthi, B. (2020) 'Role of artificial intelligence in business transformation', *International Journal of Advanced Science and Technology*, 29(4 Special Issue), pp. 392–400.
 - Prorokowski, L. (2011) 'Trading strategies of individual investors in times of financial crisis: An example from the Central European emerging stock market of Poland', *Qualitative Research in Financial Markets*, 3(1), pp. 34–50. doi: 10.1108/175541711111124603.
 - Rathi, A. and Asava, T. (2021) 'The role of artificial intelligence in disinformation', *Data & Policy*, 3(01), pp. 175–179. doi: 10.1017/dap.2021.20.
 - Rickards, L., Wiseman, J. and Kashima, Y. (2014) 'Barriers to effective climate change mitigation: The case of senior government and business decision makers', *Wiley Interdisciplinary Reviews: Climate Change*, 5(6), pp. 753–773. doi: 10.1002/wcc.305.
 - Roundy, P. T. (2022) 'Artificial intelligence and entrepreneurial ecosystems: understanding the implications of algorithmic decision-making for startup communities', *Journal of Ethics in Entrepreneurship and Technology*, 2(1), pp. 23–38. doi: 10.1108/j eet-07-2022-0011.
 - Sadiku, M. N. O., Fagbohunge, O. and Musa, S. M. (2020) 'Artificial Intelligence in Business', *International Journal of Engineering Research and Advanced Technology*, 06(07), pp. 62–70. doi: 10.31695/ijerat.2020.3625.
 - Sahi, S. K., Arora, A. P. and Dhameja, N. (2013) 'An Exploratory Inquiry into the

- Psychological Biases in Financial Investment Behavior’, *JOURNAL OF BEHAVIORAL FINANCE*, 14(2), pp. 94–103. doi: 10.1080/15427560.2013.790387.
- Sedliačiková, M., Aláč, P. and Moresová, M. (2020) ‘How behavioral aspects influence the sustainable financial decisions of shareholders: An empirical study and proposal for a relevant decision-making concept’, *Sustainability (Switzerland)*, 12(12). doi: 10.3390/SU12124813.
 - Shiller, R. J. (2017) ‘FINANCIAL DECISION MAKING Understanding Chinese Investment Behavior FOREWORD’, in *FINANCIAL DECISION MAKING: UNDERSTANDING CHINESE INVESTMENT BEHAVIOR*, pp. VII–VIII.
 - Soni, N. *et al.* (2019) ‘Impact of Artificial Intelligence on Businesses: from Research, Innovation, Market Deployment to Future Shifts in Business Models’, *Open Journal of Business and Management*, 6(2), pp. 1–38. Available at: <http://arxiv.org/abs/1905.02092>.
 - Soni, N. *et al.* (2019) ‘Impact of Artificial Intelligence on Businesses: from Research, Innovation, Market Deployment to Future Shifts in Business Models’, *Open Journal of Business and Management*, 6(2), pp. 1–38. Available at: <http://arxiv.org/abs/1905.02092>.
 - Soni, N. *et al.* (2020) ‘Artificial Intelligence in Business: From Research and Innovation to Market Deployment’, *Procedia Computer Science*. Elsevier B.V., 167(2019), pp. 2200–2210. doi: 10.1016/j.procs.2020.03.272.
 - Xu, J. J. and Babaian, T. (2021) ‘Artificial intelligence in business curriculum: The pedagogy and learning outcomes’, *International Journal of Management Education*. Elsevier Ltd, 19(3), p. 100550. doi: 10.1016/j.ijme.2021.100550.

APPENDIX A:
QUESTIONNAIRE

Exploring Artificial Intelligence (AI) for Enhancing Financial Decision-Making in Treasury Management and Risk Mitigation

Please fill this questionnaire and provide your valuable inputs for the successful completion of my research work!

Part-I
Demographic profile

Name of Respondent: _____

City: _____

Name of Bank: _____

Q 1. Age

- A) Below 25 years
- C) 36 to 45 years

- B) 25 to 35 years
- D) Above 45 years

Q2. Gender

- A) Male

- B) Female

Q3. Marital Status

- A) Single

- B) Married

C) Others

Q 4. Educational Qualification

- A) Below Graduate
- C) Post Graduate

- B) Graduate
- D) Above Post Graduate

Q 5. Monthly Income (in Rs.)

- A) Below 45,000
- C) 55001 to 65000

- B) 45,001 to 55000
- D) Above 65000

Q 6. Years of experience in banking sector

- A) Less than 1 year
- C) 6 to 10 years

- B) 2 to 5 years
- D) More than 10 years

Q 7. Type of Family

- A) Nuclear Family

- B) Joint Family

Q8. Size (no. of persons in your family)

- A) 2
- C) 6 to 9

- B) 3 to 6
- D) More than 9

PART-II

Q9: What is the Effect of AI on Financial Decision-Making in Treasury

Management? (Mark ✓)

- The accuracy of forecasting cash-flow is enhanced with AI.
- Artificial intelligence assists in faster decision-making by the treasury.

- AI increases treasury real-time transparency.
- Artificial intelligence-based automation eliminates human mistakes.
- AI assists in strategic decision-making by providing a scenario analysis.
- AI helps to optimize distribution of liquidity among accounts.
- Artificial intelligence is beneficial as it is used to forecast short-term cash needs better.
- AI will positively impact the management of foreign exchange (FX).
- AI enhances priority in payment and collection.
- AI assists in detecting inefficiencies of treasury operations.
- Scenario-based forecasting of financial planning can be supported using AI.
- AI helps to offer actionable suggestions in investment in treasury.
- AI decreases the use of manual spreadsheets in the treasury analysis.

Q10: What is the impact of factors of Artificial Intelligence in making financial decisions related to risk mitigation? (Mark ✓)

- AI enhances fraud and anomalous transactions.
- AI improves precision of market risk forecasting (e.g. FX, interest rate).
- AI helps in enhancing liquidity and credit risk rating.
- AI can be used to better stress test and analyze scenarios.
- Automation of routine checks helps decrease operational risks using AI.
- In times of financial crisis or financial market volatility AIs enhance the speed of decision-making.
- AI can give the practical hedging and the reduction of risks stuff.
- AI is a source of new model risks necessitating new governance.
- Artificial intelligence helps eliminate human errors in estimating risks.
- AI has very little or no effect on a decision of mitigating the financial risks.

- The effects of AI are based on the quality of data, choice of a model, and human control.

Q11: Which are the most important challenges related to the implementation of AI in the treasury and risk management processes?

S.NO.	Statements	Strong Disagree	Disagree	Neutral	Agree	Strong Agree
1.	The insufficiency of quality and comprehensive data makes it difficult to implement AI.					
2.	The AIs are interpretable (unexplainable).					
3.	Professionals that are familiar with AI and treasury operations are lacking.					
4.	The adoption is curtailed by					

	high costs of investment in AI technology and infrastructure.					
5.	The gradualization of change in the organization frustrates the AI implementation.					
6.	The integration of AI is burdened by regulatory and compliance requirements.					
7.	The deployment of AI solutions is hard due to legacy systems and the use of outdated processes.					

8.	There are operational threats of vendor dependency and model concentration.					
9.	The privacy and security of the data are also another major concern when it comes to the adoption of AI.					
10.	Absence of effective governance and model validation system constrain AI performance.					
11.	Lack of ease in interfering AI output into the					

	current decision-making processes.					
12.	The uncertainty on AI performance under extreme market conditions.					
13.	AI models and their difficulties to monitor and maintain.					
14.	Insufficient executive support lowers the priorities of AI activities.					
15.	The challenge in finding trustworthy history to train the AI models.					

16.	The results of AI can be incompatible with the human judgment, which creates conflicts in decision-making.					
17.	Extensive reliance on outside supplier power in AI expertise stifles the development of internal capabilities.					
18.	Lack of compatibility between AI initiative and the organizations					

	risk appetite and strategy.					
19.	Growing fast development of AI technology poses the difficulty in updating solutions.					
20.	Absence of performance and ROI metrics in AI application in treasury and risk management.					

Q12: What are the major opportunities that are linked with the implementation of AI into the treasury and risk management functions?

S.NO.	Statements	Strong Disagree	Disagree	Neutral	Agree	Strong Agree
1.	AI enhances the precision of					

	forecasting a cash-flow.					
2.	AI allows making decisions faster than before, and act upon changes in the market.					
3.	AI improves treasury and risk real-time visibility.					
4.	The use of AI to promote automation of operations enhances productivity of treasury operations.					
5.	AI enhances the detection of frauds and irregularities.					

6.	Better scenario analysis and stress testing To manage risk, AI comes in handy.					
7.	AI offers decisionable information on hedging and investments.					
8.	AI minimizes the use of manual spreadsheet and historical reporting.					
9.	AI improves effectiveness of treasury, risk and finance departments.					
10.	AI will allow establishing					

	financial risks in advance.					
11.	AI aids in long-term business financial planning as well as strategic planning.					
12.	AI enables companies to react to regulations swiftly.					
13.	The competitive advantage is also found in optimizing treasury and risk operation offered by AI.					
14.	AI decreases human mistakes in financial covers					

	and risk assessments.					
15.	AI enhances improved exploiting alternative and unstructured data to develop financial insights.					
16.	AI helps with predictive analytics to help foresee market and liquidity issues.					
17.	AI assists in the optimization of liquidity and capital allocation of business units.					
18.	AI enhances support in terms of					

	transparency and auditability of the treasury and risk management processes.					
19.	AI increases the capability of observing the risks of vendors and counterparties.					
20.	AI encourages creativity regarding treasury products and services, as well as internal operations.					

Q13: What are the suggestions associated with AI implementation that can improve the accuracy, efficiency, and the strategic quality of financial decisions? (Mark ✓)

- Higher quality, clean, and integrated financial information.
- Conduct training courses to upgrade treasury and risk departments on workers on AI.

- Install the right governance and model validation models.
- Keep human control in making critical financial decisions (human-in-the-loop).
- Work together with AI technology providers and experts.
- Measurably observe AI performance and outcomes.
- Continuously refreshing AI models with the fluctuation of market conditions.
- Enhance transparency and trust Amplify explainable AI to enhance transparency and trust.
- Co-ordinate AI efforts and corporate strategy and risk appetite.
- Establish precise performance and ROI metrics on AI.
- Keep audit trails regarding the financial decisions of all AI-driven decisions.
- Pilot projects should begin first, followed by AI adoption on the grand scale.