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THE USE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL SECTOR. A DECISION-MAKING FRAMEWORK.

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Abstract:

This study provides an overall review on current state of Artificial Intelligence (AI) and Machine Learning (ML) adoption in financial sector as well as explores a framework for identification of potential tasks for automation using AI and ML. The study utilizes a qualitative research methodology grounded in Dynamic Capabilities Theory. The research examines existing processes automated in financial institutions. The overall approach comprised review of existing literature, obtaining primary data through semi-structured interviews and performing thematic analysis. Analysis of data identified that AI & ML models are used for predictive analytics, fraud detection, credit risk assessment, investment portfolio, auditing, compliance monitoring, and customer services across the financial sector. Common criteria for selecting tasks were identified during primary data collection are also explored in this study. The study also discusses concerns shared by participants while they are selecting processes for automation. The research work also assisted in development of a framework to support the process for tasks automation for AI/ML.

Keyword:

Artificial Intelligence, Financial Management, Machine Learning, Selection Framework, Task Automation

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Introduction

Selection of tasks for automation is a big challenge for most managers in financial firms, considering the nature of data held in these organizations (Muller, 2016; Ravi & Kamaruddin, 2017). However, the development in technologies like Artificial Intelligence (AI) and Machine Learning (ML) is a timely solution for players in this industry (Polireddi, 2024). AI has been described as non-human intelligent systems that imitate cognitive roles of human beings to perform tasks through flexible adaptation like learning from external data and problem solving (Dwivedi et al., 2019). According to Grace et al. (2018), AI can overcome creative limitations of humans to perform computationally intensive tasks. Predictions from expert opinions in a survey conducted by (Müller, 2016) indicate that, by 2075, AI systems may match overall human ability. However, economic and ethical factors are likely to hinder this realization as society overall is yet to fully welcome these considerations. On the other hand, ML is a subfield of AI that offers various capabilities for defining and developing analytical models for subsequent data analysis and prediction (Singh et al., 2023). Most importantly, some of these models can be trained based on historical data (supervised technique), while others can work without being made to know the presumed response, commonly referred to as "unsupervised" learning (Singh et al., 2023). Thus, robustness of ML models depends on the quantity of data they are exposed to.

Advancements in AI and ML models have significantly reshaped financial management in the banking sector. The roles of AI and ML have evolved from simple tasks like risk management and trading processes to complex ones such as fraud detection, personalization of services, and price forecasting (Yogesh et al., 2021). These innovative decision-making procedures are associated with increased financial benefits in near future.

Researchers have discussed various merits of AI and ML in the financial sector, including speed, reliability, and efficiency (Wang et al., 2021). However, they have not dwelt on the category of tasks suitable for analysis using these technologies and how financial managers can identify them. Firms have numerous tasks for automation using advanced technologies, but selecting the most suitable ones remains a challenge (Müller, 2016). Considering the new trends and innovations, sophisticated infrastructures in the banking industry have exposed inadequate integration measures for AI and ML required to enhance operational efficiency in this sector (Bitetto et al., 2023). Moreover, as few studies have focused on this critical concern, the present research aims to fill the gap by identifying an integration framework for selecting tasks to be completed using a combination of the latest AI-ML technologies to enhance efficiency, ethical and regulatory adherence by players in financial marketplaces. The main objective of this research is to identify critical tasks requiring constant analysis in financial firms and how application of AI and ML aid this process.

Literature Review

Data availability and structure determine selection decisions on tasks to be considered for analysis using AI and ML models. For example, Sarker (2021) showed that the algorithms

designed in these models work better on massive datasets. These suit tasks like market data or transaction histories that rely on or generate large volumes of data. Also, Pattnaik et al. (2024) examined how some firms hold more data in structured formats, requiring financial managers to rely on AI/ML-based processing techniques. On the other hand, Olaolu et al. (2021) stressed that managers who wish to process unstructured data like bank reports usually apply advanced Natural Language Processing algorithms. Moreover, Gao et al. (2021) noted that effective use of AI/ML models require clean and consistent data sources for reliable processing.

Task complexity is a compelling factor for managers in financial institutions to consider application of ML models for data analysis (Xu et al., 2020). Tasks consisting of financial data with complex patterns are the most qualified for analysis using AI/ML models. They include tasks that are beyond human cognitive capacity, such as market trends and fraud detection. Secondly, AI/ML solutions have been tested for managing financial tasks that require extensive forecasting. The prime candidates include asset pricing and credit risk modelling. Additionally, Amato et al.(2024) illustrated that high-dimensional tasks like derivative pricing and portfolio optimization are characterized by multiple factors and variables perfectly leverage AI models to analyse interdependencies and draw conclusions.

Firms in the financial industry interact with repetitive and time-consuming tasks on a daily basis (Olaolu et al., 2021). Financial managers focusing on automation of repetitive and time-consuming tasks opt for AI and ML-assisted processing techniques, especially when dealing with financial reconciliations (Olaolu et al., 2021). The main advantage is that this AI-driven automation occurs in real-time, critical for faster decision-making when dealing with time-sensitive tasks like cash-flow monitoring. This strategy can partly solve human resource issues in a company. Moreover, error-prone activities including tasks with significant financial implications like auditing and compliance monitoring can benefit from AI/ML models' abilities to enhance accuracy by minimizing human error (Xu et al., 2020).

In dynamic environments like volatile markets with rapidly changing market conditions, data processing techniques based on AI and ML models can achieve desired results faster than traditional algorithms, providing flexible hedging or rebalancing strategies (Gao et al., 2021). Moreover, financial firms are currently faced with evolving customer behaviours and changing regulatory frameworks, requiring them to leverage machine learning capabilities powered by AI (Heo et al., 2020). These are tasks that need continuous learning and adaptation to fit the ever-evolving data.

The increasing need for customization and personalization of tasks in the financial industry is a prerequisite for adoption of AI/ML models in data processing (Simhadri & Polireddi, 2024). It enables finance managers to analyse user behaviour and preferences and create customer-specific financial recommendations or personalized investment portfolios. The latest area of application is chatbot-advisors that are extensively used in banks for customer service enhancement (Priya & Sharma, 2023). These virtual assistants and chatbots powered by AI can reliably handle real-time queries raised by customers, which is useful in reducing costs while improving service quality.

Regarding compliance and regulatory tasks, Abhishek et al. (2021) asserted that the use of powerful computers and advanced algorithms like high-frequency trading is useful in financial management as it ensures execution of a large number of orders within microseconds. On the same note, Aldoseri et al. (2023) showed that firms can analyse and predict market movements

with high accuracy and more precisely using large datasets like news sentiment analysis or price history.

In a related study, Abbas (2024) illustrated that this extremely high speed is made possible by algorithmic formulae that depend on complicated technological infrastructure resulting in tiny price movement capitalization across different markets. Thus, as Wang et al. (2021) concluded, banks prominently apply AI and ML with this strategy to transform their daily operations in financial markets. The implication is that the main components of high-frequency trading include algorithmic trading, latency arbitrage, and market-making strategies. In particular, AI and ML algorithms enhance algorithmic trading by analysing market data for patterns or arbitrage opportunities in real-time, signalling price movements that are likely to occur in future (Bai et al., 2024). Another explanation provided by Sen et al. (2021) is that they execute voluminous trades at high speeds, minimizing latency. However, Heo et al. (2020) noted that firms need to invest in cutting-edge infrastructure to gain latency advantage over rivals by using high-speed technologies like proximity exchange servers and fibre optic cables. The implication is that only firms with significant technological advantages over competitors can enjoy this technology, causing unfair advantages like uneven playing field (Murugan & T, 2023).

A notable concern raised by Rowena (2020), which is associated with this high-frequency trading is market instability resulting from flash crashes triggered by ML algorithms. The study concluded that rapid, automated trades can lead to sudden and large drop in prices. Furthermore, Perifanis and Kitsios (2023) noted that the complexity of high-frequency trading raises regulatory concerns as authorities and regulators attempt to ensure transparency and fairness in the market. For instance, detecting manipulative practices requires sophisticated oversight to deal with layering or quote stuffing (George, 2023). In layering, firms can employ these algorithms to create a false impression of market activity, while in quota stuffing, AI and ML can be abused to place and quickly cancel orders to create confusion. Oztas et al. (2024) suggested that AI and ML models can aid regulatory reporting through automated data collection and analysis of anti-money laundering checks, ensuring adherence to changing regulatory standards. Similarly, Miracle et al. (2024) noted that banks are enhancing risk-handling strategies by detecting anomalies in internal and external transaction patterns.

Decision support and optimization are fundamental tasks that managers perform through financial planning and analysis and operational efficiency (Oliveira et al., 2022). Similarly, Sarker (2021) found that firms rely on AI and ML to perform tasks like forecasting, budgeting, and scenario analysis, where simulations are used to illustrate multiple financial scenarios for effective decision-making in crucial areas like vendor payments, procurement, or treasury management.

This study seeks to identify application of new developments, innovations and trends in AI and ML models in the financial sector. The study uses Dynamic Capabilities Theory for exploring possibilities of business process automation. The theory describes entity's ability to sense, seize, and transform its resources and capabilities to adapt to rapidly changing environments. Similarly, business process automation through AI/ML enables businesses to survive and thrive in today's dynamic environment (Gallego-Gomez & Carmen, 2020). The concept of transformation through utilization of entity's resources is explained through AI/ML ability to perform complex transactions based on the data used for training AI/ML models as in Figure 1.

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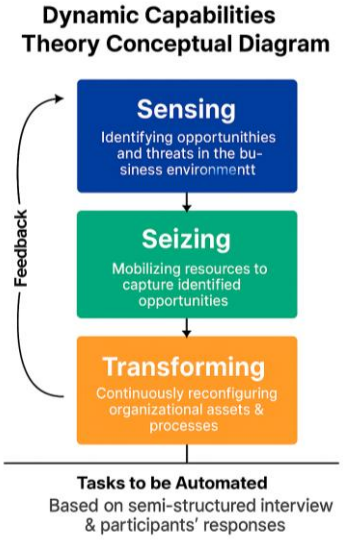

Figure 1: Conceptual Framework

Source: Gallego-Gomez & Carmen (2020)

Research Methodology

The study is a qualitative research design meant to comprehensively assist stakeholders in financial industry when selecting tasks that qualify for AI/ML analysis. The main aim of this study is to provide a framework that aids in analysing potential tasks for automation using AI and ML. This design captures the perceived ways of applying AI/ML for task automation in the financial industry from the perspective of key stakeholders like financial professionals and other end users (customers). The main target was to get insights from respondents in relation to trends and innovations of AI and ML in financial firms. Online semi-structured interviews via Zoom technology (each lasting 45 minutes) were performed with 10 experts and 2 customers from various financial fields, including bank employees, consultants, crypto agents, tech vendors, and compliance officers (Table 1). They willingly agreed to participate, and anonymity was ensured throughout the data collection process. The data in the transcripts were coded and following the recommendations by Dawadi (2020), and later extracted to create patterns and themes through thematic analysis process that aided in interpreting the study's findings.

Table 1: Characteristics Of Participants

Participant	Role	Participant	Role
P1	Finance Manager	P7	Customer
P2	Auditor	P8	Legal and Compliance Officer
P3	Financial Advisor	P9	Auditor in Chief
P4	Chief Consultant	P10	Tech Vendor
P5	Money Markets Analyst	P11	Loans Manager
P6	Customer	P12	Credit Risk Manager

Source: Author's Compilation

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Findings and Analysis

As illustrated in Table 2, qualitative analysis of participants' responses revealed useful themes and sub-themes related to factors leading criteria selection and decision-making on tasks requiring critical analysis in financial firms. The main themes include Reporting and auditing, Analysing financial ratios, Credit risk management, Stock market forecasting, Intelligent investment, Risk management, Smart marketing, Laws and regulations, and Security risks.

Table 2: Themes And Sub-Themes

Theme	Sub-themes	AI/ML Models	Sample Response
Reports and Auditing	False financial reports Financial fraud Formulating audit strategies	Artificial Neural Networks (ANN)	"We use neural networks to analyze financial data to identify fraud." (P2)
Analysing financial ratios	Liquidity, profitability, solvency, turnover	Deep learning	"We apply AI models to know the profitability and stability of our business." (P1)
Credit risk management	Credit evaluation, Unified risk modelling, user prejudgment, non-performing loans	Artificial Neural Networks (ANN), Natural Language Processing	"We do credit rating using machine learning models." (P12)
Customer background check	Loan status, loan qualifications, income level, assets, access whitelists, adjusted pre-credit lines	Chatbots, robotic process automation	"To verify a customer's qualification for loans, we check for income and credit status of customers." (P11)
Stock Market Forecasting	Stock simulation, stock reviews, investment suggestions, decision-making assistance, analysis of public opinion	ANN.	"I do reviews of stock performance using AI models." (P4)
Intelligent Investment	Asset management, asset portfolio improvement, investment income requirements, risk preference, product resources, accumulated customer network	Generative AI	"Our clients look for generative AI for portfolio management." (P10)
Risk Management	Anti-fraud, anti-money laundering, screening suspicions transactions, monitoring financial performance	Anomaly detection	"Detecting anomalies in financial statements is required to avoid fraud and suspicious deals." (P9)
Smart Marketing	Predicting customer needs, consumption preferences, customer positioning,	ANN, chatbots	"My bank uses the latest technology to tailor products for me in real-time." (P7)

Theme	Sub-themes	AI/ML Models	Sample Response
	customer portraits, personalized products		
Laws and Regulations	Hard and soft regulations, complex global regulations, standardized laws and regulations, decentralized laws, Refine supporting policies, regulatory vacuum, legal gap	Intelligent agents	"We look forward to incorporating intelligent agents to refine gaps in our regulations to enhance reporting and auditing processes" (P8)
Information Collection and Usage	Collection of large number of customer data, social problems, responsive design and development of codes, relevant collection criteria, data acquisition and legitimacy problem, data leakage, information control and disclosure, data integration and transmission	Intelligent agents, deep learning	"They collect data faster using intelligent means to prevent leakage" (P6)
Security Risks	Technical security, defects in the algorithms, loopholes in design of codes, controllability risk	Anomaly detection	"We advise banks to adopt AI to enhance security if their systems" (P3)

Source: Author's Compilation

Mapping of themes with participants in Table 3 which shows emphasis of AI application by each participant. This mapping also identifies the perceptions of AI influenced by the area of participant's expertise and experience.

Table 3: Mapping Of Themes with AI Application by Participants

Participant	Role	Themes Referenced
P1	Finance Manager	Reports & Auditing
P2	Auditor	Reports & Auditing
P3	Financial Advisor	Security Risks
P4	Chief Consultant	Stock Market Forecasting
P5	Money Markets Analyst	Market Trend forecasting
P6	Customer	Information Collection & Usage
P7	Customer	Smart Marketing
P8	Legal & Compliance Officer	Laws & Regulations
P9	Auditor in Chief	Risk Management
P10	Tech Vendor	Intelligent Investment
P11	Loans Manager	Customer Background Check

Participant	Role	Themes Referenced
P12	Credit Risk Manager	Credit Risk Management

Source: Author's Compilation

Following coding scheme was generated during the analysis of the primary data.

Financial Integrity
- AI-Enabled Fraud Detection
- Audit Enhancement through automated analysis

Credit and Customer Assessment
- Automated Credit Risk Management and Decision-making
- AI driven Customer Background Verification (KYC) and onboarding

Investment and Market Intelligence
- Stock Forecasting based on AI models
- Intelligent Investment Advisory

Operational Risk and Security Management
- AI based Operational and Financial Risk Detection
- Auto response Cybersecurity and System integrity checks

Customer Engagement and Data Governance
- Personalized Marketing through customer behavior analysis and anticipated response
- Information Collection and Data Control systems

AI-Supported Legal and Regulatory Intelligence
- Compliance Automation through real-time regulatory compliance

Regarding prediction of fraud and false financial reports, financial markets mostly apply AI and ML models to identify genuine listed firms, analyse financial reports, fraud, distress, credit risks, and stock market.

For instance, the Auditor-in-Chief asserted that: "Investors need clear information about good genuine and fake listed companies." This information might not be covered by human resources of these firms, and the only way to get authentic data is through thick financial reports analysed by AI & ML models. Therefore, using the analyses, investors can fight these risks by evaluating false reports and avoiding traps in the deep market. Secondly, AI tools and algorithms aid in detecting fraudulent transactions (manipulated financial statements) and anti-financial fraud incidences."

Findings also indicate that analysis review of transaction reports is a process that requires ML models like artificial neural networks (ANN) when auditing financial statements. The auditor said, "This is useful in detecting false financial indicators in published financial statements." Thus, in the financial field, AI/ML models assist financial managers in various ways, including investment advisory, marketing activities, and risk management".

Financial risks associated with AI and ML include regulatory risks, security risks, and user information leakage. According to the Credit Risk Manager, "Dealing with risks associated with application of AI/ML in the financial sector include standardized legal systems, and stronger data management procedures."

Customers are fascinated by the use of AI models in assessing loan qualification. One of the participants, a bank customer, asserted, "Fairer and transparent credit intermediary procedures

seek to offer equitable access to credit by eliminating biases in credit approval processes." A larger portion of participants agreed that credit assessment models utilize voluminous and unstructured data to analyse risks to achieve the impact of prejudgment, making the assessment process of non-performing loans easier. The Loan's Manager echoed similar sentiments: "This involves training AI models with relevant data points and factors such as income level and payment history. In addition, these models can incorporate large amounts of non-traditional data points like social media activity and utility payments to assess customer's creditworthiness, providing a fair assessment of underserved populations with little credit history."

The Tech Vendor remarked: "Targeted and personalized risk pricing models for individual risk profiles are useful in eliminating broad categorizations and generalized assumptions by focusing on current situations like spending habits to adjust risk pricing dynamically. Moreover, using behavioural data, AI models can provide customized scores by clustering customers into highly specific groups."

Compliance with laws and regulations is necessary to realize a rigorous and more scientific decision-making process. According to the Legal and Compliance Officer, "Banks use data-driven insights to reduce human error when analysing massive datasets in real-time, useful in making decisions like asset allocation and portfolio management. Also, the models incorporate optimization algorithms that aid in risk balancing and return in investment portfolios. Financial stability and distress (bankruptcy prediction) can be predicted using discriminatory analysis models encompassing nervous network systems."

Common Tasks Identified for AI/ML Automation

Tasks identified during the interviews are depicted below under the stages of sense, seize and transform.

Financial Management

Sense - Findings indicate that tasks in financial management can be categorized into financial analysis, and investment appraisals. Most of the respondents agreed that prediction of trends requires analysis of large datasets to recognize patterns in credit risk, asset prices, and market movements.

Seize - The key point is that managers need to consider different approaches when leveraging AI and ML models for analysis (Butterfield, 2020). It was also found that main subsets of ML used in most financial institutions are Natural Language Processing (NLP), supervised learning, and unsupervised learning. Decision-based tasks, according to participants, despite the complexity and risks involved, entail selections that influence final outcomes in financial performance, including real-time decisions and providing recommendations.

Transform - They utilize the models to process data, make predictions, and identify various patterns for decision-making. Pattnaik et al. (2024) predicted that the models are based on algorithms that aid in fraud detection, risk assessment, and portfolio management.

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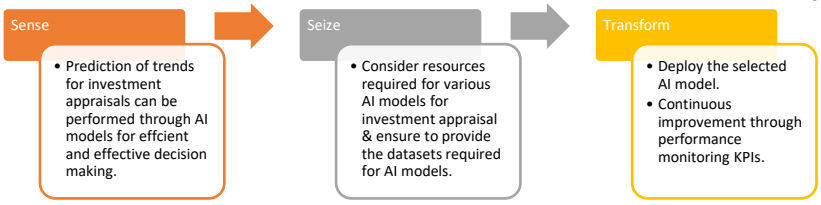

Figure 2: AI/ML Tasks Identified: Financial Management

Source: Author's Compilation

Credit Risk Management

Sense – This category of crucial tasks preferred for analysis relates to formulation of customer profiles, credit risk analysis, characteristics of customer's qualifications, income level, or assets before they are granted loans applied for.

Seize - According to the participants, it assists in adjustable pre-credit models based on customer's risk preference and determined by changes in demand according to different scenarios.

Transform - AI-based models are applied to the analysis of customer's perception of stock markets and provide decision-making assistance to investors, including stock simulation trading system with the help of machine learning models like Random Forest, and Artificial Neural Networks (ANN) (Tsai et al., 2023).

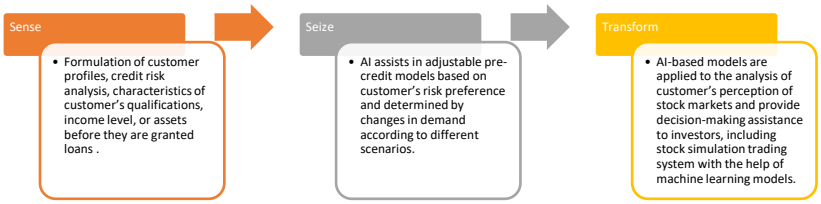

Figure 3: AI/ML Tasks Identified: Credit Risk Management

Source: Author's Compilation

Stocks and Financial Management

Sense - Another finding of this study is that global financial investors find it challenging to deal with stock market forecasting. Respondents reported that customers need investment advisory to make decisions on banking investments.

Seize – ML models can support stock market analysis and provide valuable decision-making information to traders and investment bankers.

Transform - Applying ML models like ANN, can enable them to easily use stock data to quickly and accurately forecast the future prices (Zhong & Wu, 2020).

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Figure 4: AI/ML Tasks Identified: Stocks and Financial Management

Source: Author's Compilation

Financial Asset Portfolio Management and Compliance Management

Sense - Investment bankers need visibility on market trends, future predictions as well as continuous monitoring for detecting frauds, money laundering. This information is critical while making decisions as well as advising customers on their investment portfolio.

Seize - (Abbas, 2024) concluded that intelligent risk control provides risk management strategies for maximization of profits via ML techniques. Intelligent algorithm systems (investment advisors) offer suggestions on asset portfolio improvement depending on dynamic changes in a financial market (Amato et al., 2024). Continuous monitoring of transactions can be supported through AI/ML systems.

Transform - AI and ML models provide visibility on risk control measures designed in the form of information-driven decision-making systems for credit evaluation, approval, and collection (Lokanan & Sharma, 2025). Respondents also emphasized on continuous monitoring for detecting money laundering through AI & ML.

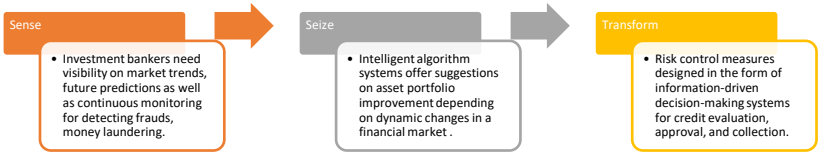

Figure 5: AI/ML Tasks Identified: Financial Assets Portfolio Management And Compliance Management

Source: Author's Compilation

Marketing Strategies

Sense - Participants provided examples of customer behaviour prediction, market trends and competitors analysis as the main areas requiring this automation.

Seize - (Heo et al., 2020) explained that data extraction from the original data is done with the help of deep neural networks to construct efficient and accurate customer portraits.

Transform - Tasks targeted by smart marketing techniques and aided by AI and ML models can be used to predict customer's needs by classifying users' data (Lokanan & Sharma, 2025).

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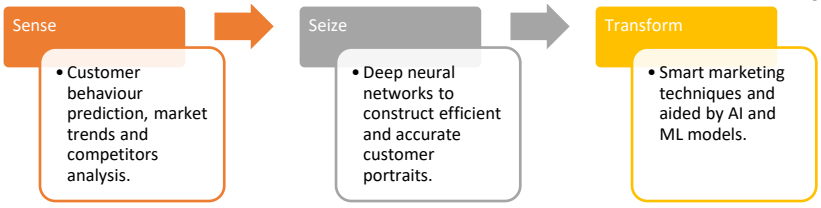

Figure 6: AI/ML Tasks Identified: Marketing Strategies

Source: Author's Compilation

Challenges Identified By Participants

The global financial regulatory environment is wide and complex (Taye, 2023). According to experts, this growth in scope consists of hard and soft regulations whose complexity poses great challenges to players in the financial industry (Zhao et al., 2023). Literature findings support this notion, including Abhishek et al. (2021) who suggested that standardized, systematic, and detailed regulatory policies and rules are needed to deal with deep application of AI and ML in this field. Additionally, respondents felt that the applicable laws are currently decentralized. The legal gap, Rowena (2020) advised, can be improved by refining supporting policies to keep pace with changing times and paying attention to standardized legal systems. Most importantly, one of the legal issues that arose from the responses is the legitimacy of the data collection process and tracking malicious behaviour of coders (Zhao et al., 2023). As George (2023) found, the financial business is an intensive information industry that depends on a range of data collected under the existing regulatory system. However, Oztas et al. (2024) had a different opinion, stating that it is difficult to define the criteria for data collection and responsibility of developers and designers of AI/ML models. Thus, attacks on financial infrastructure controlled by criminals or hackers cause loss of customer's property and personal safety due to lack of data legitimacy and relevant collection criteria (Nandi et al., 2023). Moreover, data integration and transmission are always limited due to inadequate confidentiality of AI systems, resulting in the generation of historical data with uneven quality (Chakri et al., 2023).

Other concerns as identified by George (2023) include technical security risks associated with AI/ML models, such as defects in the algorithms that often result in disconnected investment advice and reality in the market, causing huge losses of investments. According to Perifanis and Kitsios (2023), the influence of the capital hinders small-sized firms' ability and willingness to embrace AI and ML models in their strategic planning, affecting productivity in the financial markets.

Moreover, the complexity of financial risks increases as new AI models emerge with different integrated business models (Singh, 2023). In this view, Rowena (2020) advised that a working framework should improve laws and regulations that guide the application of AI and ML models by determining the scope of application, refining specific policies, and supporting a wide range of applications in the financial market.

Business Transformation Framework

Table 4 depicts task automation framework with Dynamic Capabilities Theory. The framework identifies Selection Criteria, derived through thematic analysis. Selection criteria are ranked from the most important to the least as per the recommendations of Bradley et al. (2024). These

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criteria assist finance managers to quickly identify factors to consider when applying AI and ML models for data analysis.

Table 4: Framework for AI/ML Implementation with Dynamic Capabilities Theory

Phase	Description	AI/ML-specific capabilities
Sensing	Identifying and evaluating new AI/ML opportunities and technological advancements.	*Perception and analytics*: Using ML algorithms to analyse vast datasets to detect emerging trends, forecast customer behaviour, and understand shifting business requirements. These datasets come from historical financial data, stock market & Capital market statistics, public data on industry and competitors, internal processes and metadata. Findings noted during the study identified that AI can be used for: • Prediction of trends for investment appraisals • Stock market forecasting for investment advisory • Visibility on market trends, future predictions and continuous monitoring for detecting frauds, money laundering • Customer behavior prediction *Technology identification*: Proactively monitoring new AI/ML breakthroughs, including generative AI, and understanding their potential business applications such as real-time market analytics, continuous AML and fraud monitoring, automated investment decision-making etc. Findings indicated NLP, ANN and specialized systems with intelligent algorithms are mostly considered for business transformation. *Data collection and processing*: The ability to effectively gather and process the necessary data for AI/ML models is a foundational sensing capability. Data sources can be publicly available such as or can also be internally available through internal processes and systems. During the study it was noted that companies prefer data with integrity, unbiased and fair representation of the population.
Seizing	Mobilizing resources and strategically addressing the opportunities noted in previous phase. Making decisions and investing in new initiatives.	*Decision-making*: Investing in AI and ML to support decision-making processes with accurate, real-time insights. Innovation and augmentation: Developing new AI-driven products, services, or business models. Generative AI, can assist in prototyping and creative tasks. The participants indicated that leadership prefers systems with explainability and fairness. It was also noted that robust and consistent systems are preferred.

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Phase	Description	AI/ML-specific capabilities
		Organizational culture: Transition to AI & ML system demands change management across the organization. Participants emphasized on fostering an inclusive and flexible culture that encourages experimentation and provides a structure for evaluating new AI-driven opportunities.
Transforming	Continuously adapting and reconfiguring the firm's resources, processes, and structures to sustain a competitive edge.	*Human-machine collaboration*: Redesigning business processes and redefining roles to create a symbiotic relationship between AI automation and human creativity. *Organizational and structural redesign*: Realigning organizational structures to integrate AI technologies effectively, potentially breaking down silos and establishing new routines and processes. *Strategic foresight and learning*: Implementing continuous learning and feedback loops to ensure that AI capabilities evolve over the period of time. Participants mentioned that AI & ML systems are seen as the cause of job loss and re-structuring in organization. Resistance to change is handled through re-skilling the workforce and providing opportunities for career growth.

Source: Author's Compilation

Table 5 complements the proposed framework by depicting ranking criteria for selecting tasks for automation. The highest ranked consideration is data characteristics (35%), which entail features like high-data volume tasks presented both in structured (ledgers) and unstructured (images, audio) forms. AI and ML models integrated with Natural Language Processing can assist financial managers in realizing this goal. The second criterion is the level of tax complexity and frequency of occurrence (25%). These are repetitive tasks that require sophisticated pattern recognition for predictive modelling and can best be accomplished using AI models. They include fraud detection, account reconciliation, market sentiment analysis, and customer behaviour modelling. Thirdly, real time processing needs are ranked at 20% and can be used to prioritize tasks that involve high-frequency trading in which managers need to make decisions in milliseconds. The next factor is regulatory and compliance (ranked at 10%), a criterion that directs managers to consider automation of compliance checks by scanning for anomalies, irregularities, and errors, for tax reporting and anti-money laundering to streamline financial and audit reports. Other criteria include risk management (5%), and customization and personalization requirements (5%).

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Table 5: Selection Criteria

Criterion	Rank (%)
Data characteristics (high data volume, variety, availability, historical data)	35
Task complexity and frequency (pattern recognition, repetitive tasks, predictive modelling)	25
Real-time processing requirements (algorithmic trading, risk monitoring)	20
Regulatory and compliance requirements (Regulatory reporting, audit processes)	10
Risk management (credit scoring, fraud detection)	5
Customization and personalization (chatbots, customer support)	5

Source: Author's Compilation

Conclusion

This study examined the usage of AI and ML models for automating different kinds of tasks in financial institutions. The motivation was to identify a framework that finance managers can use in selecting tasks to prioritize analysis using these latest technologies. Themes originating from qualitative analysis of participants' responses, indicated that financial institutions engage mostly in financial analysis and decision-making tasks.

A framework is developed for selection of tasks for automation while using Dynamic Capabilities Theory. Proposed framework was utilized in arranging and sanitizing the responses under sense, seize and transform realms. This categorisation assisted in identification of tasks transformation strategies. The proposed theoretical framework requires managers to prioritize task characteristics like volume, variety, and availability.

The main tasks associated with financial analysis include predictive analytics, fraud detection, risk assessment, and investment management. These tasks are accomplished using AI and ML technologies like natural language processing, artificial neural networks, supervised learning, and unsupervised learning. Other findings indicate that managers apply their human decisions with the assistance of AI and ML technologies to make appropriate recommendations in real-time. They include credit scoring and lending decisions, risks mitigation, algorithmic trading, and financial planning. Secondly, task complexity and frequency needs AI-assisted analyses, especially repetitive ones for pattern recognition and predictive modelling. The third factor is real-time processing, particularly tasks requiring risk monitoring. Other crucial aspects in their order of significance to an organization are regulatory and compliance needs, risks management, and customization needs.

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