THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL DECISION MAKING

A Dissertation submitted to Office of the Dean, Faculty of Management in partial fulfilment of the requirements for the Master's Degree

by

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Certification of Authorship

I hereby corroborate that I have researched and submitted the final draft of dissertation entitled "**THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL DECISION MAKING**". The work of this dissertation has not been submitted previously for the purpose of conferral of any degrees nor. It has been proposed and presented as part of requirements for any other academic purposes.

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

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Report of Research Committee

Miss Prakash Bhattarai has defended research proposal entitled "**THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL DECISION MAKING**", 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 supervisors Keshav Chand and Dr. Dipak Mahat and submit the thesis for evaluation and viva voce examination.

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Approval Sheet

We, the undersigned, have examined the thesis entitled **"THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL DECISION MAKING"** presented by Prakash Bhattarai a 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 thesis is worthy of acceptance.

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Prakash Bhattarai

July, 2025

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Abbreviations

AI:	Artificial Intelligence
ANN:	Analogical to a biological neural network
CV:	Computer Vision
ES:	Expert systems
FD:	Financial Decision
IA:	Intelligent Agents
Ml:	Machine Learning
NLP:	Natural Language Processing
RBFN:	Radial Basis Function Network
SD:	Standard Deviation
SPSS:	Statistical Package For the social sciences

Abstract

This research explores how Artificial Intelligence (AI) and Machine Learning (ML) technologies contribute to improving financial decision-making, emphasizing five main components: Natural Language Processing (NLP), Machine Learning algorithms, Expert Systems (ES), Computer Vision (CV), and Intelligent Agents (IA). Through correlation and regression analyses, the results indicate that NLP has a strong, statistically significant positive effect on financial decisions, underscoring its vital role in processing and interpreting unstructured financial data. In contrast, ML, ES, and CV show no significant direct influence, suggesting their impact may be indirect or dependent on specific contexts. Notably, IA demonstrates a significant but negative relationship with financial decisions, pointing to potential difficulties in aligning autonomous decision-making with optimal financial outcomes. Correlation findings further confirm NLP's leading influence, while IA's weaker associations signal challenges in implementation and integration. Overall, the study concludes that NLP stands out as the most influential AI approach in enhancing financial decision-making, highlighting the importance for organizations to invest in advanced text analytics and sentiment analysis, while carefully deploying autonomous agents to prevent decision misalignment.

Keywords: Financial Decision, Natural Language Processing, Machine Learning algorithms, Expert Systems, Computer Vision, Intelligent Agents

Chapter I
Introduction

1.1 Background of the Study

Over the past few decades, technological progress has drastically changed the financial sector. Notably, Artificial Intelligence (AI) and Machine Learning (ML) have become transformative tools, revolutionizing how financial organizations function and make decisions. Conventional methods of financial decision-making—typically manual, slow, and susceptible to mistakes—are now being improved or replaced by AI and ML models that deliver higher efficiency, precision, and forecasting power (Sangeetha et al., 2022).

As the global economy continues to evolve rapidly, financial decision-making has grown more intricate, demanding the ability to analyze vast amounts of data, detect nuanced patterns, and make swift, data-driven decisions in real time. Traditional financial analysis methods—relying largely on historical trends, expert judgment, and fixed rule-based systems—often struggle to keep up with the fast-paced, complex, and high-frequency nature of today's financial markets. This shortfall has paved the way for the adoption of Artificial Intelligence (AI) and Machine Learning (ML) in the financial industry, fundamentally transforming how decisions are made (Zhang & Lu, 2021).

Artificial Intelligence (AI) generally refers to the ability of machines, particularly computer systems, to mimic human cognitive functions. These functions include learning (gathering data and understanding how to apply it), reasoning (drawing conclusions based on established rules), and self-improvement. A key branch of AI is Machine Learning (ML), which allows systems to learn from data, recognize patterns, and enhance their performance over time without being directly programmed. ML algorithms are capable of analyzing enormous datasets far faster than human analysts, often revealing insights that would otherwise go unnoticed (Kimmel et al., 2020).

AI and ML are being applied across a wide range of financial sectors, including algorithmic trading, credit assessment, fraud prevention, risk analysis, and portfolio management. These technologies have revolutionized financial decision-making by leveraging historical and real-time data to adapt to changing conditions and deliver predictive insights. For example, hedge funds and investment banks now utilize AI-powered algorithms to execute trades in milliseconds, drawing on live market data, sentiment analysis, and forecasting models. Likewise, financial institutions increasingly rely on ML to evaluate loan applicants' creditworthiness with greater speed and accuracy than traditional methods (Raisch & Krakowski, 2021).

The integration of AI and ML into the financial sector represents more than just a passing trend—it marks a transformative change in how data is interpreted and utilized for strategic decision-making. These advanced technologies can rapidly process enormous datasets, detect patterns, predict future trends, and generate valuable insights that enhance investment strategies, risk evaluation, credit assessments, fraud prevention, and customer support. As financial data becomes increasingly complex and voluminous, the use of intelligent systems has become essential for staying competitive and making informed, effective decisions (Zhang et al., 2020).

Artificial Intelligence (AI) and Machine Learning (ML) are now essential elements of today's financial systems, providing cutting-edge solutions to intricate challenges. AI involves the replication of human cognitive functions in machines designed to think and learn, whereas ML, a branch of AI, allows systems to learn from data and enhance their performance over time without the need for explicit programming (Raisch & Krakowski, 2021).

Incorporating AI and ML into financial decision-making has paved the way for more data-centric strategies, minimizing dependence on intuition or solely past trends. These technologies are transforming finance through applications such as algorithmic trading, robo-advisory services, real-time credit risk assessment, and portfolio management. Their capacity to quickly process vast amounts of data and uncover valuable insights empowers financial professionals to make decisions that are more accurate, timely, and well-informed.

Despite the obstacles, the promising advantages of AI and ML in financial decision-making continue to fuel ongoing research and innovation. Collaboration among academic institutions, industry leaders, and regulatory authorities is growing, with efforts focused on creating frameworks and standards to ensure the ethical and responsible use of AI in finance. Interest is also rising in explainable AI (XAI), which seeks to enhance the transparency and reliability of ML models. Additionally, progress in developing hybrid systems that integrate human expertise with machine intelligence is creating new opportunities to support and enhance, rather than replace, human judgment in financial decisions (Klapper & Lusardi, 2020).

This study aims to investigate the diverse role that Artificial Intelligence (AI) and Machine Learning (ML) play in financial decision-making. By analyzing their applications, advantages, challenges, and future prospects, the research seeks to offer a thorough understanding of how these technologies are transforming the financial sector. The study will focus on key areas such as algorithmic trading, credit risk evaluation, fraud detection, and portfolio management, highlighting how AI and ML enhance the accuracy, efficiency, and strategic depth of financial decisions (Finkler et al., 2022).

Furthermore, the study will critically examine the limitations and ethical issues related to the use of AI and ML in finance. It will explore important questions such as: "How can fairness and transparency be maintained in AI-driven financial decisions?" "What is the appropriate level of human oversight in automated systems?" and "How should regulatory frameworks adapt to keep up with rapid technological advancements?" These considerations are especially relevant today, as financial decisions that were traditionally made by humans are increasingly influenced or fully handled by intelligent systems (Ucar, 2019).

This paper investigates the different uses of AI and ML in financial decision-making, evaluates their advantages and drawbacks, and considers their future effects on the financial sector. As these technologies advance, gaining a clear understanding of their functions and possible influence is crucial for all stakeholders within the financial industry.

1.2 Problem Statement

In the fast-changing world of global finance, technological advancements are playing an increasingly central role in decision-making. Artificial Intelligence (AI) and Machine Learning (ML) stand out as particularly transformative, altering conventional approaches to financial analysis, risk evaluation, trading, and investment management. Although these technologies bring notable improvements in efficiency, precision, and forecasting, they also present a variety of complex challenges that require careful scrutiny. Grasping the impact of AI and ML on financial decision-making involves not only technical understanding but also addressing ethical, economic, and regulatory considerations (Goralski & Tan, 2020).

Historically, financial decision-making has depended largely on human expertise, statistical techniques, and the analysis of historical data. Financial analysts, investment managers, and economists have traditionally relied on structured data combined with their experience to inform their choices. However, these traditional approaches often struggle to manage the enormous and varied data produced in today's digital economy. The surge of big data—including unstructured sources like social media, news reports, and live market information—means that relying solely on human analysts and conventional models is no longer enough to generate timely and dependable insights (Sangeetha et al., 2022).

AI and ML represent a fundamental shift by allowing machines to identify patterns within large datasets and make predictions or decisions with little human input. These technologies can process complex data much faster and more precisely than humans, reveal hidden relationships, and continuously refine their models as new information becomes available. In the financial sector, this has given rise to algorithmic trading, robo-advisory services, fraud detection systems, credit scoring methods, and real-time risk management solutions. Additionally, AI can analyze geopolitical events to enhance or even automate investment strategies and financial planning (De Bruyn et al., 2020).

Despite the progress made, integrating AI and ML into financial decision-making presents several significant challenges. A key concern is the lack of transparency and explainability in many AI and ML models, often called the "black box" issue. Both financial experts and regulators worry that these systems' decisions are not always fully understandable or justifiable, which is especially critical in an industry where accountability and trust are essential. For example, when an AI system rejects a loan application or makes a risky trade, it's important for stakeholders to know the reasoning behind those decisions. The lack of clarity in AI models can therefore erode confidence and potentially cause serious financial or reputational harm (Zhang et al., 2020).

Additionally, bias and fairness remain critical issues. Machine learning models depend heavily on the quality of the data they are trained with. If historical financial data contains existing biases—such as discriminatory lending or unequal credit access—AI systems might reinforce or even worsen these biases. This creates ethical dilemmas and could lead to regulatory and legal challenges for financial institutions. The key challenge is to develop AI models that are both fair and accurate, particularly when applied in sensitive fields like credit risk evaluation, insurance underwriting, or investment advice (Haenlein & Kaplan, 2019).

Another major concern is the danger of over-dependence on AI and ML systems. As these technologies grow more advanced and become deeply embedded in financial operations, decision-makers may increasingly rely on algorithmic results without enough supervision. This overtrust can create systemic risks, particularly during volatile market periods when AI systems might behave unpredictably or even worsen financial turmoil. The 2010 Flash Crash, although not solely caused by AI, demonstrated how automated trading systems can interact unexpectedly, resulting in market instability.

Moreover, data privacy and cybersecurity pose significant risks. AI and ML systems depend on large volumes of data, often containing sensitive or confidential information. Safeguarding the secure collection, storage, and handling of this data is crucial to protect clients and uphold the trustworthiness of financial institutions. Any data breaches or misuse could result in financial damage, reputational setbacks, and regulatory sanctions (Chowdhury, 2023).

Additionally, regulatory uncertainty and compliance issues add complexity to the adoption of AI in finance. Many current financial regulations were created before the rise of AI and ML, resulting in oversight gaps and unclear legal accountability. For example, it remains unclear whether the developer, the financial institution, or the end user is responsible if an AI-driven financial decision leads to harm. There is a pressing need for regulatory frameworks that can evolve alongside technological advancements while ensuring market stability and protecting consumers (Zaman et al., 2023).

From an organizational standpoint, adopting AI and ML requires substantial adjustments in infrastructure, workforce, and culture. Financial institutions need to invest in powerful computing resources, robust data engineering, and ongoing model oversight. Additionally, there is a scarcity of experts who combine strong financial expertise with advanced AI/ML skills. Closing this talent gap is essential for successfully embedding these technologies into decision-making workflows (Agung et al., 2021).

Finally, the wider economic and social impacts of AI in financial decision-making deserve careful consideration. AI-driven automation may lead to job displacement in financial sectors, especially among analysts, advisors, and underwriters. Although new roles could emerge in data science and technology fields, the shift may be uneven and challenging for many workers. It's important to study how the adoption of AI influences labor markets, financial inclusion, and the accessibility of financial services (Pramod & Raman, 2022).

Considering these diverse challenges and opportunities, this study aims to address the insufficient comprehensive understanding of how AI and ML truly influence financial decision-making—both in terms of improvements and potential drawbacks. Although many technological innovations are being introduced, there is still a lack of empirical research that thoroughly assesses their effects on decision quality, efficiency, risk management, and ethical issues. Without this insight, there is a risk of either overstating AI's benefits or downplaying its associated risks (Finkler et al., 2022).

Thus, this research intends to examine the practical applications of AI and ML in the financial sector, evaluate their performance relative to conventional approaches, highlight the key risks and obstacles to implementation, and investigate ways to promote responsible and fair use of these technologies (Njegovanović, 2018). Through this, the study aims to help establish best practices, guide policy and regulatory frameworks, and assist financial institutions in making well-informed choices regarding the adoption and management of AI systems.

- What are the dimensions that represent role of AI and machine learning in financial decision making?

- Is there any relationship between natural language processing, machine learning, expert systems, computer vision and financial decisions?
- How does natural language processing, machine learning, expert systems, computer vision effect on financial decision making of Nepalese Manufacturing companies

1.3 Objectives of the Study

The overall aim of this study is to explore the role of AI and Machine Learning in financial decision-making. The specific objectives are as follows:

- To assess the dimensions that represents the artificial intelligence and machine learning in financial decision making.
- To examine the relationship among natural language processing, machine learning, expert systems, computer vision and financial decisions of Nepalese Manufacturing companies.
- To analyze the impact of natural language processing, machine learning, expert systems, computer vision on financial decision.

1.4 Rationale of the Study

The importance of this study lies in its examination of the transformative impact that Artificial Intelligence (AI) and Machine Learning (ML) have on financial decision-making. As global financial markets grow increasingly complex and data-intensive, traditional decision-making methods are being supplemented or even replaced by sophisticated AI and ML algorithms. This research seeks to illuminate how these technologies are changing the financial environment by enabling faster, more accurate, and efficient decisions. AI and ML systems can analyze massive datasets and uncover patterns that human analysts might miss. By adopting these technologies, financial institutions can minimize human errors and make more informed, data-driven choices—especially in critical areas such as risk management, fraud detection, and investment planning.

AI and ML's capability to analyze and interpret vast amounts of data in real time greatly improves the speed and efficiency of decision-making. In financial markets, where timing is crucial, these technologies enable quicker reactions to market fluctuations, thereby boosting profitability and competitive positioning. A major strength of AI and ML lies in their ability to predict future outcomes. By examining past data and recognizing patterns, they can forecast financial trends, offering investors, banks, and other financial institutions valuable insights into market dynamics, customer behaviors, and economic conditions. Additionally, AI and ML can develop highly personalized financial strategies, products, and services tailored to the needs of individuals and organizations, which can enhance customer satisfaction and foster growth in a competitive financial landscape.

As AI and ML become key components of financial decision-making, it is essential to explore the ethical considerations and regulatory challenges they bring. This study will examine issues such as data privacy, algorithmic bias, and the importance of proper oversight to ensure these technologies are applied responsibly within the financial sector. The adoption of AI and ML is fostering innovation in finance, leading to new business models, products, and services as institutions harness these tools to better serve the changing demands of customers and investors. This research will offer valuable insights into how AI and ML are redefining conventional financial practices.

1.5 Limitation of Study

The limitations of the study are as follows:

i. Out of the total of 19 manufacturing companies, only three companies' employees are taken as a sample.
ii. Only limited statistical and financial tools are used for the study
iii. The accuracy of the study was based on the data available from the management of manufacturing companies, the various published document of the manufacturing companies, and the response made by the respondent during the informal discussion.

Chapter II
Literature Review

2.1 Introduction

This chapter presents the evidence and findings from previous research conducted by various scholars. The reviewed studies provide relevant insights that support further exploration of the relationship between corporate governance and bank performance.

2.2 Theoretical Review

2.2.1 Development of Machine Learning

The terms Artificial Intelligence and Machine Learning are well-established and have been studied, developed, and applied by computer scientists, engineers, researchers, students, and industry experts for over six decades. The mathematical roots of machine learning are grounded in algebra, statistics, and probability. Significant advancements in AI and ML began during the 1950s and 1960s, thanks to pioneers such as Alan Turing, John McCarthy, Arthur Samuel, Alan Newell, and Frank Rosenblatt. Samuel introduced the first functional machine learning model with his Optimizing Checkers Program, while Rosenblatt developed the Perceptron an influential machine learning algorithm inspired by biological neurons which laid the groundwork for Artificial Neural Networks.

2.2.2 The Generic Model of ML

Machine Learning is applied to address a range of problems that involve the machine's ability to learn. A learning problem typically includes three key components:

- Task classes (The task to be learnt)
- Performance measure to be improved
- The process of gaining experience

Each part of the model has a distinct role to perform, as outlined below.

i. Collection and Preparation of Data: The main role in the machine learning process is to gather and organize data into a format suitable for input into the algorithm. While large volumes of data may be available for many problems, web data is often unstructured and contains a significant amount of noise, including irrelevant and redundant information.

Therefore, the data must be cleaned and pre-processed to convert it into a structured format.

ii. Feature Selection: The data collected in the previous step may include many features, but not all will be relevant for the learning process. It is necessary to eliminate the irrelevant features and select a subset of the most important ones.

iii. Choice of Algorithm: Not every machine learning algorithm is suitable for every problem. Some algorithms are better suited to specific types of problems, as discussed earlier. Choosing the most appropriate machine learning algorithm for a given task is essential to achieve optimal results. A detailed discussion of various ML algorithms can be found in Section 6.

iv. Selection of Models and Parameters: Many machine learning algorithms require initial manual input to set the optimal values for different parameters.

v. Training: Once the suitable algorithm and parameter values are chosen, the model must be trained using a portion of the dataset designated as training data.

vi. Performance Evaluation: Prior to deploying the system in real-time, the model should be tested on unseen data to assess its learning effectiveness using performance metrics such as accuracy, precision, and recall.

2.2.3 Machine Learning Paradigms

Machine learning paradigms can be categorized into ten types based on the training method and whether output data is available during training. These categories include supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning, evolutionary learning, ensemble learning, artificial neural networks, instance-based learning, dimensionality reduction algorithms, and hybrid learning.

Supervised Learning

In supervised learning, the algorithm is provided with a set of examples or training data that include the correct outputs. Using these training sets, the algorithm learns to produce more accurate responses by comparing its predictions with the given outputs. This approach is also referred to as learning from examples or learning from exemplars. Supervised learning is commonly used for making predictions based on historical data. For instance, it can predict the species of an Iris flower based on its measurements, identify whether an object in a telescope image is a galaxy, quasar, or star, or recommend products to users based on their e-commerce browsing history. Supervised learning tasks are divided into classification and regression categories. Classification involves predicting discrete output labels, while regression deals with continuous output values.

Unsupervised Learning

Unsupervised learning focuses on identifying unknown patterns within data to extract meaningful rules. This method is suitable when the data categories are not predefined, and the training data lacks labels. Often considered a statistics-based approach, unsupervised learning aims to discover hidden structures within unlabeled datasets.

Reinforcement Learning

Reinforcement learning is considered a middle ground in learning types because the algorithm receives only feedback indicating whether its output is correct or not. The algorithm must explore different options and eliminate incorrect ones to arrive at the right solution. This approach is often described as learning with a critic, as the algorithm does not generate suggestions or solutions itself but learns from the feedback provided.

Evolutionary Learning

This approach is inspired by biological organisms that adapt to their surroundings. The algorithm learns to interpret behavior, adjusts to the inputs, and eliminates less probable solutions. It operates on the principle of fitness, aiming to identify the best possible solution to the problem.

Semi-Supervised Learning

These algorithms combine the strengths of both supervised and unsupervised learning. While supervised learning uses labeled data for all observations and unsupervised learning uses none, there are cases where only a portion of the data is labeled, often due to the high cost of labeling or limited expert availability. In such scenarios, semi-supervised learning algorithms are ideal for building models. This approach can be applied to tasks such as classification, regression, and prediction.

Ensemble Learning

Ensemble learning is a machine learning approach where multiple individual models, called learners, are trained to address the same problem. Unlike traditional methods that generate a single hypothesis from the training data, ensemble learning builds a collection of hypotheses and combines them to create a prediction model. This process helps reduce bias (through boosting), decrease variance (through bagging), or enhance overall prediction accuracy (through stacking). Ensemble learning techniques can be categorized into two main groups:

- Sequential ensemble methods involve building base learners one after another in a sequence (e.g., AdaBoost). This approach takes advantage of the dependency between the base learners.
- Parallel ensemble methods build base learners independently of one another, allowing them to be constructed simultaneously (e.g., Random Forest).

Artificial Neural Network

Artificial Neural Networks (ANNs) are inspired by the biological neural networks found in the brain. A neural network is made up of interconnected nerve cells that transmit electrical impulses throughout the brain. The fundamental learning unit in a neural network is the neuron, which is a type of nerve cell. A neuron has four main components: dendrites (which receive signals), the soma (which processes the electrical signals), the nucleus (the neuron's core), and the axon (which transmits signals). Similarly, an ANN is structured with three layers: an input layer, one or more hidden layers, and an output layer. These networks feature weighted connections and learn by adjusting these weights to enable parallel distributed processing. Some well-known ANN algorithms include the Perceptron learning algorithm, Backpropagation, Hopfield Networks, and Radial Basis Function Networks (RBFN). ANNs can be further categorized based on their learning behavior as follows:

- **Supervised Neural Network** – The network is trained using input-output pairs as training data. It adjusts the connection weights to produce accurate results during training and, once fully trained, uses this learning to predict outputs for new, unseen data.
- **Unsupervised Neural Network** – In this type of network, no output data is provided during training. Instead, the network identifies patterns or relationships within the input data and groups similar data points into clusters or classes. When new input data is introduced, the network analyzes its features and assigns it to one of these groups based on similarity.

- **Reinforcement Neural Network** – Similar to how humans learn from interacting with their environment, a reinforcement neural network learns from its past actions by receiving penalties for incorrect decisions and rewards for correct ones. The network strengthens the connections that lead to accurate outputs and weakens those that result in errors.

Instance based learning

Unlike other machine learning approaches that define a target function during training, this method does not specify any target function upfront. Instead, it stores the training examples and delays generalization until a new instance needs to be classified, which is why it is called a lazy learner. These methods maintain a database of training instances and, when given new input, compare it to existing examples using a similarity measure to find the closest match and make predictions. Unlike global estimation of the target function, the lazy learner estimates it locally for each new instance, making training faster but prediction slower. Popular instance-based algorithms include KMeans, k-medians, hierarchical clustering, and expectation maximization.

Dimensionality reduction algorithms

Over the past few decades, intelligent machine learning models have been widely adopted in complex, data-intensive fields such as climatology, biology, astronomy, medicine, economics, and finance. However, many existing ML systems struggle with efficiency and scalability when handling massive, high-dimensional datasets. High dimensionality often becomes a significant obstacle in data processing, while data sparsity further complicates the search for a global optimum, making it computationally expensive. Dimensionality reduction algorithms address these challenges by decreasing the number of data features, removing redundant and irrelevant information, and cleaning the data, thereby improving computational efficiency and result accuracy. These algorithms typically operate in an unsupervised manner, uncovering and exploiting the inherent structure within the data. Common dimensionality reduction techniques that complement classification and regression tasks include Multidimensional Scaling (MDS), Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Principal Component Regression (PCR).

2.2.4 How AI and ML Differ from Traditional Computational Models

AI and ML differ significantly from conventional computational approaches in finance by employing algorithms that can self-learn from data and make decisions autonomously. Traditional computational finance methods typically involve designing algorithms with fixed decision-making rules that analyze data according to predefined guidelines. These methods are limited to recognizing and categorizing data patterns explicitly programmed by their developers and struggle to adapt to new or large, unstructured datasets (Bishop, 2006). In contrast, AI and ML algorithms can handle vast and complex data, continuously learning and improving their predictions over time. This capability enables them to outperform traditional models, especially when dealing with large-scale, unsystematic data such as stock market fluctuations or customer behavior patterns. For example, while conventional credit risk prediction models often rely on a fixed set of factors, heuristic AI-driven credit risk models can dynamically incorporate diverse features like transaction history, social media activity, and spending behaviors (Khandani, Kim & Lo, 2010). Furthermore, AI and ML offer the advantage of processing information at speeds far exceeding traditional models, making them highly effective in real-time financial applications such as high-frequency trading and fraud detection (Brynjolfsson & McAfee, 2017).

2.2.5 Enhancing Efficiency through AI and ML

Algorithmic Trading and Its Impact on Market Efficiency

Algorithmic trading, driven by artificial intelligence and machine learning, is transforming global trading by automating decisions on buying and selling stocks, bonds, and other securities in real time. Unlike traditional methods that rely on human judgment and static models, AI-powered algorithms continuously update their strategies based on new market data, significantly enhancing market efficiency by reducing trading costs and exploiting fleeting arbitrage opportunities within microseconds (Brynjolfsson & McAfee, 2017; Goodfellow et al., 2016). This rapid execution leads to narrower bid-ask spreads and increased liquidity through high-frequency trading, while also minimizing emotional biases common in human traders (Mihov, Firoozye, & Treleaven, 2022). However, algorithmic trading carries risks such as market disruptions caused by flawed algorithms or unfavorable economic conditions, exemplified by flash crashes that can cause sudden price drops, underscoring the need for careful oversight and regulation (Khandani, Kim &

Lo, 2010). Overall, despite these challenges, algorithmic trading has notably improved market liquidity, competition, and efficiency.

2.2 Empirical Review

Udeh (2025) researched on artificial intelligence and machine learning in finance: Enhancing efficiency, innovation and decision-making. The rapid integration of Artificial Intelligence (AI) and Machine Learning (ML) into the financial industry is revolutionizing traditional financial practices by enhancing operational efficiency, fostering innovation, and improving decision-making. These technologies enable financial institutions to leverage vast datasets, predict market trends, streamline processes, and deliver personalized services, transforming key areas such as fraud detection, risk management, and algorithmic trading. This study explores the primary applications of AI and ML in finance, highlighting their role in increasing efficiency through automation and real-time data processing, developing innovative financial products, and supporting data-driven decisions. Despite these advancements, significant challenges persist, including data privacy concerns, model interpretability, algorithmic bias, and the urgent need for comprehensive regulatory frameworks. Employing a mixed-methods approach—combining literature review with case studies of industry practices—the study provides insights into both the opportunities and risks of adopting AI and ML in finance. It concludes by emphasizing the necessity for ongoing research aimed at enhancing transparency, security, and ethical standards, ensuring these technologies fulfill their potential while safeguarding stakeholders' interests.

Wahab (2025) examined on enhancing financial forecasting with AI and machine learning: a path to financial security. This paper explores how Artificial Intelligence (AI) and Machine Learning (ML) enhance financial forecasting, contributing to greater financial security. The integration of AI and ML enables the analysis of vast datasets, uncovering complex patterns often missed by human analysts. Advanced algorithms such as neural networks and decision trees improve prediction accuracy, offering valuable insights into market fluctuations, credit risk assessment, and portfolio optimization. These adaptive tools provide real-time analysis, empowering stakeholders to make proactive, informed decisions while reducing human biases and errors. AI-driven forecasting excels in fraud detection, anomaly identification, and risk management, particularly in volatile markets. By leveraging historical and real-time data, these models generate actionable intelligence that fosters resilience amid economic uncertainty. The paper also addresses challenges including data privacy, ethical considerations, and the need for model explainability—critical factors for ensuring transparency and trust. Combining AI and ML with traditional methods can enhance accuracy, adaptability, and efficiency, ultimately supporting sustainable economic growth.

Chhikara et al. (2025) investigated on predictive analytics in finance: leveraging AI and machine learning for investment strategies. This chapter explores the transformative impact of artificial intelligence (AI) across multiple sectors, with a focus on financial decision-making, business analytics, and risk management. It highlights how AI technologies—such as machine learning and predictive modeling—enhance decision accuracy and operational efficiency in finance and supply chain management. The discussion extends to AI's role in fostering economic growth and innovation in emerging economies, while also addressing key ethical concerns like data privacy and the importance of Explainable AI (XAI) to promote transparency and trust. Overall, the chapter emphasizes AI's potential to reshape industries and improve decision-making processes, alongside the need to carefully manage its associated challenges.

Sani (2025) conducted a research on AI and machine learning in financial forecasting: supporting sustainable finance and energy policy. The integration of Artificial Intelligence (AI) and Machine Learning (ML) into financial forecasting is revolutionizing sustainable finance, particularly influencing energy policy. These technologies enhance the accuracy and efficiency of predicting financial trends, market behavior, and investment opportunities, enabling investors, policymakers, and institutions to make decisions aligned with sustainability goals. In energy markets, AI and ML analyze extensive data to forecast demand, optimize distribution, and identify renewable energy investments. AI-driven models improve risk management, green asset pricing, and recognition of long-term sustainability trends, facilitating the incorporation of environmental, social, and governance (ESG) factors into financial strategies. Additionally, these tools assist policymakers in simulating policy impacts to design more effective energy transition strategies. By providing real-time data analysis and reducing human error, AI and ML increase transparency and accountability in financial markets. Ultimately, these technologies direct capital towards renewable projects, boost energy market efficiency, and support global efforts to reach net-zero emissions, positioning AI and ML as critical drivers in shaping a sustainable, low-carbon future.

Olubusola et al. (2024) examined on machine learning in financial forecasting: A U.S. review: exploring the advancements, challenges, and implications of AI-driven predictions in financial markets. This study investigates the integration of Artificial Intelligence (AI) and Machine Learning (ML) in financial forecasting within the United States, focusing on advancements, challenges, and implications for market stakeholders. Through a systematic literature review and content analysis of peer-reviewed publications and institutional reports from 2010 to 2024, the research highlights how AI and ML—particularly deep learning, reinforcement learning, and hybrid models—have enhanced prediction accuracy and efficiency in financial markets. Despite these technological gains, persistent issues such as data quality, model interpretability, and ethical concerns call for robust regulatory frameworks to ensure responsible AI deployment. The study concludes that while AI and ML hold transformative potential for financial forecasting, addressing ethical and operational challenges is essential for their effective adoption. It recommends that financial leaders and policymakers prioritize innovation, AI literacy, and the creation of international standards, with future research focusing on emerging technologies and adaptive regulations to sustain progress in this dynamic field.

Rane et al. (2024) researched on artificial intelligence and machine learning in business intelligence, finance, and e-commerce: a review. This research explores the transformative impact of artificial intelligence (AI) and machine learning (ML) on business intelligence (BI), finance, and e-commerce, emphasizing recent advancements and emerging trends. AI and ML have enhanced BI through improved predictive analytics, real-time data processing, and smarter decision-making. In finance, these technologies are revolutionizing risk management, fraud detection, and personalized services, resulting in more secure and efficient systems. Meanwhile, e-commerce benefits from AI-driven personalized recommendations, dynamic pricing, and intelligent chatbots that elevate customer experiences. The study also highlights AI's integration with big data analytics and the Internet of Things (IoT), fostering a more interconnected, data-driven business environment. Ethical challenges such as data privacy, algorithmic bias, and the need for regulatory oversight are examined, alongside future research directions including the development of explainable AI (XAI) to enhance transparency and trust, and AI's role in promoting sustainable business practices. This paper offers comprehensive insights for researchers, practitioners, and policymakers aiming to harness AI and ML for competitive advantage and sustainable growth.

Huang and You (2023) researched on artificial intelligence in financial decision making. Artificial intelligence (AI), driven by machine learning algorithms, excels at efficiently extracting valuable insights from big data, offering significant potential to enhance financial decision-making. This chapter reviews key AI applications in finance, beginning with algorithms that process unstructured data, particularly natural language processing techniques. It then explores how AI integrates information from both unstructured and structured data sources to support critical financial decisions, including investment strategies and FinTech lending. Finally, the chapter highlights the complementary roles of AI and human expertise in improving the accuracy and effectiveness of financial decision-making.

Sujith et al. (2022) researched on a comparative analysis of business machine learning in making effective financial decisions using structural equation model (SEM). This research aims to examine the key components of machine learning (ML) in enabling efficient financial decision-making. In today's data-driven business environment, leaders face vast volumes of data that must be stored, analyzed, and utilized to gain a competitive edge. ML, a subset of artificial intelligence, focuses on optimizing business processes with minimal human intervention by identifying patterns in large datasets. These techniques provide management with valuable insights across various domains such as finance, marketing, supply chain, and human resources. ML facilitates the extraction of meaningful patterns and accurate forecasting, supporting the transition from physical to electronic data storage, enhancing organizational memory, and improving decision-making. This study specifically investigates the application of ML in financial decision-making within companies, recognizing ML as a critical technology that offers significant opportunities in today's competitive markets. Data will be collected from employees, managers, and business leaders across industries to understand the influence of ML on financial decisions.

Ahmed et al. (2022) examined on artificial intelligence and machine learning in finance: A bibliometric review. This study reviewed the literature on artificial intelligence (AI) and machine learning (ML) in finance using a bibliometric approach. A total of 348 articles published between 2011 and 2021 were collected from the Scopus database and analyzed with RStudio, VOSviewer, and Excel to identify leading countries, institutions, journals, documents, and authors. The review revealed a growing publication trend since 2015 and highlighted key applications of AI and ML, including bankruptcy prediction, stock price forecasting, portfolio management, oil price prediction, anti-money laundering, behavioral finance, big data analytics, and blockchain. The United States, China, and the United Kingdom emerged as the top contributors to this research. These findings offer practical insights for fintech and finance companies on leveraging AI and ML for enhanced decision-making.

Lakhchini et al. (2022) investigated on artificial intelligence & machine learning in finance: A literature review. This study aims to trace the intellectual development of artificial intelligence (AI) and machine learning (ML) research in finance by conducting a scoping review combined with an embedded bibliometric analysis. Following the five stages of scoping review methodology alongside Donthu et al.'s (2021) bibliometric approach, the study examines trends in AI and ML applications in finance from 1989 to 2022, covering both developed and emerging economies. The primary objective is to detail various research areas illustrating the use of AI and ML in finance. The findings are organized into seven key fields: (1) Portfolio Management and Robo-Advisory, (2) Risk Management and Financial Distress, (3) Financial Fraud Detection and Anti-Money Laundering, (4) Sentiment Analysis and Investor Behavior, (5) Algorithmic Stock Market Prediction and High-Frequency Trading, (6) Data Protection and Cybersecurity, and (7) Big Data Analytics, Blockchain, and Fintech. For each field, the study highlights how AI and ML research is advancing the financial sector and offering innovative solutions for financial institutions. The study concludes with a global mapping of 110 documents across these seven application areas, providing a comprehensive overview of the field.

Mhlanga (2021) researched on financial inclusion in emerging economies: the application of machine learning and artificial intelligence in credit risk assessment. Credit risk is a critical issue in banking and finance, as issuing loans requires careful assessment of the likelihood of repayment. In emerging markets, many underbanked individuals lack traditional forms of collateral or identification, limiting their access to credit from financial institutions. Through a literature review employing documentary and conceptual analysis, this study explores the impact of artificial intelligence (AI) and machine learning (ML) on credit risk assessment. It finds that AI and ML significantly enhance credit risk evaluation by utilizing alternative data sources—such as public data—to address challenges like information asymmetry, adverse selection, and moral hazard. These technologies enable lenders to conduct thorough credit risk analyses, better understand customer behavior, and accurately assess borrowers' repayment capacity, thereby expanding credit access to underserved populations. The study recommends that financial institutions, including banks and lending agencies, increase their investment in AI and ML to promote financial inclusion for marginalized households.

Pothumsetty (2020) investigated on implementation of artificial intelligence and machine learning in financial services. Recent technological innovations have profoundly impacted every aspect of life over the past decades. Among these, artificial intelligence (AI) stands out as a transformative technology capable of changing the world. AI refers to computer software that can mimic human thinking and decision-making processes. Today, AI is increasingly integrated across various business functions, with the financial services industry being one of the fastest adopters. In finance, AI is revolutionizing core areas such as risk assessment, stock trading, and credit lending. Importantly, AI is not meant to replace finance professionals but rather to assist them by automating repetitive tasks, allowing managers to concentrate on strategic and value-driven activities. This research employs a qualitative approach to explore the implementation of AI across different financial functions and examines its impact on employees, finance professionals, and business organizations.

Shukla (2020) analyzed on approaches for machine learning in finance. Financial institutions have been fundamentally transformed by machine learning (ML) technology, which they employ for advanced data analytics, decision support, and risk management. By leveraging powerful ML algorithms, organizations can accurately detect patterns, automate processes, and forecast market trends from vast and diverse datasets. Incorporating soft data, such as news and social media sentiment, further enhances forecasting accuracy and decision-making capabilities. Unlike traditional static models relying on historical data, ML systems utilize real-time, time-sensitive analysis to identify anomalies and predict emerging risks more effectively. ML also detects fraudulent activities by recognizing abnormal behaviors that deviate from standard patterns. To ensure trust and regulatory compliance, financial organizations must prioritize transparency, fairness, and robust data protection in their ML implementations. Achieving full potential in ML-driven finance requires close collaboration among technologists, financial experts, and regulators to address operational challenges and continuously improve systems. Proper implementation and ongoing development will propel innovation and maximize the benefits of ML in finance.

Table 1

Summary of Empirical Review

Authors	Title	Objective	Methodology	Findings
Udeh (2025)	Artificial intelligence and machine learning in finance: Enhancing efficiency, innovation and decision-making	To examine how they contribute to increased efficiency through automation and real-time data processing	Used mixed-methods approach	The study emphasized the need for ongoing research to enhance AI systems' transparency, security, and ethical standards in financial services, ensuring their full potential is realized while protecting stakeholders' interests.
Wahab (2025)	Enhancing financial forecasting with AI and machine learning: a path to financial security	To explore how AI and ML enhance financial forecasting, paving the way for greater financial security	Used advanced algorithms, such as neural networks and decision trees	The study demonstrates that AI-driven forecasting reduces human biases and errors, thereby enhancing the robustness of financial models. Additionally, machine learning-powered predictive analytics have proven highly effective in fraud detection, anomaly identification, and risk management in volatile

				financial markets.
Chhikara et al. (2025)	Predictive analytics in finance: leveraging AI and machine learning for investment strategies	To examine the transformative role of artificial intelligence (AI) across various sectors	The study used literature method	The study found that machine learning and predictive modeling are improving decision-making accuracy and operational efficiency in both financial sectors and supply chain management.
Sani (2025)	AI and machine learning in financial forecasting: supporting sustainable finance and energy policy	To identify investment opportunities in renewable energy sources	Used long-term sustainability trends, nuanced approach	The study found that integrating environmental, social, and governance (ESG) factors into investment strategies helps align capital flows with sustainable energy projects aimed at mitigating climate change.
Olubusola et al. (2024)	Machine learning in financial forecasting: A U.S. review: exploring the advancements, challenges, and implications of AI-driven predictions in financial markets	To uncover the advancements, challenges, and broader implications for stakeholders in the financial markets	Employing a systematic literature review and content analysis	The results show that artificial intelligence and machine learning have greatly transformed financial forecasting by enhancing the accuracy of market trend analysis and asset price prediction, thanks to advancements in deep learning, reinforcement learning, and hybrid approaches.
Rane et	Artificial	To examine the	Study	Artificial intelligence and

al. (2024)	intelligence and machine learning in business intelligence, finance, and e-commerce: a review	transformative effects of artificial intelligence and machine learning on business intelligence, finance, and e-commerce, focusing on recent advancements and emerging trends	used cross sectional data	machine learning have greatly improved business intelligence by supporting more precise predictive analytics, facilitating real-time data analysis, and strengthening decision-making processes.
Huang and You (2023)	Artificial intelligence in financial decision making.	To examine the complementary roles of AI and humans in improving financial decision-making.	Used AI algorithms	The study revealed that AI gathers and synthesizes data from both structured and unstructured sources to support financial decision-making, including investments and FinTech lending.
Sujith et al. (2022)	Comparative analysis of business machine learning in making effective financial decisions	To examine the key components of machine learning in making efficient financial decisions	Used structural equation model (SEM)	The study found that machine learning plays a crucial role in enabling swift financial decision-making. It allows business leaders to concentrate on key areas that can boost profitability, with effective risk management being a vital component.
Ahmed	Artificial	To review the	Study	The findings offer actionable

et al. (2022)	intelligence and machine learning in finance: A bibliometric review	artificial intelligence (AI) and machine learning (ML) literature in the finance fiel d	used bibliometr ic approach	insights for market participants—particularly fintech and financial firms—on how to leverage AI and machine learning in their decision-making processes.
Lakhchini et al. (2022)	Artificial intelligence & machine learning in finance: A literature review	To infer the intellectual development of AI and ML in finance research	Used bibliometr ic review method	The study found that research in AI and ML advances the financial sector by offering new opportunities and solutions for a wide range of financial institutions and organizations.
Mhlanga (2021)	Financial inclusion in emerging economies: the application of machine learning and artificial intelligence in credit risk assessment	to investigate the impact of machine learning and artificial intelligence in credit risk assessment	Used literature review approach through document ary and conceptual analysis	The study revealed that artificial intelligence and machine learning significantly influence credit risk evaluation by utilizing alternative data sources.
Pothumsetty (2020)	Implementation of artificial intelligence and machine learning in financial	to interpret how AI has been implemented in various finance	Used qualitative research	The study found that AI is increasingly handling key financial functions, including risk assessment, stock trading, and the credit lending process for loan

	services	functions and its influence towards employees		applicants.
Shukla (2020)	Approaches for machine learning in finance	To detect patterns and automate processes while forecasting market trends for large amounts of data	Study used analytical data processing, decision support systems, and risk management processes	The study found that machine learning stands apart from traditional systems by utilizing time-sensitive data analysis to accurately identify issues and predict potential threats. It detects fraudulent activities by recognizing unusual behaviors that deviate from standard patterns.

2.3 Research Gap

In recent years, the use of Artificial Intelligence (AI) and Machine Learning (ML) in financial decision-making has attracted significant attention from both academia and industry. Many studies have examined the technical abilities and predictive accuracy of AI/ML in areas like credit scoring, algorithmic trading, fraud detection, and risk evaluation (Dastile et al., 2020; Brynjolfsson & McAfee, 2017). However, most research focuses on technical or algorithmic aspects, often using secondary data or simulations to assess model performance, which leaves a gap in understanding how AI/ML adoption is perceived and behaves in actual financial decision-making. This study uses a descriptive and causal research design with convenience sampling of 400 participants who completed a structured questionnaire, analyzed through descriptive statistics, correlation, and regression methods. While this approach offers valuable user-centered insights into the link between AI/ML tools and financial behavior, it also reveals some methodological limitations in prior research.

The study did not gather primary data from company employees as respondents, instead relying on institutional or market data (Chen et al., 2019). In contrast, this research directly examines the perceptions, usage habits, and behavioral reactions to AI/ML tools among financial decision-makers. However, the reliance on convenience sampling may introduce bias and restrict the ability to generalize the findings, highlighting the need for future studies to use probabilistic or stratified sampling methods to better represent a broader range of financial professionals across different sectors.

Ionescu et al. (2021) employed machine learning models to enhance prediction accuracy in financial forecasting but rarely examined the causal impact of AI/ML on decision-making quality, confidence, or ethical issues. This study seeks to explore these aspects using regression and correlation analysis; however, its cross-sectional design limits the ability to assess long-term effects or changes in behavior over time.

This study primarily assesses the perceived roles and effectiveness of AI/ML through quantitative data, while other researchers advocate for incorporating qualitative or mixed-method approaches to better understand the cognitive, cultural, and organizational factors influencing AI/ML adoption (Jöhnk et al., 2021). Consequently, a significant research gap exists in integrating quantitative results with detailed interviews or case studies to develop a more comprehensive framework of how AI/ML impacts financial decision-making at both micro and macro levels.

Chapter III
Research Methodology

Research methodology describes the methods and procedures used throughout the entire study. Every research project should be organized systematically, making research methodology a crucial component. To meet the main objectives of this study, various methodologies have been applied, including research design, population and sampling, data sources, and data collection procedures.

3.1 Research Design

This study employs both descriptive and causal research designs. The descriptive design is used to detail variables such as risk management, financial performance, and effective cash management. Meanwhile, the causal design examines the cause-and-effect relationships between these factors—risk management, financial performance, and cash management—and their influence on financial decision-making.

3.2 Population and Sample, and Sampling Design

The market comprises various sectors such as financial institutions, commercial banks in Nepal, manufacturing and processing, hospitality, trading, hydropower, and others. This study focuses on 19 manufacturing companies as its population. Among these, three companies—Dabur Nepal, Bottlers Nepal, and Unilever Nepal—employ a total of 1,800 people (according to their official websites). The population for this study includes 950 employees from Dabur Nepal, 650 from Bottlers Nepal, and 250 from Unilever. Based on this distribution, the sample consists of 200 employees from Dabur Nepal, 145 from Bottlers Nepal, and 55 from Unilever. A convenience sampling method was used to select the sample organizations for the study.

The study applies the following formula to determine the sample size for populations of unknown size (Charan, 2013).

$n = Z^2 \times (p \times q)/E^2$

Where,

z = Z-score or a standard normal deviation

p = estimated proportion of the study variables

q = 1-p

E^2 = acceptable error

The study uses 95% confidence level (Z = 1.96), a 5% margin of error (e = 0.05), and has no prior estimate of p, so the calculation would be:

$n = (1.96)^2 * 0.5 * (1-0.5)/0.05^2$ (p = 0.5, if there is no prior information of 'p', the study uses 0.5 which maximize variability and gives the largest sample size).

n = 3.8416 * 0.25 / 0.0025

n = 384.16

Therefore, we need around 385 respondents for the sample of the study while this study used 400 respondents for the sample.

3.3 Nature and Sources of Data

This study relied solely on primary data collected through a survey of individual employees working in manufacturing. A structured questionnaire featuring a five-point Likert scale was used to gather the information. The data support generalization because the study employed a descriptive methodology to explore causal relationships among the variables. To ensure reliability, experts reviewed the questionnaire data. Additionally, some parts of the questionnaire were revised based on expert feedback to enhance the validity of the data, thereby assessing the questionnaire's face validity.

3.4 Data Collection Procedure

Data were collected by distributing electronic questionnaires via email to 400 respondents. After data collection, various analytical tools in the SPSS program were utilized to analyze the information. To achieve the study's objectives, several statistical and mathematical techniques were applied, including regression analysis, correlation analysis, and descriptive statistics.

3.5 Method of Data Analysis

Primary data were collected using questionnaires, which the researcher personally reviewed. Data analysis and presentation are fundamental steps in any research project. To ensure accurate results, the study employed various descriptive and inferential tools to analyze the data. A range of statistical and mathematical methods was applied to achieve the study's objectives.

a. Descriptive Analysis

Descriptive statistics are concise numerical summaries that provide an overview of a data set, whether it represents a whole population or just a sample. They are categorized into measures of central tendency and measures of variability. Measures of central tendency, such as the mean, describe the average value, while measures of variability, like the standard deviation, indicate the spread or dispersion of the data.

Mean

The arithmetic mean is the most frequently used measure for summarizing data of a single variable. It is determined by dividing the sum of all observations by the total number of observations. The mean for various variables represents the average value throughout the study period.

$$\text{Mean } (\bar{X}) = \frac{\Sigma x}{n}$$

Standard Deviation

Variance indicates how much individual data points differ from the central value. Standard deviation measures the absolute amount of dispersion in the data. A higher variance corresponds to a larger standard deviation. Conversely, a small standard deviation suggests that the observations are closely clustered, indicating a high level of consistency within the data set.

$$\text{Standard Deviation (SD)} = \sqrt{\frac{\sum(X - \text{\o(¯,X)})^2}{n}}$$

b. Correlation Analysis

Correlation analysis is a statistical method used to describe how strongly one variable is linearly related to another (Levin & David, 1994). It measures the strength and direction of the linear relationship between two variables. When the variables increase or decrease together, the correlation is positive. Conversely, if one variable increases while the other decreases, the correlation is negative. The correlation coefficient always ranges between

+1 and -1. The coefficient (r) for two variables, x and y, can be calculated using the following formula.

$$\text{Correlation Coefficient (r)} = \frac{n\Sigma xy - \Sigma x\Sigma y}{\sqrt{n\Sigma x^2 - (\Sigma x)^2}\sqrt{n\Sigma y^2 - (\Sigma y)^2}}$$

Where,

r = coefficient of correlation

ΣXY = Sum of product of two series.

ΣX^2 = Sum of squared in X series

ΣY^2 = Sum of squared in Y series

n = number of years

The value of the correlation coefficient cannot exceed +1 or fall below -1, making these the boundaries of the coefficient. A value of +1 indicates a perfect positive correlation between the variables, while -1 signifies a perfect negative correlation. A value of zero means there is no correlation between the variables.

c. Regression Analysis

Regression analysis comprises statistical techniques used to estimate the relationship between a dependent variable and one or more independent variables. It helps evaluate the strength of these relationships and can be used to predict future outcomes based on the model.

Model 1

$FD= \beta_0 + \beta_1 NLP + \beta_2 ML + \beta_3 ES + \beta_3 CV ......+e$

Where,

FD = Financial Decision

NLP = Natural Language Processing

ML = Machine Learnings

ES = Expert Systems

CV = Computer Vision

β_0 = Constant when all independent variables are Zero

$\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \ldots$ = Corresponding coefficients

3.6 Research Framework

Drawing from the literature review and research objectives, this study develops a research framework. The conceptual framework provides a systematic explanation of the relationships between dependent and independent variables. It guides the focus on the research problem and supports the achievement of the study's objectives. Describing the framework serves two purposes: it identifies the key research variables and clarifies how they relate to each other. Connected to the problem statement, the conceptual framework lays the foundation for presenting the specific research questions that drive the study. The research framework for this study is illustrated in the diagram below.

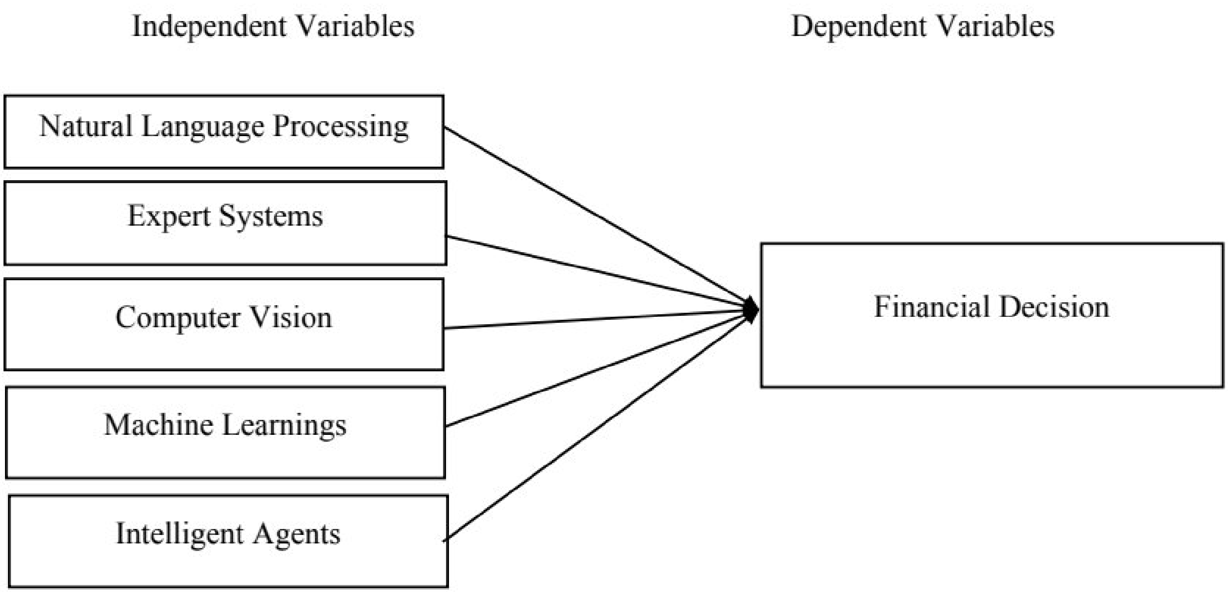

Figure 1

Research Framework

Source: (Akour et al., 2022)

Natural Language Processing

Natural language processing (NLP) is a subfield of computer science and artificial intelligence (AI) that uses machine learning to enable computers to understand and communicate with human language (Ahakhatreh &Al-Hawary, 2022).

Expert Systems

Expert systems, a subset of artificial intelligence, aim to replicate the decision-making skills of human experts. In financial decision-making, they function as computer-based applications that apply predefined rules, facts, and heuristics to offer guidance, forecasts, or solutions for complex financial issues (Agung et al., 2021).

Computer Vision

Computer vision, a branch of artificial intelligence, focuses on enabling machines to "see" and interpret images and videos in a way similar to human vision. It utilizes algorithms that process visual data, detect objects, comprehend scenes, and make informed decisions based on the information perceived. In essence, it is the science of training computers to interpret and understand the visual environment (Akour et al., 2024).

Machine Learnings

Machine Learning (ML) in financial decision-making involves applying data-driven algorithms and statistical techniques that allow computer systems to learn from past financial data and generate predictions or decisions without direct programming. It is used to examine intricate financial patterns, detect potential risks and opportunities, forecast market trends, and automate decision-making processes, thereby improving accuracy, efficiency, and impartiality in areas such as financial planning, investments, credit evaluation, fraud prevention, and portfolio management (Dastile et al., 2020).

Intelligent Agents

Intelligent Agents are self-governing software programs that gather financial data from their surroundings, process and evaluate this information, and then act or provide suggestions to aid or automate financial decision-making. Leveraging Artificial Intelligence (AI) methods—such as machine learning, expert systems, and natural language processing—these agents can analyze market trends, evaluate risks, and enhance strategies for investment or budgeting (Al-Alwan et al., 2022).

Chapter IV

Results and Discussion

4.1 Results

4.1.1 Demographic Characteristics

Demographic variables are measurable traits of a population used to describe a sample or segment a market. These characteristics—such as age, gender, or race—are sometimes called 'boxcar variables' because of their substantial influence. This chapter presents the results of the data analysis conducted during the study. It focuses on examining and interpreting the primary data collected from 400 respondents through questionnaires.

Table 2

Demographics Characteristics of Respondents (N=400)

Respondent Character	Frequency	Percentage
Gender		
Male	136	34
Female	264	66
Total	400	100
Age		
Under 24	8	2
24-36	336	84
37-46	40	10
47-56	12	3
Over 56	4	1
Total	400	100
Present Position		
Manager	12	3
Officer	64	16
Junior Assistant	280	70
Senior Assistant	40	10
Other	4	1
Total	400	100
Qualification		
+2	12	3
Bachelors	96	24

Masters	292	72
Total	400	100
Work Experience		
Less than 5 Years	188	47
5-15 Years	204	51
More than 15 Years	8	2
Total	400	100
Earnings per Month		
Up to 26,000	12	3.0
26,001-60,000	284	71.0
60,001-80,000	104	26.0
Total	400	100.0

Table 2 shows that most respondents in the study were female, totaling 264 individuals or 66% of the sample, while males accounted for 34%, with 136 respondents. The participants were divided into five age groups, with the largest group being those aged 24 to 36, representing 336 respondents or 84% of the total. Respondents younger than 24 and older than 47 made up only 6% of the sample.

Seventy-three percent of the respondents (292 individuals) held higher educational degrees, while 96 respondents, or 24%, had a Bachelor's degree. Only 3% possessed educational qualifications at the +2 level. Among the five job positions, junior assistant was the most common, with 280 respondents representing 70% of the total. Officers and senior assistants accounted for 16% and 10% of the respondents, respectively.

Work experience was divided into three categories, with the majority of respondents (51%) having 5 to 15 years of experience. Only 2% had more than 15 years of experience. Additionally, 71% of respondents reported a monthly income between 26,001 and 60,000, while just 3% earned less than 26,000.

4.1.2 Descriptive Analysis for Variable Wise

The scale ranged from 1 to 5, with each question on the five-point Likert scale spanning from "strongly disagree" to "strongly agree."

Table 3

Descriptive Statistics of Natural Language Processing (N=400)

Code	Statements	Mean	Std. dev.
NLP1	I believe Natural Language Processing enhances the accuracy of financial market predictions.	3.067	1.145
NLP2	I trust AI systems that use NLP to analyze earnings calls and financial reports.	3.157	1.160
NLP3	I feel confident in the ability of AI models using NLP to make high-stakes trading decisions.	2.950	1.114
NLP4	I consider the interpretability of NLP models important in financial decision-making.	3.287	1.172
NLP5	NLP contributes to better risk assessment and mitigation in financial operations.	3.050	1.154
Overall Mean and SD		3.921	1.149

Source: SPSS output

Table 3 displays the descriptive statistics for each item as well as for the budgeting and planning sub-factor overall. The variables were assessed using five statements, with all respondents providing their answers on a five-point Likert scale. The standard deviation for budgeting and planning practices was 1.149, while the mean was 3.921. These results suggest that effective budgeting and planning contribute to better organizational performance.

Table 4

Descriptive Statistics of Machine Learnings (N=400)

Code	Statements	Mean	Std. dev.
ML1	I understand how machine learning differs from traditional programming approaches.	3.122	1.169
ML2	I believe machine learning can significantly impact decision-making in modern industries.	3.145	1.159
ML3	I trust the use of AI in detecting financial fraud or anomalies.	2.980	1.119
ML4	I believe machine learning can help reduce human bias in financial decisions.	3.322	1.169
ML5	I believe financial institutions should disclose when decisions are made using machine learning models.	3.100	1.146
	Overall mean and Std.	3.820	1.152

Source: SPSS output

Table 4 presents the descriptive statistics for each item and the costing systems sub-factor as a whole. The variables were assessed using five statements, with all respondents answering on a five-point Likert scale. The standard deviation for costing practices was

1.152, and the overall mean was 3.82, exceeding 3. This indicates that effective costing systems can lead to improved organizational performance.

Table 5

Descriptive Statistics of Expert Systems (N=400)

Code	Statements	Mean	Std. dev.
ES1	The use of expert systems reduces the risk of human error in financial analysis.	3.457	1.047
ES2	Expert systems improve consistency in financial decision-making processes.	3.035	1.037
ES3	AI-based expert systems can predict financial market trends with reasonable accuracy.	3.337	1.150
ES4	Expert systems provide useful support for regulatory compliance in financial services.	3.305	1.179
ES5	Expert systems can adapt to new financial regulations and market changes efficiently.	3.360	1.113
	Over all mean and std.	3.86	1.105

Source: SPSS output.

Table 5 shows the descriptive statistics for each item and for the controlling and reporting sub-factor overall. The variables were measured using five statements, with all respondents providing answers on a five-point Likert scale. The mean for controlling and reporting practices was 3.86, above 3, with a standard deviation of 1.105. This suggests that effective controlling and reporting methods can enhance organizational performance.

Table 6

Descriptive Statistics of Computer Vision (N=400)

Code	Statements	Mean	Std. dev.
CV1	I understand the role of artificial intelligence in analyzing visual data.	3.152	1.178
CV2	I believe computer vision can be effectively integrated with financial analytics.	3.372	1.165
CV3	I am familiar with the basic concepts of computer vision and how it works.	2.920	1.123
CV4	The use of computer vision in finance raises significant privacy concerns.	3.465	1.186
CV5	I trust financial decisions made by AI systems that incorporate visual data.	3.165	1.198
	Over all mean and std. deviation	3.57	1.170

Source: SPSS output

Table 6 presents the descriptive statistics for each item and for the performance evaluation sub-factor as a whole. The variables were measured using five statements, with respondents expressing their views on a five-point Likert scale. The overall mean for performance evaluation techniques was 3.57, higher than 3, with a standard deviation of 1.170. This indicates that effective performance evaluation methods can contribute to improved organizational performance.

Table 7

Descriptive Statistics of Intelligent Agents (N=400)

Code	Statements	Mean	Std. dev.
IA1	I trust intelligent agents to provide accurate financial recommendations.	3.012	1.102
IA2	The integration of AI in financial systems has increased decision-making transparency.	2.922	1.147
IA3	AI-powered agents contribute to better portfolio management..	2.895	1.132
IA4	I rely on intelligent agents for real-time financial updates and advice.	3.160	1.112
IA5	I am concerned about the ethical implications of using intelligent agents in finance.	3.200	1.263
	Over all mean and standard deviation	3.04	1.151

Source: SPSS output

Table 7 presents the descriptive statistics for each item and the decision-making sub-factor overall. The variables were assessed using five statements, with respondents providing answers on a five-point Likert scale. The overall mean for decision-making practices was 4.29, well above 3, with a standard deviation of 1.151. This highlights that effective decision-making can lead to improved business performance.

Table 8

Descriptive Statistics of Financial Decision

Code	Statements	Mean	Std. dev.
FD1	I regularly create and follow a budget to manage my financial resources.	3.300	1.115
FD2	I consider both short-term and long-term consequences before making financial commitments.	3.465	1.075
FD3	I use digital tools or platforms to support my financial decision-making.	3.357	1.097
FD4	I rely on professional advice when making major financial decisions.	3.305	1.061
FD5	I have changed my financial strategies based on insights from AI-driven platforms.	3.422	1.117
	Overall mean and standard deviation.	3.369	1.093

Source: SPSS output

Table 8 displays the descriptive statistics for each item and the organizational performance sub-factor as a whole. The variables were measured using five statements, with all respondents answering on a five-point Likert scale. The standard deviation for organizational performance was 1.093, and the overall mean was 4.204, exceeding 3. This indicates a high level of organizational efficiency.

Table 9

Descriptive Statistics of Composite Dependent and Independent Variables

Variables	N	Min	Max	Mean	SD
Independent Variables:					
Natural Language Processing	400	1.00	5.00	3.103	1.149
Machine Learnings	400	1.00	5.00	3.134	1.152
Expert Systems	400	1.00	5.00	3.299	1.105
Computer Vision	400	1.00	5.00	3.215	1.170
Intelligent Agents	400	1.00	5.00	3.038	1.151
Dependent Variables:					
Financial Decision	400	1.00	5.00	3.370	1.093

Source: SPSS Output

Table 9 presents the descriptive statistics for the study's dependent and independent variables. Natural Language Processing (NLP) has a mean of 3.103 and a standard deviation of 1.149, indicating a moderate level of perception or use with some variation among respondents. Machine Learning (ML) shows a similar pattern, with a mean of 3.134 and a standard deviation of 1.152. Expert Systems have the highest mean among the independent variables at 3.299, with a standard deviation of 1.105, suggesting stronger agreement or usage. Computer Vision has a mean of 3.215 and a standard deviation of 1.170, slightly higher than NLP and ML, reflecting moderate familiarity or application. Intelligent Agents have the lowest mean at 3.038 and a standard deviation of 1.151, indicating comparatively less engagement or perception.

Among the AI technologies, expert systems and computer vision are perceived somewhat more positively, whereas intelligent agents receive slightly less favorable views. Financial decision-making scores the highest, suggesting that respondents generally recognize a moderate to positive impact of AI technologies on financial decision processes.

4.1.3 Correlation Analysis

Yadav and Acharya (2013) explain that correlation is a statistical measure used to assess the strength of the relationship between two or more variables. If only two variables are involved, there should be a direct relationship between them. When multiple variables are considered, there can be various connections among them in the interaction.

Table 10

Correlation Analysis

Variables	NLP	ML	ES	CV	IA	FD
Natural Language Processing	1					
Machine Learnings	.353**	1				
Expert Systems	.017	.016	1			
Computer Vision	-.037	-.009	-.022	1		
Intelligent Agents	.093*	.097*	.138**	.107*	1	
Financial Decision	-.110*	.008	-.030	.004	-.025	1

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

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

Machine Learning (ML) exhibits a strong positive correlation with Natural Language Processing (NLP) ($r = .353$, $p < 0.01$), indicating that these two technologies frequently occur together or have a significant mutual influence. Intelligent Agents (IA) show small but statistically significant positive correlations with NLP ($r = .093$, $p < 0.05$), ML ($r = .097$, $p < 0.05$), Expert Systems (ES) ($r = .138$, $p < 0.01$), and Computer Vision (CV) ($r = .107$, $p < 0.05$), reflecting moderate interconnectedness among these AI technologies.

Financial Decision (FD) has a slight negative correlation with NLP ($r = -0.110$, $p < 0.05$), indicating a minor inverse relationship. Its correlations with other variables are weak and statistically insignificant. Similarly, Expert Systems (ES) and Computer Vision (CV) exhibit very weak or negligible correlations with the other variables, none reaching significance, suggesting limited direct connections. Overall, the data indicates that ML and NLP are closely linked, with Intelligent Agents (IA) acting as a connecting element among several technologies. In contrast, FD appears relatively isolated in terms of its relationships with the other variables.

4.1.4 Regression Analysis

Regression analysis is a statistical method used to determine the relationship between two or more quantitative variables. The independent (or explanatory) variable is the one we know or control, while the dependent variable is the one we aim to predict. This technique helps to develop an equation that describes the relationship between these variables. In multiple regression, an equation is generated to predict the dependent variable based on two or more independent variables.

Table 11

Model Summary

Model	R	R square	Adjusted R square	Std. error of the estimated
1	.376a	.141	.131	.40306

a. Predictors: (Constant), NLP, ML, ES, CV, IA

Table 12

ANOVA Table

	Model	Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	10.548	5	2.110	12.986	.000b
	Residual	64.009	394	.162		
	Total	74.558	399			

a. Dependent Variable: FD

Predictors: (Constant), NLP, ML, ES, CV, IA

Source: SPSS output

Table 13

Regression Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	Test (T)	P-Value
	B	Std. err.	Beta		
Constant	2.269	.345		6.578	.000
Natural Language Processing	.374	.051	.347	7.399	.000
Machine Learnings	-.002	.055	-.001	-.030	.976
Expert Systems	-.048	.057	-.040	-.841	.401
Computer Vision	.054	.043	.060	1.267	.206
Intelligent Agents	-.102	.043	-.110	-2.354	.019

Dependent variable: Financial Decision

From the above results, the assessed condition can be composed by taking the qualities from the model-1

$Y= a+ \beta_1X_1+ \beta_2x_2+ \beta_3X_3+ \beta_4X_4+ \beta_5X_5$

Therefore, $Y= 2.269 + 0.374X_1 - 0.002X_2 - 0.048X_3 + 0.054\ X_4 - 0.102X_5$

The regression analysis shows that Natural Language Processing (NLP) has a statistically significant positive impact on the dependent variable, with an unstandardized coefficient of 0.374 and a standardized beta of 0.347 ($p < .001$). This suggests that increases in NLP correspond to meaningful increases in the outcome. Conversely, Machine Learning, Expert Systems, and Computer Vision do not have a significant effect, as their p-values are high (.976, .401, and .206, respectively). Interestingly, Intelligent Agents exhibit a statistically significant negative relationship with the dependent variable ($\beta = -0.110$, $p = .019$), indicating that greater use or presence of Intelligent Agents is associated with a slight decrease in the outcome. The constant term is also significant ($p < .001$), representing the baseline level of the outcome when all predictors are zero.

4.2 Discussion

This study aims to investigate the impact of natural language processing, machine learning, expert systems, and computer vision on the financial decision-making of manufacturing companies in Nepal. The research utilized statistical measures including mean, maximum, minimum, and standard deviation. The "mean" represents the average value of each variable; for instance, the mean NLP indicates the average level of natural language processing used among the manufacturing companies examined.

The analysis offers an understanding of the connections between different artificial intelligence technologies and financial decision-making. Descriptive statistics reveal that all independent variables—Natural Language Processing (NLP), Machine Learning (ML), Expert Systems (ES), Computer Vision (CV), and Intelligent Agents (IA)—were assessed using a uniform scale, with their average scores indicating a moderate level of perceived use or impact among respondents. The standard deviations reflect a considerable variation in responses, showing differences in how individuals perceive or experience each technology.

The correlation analysis reveals a positive and statistically significant relationship between Natural Language Processing and Machine Learning, indicating that these technologies are commonly seen as complementary in their use. Intelligent Agents show positive correlations with all other AI technologies at varying levels, with most of these correlations being statistically significant, suggesting their wide-ranging integrative role within AI systems. Notably, only NLP has a significant negative correlation with Financial Decision, whereas the other technologies show weak or insignificant connections.

The regression analysis provides a clearer understanding by pinpointing the predictive influence of these technologies on financial decision-making. Natural Language Processing emerges as having a strong and statistically significant positive effect, indicating it plays a key role in enhancing financial decisions. This implies that NLP capabilities—such as sentiment analysis, language modeling, or chatbot support—can improve clarity and efficiency within financial settings. On the other hand, Machine Learning, Expert Systems, and Computer Vision do not exhibit significant effects, suggesting their impact on financial decision-making may be indirect or dependent on specific contexts.

Conversely, Intelligent Agents show a statistically significant negative impact on financial decisions. This could suggest that despite their integration with various AI technologies, the autonomous nature or decision-making processes of Intelligent Agents might introduce complexity or diminish user control, potentially causing hesitation or lower confidence in financial decision-making.

In summary, the findings highlight that AI technologies do not have uniform effects on financial decision-making. Natural Language Processing shows clear benefits, whereas the impact of Intelligent Agents is more nuanced and may even be detrimental in some financial contexts, suggesting that their adoption should be approached with careful consideration.

Chapter V
Summary and Conclusion

5.1 Summary

The study titled "The Role of Artificial Intelligence and Machine Learning in Financial Decision Making" utilizes both descriptive and causal research designs to investigate the impact of AI and ML technologies on financial decisions within manufacturing companies in Nepal. The research considers natural language processing, machine learning, expert systems, and computer vision as independent variables, with financial decision-making as the dependent variable. The analysis employs a limited set of statistical methods, including descriptive statistics, correlation, and regression analysis. The study focuses on three major companies—Dabur Nepal, Bottlers Nepal, and Unilever Nepal—together employing 1,800 workers. Using convenience sampling and proportional representation, a sample of 400 employees was selected: 200 from Dabur Nepal, 145 from Bottlers Nepal, and 55 from Unilever Nepal.

The researcher personally reviewed all responses to ensure their accuracy and completeness. Primary data was collected through a self-administered questionnaire, adapted from Khan (2023) and Yogi (2020) to measure both independent and dependent variables. The survey was completed by 400 respondents with diverse ages, marital statuses, and educational backgrounds. Questionnaires were distributed and collected during onsite field visits. The gathered data from the surveys and interviews were compiled and analyzed using SPSS software, employing various statistical techniques to interpret the results. This study offers valuable insights into how AI and ML are practically applied in financial decision-making within Nepal's manufacturing industry.

5.2 Conclusion

The analysis results reveal that different AI components have varying effects on financial decision-making. Notably, Natural Language Processing (NLP) demonstrates a strong and statistically significant positive correlation with financial decisions, suggesting that NLP applications enhance decision quality by improving the processing and understanding of financial information.

Conversely, Intelligent Agents show a statistically significant negative relationship with financial decision-making. This suggests that although Intelligent Agents can automate or support decision processes, their impact may sometimes hinder optimal financial outcomes, possibly due to excessive dependence on automation or insufficient consideration of contextual factors.

In this study, Machine Learning, Expert Systems, and Computer Vision do not demonstrate a statistically significant impact on financial decision-making. While these technologies may be interconnected, their individual influence on financial decisions seems limited or dependent on specific contexts. The lack of significant relationships implies that, on their own, these AI technologies may not be reliable predictors of the quality of financial decisions, or their effects might be influenced by other variables not included in this model.

In summary, the findings highlight that AI technologies play diverse roles in financial decision-making, with their effectiveness largely influenced by the particular application and context. Natural Language Processing (NLP) stands out as a notably beneficial tool, while Intelligent Agents, though increasingly utilized, call for cautious implementation to maximize their positive contribution to financial outcomes.

5.3 Implications

i. Managers should deliberately implement AI and ML technologies to boost decision-making accuracy, refine customer profiling, automate financial forecasting, and enhance resource allocation efficiency within their organizations.
ii. Management should invest in upskilling current employees and hiring AI/ML specialists to ensure the workforce can accurately interpret model results and integrate AI-driven insights with the organization's objectives.
iii. As dependence on AI increases, managers must guarantee transparency in the model's workings and keep human oversight in place. AI should serve as a decision support tool, complementing rather than replacing human judgment.
iv. AI and ML provide deeper insights into customer behavior. Managers should leverage these technologies to offer personalized financial products, improve customer service, and foster long-term client relationships.

v. Managers can utilize AI and ML for real-time risk assessment, credit scoring, fraud detection, and stress testing, enabling more proactive and data-driven risk management strategies.

vi. Integrating AI requires a cultural shift within organizations. Leaders should promote a data-driven mindset, encourage innovation, and proactively address employee resistance to technological change to ensure smooth adoption.

vii. Policymakers must establish clear ethical standards and regulatory frameworks for AI and ML use in financial systems. This should cover algorithmic transparency, data privacy, accountability, and measures to prevent bias in automated decision-making.

viii. Governments and regulatory bodies should encourage the adoption of AI/ML to promote financial inclusion, particularly for underserved populations. Policy incentives can support fintech innovations that reduce barriers to credit and banking access, fostering broader economic participation.

ix. Regulators themselves should integrate AI and ML tools into their supervisory processes. The use of Supervisory Technology (SupTech) can enhance real-time risk monitoring, fraud detection, and predictive supervision, thereby strengthening oversight and stability within the financial sector.

x. Given the data-intensive nature of AI and ML, strong data protection laws are essential. Policies should enforce robust cybersecurity protocols to safeguard sensitive financial and personal information, ensuring trust and compliance in AI-driven financial systems.

xi. Governments should support educational programs, research initiatives, and digital infrastructure development to strengthen national capabilities in AI and ML, thereby promoting innovation and effective application of these technologies in financial services.

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Annex: Questionnaires

Dear respondent,

I am conducting this questionnaire survey for an academic research as required by the MBS program. The title of my research is "The Role of Artificial Intelligence and Machine Learning in Financial Decision Making" I would like to state that this research is purely for an academic purpose and I am simply interested in your candid and honest opinion. I assure you that strict confidentiality will be maintained and the information furnished by you will be used only for the academic purpose.

Thanking for your Cooperation

Prakash Bhattarai

MBS student

Shanker Dev Campus, Kathmandu

Part I

Bank	
Department	
Gender	a) Male b)Female
Age	a)Under 25 b)25-35 c)36-45 d)46-55 e)Above 55
Qualification(Highest Degree)	a)+2 b) Bachelors c) Masters
Present Position: (Please tick)	a)Manager b)Officer c)Sr. Assistant d) Jr. Assistant e)Other if any (please specify)
Years of Experience	a) Less than 5 b) 5-15 c) More than 15
Year of joining the present organization(AD)	
Earning per month	a)up to 25000 b)25001-50000 c)50001-75000 d)above 75000

Part II

Below are several statements about you with which you may agree or disagree. Using the response scale below, indicate your agreement or disagreement with each item by choosing the appropriate number. Please give your responses as followings:

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

Natural Language Processing

Code	Particular	1	2	3	4	5
NLP1	I believe Natural Language Processing enhances the accuracy of financial market predictions.					
NLP2	I trust AI systems that use NLP to analyze earnings calls and financial reports.					
NLP3	I feel confident in the ability of AI models using NLP to make high-stakes trading decisions.					
NLP4	I consider the interpretability of NLP models important in financial decision-making.					
NLP5	NLP contributes to better risk assessment and mitigation in financial operations.					

Machine Learnings

Code	Particular	1	2	3	4	5
ML1	I understand how machine learning differs from traditional programming approaches.					
ML2	I believe machine learning can significantly impact decision-making in modern industries.					
ML3	I trust the use of AI in detecting financial fraud or anomalies.					
ML4	I believe machine learning can help reduce human bias in financial decisions.					
ML5	I believe financial institutions should disclose when decisions are made using machine learning models.					

Expert Systems

Code	Particular	1	2	3	4	5
ES1	The use of expert systems reduces the risk of human error in financial analysis.					
ES2	Expert systems improve consistency in financial decision-making processes.					
ES3	AI-based expert systems can predict financial market trends with reasonable accuracy.					
ES4	Expert systems provide useful support for regulatory compliance in financial services.					
ES5	Expert systems can adapt to new financial regulations and market changes efficiently.					

Computer Vision

Code	Particular	1	2	3	4	5
CV1	I understand the role of artificial intelligence in analyzing visual data.					
CV2	I believe computer vision can be effectively integrated with financial analytics.					
CV3	I am familiar with the basic concepts of computer vision and how it works.					
CV4	The use of computer vision in finance raises significant privacy concerns.					
CV5	I trust financial decisions made by AI systems that incorporate visual data.					

Intelligent Agents

Code	Particular	1	2	3	4	5
IA1	I trust intelligent agents to provide accurate financial recommendations.					
IA2	The integration of AI in financial systems has increased decision-making transparency.					
IA3	AI-powered agents contribute to better portfolio management..					
IA4	I rely on intelligent agents for real-time financial updates and advice.					
IA5	I am concerned about the ethical implications of using intelligent agents in finance.					

Financial Decision

Code	Particular	1	2	3	4	5
FD1	I regularly create and follow a budget to manage my financial resources.					
FD2	I consider both short-term and long-term consequences before making financial commitments.					
FD3	I use digital tools or platforms to support my financial decision-making.					
FD4	I rely on professional advice when making major financial decisions.					
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THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIA L DECISION MAKING

AUTHOR

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Abstract

This research explores how Artificial Intelligence (AI) and Machine Learning (ML) technologies contribute to improving financial decision-making, emphasizing five main components: Natural Language Processing (NLP), Machine Learning algorithms, Expert Systems (ES), Computer Vision (CV), and Intelligent Agents (IA). Through correlation and regression analyses, the results indicate that NLP has a strong, statistically significant positive effect on financial decisions, underscoring its vital role in processing and interpreting unstructured financial data. In contrast, ML, ES, and CV show no significant direct influence, suggesting their impact may be indirect or dependent on specific contexts. Notably, IA demonstrates a significant but negative relationship with financial decisions, pointing to potential difficulties in aligning autonomous decision-making with optimal financial outcomes. Correlation findings further confirm NLP's leading influence, while IA's weaker associations signal challenges in implementation and integration. Overall, the study concludes that NLP stands out as the most influential AI approach in enhancing financial decision-making, highlighting the importance for organizations to invest in advanced text analytics and sentiment analysis, while carefully deploying autonomous agents to prevent decision misalignment.

Keywords: Financial Decision, Natural Language Processing, Machine Learning algorithms, Expert Systems, Computer Vision, Intelligent Agents

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