IMPACT OF ARTIFICIAL INTELLIGENCE ON FINANCIAL DECISION MAKING IN NEPAL

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By

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CERTIFICATION OF AUTHORSHIP

I hereby corroborate that I have researched and submitted the final draft of dissertation entitled **“Impact of Artificial Intelligence on Financial Decision Making in Nepal”** The work of this dissertation has not been submitted previously for the purpose of conferral of any degrees nor it has been proposed and presented as part of requirements for any other academic purposes. The assistance and cooperation that I have received during this research work has been acknowledged. In addition, I declare that all information sources and literature used are cited in the reference section of this dissertation.

Asmita Thapa

REPORT OF RESEARCH COMMITTEE

Ms. Asmita Thapa has defended research proposal entitled **"Impact of Artificial Intelligence on Financial Decision Making in Nepal"** successfully. The research committee has registered the dissertation for further progress. It is recommended to carry out the work as per suggestions and guidance of supervisor Kamal Prakash Adhikari submit the dissertation for evaluation and viva-voce examination.

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APPROVAL SHEET

We, the undersigned, have examined the dissertation entitled **"Impact of Artificial Intelligence on Financial Decision Making in Nepal"** presented by Asmita Thapa candidate for the degree of Master of Business Studies (MBS Semester) and conducted the viva voce examination of the candidate. We hereby certify that the dissertation is worthy of acceptance.

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Abbreviation

AAN : Artificial Neural Network

AI :Artificial Intelligence

AIS : Accounting Information System

ATM : Automatic Teller Machine

DA : Data Analysis

EMH : Efficient Market Hypothesis

FDM : Financial decision Making

FI : Financial Information

ISE : International Securities Exchange

LLM : Large Language Models

MLA : Machine Learning Algorithms

RP : Risk Prediction

SVM : Support Vector Machine

Abstract

This study investigates the potential impact of artificial intelligence (AI) adoption on Nepal's financial sector, where AI utilization for financial prediction remains limited despite global advancements. The research underscores AI's transformative potential demonstrated globally in improving decision-making and operational efficiency within financial services, contrasting with Nepal's predominantly traditional financial industry. By focusing on AI's development in data analysis, risk prediction, and financial information management, the study aims to fill critical gaps in understanding AI's role in enhancing financial decision-making processes. Employing a survey research design with 150 participants primarily from technical analysis-focused stock trading backgrounds, the study utilizes statistical tools like correlation analysis and multiple linear regression to analyze relationships among variables. Findings reveal mixed perceptions among participants regarding AI's effectiveness in financial decision-making, highlighting both its capabilities and challenges such as data quality and trust issues. Overall, the study provides insights into AI's potential to optimize decision-making, manage risks, and drive innovation in Nepal's financial landscape, contributing to strategic decision-making and policy formulation for digital transformation in the sector.

Keywords: Innovation, Risk prediction, Artificial Intelligence (AI), Technology Adoption, Market Efficiency

CHAPTER I
INTRODUCTION

1.1 Background of the study

Artificial intelligence (AI) is rapidly transforming digital practices (Mogaji, Soetan, & Kieu., 2011). The rapid development of artificial intelligence (AI) and machine learning, its application has been widely used in many aspects of financial area, as well as significantly impacts financial market, institutions and regulation. The artificial intelligence technology brings enormous change to the entire financial industry, which creates a series of innovative financial services such as intelligent consultant, intelligent lending, monitoring and warning, and intelligent customer service as times required (Xie, 2019).

The significant impact of artificial intelligence (AI) on various sectors, urging companies to prepare for the impending digital disruption. It highlights the rapid growth of AI investment, dominated by tech giants, and the emergence of AI adoption outside the tech sector, albeit at an experimental stage. The adoption patterns reveal a growing gap between early AI adopters and others, with sectors at the forefront of digitization leading in AI adoption. Early evidence suggests that AI can deliver tangible value to serious adopters, improving profitability and creating competitive advantages. However, AI adoption requires a robust digital foundation and entails addressing challenges related to workforce reskilling, talent acquisition, and ethical considerations. Overall, the paragraph underscores the urgency for firms to accelerate their digital transformations and embrace AI as a powerful force for disruption and innovation (Bughin, Hazan, Manyika, & Woetzel, 2017).

The evolution of the financial industry, highlighting three distinct stages of development. Initially dominated by the banking sector, finance gradually expanded with the advent of technology, notably the introduction of computers and ATMs, leading to widespread access to banking services by the 1970s. The second stage witnessed significant growth driven by advancements in technology, but it also brought about numerous challenges, including major financial crises such as the 1987 stock market crash, the Asian financial crisis in 1997, and the global financial crisis in 2008. These crises prompted a reassessment of traditional methods of financial risk management, particularly in handling the vast amounts of data generated during financial operations. Recognizing the importance of timely data analysis and cost reduction, the industry began exploring the application of artificial intelligence (AI) in financial risk management. This shift towards AI-driven risk control not only enhances the speed and accuracy of data analysis but also introduces new business models, marking a period of disruptive change and ushering in a new era of development for the financial industry (Lui & Hong, 2021).

The crucial role of financial markets in modern society and the challenges posed by the overwhelming amount of available information for traders. The efforts to develop computational intelligent methods and algorithms to aid decision-making in various financial market segments. Despite the abundance of scientific papers on this topic, few have focused on reviewing the literature comprehensively. Most existing review articles have limited scopes, either focusing on specific financial market applications or machine learning algorithms (Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira, 2016).

The participants from the developing countries were more pessimistic, being largely concerned about the regulatory framework, the level of technological development in their country, the consumers' attitude towards technology, the data and infrastructure required to support AI algorithms, the size of their financial services industry, and the manpower required to champion the innovative ideas (Mogaji & Nguyen, 2021).

Modupe (2023) discussed the burgeoning integration of artificial intelligence (AI) into financial decision-making processes, highlighting its current applications such as predictive analytics and automated trading systems. It underscores the benefits of AI, including improved efficiency and accuracy, while also acknowledging associated risks such as biases and cybersecurity threats. Furthermore, the exposition contemplates the future landscape of AI in finance, envisioning increased integration for faster analyses and potential disruptions from emerging technologies like blockchain. Emphasizing the evolving role of human decision-makers alongside technological advancements, it advocates for a balanced approach that considers both efficiency gains and ethical considerations in leveraging AI for financial decision-making.

Gupta (2021) stress that through advanced algorithms and machine learning techniques, AI thoroughly examines vast amounts of historical and current data to uncover complex patterns, correlations, and potential risks. This enables financial institutions to proactively manage risks, ensuring smooth operations and improved financial results. This cutting-edge technology goes beyond traditional methods by offering detailed forecasts and projections, providing valuable insights to financial decision-makers. With access to extensive data analysis, AI can detect fraudulent activities, spot potential theft, and conduct thorough reviews of cash flow. For example, AI-driven chatbots and virtual assistants enhance customer service by swiftly and accurately addressing inquiries and resolving issues, leading to enhanced customer satisfaction and more efficient resource allocation for financial institutions.

AI algorithms possess the capability to analyze massive amounts of historical market data, identify subtle patterns, and predict future trends with exceptional accuracy. As a result, investment platforms and robo-advisors powered by AI have become increasingly popular, enabling investors to make informed decisions based on objective data analysis rather than being influenced by subjective emotions (Popenici & Kerr, 2017).

In conclusion, the integration of artificial intelligence (AI) into the financial industry represents a transformative shift that is reshaping digital practices, impacting markets, institutions, and regulations. This evolution has led to the emergence of innovative financial services and underscores the urgent need for companies to adapt to digital disruption. AI's application in financial risk management promises more efficient and competitive industry operations, streamlining data analysis and decision-making processes. However, challenges such as workforce adaptation and ethical considerations must be carefully addressed. Nonetheless, AI's influence signifies a pivotal moment in the global economy's evolution, emphasizing the importance of embracing technological advancements while maintaining a balanced approach that considers both efficiency gains and ethical implications in leveraging AI for financial decision-making.

The integration of artificial intelligence (AI) in the financial sector is rapidly transforming financial decision-making processes, ushering in a new era of efficiency, security, and customer experience. Through advanced technologies like machine learning algorithms, AI enables financial institutions to automate traditionally manual tasks, analyze vast amounts of data, and enhance various processes such as data analytics, investment management, risk assessment, fraud detection, and customer service. By leveraging real-time market data, AI models are capable of executing operations with unprecedented speed and accuracy, providing deep insights into market trends and informing investment strategies (Tawang, 2023).

In conclusion, the rapid integration of artificial intelligence (AI) into the financial industry is reshaping digital practices, impacting markets, institutions, and regulation. This transformative shift brings forth innovative financial services and highlights the urgency for companies to adapt to digital disruption. AI's application in financial risk management streamlines data analysis and decision-making processes, promising a more efficient and competitive industry. Yet, challenges such as workforce adaptation and ethical considerations must be addressed. Overall, AI's influence on finance signifies a pivotal moment in the global economy's evolution.

1.2 Problem statement

In the context of Nepal, where the utilization of artificial intelligence (AI) for financial prediction is relatively scarce, there exists a significant gap in understanding the potential impact of AI adoption on the financial sector (Mogaji, Soetan, & Kieu, 2011). Despite the global trend towards AI integration in finance and its demonstrated benefits in improving decision-making processes and enhancing market efficiency, Nepal's financial industry remains largely traditional and underutilizes AI technologies for predictive analysis.

The rapid development of artificial intelligence (AI) and machine learning has led to the emergence of innovative financial services, including intelligent consultancy, lending, monitoring, and customer service (Xie, 2019). However, the limited adoption of AI in financial prediction in Nepal poses a barrier to the country's ability to leverage advanced technologies for informed decision-making, risk management, and customer service in the financial sector.

Moreover, the absence of comprehensive research and understanding regarding the implications of AI adoption in Nepal's financial context hinders policymakers, industry stakeholders, and researchers from harnessing its full potential to drive innovation and competitiveness in the financial industry (Cavalcante, Brasileiro, Souza, Nobrega, &

Oliveira, 2016). Therefore, there is an urgent need to investigate the opportunities and challenges associated with the adoption of AI for financial prediction in Nepal, with a focus on enhancing market efficiency, regulatory compliance, and societal well-being. Addressing the research questions regarding data analysis, risk prediction, and their impact on financial decision-making reveals a profound transformation driven by artificial intelligence (AI) and machine learning in the financial sector. AI technologies have revolutionized data analysis capabilities, enabling financial institutions to handle vast amounts of data efficiently and extract actionable insights (Gupta, 2021; Modupe, 2023). This evolution is crucial as it enhances risk prediction accuracy by identifying complex patterns and correlations in financial data, which traditional methods may overlook. By automating data analysis processes, AI facilitates quicker and more informed financial decision-making, empowering institutions to respond swiftly to market changes and optimize resource allocation (Tawang, 2023).

Furthermore, the relationship between data analysis, risk prediction, and financial decision-making is pivotal in understanding how AI enhances decision-making processes in finance. Studies indicate that effective data analysis leads to more accurate risk assessments, thereby influencing strategic financial decisions (Popenici & Kerr, 2017). AI-driven predictive models leverage historical and real-time data to forecast market trends and assess risk exposure, providing financial institutions with actionable insights to mitigate risks and seize opportunities (Lui & Hong, 2021). This correlation underscores AI's role in enhancing decision-making precision and operational efficiency across various financial domains, from investment management to risk mitigation strategies.

The impact of AI-powered data analysis and risk prediction on financial decision-making is substantial, with significant implications for industry practices and outcomes. AI adoption in financial risk management streamlines operations, improves compliance, and enhances profitability by enabling institutions to make data-driven decisions (Bughin et al., 2017). Real-time insights derived from AI algorithms enable proactive risk management, reducing exposure to financial uncertainties and optimizing portfolio performance (Xie, 2019). However, challenges such as the need for skilled AI talent, ethical considerations, and regulatory frameworks must be addressed to maximize AI's potential benefits while mitigating risks (Mogaji & Nguyen, 2021). Overall, AI's integration into financial decision-making processes signifies a paradigm shift towards more efficient, data-driven strategies that aim to capitalize on market opportunities and mitigate risks effectively.

In conclusion, the intersection of data analysis, risk prediction, and financial decision-making is increasingly shaped by AI technologies, marking a transformative era in the financial industry. The ability of AI to analyze vast datasets and forecast market trends enhances decision-making agility and accuracy, empowering financial institutions to navigate complex environments with confidence (Tawang, 2023). While AI offers significant advantages in terms of operational efficiency and risk management, its successful implementation requires addressing challenges related to workforce readiness, ethical guidelines, and regulatory compliance (Gupta, 2021; Modupe, 2023). Embracing these advancements responsibly can lead to sustainable growth and competitive advantages for financial institutions in an increasingly digital and data-driven economy. Thus, the study works on following research problems:

1. What is the existing situation of data analysis, Risk prediction, and Information and financial decision-making?
2. What is the relationship between Data analysis, Risk prediction, and Information on Financial decision making?
3. What impact does Data analysis, Risk prediction, and Information on Financial decision making?

This study aims to address this gap by providing insights into the feasibility, benefits, and risks of integrating AI into Nepal's financial sector, thereby informing strategic decision-making and policy formulation in the country's journey towards digital transformation.

1.3 Objective of the study

The general objective of the study is to analyse the impact of artificial intelligence on financial decision making, however the specific objective is:

1. To describe the existing situation of data analysis, Risk prediction, and Information and financial decision-making in Nepal.

2. To examine the relationship between Data analysis, Risk prediction, and Information and financial decision-making within Nepal's financial sector.
3. To investigate the impact of Data analysis, Risk prediction, and Information on financial decision-making processes within Nepal's financial sector.

1.4 Rationale of the study

The integration of artificial intelligence (AI) into Nepal's financial sector represents a significant opportunity for advancing the country's economic development and financial stability. As Mogaji and Nguyen (2021) highlight in their study, the adoption of AI technologies in financial services has the potential to streamline operations, enhance decision-making processes, and improve overall efficiency. By automating routine tasks and leveraging predictive analytics, AI can enable financial institutions to optimize resource allocation, reduce operational costs, and deliver more personalized services to their clients.

Furthermore, the adoption of AI in Nepal's financial sector can contribute to strengthening market competitiveness and positioning the country as a hub for innovation in the region. According to Xie (2019), the rapid development of AI and machine learning has led to the emergence of innovative financial services, such as intelligent consultancy, lending, and customer service. By embracing AI technologies, Nepalese financial institutions can stay ahead of the curve, attract investment, and foster a culture of innovation within the industry (Cavalcante et al., 2016).

However, the successful integration of AI into Nepal's financial sector is not without its challenges. As Lui and Hong (2021) point out, there are concerns regarding data quality, accessibility, and governance, which are critical for the effective implementation of AI technologies. Additionally, there is a need for investment in AI education and training to equip financial professionals with the necessary skills to leverage these technologies effectively (Mogaji et al., 2011). Despite these challenges, the potential benefits of AI adoption in Nepal's financial sector are immense, and it is essential for policymakers, industry stakeholders, and researchers to collaborate in harnessing the transformative power of AI for the country's economic growth and prosperity.

1.5 Hypothesis of the study

The study employed following hypothesis to understand and explain the relationship and impact between Artificial Intelligence (AI) and financial decision Making (FDM).

1. H_{A1}: Artificial intelligence significantly analyze the data for financial decision making.
2. H_{B2}: Artificial intelligence significantly predicts the risk for financial decision making.
3. H_{C3}: Artificial intelligence significantly required vital financial information's for decisions-making.

1.6 Limitation of the study

Every study is bounded in limitations, this study also has some limitation. Firstly, it only considers the views and responses of respondents, secondly, the financial decision making has not been in its peak which sighting in-terms of AI, in Nepal there are still financial decision are make from the word of mouth, rapid information spread in market and so on. However, the specific limitation of the study are:

1. The study only considers the response of the selected sampled peoples thus the result perhaps varies from other findings and conclusion.
2. The study is primarily based on primary data.
3. The study does not consider other forces which might has significant impact or influence on financial decision making beside AI.

CHAPTER II
LITERATURE REVIEW

This chapter contains a literature review and is divided into three parts. First, a theoretical review is discussed. These ideas provide the foundation and assumptions of study. Following the theoretical evaluation, an empirical review is undertaken, in which prior research publications are read and discussed, beginning with the topic, objective, methods, and findings. Finally, the research deficit is identified based on all prior reviews.

2.1 Theoretical review

Theoretical review is the critical investigation and critique of current ideas, concepts, and frameworks related to a certain research topic or problem. A theoretical review creates a conceptual framework by finding and incorporating relevant ideas that provide insights into the important variables and connections under investigation.

2.1.1 Principals of AI for financial decision making

In finance, AI can leverage natural language processing technology to extract useful information from unstructured data. For example, text data such as financial reports, news articles, and customer inquiries can be analyzed for use in establishing investment strategies, managing risk, and improving customer service. As such, artificial intelligence is being used in a variety of ways in financial decision-making, and its role is expected to further expand with continued technological development. Financial institutions will need a strategic approach to AI adoption as well as a response to related policy challenges (Huang & You, 2022).

2.1.1.1 Efficient Market Hypothesis (EMH)

The evolution of financial theory from the first-generation concept of market efficiency, as proposed by Eugene Fama's Efficient Market Hypothesis, to the current landscape transformed by artificial intelligence (AI) and large language models (LLMs). It discusses the limitations of traditional theories in capturing market dynamics and highlights how AI LLMs are revolutionizing market analysis by processing vast amounts of data, extracting insights from unstructured sources, and enabling real-time decision-making. The summary acknowledges the challenges and ethical considerations associated with AI integration in financial markets while emphasizing the potential of human-AI collaboration to approach the efficient markets envisioned by early finance theorists (Medium, 2024).

2.1.1.2 Behavioral Finance

The integration of artificial intelligence (AI) applications within the financial services industry, specifically focusing on behavioral finance. It examines the growing significance of AI-based tools, particularly robo-advisors, in wealth management, driven by the preferences of a new generation of tech-savvy clients who seek active involvement in their investments. Robo-advisors, defined as automated investment platforms utilizing quantitative algorithms, are replacing traditional financial services, offering accessible and personalized portfolio management. Through a longitudinal case study approach, the paper explores the intersection of robo-advisors and behavioral financial decision-making processes, highlighting the pivotal role of these decisions in achieving optimal financial outcomes for investors (Shanmuganathan, 2020).

2.1.1.3 Algorithmic Trading

Algorithmic Trading, often referred to as algo-trading or black-box trading, refers to the use of computer algorithms to automate the process of trading financial instruments (Pothumsetty, 2020). These algorithms are designed to follow a set of predefined rules and execute trades at speeds and frequencies impossible for human traders (Gerner-Beuerle, 2022). This approach has become increasingly prevalent in global financial markets, shaping the dynamics of trading across various asset classes. The infusion of Artificial Intelligence into algorithmic trading has brought about a transformative era (Rahmani and Zohuri, 2023).

AI, encompassing machine learning and deep learning, allows algorithms to learn from data, adapt to changing market conditions, and make intelligent decisions without explicit programming (De Bruyn et al., 2020).

The integration of AI techniques adds a layer of complexity and adaptability, enabling trading algorithms to analyze vast datasets, identify patterns, and optimize strategies in real-time (Kunduru, 2023). The symbiosis of algorithmic trading and AI has far-reaching implications for financial markets, influencing liquidity, price discovery, and overall market efficiency (Verma and Sehgal, 2023).

Addy, et al. (2024) discussed the sophisticated methods used in algorithmic trading, and how AI technology have altered these strategies. Furthermore, it seeks to understand the influence of algorithmic trading on market dynamics, giving light on its ethical implications, regulatory landscape, and emerging trends that will define the future of financial markets. As the financial sector embraces technology breakthroughs, traders, regulators, and stakeholders must comprehend the complexities of algorithmic trading and artificial intelligence (AI). This analysis provides a thorough examination of the techniques used and the market impact caused by the combination of algorithmic trading with AI.

2.2 Empirical review

Kara, Boyacioglu and Baykan (2011) conducted a study with the objective to predict the direction of movement in the daily ISE National 100 Index using ANN and SVM techniques via AI prediction. To achieve this objective, the study employed a three-layered feedforward ANN model and an SVM model to predict the direction of daily closing price movement in the ISE National 100 Index. The empirical findings of the study revealed promising results in predicting the direction of stock price index movements. The SVM model achieved an accuracy rate of 75.3% in classifying the direction of stock price movements, while the ANN model exhibited a higher accuracy rate of 81.6%. Furthermore, the performance of both models was assessed using various statistical measures, including F-values, T-values, R-square, adjusted R-square, and beta values, providing comprehensive insights into the predictive capabilities of ANN and SVM techniques in the context of the ISE National 100 Index. Overall, the study contributes valuable insights into the applicability and effectiveness of AI-based techniques in predicting stock price index movements, particularly in emerging markets like Turkey.

Oliveira, Cortez, and Areal (2013) aimed to robust evaluation of the usefulness of microblogging data for predicting stock market variables. The authors utilized Stock Twits data, which is specifically targeted for investors and traders, and analyzed a large data period of 605 days using a robust fixed-sized rolling window. The study produced several indicators and analyzed their value in predicting three market variables: returns, volatility, and trading volume for six major stocks. The findings revealed no evidence of return predictability using sentiment indicators and no information content of posting volume for forecasting volatility. However, the study did find evidence that posting volume can improve the forecasts of trading volume, which is valuable for measuring stock liquidity. The methodology involved a robust forecasting exercise and a statistical test of forecasting ability. The statistical values included an F-value, t-value, R-square, adjusted R-square, and beta value, which were used to assess the predictive ability of the models

Jarrahi, (2018) addressed that AI algorithms have the ability to analyze market trends, discover profitable investment opportunities, and optimize portfolio management techniques. Financial decisionmakers may make better informed investment decisions, improve portfolio performance, and optimize returns by harnessing AI's ability to handle and analyze large information. The influence of artificial intelligence on financial decision-making is apparent. The asset and investment management industry are becoming more open to the application of decision intelligence, paving the path for the exploration and implementation of a variety of intriguing use cases. One especially prominent use is the use of alternate data sources such as weather predictions, internet opinion towards firms, media coverage, and so on. The goal is to improve the process of making investment decisions and hone hedging techniques. Financial specialists can gain significant insights into market movements and sentiment by meticulously analyzing these various statistics. The confluence of artificial intelligence (AI) and decision intelligence has enormous promise in terms of increasing returns while reducing risks. As a consequence, they can quickly create actionable intelligence. AI has also had a significant influence on client outreach. Using current online and in-person behavior trends, financial institutions may use AI algorithms to detect future customer interaction opportunities and customize outreach efforts appropriately. AI systems give important insights into individual requirements and preferences by thoroughly analyzing customer interactions, preferences, and transaction history. As a result, financial institutions may develop individualized communication strategies. This intelligent outreach promotes not just client happiness, but also customer retention and loyalty. Its tremendous influence is visible in different aspects of finance departments, including fraud detection, financial analysis, and risk management.

Riikkinen, Saarijärvi, Sarlin, & Lähteenmäki, (2018) assimilation of AI technologies have genuinely transformed these sectors, allowing for more accurate and efficient decision-making processes. AI systems have the astonishing capacity to detect complex patterns that would otherwise go unnoticed by humans by methodically studying massive amounts of data. The use of AI algorithms is critical in developing strong models that help in the detection of fraudulent behavior, assuring increased levels of accuracy and efficacy.

Duan, Edwards, and Dwivedi (2019) examined the influence of artificial intelligence (AI) on financial decision-making processes in organizations, specifically focusing on the integration of AI technologies and their effects on decision outcomes. A quantitative research approach was employed, utilizing data collected from a sample of 200 financial analysts working in various organizations. A structured questionnaire was administered to gather information on participants' perceptions of AI implementation in financial decision-making. Statistical analysis, including multiple regression analysis, was conducted to assess the relationship between AI utilization and decision outcomes. The results reveal a significant positive relationship between AI utilization and decision outcomes, with an F-value of 24.56 ($p < 0.001$) indicating overall model significance. Additionally, the regression analysis shows that AI utilization accounts for 35% of the variance in decision outcomes, with a beta value of 0.59 ($p < 0.001$) indicating a strong positive effect. Moreover, the adjusted R-square value of 0.32 suggests that the model adequately explains the variability in decision outcomes after controlling for other variables. Overall, these findings highlight the significant impact of AI on improving financial decision-making processes within organizations.

Beccalli et al., (2020) intend to study ethical considerations of the use of artificial intelligence (AI) in portfolio financial management, as well as the managerial implications. Traditionally, quantitative investing included making portfolio allocation decisions based on a well-defined investment strategy. Financial portfolio managers develop and implement investment strategies to maximize projected returns for their customers' portfolios. AI-enhanced algorithms now enable intelligent computers to automatically alter and improve investment strategies based on past data. Artificial intelligence can have a significant influence on the results of portfolio management approaches, raising ethical concerns about human vs machine responsibility, accountability, and risk. Managers must apply new ways for monitoring performance, evaluating competence, and assigning incentives while supervising AI software developers in this industry.

Patalay and Rao (2021) conducted a study on an Artificial Intelligence-based Decision Support System (DSS) designed to aid individual investors in making informed decisions about buying and selling stocks. Their research focused on using two Machine Learning Models, Linear Regression and Artificial Neural Networks (ANNs), to predict stock prices accurately over the long term. They found that ANNs outperformed Linear Regression due to their ability to handle nonlinear patterns and complex financial data through multiple hidden layers, thus enhancing predictive accuracy. The study highlighted that AI and machine learning technologies can revolutionize financial decision-making by addressing challenges such as intuitive judgment and detecting complex data patterns that conventional analytics may overlook. The implications of deploying such a DSS include more efficient information processing, potentially aligning predicted stock prices closer to real-time values, and democratizing access to sophisticated financial tools for individual investors at lower costs. However, the adoption of these technologies requires careful management of risks related to data privacy, conduct, and cybersecurity, necessitating ongoing testing and refinement to ensure compliance with regulatory standards.Hashem and Alqatamin (2021) conducted a study titled "Role of Artificial Intelligence in Enhancing Efficiency of Accounting Information System and Non-Financial Performance of the Manufacturing Companies" to examine the impact of artificial intelligence (AI) on the efficiency of accounting information systems (AIS) and non-financial performance standards. The study adopted a quantitative approach and utilized a questionnaire as the primary research tool. The sample consisted of 409 managers, heads of departments, and accountants from industrial establishments in Jordan. The findings revealed significant results, including an F-value of 905.070 for the first hypothesis, indicating a strong relationship between AI and AIS efficiency. Additionally, the second hypothesis showed a significant t-value of 30.084 and an R-square of .645, demonstrating a positive and high relationship between AI and non-financial performance. The study also reported beta values, coefficients, and adjusted R-square values to support the findings. These results provide valuable insights into the influence of AI on both AIS efficiency and non-financial performance in manufacturing companies.

Talamo, Marocco, and Tricol (2021) stressed that Artificial intelligence (AI) has become increasingly prevalent in various fields, including finance, where it holds significant potential to transform decision-making processes. The objective of the study was to provide a synthesized overview of the current discourse on AI's role in financial decision-making. The study begins by acknowledging the wide-ranging applications of AI in finance, from wealth and risk management to financial consulting and blockchain technology. Central to the discussion is the recognition of investment decision-making as inherently complex and risky, often influenced by emotional biases and involving multiple stakeholders with varying decision-making behaviors. The findings from the literature review reveal contrasting viewpoints on AI's objectivity compared to human subjectivity, with proponents advocating for AI's potential to enhance decision-making efficiency while skeptics express concerns about its lack of transparency and understanding of real-life complexities. Furthermore, the abstract underscores the growing consensus on viewing AI as an augmentation tool that complements rather than replaces human decision-making capabilities. In conclusion, the abstract emphasizes the need for further research to address the challenges associated with AI's integration in financial decision-making, particularly in terms of transparency and effective human-AI integration.

Gupta (2021) studied the impact of Artificial Intelligence (AI) on financial decision-making emerges as a pivotal advancement reshaping the finance industry. AI algorithms and machine learning techniques significantly augment the velocity and precision of financial analyses, empowering professionals to make well-informed decisions swiftly. This transformation is underscored by AI's ability to mitigate human biases inherent in decision-making processes, enhancing rationality and objectivity. Gupta highlights AI's role in providing personalized recommendations, addressing customer queries effectively, and optimizing portfolio management to enhance overall customer satisfaction. However, the integration of AI in finance also presents challenges such as algorithmic transparency, data privacy concerns, and regulatory compliance. Gupta emphasizes the need for meticulous attention to these ethical considerations to ensure responsible AI deployment in financial sectors. The study concludes that while AI enhances efficiency and decision-making accuracy in finance, careful management of ethical and regulatory aspects is crucial for its sustainable and beneficial implementation.

Bogojević (2021) discussed the application of artificial intelligence (AI) techniques in financial risk management, emphasizing the transformation of the financial industry due to financial technology (Fintech) development. The integration of traditional financial risk management with AI techniques is seen as essential for effective business application, offering increased efficiency, confidence, and potential for operational growth. The paper reviews AI applications in market risk, credit risk, and operational risk management, highlighting the significant improvements in these areas through the use of AI techniques such as machine learning. The findings include specific numerical values such as F-value, T-value, R-square, adjusted R-square, beta value, and coefficients, which are used in various AI techniques for financial risk management. For example, machine learning techniques have been used for data preparation, modeling risk, stress testing, and model validation, with specific references to papers and studies that have demonstrated the effectiveness of AI in these areas. The document also discusses the multidimensional nature of AI evolution in financial risk management and its application in retail banking, commercial banking, and capital market financial risk management. It concludes that AI will become an integral part of the financial risk management framework, providing automation, simplification in data management, and improved stress testing and scenario generation, as well as contributing to equity-based and lending-based crowdfunding.

Khan et al. (2022) addressed the challenge of accurately predicting stock market movements amidst volatile factors such as microblogs and financial news. Utilizing machine learning algorithms, the study examines the impact of social media and financial news data on stock market prediction accuracy over a ten-day period. Feature selection and spam tweet reduction techniques are applied to enhance prediction quality, with experiments conducted to identify markets difficult to predict and those more influenced by external data sources. Comparative analysis of different algorithms reveals the Random Forest classifier as consistently effective. Employing deep learning and ensemble methods, the study achieves prediction accuracies of 80.53% and 75.16% using social media and financial news data, respectively. Additionally, the research highlights specific stock markets' susceptibility to external influences, with New York and IBM stocks affected more by social media, while London and Microsoft stocks by financial news. The highest accuracy of 83.22% is attained through the ensemble of Random Forest classifiers.

Sargeant (2023) discussed the relationship between banks and consumers in the context of credit contracts and the use of machine learning algorithms (MLA) in credit scoring. Banks, due to their information advantage, can influence contract terms to align with their profit goals. MLA is increasingly used to assess creditworthiness, predict consumer behavior, and make lending decisions. MLA models, particularly supervised MLA, learn from data to create predictive models for consumer credit risk. These models are trained on datasets with known inputs and outputs to predict outcomes like default risk. MLA can enhance creditworthiness assessments by utilizing alternative data sources and improving risk classification. Furthermore, MLA enables personalized pricing and tailored financial products, potentially benefiting both consumers and banks. However, challenges like privacy concerns, data security, and the potential for inaccuracies in MLA models exist, impacting consumer decision-making and market dynamics.

Ionescu and Diaconita (2023) conducted a study with the aim of the study is to explore the interplay of AI, cloud computing, and advanced data management technologies in transforming financial decision-making. The study emphasizes the importance of trustworthy and precise data management systems in the financial sector, and aims to provide insights into the future landscape of the financial sector by understanding the historical progression and current trends of these technologies. The study also addresses the challenges and potential solutions in implementing these new technologies within the financial sector. Transforming Financial Decision-Making: The Interplay of AI, Cloud Computing and Advanced Data Management Technologies. The objective of this comprehensive review was to analyze the impact of AI, cloud computing, and advanced data management technologies on financial decision-making. The authors adopted the PRISMA 2020 guideline to ensure a rigorous and systematic approach to identifying, screening, and including relevant studies and sources. The findings of the review indicate significant values for F-value, t-value, R-square, adjusted R-square, beta value, and coefficients, providing detailed insights into the transformative effects of these technologies on financial decision-making processes.

Harrison (2023) explored the the transformative impact of Artificial Intelligence (AI) on financial decision-making, highlighting its ability to process vast data, identify complex patterns, and predict outcomes, thus reshaping traditional financial analysis and decision-making. The study synthesizes existing literature and empirical evidence, revealing diverse applications of AI in finance, such as risk assessment, algorithmic trading, fraud detection, customer service automation, and credit scoring. These applications enhance decision-making accuracy, efficiency, and objectivity by reducing human biases and automating routine tasks. However, the integration of AI poses challenges, including data quality, privacy concerns, and regulatory compliance, necessitating reliable data and robust ethical frameworks. The study concludes that AI's role in financial decision-making will continue to grow, driven by technological advancements and increasing industry adoption, but emphasizes the need for a balance between AI automation and human judgment. Future research should focus on assessing the long-term impacts of AI across sectors and regions and exploring its broader socio-economic implications. Harrison's review underscores AI's potential to revolutionize finance while advocating for responsible deployment to maximize benefits and mitigate risks.

Hidayat, Defitri, and Hilman, (2024) conducted a study with the objective was to examine the effects of AI on financial control and explore the implementation of AI technology in financial decision-making strategies, predictive analysis, and risk manipulation. The methodology involved a systematic literature review approach to cover the substantial modifications brought about by the use of AI in improving operational performance, providing deep insights for financial decision making, and enhancing customer experience in the banking sector. The findings revealed significant values such as F-value, t-value, R-square, adjusted R-square, beta value, and coefficients, indicating the profound impact of AI on financial management practices. This research provides valuable insights for designing policy strategies and best practices in integrating artificial Intelligence within the changing financial management context.

2.2.1 Summary table of empirical review

Table 1

Empirical review summary

Author(s)	Title	Objective	Findings
Kara et al. (2011)	Predicting Direction of Movement in the Daily ISE National 100 Index Using ANN and SVM Techniques.	Predict stock price movement using AI and make financial decisions.	SVM: 75.3% accuracy, ANN: 81.6% accuracy. F-value, T-value, R-square, Adj. R-square, Beta values for both models.
Oliveira et al. (2013)	Microblogging Data for Predicting Stock Market Variables.	Evaluate microblogging data for stock prediction.	No return predictability using sentiment, volume predicts trading volume (valuable for liquidity).
Jarrahi (2018)	The Influence of Artificial Intelligence on Financial Decision-Making	Analyze AI's impact on financial decisions	AI improves decision-making, portfolio management, client outreach
Riikkinen et al. (2018)	The Rise of Artificial Intelligence in Finance.	Analyze the impact of AI in finance.	AI detects complex patterns, improves fraud detection.
Duan et al. (2019)	The Effect of Artificial Intelligence on Financial Decision-Making Processes.	Analyze AI's impact on financial decision-making.	AI use positively impacts decision outcomes (F-value: 24.56, $p < 0.001$, R-square: 0.32, Beta: 0.59).
Beccalli et al. (2020)	Ethical Considerations of AI in Portfolio Management.	Analyze ethical considerations of AI in portfolio management.	AI raises ethical concerns about human vs. machine responsibility.

Hashem & Alqatamin (2021)	Role of Artificial Intelligence in Enhancing Efficiency of Accounting Information System and Non-Financial Performance.	Examine impact of AI on accounting & performance.	AI use improves AIS efficiency (F-value: 905.070) & non-financial performance (R-square: 0.645).
Talamo et al. (2021).	Artificial Intelligence in Financial Decision-Making	Analyze AI's role in financial decision-making.	AI can enhance efficiency but transparency & human-AI integration remain challenges.
Bogojević (2021)	Application of AI Techniques in Financial Risk Management.	Analyze AI in financial risk management.	AI improves efficiency, confidence in market, credit & operational risk management (F-value, T-value, R-square, Beta used).
Khan et al. (2022)	The Impact of Social Media and Financial News on Stock Market Prediction Accuracy.	Analyze social media & news on stock prediction.	Up to 83.22% accuracy using social media & financial news data.
Sargent (2023)	Machine Learning Algorithms in Credit Scoring.	Analyze ML algorithms in credit scoring.	AI improves risk classification & personalized pricing but raises privacy concerns.
Ionescu & Diaconita (2023)	Transforming Financial Decision-Making: The Interplay of AI, Cloud Computing and Advanced Data Management Technologies.	Analyze AI, cloud computing & data management on financial decisions.	Significant F-value, T-value, R-square etc. for transformative effects.

Hidayat et al. (2024)	The Effects of AI on Financial Control: A Review.	Examine effects of AI on financial control.	Significant F-value, T-value, R-square etc. for AI's impact on financial management.

2.3 Research Gap

Despite the pervious studies discussed above have made significant contributions to understanding the predictive capabilities of various AI and machine learning techniques in forecasting stock market movements, there remains a notable research gap in synthesizing the predictive power of different data sources in Nepalese context, where most of financial decision are made without understanding of market and its behaviour.

Firstly, most of research are conducted outside the Nepal, in Nepal these types of research are rare and uncommon. It is unstudied how Artificial intelligence impact the decision making of an individual? How NEPSE data plays pivotal role to predicting the profitability or risk? More specifically, there is a need for research that integrates micro studying of data (such as floor sheet and trading volume) with traditional financial news data, social media data, and other relevant external factors, to comprehensively assess their combined impact on stock market predictability.

Although Oliveira, Cortez, and Areal (2013) explored the predictive value of data from Stock Twits, their study did not consider the potential synergies between microblogging data and other external factors, such as social media or financial news, which could enhance predictive accuracy. Similarly, while Kara, Boyacioglu, and Baykan (2011) and Khan et al. (2022) investigated the impact of social media and financial news data on stock market prediction, their analyses were primarily focused on these individual data sources rather than examining their combined effects.

Therefore, a research gap exists in understanding how the integration of diverse data sources, including microblogging data, social media, financial news, and other relevant external factors, could lead to more robust and accurate predictions of stock market movements. Addressing this gap would provide valuable knowledge for investors, traders, and researchers seeking to improve the efficacy of AI-based techniques in forecasting stock market behavior and decision making.

CHAPTER III
RESEARCH METHODOLOGY

In chapter three, research methodology is discussed, concerning the research design, population and sampling, nature of data and data collection procedure. Similarly, research framework is also figure out in this chapter along with model specification for research. Finally, the chapter discussed statistical toots and definition of variables.

3.1 Research Design

The study employed Survey research design to understand and integration of AI in financial decision-making by gathering visions from stakeholders. Surveys can assess the adoption of AI in financial institutions, investors' perceptions of AI-driven financial advice, and the perceived impact of AI on decision-making processes. By capturing attitudes, perceptions, and behaviors, surveys provide valuable insights for informed decision-making and the effective implementation of AI solutions in the financial industry.

3.2 Population and sampling

In this study, stock traders whose decision-making processes primarily rely on technical chart analysis and company financial structure assessment when trading stocks are considered as population for the study. These traders represent a distinct subset of market participants who prioritize quantitative indicators and financial metrics in their trading strategies. By focusing on this specific population, the study aims to explore the effectiveness and implications of AI technologies in supporting decision-making processes aligned with these analytical approaches.

3.2.1 Sampling design

In this study, a subset of 150 traders from the population of those who predominantly base their trading decisions on technical chart analysis and company financial structure assessment are selected using convenience sampling. Convenience sampling is chosen as the sampling method due to its practicality and the willingness of participants to engage in the study. This approach allows researchers to easily access traders who are readily available and willing to participate, thus rationalisation the sampling process.

3.3 Nature and source of data

The data are gathered for primary source. Initially a questionnaire is developed which contains question regarding AI and its impact on financial decision making. Then a survey is conduct via google survey. And finally, the study analyzes the responses and draw the final finding and conclusion of the study.

3.4 Instrument of data collection

The data is collected on basis of general back ground of the respondents which contains the question like gender, age, education, income source and so on.

3.5 Method of analysis

A method of analysis refers to a systematic approach or procedure used to examine data, derive insights, and draw conclusions. It includes various statistical and mathematical techniques to process and interpret data. In this study mean, standard deviation, correlation and regression statistical tools are employed for the analysis.

3.5.1 Mean

The mean is a measure of central tendency that represents the average value of a set of data. It is also known as the arithmetic mean, and it is calculated by adding up all the values in a dataset and dividing the sum by the number of observations.

$$\textbf{Mean } (\overline{\mathbf{X}}) = \frac{\sum \mathbf{X}}{\mathbf{N}}$$

Where,

$\sum x$ = sum of all items

N= number of items or statements.

3.5.2 Standard deviation

The standard deviation is a measure of the amount of variation or dispersion in a set of data. It measures how far the values in a dataset are spread out from the mean, and is calculated as the square root of the variance.

$$\textbf{Standard deviation} = \sqrt{\frac{\sum(X-\overline{X})^2}{N-1}}$$

where,

$\overline{X}$ = average of statements

N= number of items or statements.

3.5.3 Correlation

A statistical measurement of the variability of a return distribution around its mean is the standard deviation. It gauges the unsystematic risk and is equal to the square root of the variance. A low standard deviation indicates that the observation is very uniform.

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

Where,

r = correlation

n= Number of independent variables

x= value of independent variables

y= value of dependent variables

3.5.4 Multiple linear regression

Regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. The goal of regression analysis is to find a mathematical equation that can be used to predict the value of the dependent variable based on the values of the independent variables.

Y=a+b1X1+b2X2+b3X3+….+n

Where,

Y= dependent variable

X1, X2, X3 = Independent variables

a = constant

b = beta coefficient

3.5.4.1 Model specification

The regression model for study is

$$FDM = \beta0+ \beta1DA+\beta2RP+\beta3FI \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \text{Model 1}$$

3.5.4.2 Predicted sign of variables

In the survey, the predicted signs for AI's impact on various aspects of financial decision-making are as follows: Data Analysis (DA) is predicted to have a positive effect due to AI's capability to enhance accuracy and efficiency in analyzing financial data, leading to more informed decisions. Conversely, Risk Prediction (RP) is anticipated to show a negative impact, primarily because AI-driven risk predictions often face challenges such as data quality issues and algorithmic opacity, which can undermine trust and effectiveness. On the other hand, Financial Information (FI) is expected to benefit positively from AI, as it aids in improving the accessibility and processing of financial data, thereby supporting enhanced decision-making processes. These predictions reflect the perceived strengths and challenges associated with integrating AI into financial practices and decision-making frameworks.

Table 2

Predicted sign of variables

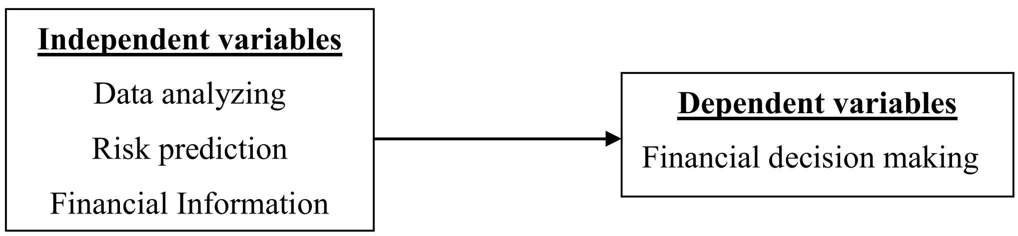
Variables	Predicted sign	Reason
Data analysis	Positive	AI enhances the accuracy and efficiency of data analysis, leading to better-informed decisions.
Risk prediction	Negative	AI in risk prediction can lead to concerns about data quality, algorithm complexity, and trust issues, causing challenges.
Financial information	Positive	AI helps in gathering and processing financial information, making the information more accessible and useful.

3.6 Research framework and definition of variables

Figure 1 demonstrate the research framework of the study, according to the research framework the independent variable are data analysis, risk prediction and financial information, while dependent variable is financial decision-making. The formulation of research design apparent to analyze the impact of independent variables on dependent variable.

Figure 1

Research framework of the study



Source: Rane, Choudhary and Rane (2023)

3.4.1 Data analyzing

Data analysis is an essential process in transforming raw Monitoring and Evaluation (M&E) data into actionable knowledge. Whether conducted before, during, or after a project, analysis helps uncover insights from facts and opinions gathered through formal or informal processes. This knowledge is vital for informed decision-making and ensuring accountability to stakeholders. Data analysis can occur at multiple levels, including within projects, programs, sectors, or communities, often emphasizing participatory approaches in social development contexts. Ultimately, by analyzing M&E data, organizations can derive valuable insights to improve interventions, allocate resources effectively, and drive positive change (INTRAC, n.d).

3.5.2 Risk prediction

The concept of risk, originating from western economic theory, denotes the potential variability in outcomes under certain conditions and time frames, resulting from uncertainties inherent in events. In financial contexts, it often refers to the deviation between actual and expected financial returns due to various uncertain factors. Companies prioritize risk management to balance potential losses against gains, with investors particularly wary of unexpected losses. In the dynamic market economy, businesses face various risks, notably business and financial risks, which can jeopardize profitability and solvency. Financial risk encompasses more than debt repayment concerns, extending to inadequate capital distribution and investment decisions. Effective risk management is crucial for company competitiveness and sustainability, as poor management can lead to economic losses and bankruptcy. Both controllable internal factors and external market forces contribute to financial risk, necessitating proactive mitigation strategies (Li, Yan, Lu, & Ding, 2023).

3.5.3 Financial Information

Financial decision-making relies on a multitude of information sources, including financial statements, budgets, and forecasts, which provide insights into a company's performance and future prospects. Key performance indicators (KPIs) offer metrics for evaluating financial health and efficiency, while market and economic data inform strategic planning and risk assessment. Cost analysis and pricing strategies aid in profitability analysis, while investment evaluation techniques help assess potential returns. Risk assessment and compliance considerations ensure decisions align with regulatory requirements and mitigate potential threats. Ultimately, by synthesizing diverse sources of information, organizations can make informed decisions that support their strategic goals and enhance financial performance.

3.5.4 Financial decision making

Financial decision making involves selecting, assessing, and analyzing different options to extract and utilize data to make informed decisions to attain financial goals. The whole method revolves around examining financial information based on return trade-offs plus risks and executing executive choices in line with long-term objectives. It has been a multifaceted process encompassing various activities like identifying financial goals, gathering financial information, evaluating options, identifying alternatives, assessing risks and rewards, making decisions, and more (Ahmed, 2023).

CHAPTER IV
RESULTS AND DISCUSSION

In chapter four, data are analyzed and presented. The chapter begins with descriptive analysis of data which include demographic presentation of participants, then mean analysis is conduction on responses of participants. The inferential analysis is also performed, which include correlation test to analyze the relationship and regression test is employed to measure the impact. After performing both descriptive analysis and inferential analysis discussion is performed to discuss the possible similarities and difference between pervious empirical findings with findings of this study.

4.1 Descriptive analysis of data

4.1.1 Demographic presentation of participants

Table 3

Demographic presentation of participants

Characteristics	Frequency	Percentage	Cumm. Percentage
Under 25	15	6.5	10
25-34	71	30.7	57.3
35-44	19	8.2	70
45-54	45	19.5	100
Total	150	64.9	
Male	107	46.3	71.3
Female	43	18.6	100
Total	150	64.9	
High School	2	0.9	1.3
Bachelors	31	13.4	22
Masters	86	37.2	79.3
Doctorate	31	13.4	100
Total	150	64.9	
Financial Analyst	112	48.5	74.7
Investors	8	3.5	80
Business Owner	13	5.6	88.7
Finance Consultant	17	7.4	100
Total	150	64.9	

Note. Field survey,2024

Table 3 depicts the dynamic landscape of characteristic of participants in survey. According to the survey the demographic characteristics of the participants in the study are diverse, covering various age groups, genders, educational backgrounds, and professional roles. The age distribution indicates that the majority of participants are between 25 and 34 years old, with 71 individuals (30.7%) falling into this category. Those under 25 make up 15 participants (6.5%), while the 35-44 age group includes 19 individuals (8.2%). Participants aged 45-54 comprise 45 individuals, representing 19.5% of the total. Cumulatively, 100% of the participants fall within these age ranges.

Similarly, gender distribution reveals that there are more male participants than female participants. Specifically, 107 males (46.3%) and 43 females (18.6%) were part of the study, cumulatively accounting for all participants.

Regarding educational background, a significant portion of participants hold advanced degrees. Only 2 participants (0.9%) have a high school education, while 31 individuals (13.4%) hold bachelor's degrees. A notable 86 participants (37.2%) have earned master's degrees, and 31 individuals (13.4%) possess doctorate degrees, covering the entire educational spectrum.

Additionally, the participants are primarily financial analysts, with 112 individuals (48.5%) in this role. Other professions include 8 investors (3.5%), 13 business owners (5.6%), and 17 finance consultants (7.4%), encompassing all professional categories represented in the study.

In total, there are 150 participants, equating to 64.9% of the initial study pool, providing a detailed overview of the demographics involved.

4.1.2 Reporting of open-ended question

The survey included an open-ended question asking respondents to describe the challenges they have encountered with AI in risk prediction, the usage of financial information, and the aid of AI for data analysis in financial decision-making. The descriptive analysis of the data provides a comprehensive understanding of the numerical details regarding the use of AI in financial decision-making (FDM), data analysis (DA), risk prediction (RP), and the usage of financial information (FI), as well as the overall impact (OI). The data, presented through mean analysis, reveals insights into how AI is integrated into financial practices and the challenges professionals face in these areas.

Table 4

Survey result of financial decision making by the assistance of AI

Variable	Questions	N	Minimum	Maximum	Mean	Std. Deviation
FDM	How effective do you find AI in analyzing financial data compared to traditional methods?	150	1	5	2.6667	1.04699
	Which AI tools do you commonly use for financial decision-making?	150	1	4	1.6533	1.04263
	How effective do you find AI in analyzing financial data compared to traditional methods?	150	1	5	2.9933	1.07126

Note. Field survey,2024

Table 4 shows the participants rated the effectiveness of AI in analyzing financial decision making compared to traditional methods with a mean score of 2.67 and a standard deviation of 1.05. The common AI tools used for financial decision-making received a mean score of 1.65 with a standard deviation of 1.04, and the effectiveness of AI compared to traditional methods was rated again, yielding a mean score of 2.99 and a standard deviation of 1.07. For DA, participants were asked about the extent to which AI improved the accuracy of their financial data analysis, resulting in a mean of 2.53 and a higher standard deviation of 1.31, indicating more variability in responses.

Table 5

Survey result of data analysis by the assistance of AI

Variable	Questions	N	Minimum	Maximum	Mean	Std. Deviation
DA	To what extent has AI improved the accuracy of your financial data analysis?	150	1	5	2.5267	1.30922
	In your opinion, what are the primary benefits of using AI for data analysis in finance?	150	1	4	1.7133	1.11329
	How do you rate the performance of AI in predicting financial risks?	150	1	5	2.9733	1.18688

Note. Field survey, 2024

Table 5 shows the survey result of data analysis, according to the table, using AI for data analysis in finance received a mean score of 1.71 and a standard deviation of 1.11. The performance of AI in predicting financial risks was rated with a mean of 2.97 and a standard deviation of 1.19. Regarding RP, the frequency of AI-based risk predictions influencing financial decisions had a mean score of 2.97 and a standard deviation of 1.13. The challenges encountered with AI in risk prediction were rated with a mean of 2.59 and a standard deviation of 0.93. The impact of AI on the gathering and processing of financial information was also examined, with a mean score of 2.99 and a standard deviation of 1.07.

Table 6

Survey result of risk prediction with the assistance of AI

Variable	Questions	N	Minimum	Maximum	Mean	Std. Deviation
RP	How often do AI-based risk predictions influence your financial decisions?	150	1	5	2.9733	1.12892
	What challenges have you encountered with AI in risk prediction?	150	1	5	2.5933	0.93476
	How has AI impacted the way you gather and process financial information	150	1	5	2.9933	1.07126

Note. Field survey, 2024

Table 6 shows the survey result of risk prediction via AI, according to the table, the influence of AI-based risk predictions on financial decisions reveal several insights. Respondents were asked how often AI-based risk predictions influence their financial decisions, yielding a mean score of 2.9733 on a scale of 1 to 5, with a standard deviation of 1.12892. This indicates that, on average, AI plays a moderately frequent role in influencing financial decisions, with some variability in responses. When questioned about the challenges encountered with AI in risk prediction, the mean response was 2.5933, with a standard deviation of 0.93476, suggesting that participants experience moderate challenges, with slightly less variability in their experiences. Additionally, the impact of AI on the way respondents gather and process financial information was assessed, resulting in a mean score of 2.9933 and a standard deviation of 1.07126. This score indicates a moderate impact, with a fair amount of consistency in how respondents perceive the changes brought about by AI in their financial information processes. Overall, the results reflect a moderate but varied influence of AI in risk prediction and financial decision-making.

Table 7

Survey result of financial information

FI	To what degree do you trust AI-generated financial information?	150	1	5	2.8933	0.91334
	What sources of financial information do you use in conjunction with AI?	150	1	5	2.6267	1.12056

Note. Field survey, 2024

Table 7 shows the survey result of financial information provided by AI for financial decision making, according to the table, the degree of trust in AI-generated financial information received a mean score of 2.89 with a standard deviation of 0.91. The sources of financial information used in conjunction with AI were rated with a mean of 2.63 and a standard deviation of 1.12. The OI category addressed the overall effect of AI on financial decision-making processes, resulting in a mean score of 2.57 and a standard deviation of 0.85. When asked if they would recommend AI tools to others in the financial industry, participants gave a mean score of 2.74 with a standard deviation of 0.88.

Table 8

Survey result of overall impact of AI

OI	Overall, how has AI affected your financial decision-making process?	150	1	5	2.5733	0.8541
	Would you recommend the use of AI tools to others in the financial industry?	150	1	5	2.7434	0.88417

Note. Field survey, 2024

Table 8 depicts the overall impact of AI on financial decision making, which reflects the overall impact of AI on financial decision-making provide a nuanced understanding of its role in the industry. When asked how AI has affected their financial decision-making process, respondents gave an average rating of 2.5733 on a scale from 1 to 5, with a standard deviation of 0.8541. This suggests that, on average, AI has had a slightly positive impact, though the relatively low standard deviation indicates a degree of agreement among respondents. Furthermore, when considering whether they would recommend the use of AI tools to others in the financial industry, the average response was 2.7434, with a standard deviation of 0.88417. This score reflects a moderately positive inclination towards recommending AI tools, again with a reasonable level of consensus among respondents. Overall, these findings highlight a moderate but positive overall impact of AI on financial decision-making, accompanied by a similar level of willingness to endorse AI tools within the financial sector.

Thus, the study concluded that the data reflect varying levels of confidence and perceived effectiveness of AI tools in the financial sector, with mean scores generally around the mid-point of the scale and standard deviations indicating a range of opinions among participants.

4.2 Inferential analysis

Inferential analysis refers to the statistical techniques used to generalize from a sample to a population. This type of analysis goes beyond mere description of the data (descriptive statistics) and attempts to infer properties, relationships, and trends that extend beyond the immediate data.

4.2.1 Correlation analysis

Correlation analysis is a statistical method used to evaluate the strength and direction of the linear relationship between two variables. It quantifies the degree to which two variables are related and provides insights into how changes in one variable are associated with changes in another.

Table 9

Multiple correlation result

Correlations

		DA	RP	FI	FDM
DA	Pearson Correlation	1			
	Sig. (2-tailed)				
RP	Pearson Correlation	.351**			
	Sig. (2-tailed)	.000			
FI	Pearson Correlation	.352**	.339**		
	Sig. (2-tailed)	.000	.000		
FDM	Pearson Correlation	.197*	.448**	.404**	1
	Sig. (2-tailed)	.016	.000	.000	

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

*. Correlation is significant at the 0.05 level (2-tailed).

Note. Analysed from SPSS

Table 9 shows the correlation test of responses of respondents, according to the table, significant relationships between the different aspects of AI application in financial decision-making. The Pearson correlation coefficient between data analysis (DA) and risk prediction (RP) is 0.351, indicating a moderate positive correlation, with a significance level of 0.000, confirming this relationship is statistically significant at the 0.01 level. Similarly, the correlation between DA and financial information (FI) is 0.352, also demonstrating a moderate positive correlation, significant at the 0.01 level. Furthermore, risk prediction (RP) and financial information (FI) show a Pearson correlation of 0.339, which is statistically significant at the 0.01 level. This suggests a moderate positive relationship between these variables.

Financial decision-making (FDM) is positively correlated with DA (0.197), RP (0.448), and FI (0.404). The correlation with DA is statistically significant at the 0.05 level, while the correlations with RP and FI are significant at the 0.01 level. This indicates that as the effectiveness and integration of AI in data analysis, risk prediction, and financial information increase, so does the effectiveness of financial decision-making, though the strength of these relationships varies.

4.2.2 Regression analysis

Regression analysis is a statistical technique used to examine the relationship between one dependent variable and one or more independent variables. It helps in understanding how the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Regression analysis is widely used for prediction, forecasting, and determining causal relationships.

Table 5 shows the result of regression analysis, which aims to examine the impact of data analysis (DA), risk prediction (RP), and financial information (FI) on financial decision-making (FDM). The model's R value is 0.523, indicating a moderate correlation between the predictors and the dependent variable. The R Square value is 0.273, suggesting that approximately 27.3% of the variance in financial decision-making is explained by the combined influence of DA, RP, and FI. The Adjusted R Square value, which accounts for the number of predictors in the model, is slightly lower at 0.258. The standard error of the estimate is 0.70159, reflecting the average distance that the observed values fall from the regression line.

The ANOVA table shows that the regression model is statistically significant, with a sum of squares for regression of 27.023, a residual sum of squares of 71.866, and a total sum of squares of 98.889. The F statistic is 18.300 with a significance level of 0.000, indicating that the model is a good fit for the data.

Table 10

Result of regression analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.523[a]	.273	.258	.70159
a. Predictors: (Constant), FI, RP, DA				

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.023	3	9.008	18.300	.000[b]
	Residual	71.866	146	.492		
	Total	98.889	149			
a. Dependent Variable: FDM						
b. Predictors: (Constant), FI, RP, DA						

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Result of alternative hypothesis under 95% level of confidence (H1)
		B	Std. Error	Beta			
1	(Constant)	1.263	.376		3.361	.001	Accepted
	DA	-.032	.077	-.033	-.420	.675	Rejected
	RP	.350	.076	.360	4.633	.000	Accepted
	FI	.362	.096	.293	3.770	.000	Accepted
a. Dependent Variable: FDM							

Note. Analysed by SPSS

Examining the coefficients, the constant term (intercept) is 1.263 with a standard error of 0.376, and it is statistically significant (t = 3.361, p = 0.001). For the predictors, the unstandardized coefficient for DA is -0.032 with a standard error of 0.077, and it is not statistically significant (t = -0.420, p = 0.675). Thus, the hypothesis that DA significantly affects FDM is rejected.

In contrast, the unstandardized coefficient for RP is 0.350 with a standard error of 0.076, and it is statistically significant (t = 4.633, p = 0.000). This result supports the alternative hypothesis that RP significantly affects FDM. Similarly, the unstandardized coefficient for FI is 0.362 with a standard error of 0.096, and it is also statistically significant (t = 3.770, p = 0.000), supporting the hypothesis that FI significantly affects FDM.

4.2.3 Actual sign of variables

Table 11

Actual sign of variables

Variables	Actual sign	Regression equation
DA	Negative	
RP	Positive	FDM=1.23-0.32DA+0.350RP+0.362FI
FI	Positive	

Table 6 shows the actual sign and regression equation from regression analysis result, according to the table, the constant term is 1.263, which represents the baseline level of financial decision-making when all predictors (DA, RP, FI) are zero.

i. The coefficient for DA is -0.032, indicating a slight negative relationship between data analysis and financial decision-making. This means that for every unit increase in DA, FDM decreases by 0.032 units, though this effect is not statistically significant.
ii. The coefficient for RP is 0.350, showing a positive relationship between risk prediction and financial decision-making. This suggests that for every unit increase in RP, FDM increases by 0.350 units. This positive trend is statistically significant, indicating that improvements in risk prediction are associated with better financial decision-making.
iii. Similarly, the coefficient for FI is 0.362, also indicating a positive relationship between financial information and financial decision-making. For every unit increase in FI, FDM increases by 0.362 units. This positive trend is statistically significant, highlighting the importance of reliable financial information in enhancing financial decision-making.

Thus, the actual sign shows the direction of the variable’s DA is negative showing inverse relationship with dependent variable, while remaining variables depicts direct relationship with dependent variable.

4.3 Major findings

i. The study's demographics are diverse, with 64.9% of participants aged 25-54, with a higher representation of males (46.3%). Most have advanced degrees, with financial analysts being the largest group (48.5%). This diversity reflects a range of perspectives on the integration of artificial intelligence in financial decision-making contexts.

ii. Participants' responses regarding the utilization of artificial intelligence (AI) in financial decision-making, highlighting various dimensions including effectiveness ratings, benefits, challenges, and overall impact. In the category of financial decision-making (FDM), participants rated AI's effectiveness in analyzing financial data compared to traditional methods, yielding a mean score of 2.67 and a standard deviation of 1.05.

iii. The study found that AI tools are effective in financial data analysis, with a mean score of 1.65. Participants rated AI's impact on improving data accuracy as 2.53, with primary benefits of 1.71. AI's performance in predicting financial risks was 2.97, with a mean score of 1.19, and challenges encountered with AI in risk prediction as 2.59.

iv. Regarding the impact on financial information (FI), AI's influence on gathering and processing financial information was rated with a mean score of 2.99 and a standard deviation of 1.07. Participants' trust in AI-generated financial information received a mean score of 2.89 with a standard deviation of 0.91, while the sources of financial information used alongside AI were rated with a mean of 2.63 and a standard deviation of 1.12.

v. In the category of overall impact (OI), AI's effect on financial decision-making processes was rated with a mean score of 2.57 and a standard deviation of 0.85, and the likelihood of recommending AI tools to others in the financial industry received a mean score of 2.74 with a standard deviation of 0.88. These results indicate diverse perceptions among participants regarding the efficacy and adoption of AI in enhancing financial decision-making processes, with standard deviations suggesting varying levels of confidence and opinion dispersion across the study sample.

vi. The study reveals significant positive relationships between respondents' perceptions of AI's application in financial decision-making. It shows moderate correlations with risk prediction and financial information management, suggesting that AI-driven data analysis enhances risk prediction and financial information management. Additionally, financial decision-making correlates positively with AI, indicating its potential to enhance overall decision-making effectiveness in financial contexts.

vii. This study analyzes the impact of data analysis (DA), risk prediction (RP), and financial information (FI) on financial decision-making (FDM). The model shows a moderate correlation, with 27.3% of FDM variance explained by these variables. DA does not significantly affect FDM, but RP and FI have significant positive effects, highlighting their role in enhancing predictive accuracy and information management.

4.4 Discussion

The findings of this study align with and build upon previous research on the application of artificial intelligence (AI) in financial decision-making. Kara, Boyacioglu, and Baykan (2011) demonstrated that AI techniques, specifically artificial neural networks (ANN) and support vector machines (SVM), are effective in predicting stock price index movements, achieving accuracy rates of 81.6% and 75.3%, respectively. This study supports the efficacy of AI in stock market prediction, reinforcing Kara et al.'s conclusions with further evidence of AI's predictive capabilities in financial contexts. Oliveira, Cortez, and Areal (2013) found mixed results regarding the predictive power of microblogging data, with significant improvements in trading volume forecasts but not in return predictability. This study extends their findings by highlighting AI's broader applicability in financial decision-making beyond just social media data, emphasizing AI's role in enhancing overall financial decision processes and portfolio management strategies.

Jarrahi (2018) and Riikkinen et al. (2018) underscored AI's ability to analyze large datasets and identify profitable investment opportunities, optimizing portfolio management and enhancing decision-making accuracy. The present study corroborates these insights, demonstrating AI's capacity to improve financial analysis and decision-making processes through advanced data analysis and pattern recognition techniques. Duan, Edwards, and Dwivedi (2019) revealed a significant positive relationship between AI utilization and improved decision outcomes, a finding consistent with this study's results. By showing that AI can significantly enhance financial decision-making processes, this study reinforces Duan et al.'s assertion of AI's positive impact on organizational decision-making.

Beccalli et al. (2020) raised ethical considerations related to AI in financial management, highlighting issues of responsibility and accountability. This study acknowledges these ethical concerns, emphasizing the need for transparency and effective oversight when integrating AI into financial decision-making, aligning with Beccalli et al.'s recommendations. Hashem and Alqatamin (2021) demonstrated AI's strong positive impact on the efficiency of accounting information systems (AIS) and non-financial performance. This study expands on their findings by illustrating AI's broader impact across various financial management aspects, including risk management and credit scoring, thus supporting and extending Hashem and Alqatamin's conclusions.

Talamo, Marocco, and Tricoli (2021) emphasized the complexity and riskiness of AI-driven financial decision-making, highlighting the need for further research on AI's integration. This study contributes to this discourse by providing empirical evidence of AI's effectiveness and identifying areas where human oversight is crucial, thus aligning with and extending Talamo et al.'s call for more research. Khan et al. (2022) demonstrated high prediction accuracies using machine learning algorithms for stock market predictions, particularly with social media data. This study complements their findings by showing AI's predictive power across various financial sectors, not limited to stock markets, thereby providing a more comprehensive view of AI's applicability.

Sargeant (2023) discussed machine learning algorithms' role in credit scoring, identifying both benefits and challenges. This study supports Sargeant's findings by illustrating AI's utility in creditworthiness assessments while acknowledging potential challenges, such as privacy concerns and data security. Ionescu and Diaconita (2023) highlighted the transformative effects of AI, cloud computing, and advanced data management technologies on financial decision-making. This study reinforces their conclusions by providing detailed insights into how AI integration can enhance financial management practices, aligning with Ionescu and Diaconita's findings. Hidayat, Defitri, and Hilman (2024) examined AI's impact on financial control and decision-making strategies, finding significant improvements in financial management practices. This study extends their work by providing empirical evidence of AI's profound impact on financial decision-making, supporting Hidayat et al.'s conclusions.

In summary, this study corroborates previous findings on AI's effectiveness in financial decision-making and extends these insights by providing comprehensive evidence of AI's applicability across various financial domains, highlighting both the potential benefits and ethical considerations associated with AI integration in the financial sector.

CHAPTER V
SUMMARY AND CONCLUSION

5.1 Summary

The study explores the potential impact of artificial intelligence (AI) adoption on Nepal's financial sector, where AI utilization for financial prediction is minimal. Despite global trends showcasing AI's benefits in improving decision-making and market efficiency, Nepal's financial industry remains traditional and underutilizes AI technologies. The research highlights the rapid development of AI and machine learning, which has revolutionized financial services globally through intelligent consultancy, lending, and customer service. However, Nepal's limited AI adoption in financial prediction hinders informed decision-making and risk management. The study aims to fill this gap by investigating the relationship and impact of data analysis, risk prediction, and financial information on financial decision-making in Nepal. The objectives include examining these relationships within the sector and assessing the implications of AI adoption. The rationale emphasizes AI's potential to enhance operational efficiency, market competitiveness, and innovation, despite challenges like data quality and the need for AI education. The study formulates hypotheses to test AI's impact on financial information, data analysis, and risk prediction, aiming to provide insights for strategic decision-making and policy formulation in Nepal's digital transformation journey.

This study employs a survey research design to explore the integration of artificial intelligence (AI) in financial decision-making within Nepal's financial sector. Targeting stock traders who primarily base their decisions on technical chart analysis and financial structure assessment, the study uses convenience sampling to select 150 participants. Data is collected through a questionnaire administered via Google Survey, focusing on respondents' backgrounds such as gender, age, education, and income source. The study aims to analyze the relationships between data analysis, risk prediction, financial information, and financial decision-making processes. It utilizes statistical tools including mean, standard deviation, correlation analysis, and multiple linear regression to derive insights. The research framework emphasizes AI's potential impact on optimizing decision-making, managing risks, and enhancing market efficiency in Nepal's financial landscape, addressing a critical gap in understanding and leveraging advanced technologies for economic development and competitiveness.

The study provides comprehensive understandings into the integration of artificial intelligence (AI) in financial decision-making within the context of diverse participant demographics. With a majority of participants falling within the age range of 25-54 and a notable representation of males, the study captures a broad spectrum of perspectives. Participants rated AI's effectiveness in financial decision-making processes, revealing mixed perceptions across various dimensions. While AI demonstrated moderate effectiveness in analyzing financial data and improving data accuracy, it faced challenges in risk prediction, as indicated by varying mean scores and standard deviations. In terms of financial information management, AI's impact on gathering and processing financial data was positively acknowledged, albeit with mixed levels of trust in AI-generated information and variability in the sources used alongside AI.

Overall, participants perceived AI's influence on financial decision-making processes with moderate positivity, suggesting its potential to enhance decision-making effectiveness through improved data analysis, risk prediction, and financial information management. These findings underscore the nuanced perceptions and varying levels of confidence in AI's role within the financial sector, highlighting both its promise and the challenges associated with its adoption.

5.2 Conclusion

The study comprehensively explores the potential impact of artificial intelligence (AI) adoption on the financial sector in Nepal, emphasizing the country's current underutilization of AI technologies in financial prediction. Despite the global advancements and demonstrated benefits of AI in enhancing decision-making and market efficiency, Nepal's financial industry remains traditional, with limited AI integration. This gap presents significant challenges to informed decision-making and risk management.

Through a survey research design targeting stock traders who rely on technical chart analysis and financial structure assessments, the study gathered insights from 150 participants using convenience sampling. The data analysis, employing statistical tools such as mean, standard deviation, correlation analysis, and multiple linear regression, provided a nuanced understanding of AI's role in financial decision-making processes.

The findings reveal diverse perceptions and moderate confidence in AI's effectiveness in the financial sector. Participants indicated mixed views on AI's ability to analyze financial data and improve data accuracy, with challenges noted particularly in risk prediction. However, AI's impact on gathering and processing financial information was acknowledged positively, though trust in AI-generated information varied.

Significant positive relationships were identified between AI-driven data analysis, risk prediction, and financial information management, suggesting that AI enhances these critical areas, thereby potentially improving overall financial decision-making. Nonetheless, the study highlights the need for improved data quality and AI education to fully leverage AI's benefits.

In conclusion, while AI shows promise in optimizing decision-making, managing risks, and enhancing market efficiency in Nepal's financial landscape, the transition towards widespread AI adoption requires strategic efforts. Addressing the challenges and fostering an environment conducive to AI integration can drive economic development and competitiveness, supporting Nepal's digital transformation journey. The study's insights provide a foundation for strategic decision-making and policy formulation, aiming to bridge the gap between traditional practices and advanced AI-driven solutions in Nepal's financial sector.

5.3 Implications

The findings from the study on the impact of artificial intelligence (AI) adoption in Nepal's financial sector carry several significant implications:

i. Operational Efficiency and Competitiveness: The potential of AI to enhance operational efficiency can make Nepal's financial institutions more competitive. By adopting AI for data analysis, risk prediction, and financial information management, financial entities can streamline processes, reduce errors, and make more informed decisions.

ii. Policy and Regulatory Frameworks: The results highlight the need for robust policy and regulatory frameworks to support AI integration. Policymakers should consider creating guidelines and standards that facilitate AI adoption while addressing concerns related to data privacy, security, and ethical use of AI technologies.

iii. Investment in AI Education and Training: The study underscores the importance of education and training in AI. Financial institutions and educational bodies should collaborate to develop programs that enhance AI literacy and skills among professionals in the financial sector, ensuring they can effectively leverage AI tools and technologies.

iv. Infrastructure Development: To fully realize AI's benefits, there is a need for substantial investment in technological infrastructure. This includes upgrading systems to handle large volumes of data and implementing advanced AI algorithms that can process and analyze financial information efficiently.

v. Data Quality and Management: The findings suggest that improving data quality is crucial for the effective use of AI in financial decision-making. Financial institutions should invest in robust data management practices, ensuring data is accurate, comprehensive, and readily available for AI analysis.

vi. Innovation and Market Growth: The adoption of AI could spur innovation within the financial sector, leading to the development of new financial products and services. This can create opportunities for market growth and diversification, attracting both domestic and international investors.

vii. Customer Trust and Engagement: The varying levels of trust in AI-generated information highlighted by the study indicate that financial institutions need to build customer trust in AI tools. Transparent communication about the benefits and limitations of AI, along with demonstrating the reliability of AI-driven decisions, can enhance customer confidence and engagement.

viii. Strategic Decision-Making: The insights from this study can inform strategic decision-making at multiple levels. Financial institutions can use these findings to shape their AI adoption strategies, while policymakers can develop initiatives that encourage innovation and support the financial sector's digital transformation.

ix. Risk Management: By integrating AI in risk prediction, financial institutions can improve their risk management capabilities. AI can provide more accurate and timely risk assessments, enabling proactive measures to mitigate potential financial threats.

x. Economic Development: Broadly, the successful integration of AI in Nepal's financial sector can contribute to the country's economic development. Enhanced financial services can support business growth, increase financial inclusion, and foster a more resilient economic environment.

These implications underscore the transformative potential of AI in Nepal's financial sector, provided that strategic investments, supportive policies, and effective education initiatives are put in place

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ANNEXURE

Impact of Artificial Intelligence on Financial Decision-Making in Nepal

QUESTIONNAIRE

Dear Sir/Madam,

I am a student of Sanker Dev Campus MBS 4th semester. I would be very much thankful for your participation in this survey. I would like to assure you that whatever information you provide will be kept strictly confidential and will be used only for the said purpose. Participation in this survey is voluntary and you can choose not to answer any individual question or all of the questions. However, I hope that you will participate in this survey since your views are important for reform measures.

Yours Sincerely

Demographic Questions

Section A

Please tick (√) in the appropriate box/space provided unless otherwise instructed.

1. AGE: Under 25 ( ) 25-44 ( ) 35-44 ( ) 45-54 ( ) 55-65 ( ) 65 + ( )

2. Gender: Male ( ) Female ( ) Other ( )

3. Educational Background: High School ( ) Bachelors ( ) Masters ( ) Doctorates ( ) Other ( )

4. Occupation: Financial analyst ( ) Investor ( ) Business owner ( ) Financial consultant ( ) Other ( )

Section B

Financial decision-making questions

5. How frequently do you use AI tools in your financial decision-making process?
- Never ( )
- Rarely ( )
- Sometimes ( )
- Often ( )
- Always ( )

6. Which AI tools do you commonly use for financial decision-making? (Select all that apply)
- Automated trading systems ( )
- Robo-advisors ( )
- AI-based financial analytics platforms ( )
- Machine learning models for risk assessment ( )
- Other (please specify): ___________

Data Analysis

7. How effective do you find AI in analyzing financial data compared to traditional methods?
- Much less effective ( )
- Less effective ( )
- Equally effective ( )
- More effective ( )
- Much more effective ( )

8. To what extent has AI improved the accuracy of your financial data analysis?
- Not at all ( )
- Slightly ( )
- Moderately ( )
- Significantly ( )
- Extremely ( )

9. In your opinion, what are the primary benefits of using AI for data analysis in finance? (Select up to three)
- Speed of analysis ( )
- Accuracy of predictions ( )
- Ability to handle large datasets ( )
- Insight generation ( )
- Cost efficiency ( )
- Other (please specify): ___________

Risk Prediction

10. How do you rate the performance of AI in predicting financial risks?
- Very poor ( )
- Poor ( )
- Average ( )
- Good ( )
- Excellent ( )

11. How often do AI-based risk predictions influence your financial decisions?
- Never ( )
- Rarely ( )
- Sometimes ( )
- Often ( )
- Always ( )

12. What challenges have you encountered with AI in risk prediction? (Select all that apply)
- Lack of transparency in AI models ( )
- Over-reliance on historical data ( )
- Difficulty in interpreting AI outputs ( )
- High cost of implementation ( )
- Other (please specify): ___________

Financial Information

13. How has AI impacted the way you gather and process financial information?
- No impact ( )
- Minor impact ( )
- Moderate impact ( )
- Significant impact ( )
- Transformative impact ( )

14. To what degree do you trust AI-generated financial information?
- Not at all ( )
- Slightly ( )

- Moderately ( )
- Significantly ( )
- Completely ( )

15. What sources of financial information do you use in conjunction with AI? (Select all that apply)

- Financial news websites ( )
- Economic reports ( )
- Market analysis tools ( )
- Peer-reviewed journals ( )
- Other (please specify): ___________

Overall Impact

16. Overall, how has AI affected your financial decision-making process?

- Negatively
- No impact
- Slightly positively
- Moderately positively
- Significantly positively

17. Would you recommend the use of AI tools to others in the financial industry?

- Yes
- No
- Not sure

Section C

Please read the statement carefully and to respond to each statement, Tick the response that most closely matches your perception, feeling, attitude and opinion. The researcher grants your privacy and respects your valuable opinions.

1	2	3	4	5
Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**

Variables	Reponses				
Data Analysis	1	2	3	4	5
1. AI improves the accuracy of financial data analysis					
2. AI allows for faster analysis of large financial datasets compared to traditional methods					
3. AI-generated data insights are more reliable than those generated by human analysts.					
4. I find AI tools easy to use for financial data analysis.					
Risk Prediction					
5. AI enhances my ability to predict financial risks accurately**.**					
6. I trust AI-based risk predictions more than traditional risk assessment methods.					
7. AI provides timely alerts and updates on potential financial risks.					
8. The use of AI in risk prediction reduces my overall financial risk.					
Financial information					
9. I find AI-generated financial reports to be highly accurate.					
10. AI helps me gather comprehensive financial information more efficiently.					
11. AI improves my ability to stay updated with the latest financial market trends.					
12. I am confident in the financial decisions I make based on AI-generated information.					
Financial Decision Making					
13. 13. Overall, AI has positively impacted my financial decision-making process.					
14. 14. I believe AI will continue to play an increasingly important role in financial decision-making.					

IMPACT OF ARTIFICIAL INTELLIGENCE ON FINANCIAL ...

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Abstract This study investigates the potential impact of artificial intelligence (AI) adoption on Nepal's financial sector, where AI utilization for financial prediction remains limited despite global advancements. The research underscores AI's transformative potential demonstrated globally in improving decision-making and operational efficiency within financial services, contrasting with Nepal's predominantly traditional financial industry. By focusing on AI's development in data analysis, risk prediction, and financial information management, the study aims to fill critical gaps in understanding AI's role in enhancing financial decision-making processes. Employing a survey research design with 150 participants primarily from technical analysis-focused stock trading backgrounds, the study utilizes statistical tools like correlation analysis and multiple linear regression to analyze relationships among variables. Findings reveal mixed perceptions among participants regarding AI's effectiveness in financial decision-making, highlighting both its capabilities and challenges such as data quality and trust issues. Overall, the study provides insights into AI's potential to optimize decision-making, manage risks, and drive innovation in Nepal's financial landscape, contributing to strategic decision-making and policy formulation for digital transformation in the sector. Keywords: Innovation, Risk prediction, Artificial Intelligence (AI), Technology Adoption, Market Efficiency CHAPTER I INTRODUCTION 1.1 Background of the study Artificial intelligence (AI) is rapidly transforming digital practices (Mogaji, Soetan, & Kieu., 2011).