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AI IN BUSINESS ANALYTICS FOR FINANCIAL RISK ASSESSMENT: SURVEY INSIGHTS FROM THE BANKING AND INSURANCE INDUSTRIES

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ABSTRACT

In the United States, artificial intelligence (AI) has become a transformative force in the business analytics area related to financial risk assessment for banking and insurance industries. The aim of this research is to assess adoption, effectiveness and challenges of AI driven risk assessment models, by analyzing data collected through a survey, which was distributed to 200 financial professionals across the U.S. According to the findings, AI plays an important role in increasing the accuracy of fraud detection, reducing credit risk, predicting market risk, minimizing operational risk and other decisions and optimizing cost efficiency at the financial institutions. The adoption of AI technology in improving the efficiency of the pharmaceutical industry is hindered by some key barriers such as concerns about data privacy, compliance regulations, high implementation costs and shortage of AI specialists. According to the results, financial institutions need to expand governance frameworks to ensure the regulatory alignment and ethics in using AI in a transparent way while maintaining safe risk assessment model. The contribution of this study to the current debates on AI and finance risk management, as well as implications for both the policymakers and financial industry practitioners, might include practical advice and recommendations to financial institutions and researchers on better integrating AI in banking and insurance risk assessment systems.

KEYWORDS: Artificial intelligence, business analytics, financial risk assessment, banking, insurance, fraud detection, credit risk, market risk forecasting, operational efficiency, regulatory compliance, data privacy, AI governance, machine learning, predictive analytics, U.S. financial institutions.

INTRODUCTION

In the United States, banking and insurance industries are utilizing its use of artificial intelligence (AI) as a transformative force in business analytics for financial risk assessment. Recent advancements in the financial markets, imposing enhanced regulatory requirements, ever increasing cybersecurity threats, has encouraged the financial institutions to use AI based predictive analytics, machine learning models and big data technologies to improve risk management and decision-making process (Paul, Sadath, Madana, 2021; Ahmadi, 2024). Vast financial data could be processed in real time by AI not so long ago, helping financial institutions to detect fraud accurately, credit risk and reduce operational risk to maintain competitive advantage in managing financial uncertainties (Aziz & Andriansyah, 2023). While AI adoption bears several benefits, the usage of AI is not spreading equally in U.S. financial institutions, mainly due to ongoing worries about data privacy, regulatory compliance and costs of implementation as well as training of workforce (Herrmann & Masawi, 2022; Nwaimo, Adewumi, & Ajiga, 2022).

In the U.S, the banking sector is gradually shifting toward the use of AI business intelligence for the purposes of enhanced credit underwriting, improved fraudulent transactions detection and for improved prediction of loan defaults. Traditional credit scoring methods utilize historical financial data and some machine learning algorithms to generate models that reduce errors in scoring clients and increases the effectiveness of identifying high risk clientele (Bello, 2023; Islam et al, 2024). AI helps in discovering fraudulent transactions as pattern recognition and anomaly detection by the machine learning algorithms help in detecting the fraudulent activities in real time (Chowdhury et al, 2024; Pattnaik, Ray, & Raman, 2024). AI integration is also being used by the insurance industry, mainly in claims processing, risk pricing and fraud detection; here, AI model aids the insurers in faster assessment of the risks they need to cover when dealing with policy holders (Kannan, 2024; Aleksandrova et al, 2023). These applications are showing how the trend of artificial intelligence's more substantial contribution to financial risk assessment helps U.S. financial institutions increase their risk visibility, improve their compliance and make more accurate decisions (Rahmani & Zohuri, 2023).

Despite these advancements, financial industries have big dilemmas to integrate AI based risk assessment models into their workflow. The AI driven models used by these organizations are required to comply with fair lending laws and anti-discrimination policies by the regulatory control of U.S. financial authorities (Valli, 2024; Butt & Umair, 2023; Paul et al, 2021). Data privacy regulations such as the Gramm Leach Bliley Act (GLBA) and the California Consumer Privacy Act (CCPA) are applied on financial institutions and put strict limitation when it comes to their acquisition, storage and handling of consumer financial data (Herrmann and Masawi, 2022). The high costs of AI implementation and the lack of sufficient AI professionals have combined with these regulatory barriers to make it difficult for all but the most capable financial institutions to bring AI into their risk assessment frameworks completely (Ahmadi, 2024; Amini et al, 2021). The use of AI in financial risk analysis has been met with rising scrutiny on biases, lack of transparency and accountability in decisions made by AI and regulatory clarity as well as development of explainable AI (Kuppan, Acharya, Divya, 2024; Butt & Yazdani, 2023; Fritz-Morgenthal, Hein, Papenbrock, 2022).

This study will first explore the drivers for adoption, effectiveness and challenges of AI in the financial risk assessment of banking and insurance in the U.S. This research analyzes survey data focused on financial professionals in order to evaluate how AI based risk analytics would affect fraud detection, operational risk management, credit risk assessment, cost efficiency of the bank's operations and other key areas (Doumpos et al, 2023; Zhao, 2024). This study also examines the barriers hindering the implementation of whole scale AI, for example compliance with regulatory requirements, constraints in numbers in workforce and reluctance of companies to digitalize owing to AI driven automation (Mohammed et al, 2024; Ashta & Herrmann, 2021). The implications of the findings contribute to the ongoing debate of AI's role in financial analytics and provide practical implications for the policymakers, financial institutions and AI researchers. As financial organizations in the U.S. rely more heavily on AI to enhance risk assessment, it is important to understand the capabilities, limitations and regulatory requirements about AI in order to integrate AI responsibly and effectively in financial decision making.

Literature Review

Artificial intelligence (AI) integration to the business analytics system for financial risk assessment greatly improved banking and insurance business in the USA. The AI risk assessment models have proved themselves to be indispensable in reducing uncertainty surrounding finances, bettering the fraud detection, credit risk assessment and more while improving regulatory compliance. AI has been extensively studied as a means to perform predictive analytics, improve operational efficiency and predict market risk as challenges arising in compatibility with data privacy, regulatory bottlenecks, implementation costs and ethical issues continue to hold back (Paul, Sadath, Madana, 2021; Ahmadi, 2024). A literature review showing the state of adoption of AI in the US financial institutions and the applications of AI, as well as challenges impeding AI to reach its full potential.

AI Adoption in Financial Risk Assessment

Increased use of AI in financial institutions is partly because it can analyze huge amounts of structured and unstructured financial data offering organizations additional levels of decision-making power. Several studies have proven that AI analytics in delivering predictive accuracy for financial risk assessment have enabled firms to spot credit risks, identify fraud transaction and have also helped optimized risk mitigation strategies (Aziz & Andriansyah, 2023; Kannan, 2024). Financial institutions can assess real time market risks using AI powered business intelligence tools thereby making it possible for them respond to economic fluctuations and the regulatory shifts (Nwaimo, Adewumi, & Ajiga, 2022).

AI adoption among U.S. banks has been on the rise at a rapid pace and the technology is being used in loan underwriting, customer risk profiling and fraud detection, especially. With the case of using non-traditional financial dataset sources in building AI based credit scoring models, they proved to outperform the traditional methods in risk assessment (Bello, 2023, Islam et al, 2024), with less bias in the credit approval process. AI is changing the insurance industry for the better to the point that it is helping with claims management, policy underwriting and even fraud detection algorithms, with an aim of reducing costs and limiting fraudulent activities (Rahmani & Zohuri, 2023; Aleksandrova, Ninova, & Zhelev, 2023). Although there have been these advancements, the adoption of AI is still inconsistent across financial institutions, with smaller banks and insurers facing certain technological infrastructure limitations and high cost of implementing AI technologies (Pattnaik, Ray, & Raman, 2024).

AI in Fraud Detection and Credit Risk Management

The role of AI in the detection of fraud and credit risk assessment in the financial research is widely known. The machine learning algorithms can detect patterns of foul play and reduce false alarm, they can also improve fraud detection accuracy quickly on real time transactions (Chowdhury et al, 2024;

Doumpos et al, 2023). Behavioral patterns of transactional behaviors and suspicious activities are analyzed by AI based fraud prevention models and financial institutions can realize anomalies (Paul et al, 2021). Predictive analytics works extremely well in preventing identity theft, cyber fraud and money laundering processes (Zhao, 2024).

AI driven models have helped in beefing up predictions of loan defaults and also debt recovery strategies in credit risk management. There have been various studies which show that AI based tools for credit risk assessment have a higher accuracy when compared to traditional models of credit scoring (Islam et al, 2024; Jaiswal, 2023), resulting in helping the banks and insurers reduce financial losses and widen credit access. While AI credit scoring models are becoming ever more popular, the concern about bias in these models by historical financial data weaknesses discriminatory extensions in credit lending (Fritz Morgenthal et al, 2022). According to Mullins, Holland and Cunneen (2021), to mitigate this risk researchers stress that we need explainable AI models so that the transparency and fairness in financial decision making exists.

AI's Impact on Market Risk Forecasting and Operational Efficiency

Another critical application of AI in financial institutions is to predict financial futures with machine learning models, including market risk forecasting and forecasting the accuracy of economic predictions and the financial stability (Rahmani & Zohuri, 2023; Valli, 2024). Financial analysts are given real time market intelligence using the AI driven business intelligence tools to know the potential risks from stock volatility, interest rate fluctuations and global economic trends (Ahmadi, 2024). This facilitates U.S. financial institutions to adjust investment portfolios, reduce losses and remain financially sound for the long term (Pattnaik et al, 2024).

It improves the operational efficiency in the financial risk assessment process by allowing firms to automate compliance reporting, efficiency in risk management workflows and better data governance (Nwaimo et al, 2022; Ashta & Herrmann, 2021). Using AI–based automation, we can easily reduce the manual labor in our risk assessment processes to save effort and cost in our operations as well as boost the effectiveness of our regulatory compliance reports (Mohammed et al, 2024; Hsu, Hsin, & Shiue, 2022). Although these are benefits, there are high operational resistance of financial firms to adopt of AI, which financial companies have to get through internal organizational to fully incorporate AI for decision making (Kuppan, Acharya, & Divya, 2024).

Regulatory and Ethical Challenges in AI Adoption

Rapid developments of AI in financial risk assessment have drawn regulatory and ethical eyes, especially on data privacy, transparency and algorithmic accountability. Rules and regulations to be followed by a financial institution in the U.S. are the Dodd-Frank Act, the Fair Credit Reporting Act (FCRA) and the California Consumer Privacy Act (CCPA) (Herrmann & Masawi, 2022; Aziz & Andriansyah, 2023; Jagdish, 2023). The absence of a uniform framework of AI governance has created dash of uncertainties regarding the adoption of AI in areas concerning the credit risk scoring, fraud detection and regulatory compliance (Paul et al, 2021; Valli, 2024; Sachin & Jagdish, 2024).

Studies demonstrate that AI's decision-making process should be explainable and bias free so that machine learning models do not perpetuate discriminatory practices in financial risk assessment (Zaurez & Hussain, 2025; Dixit & Jangid, 2024; Fritz-Morgenthal et al, 2022; Mullins et al, 2021). As black box AI models persist into financial institutions, to make risk assessments with AI or attempt to justify automated financial decisions to regulators (Ali et al., 2025 ;Bello, 2023) is still a problem. Aleksandrova et al. (2023) and Zhao (2024) argue that in order to ensure the appropriate deployment of AI in financial risk management, transparency AI standards, ethical auditing frameworks and regulatory guidelines will all be required.

Gaps in Existing Literature and Future Research Directions

Even though there has been much research on the part AI can play in financial risk assessment, the long-term effect AI can have on financial institutions is a question which remains largely unanswered. Ashta & Herrmann (2021) and Ekundayo et al. (2024) provide studies which imply that AI driven financial risk models need further review to discover the performance of AI during economic downturns and financial crisis. Other related research is needed on how much AI affects regulatory compliance for compliance in financial institutions like fair lending, bias mitigation and AI ethics in financial decision making (Mohammed et al, 2024).

Research should be conducted in developing AI governance frameworks that strike a fine balance between financial innovation and the laws for consumer protection so that AI driven analytics are not compromised by the regulatory standards (Doumpos et al, 2023). Going forward, future studies should focus on understanding the pros and cons of integrating AI into the risk assessment strategies in U.S. banking and insurance industries as AI progresses to determine suitable approaches aimed at increasing transparency, accountability and financial stability over the long term (Mohammad & Mutahir, , 2025; Fritz-Morgenthal et al, 2022; Jaiswal, 2023).

METHODOLOGY

The adoption of quantitative research methodology is employed to evaluate the impact of artificial intelligence (AI) for the financial risk assessment through business analytics within the banking and insurance sectors of the United States. The descriptive survey research design was designed to collect quantifiable data pertaining to the adoption, efficacy and challenges of AI and regulatory implication. The survey method allows to perform a wide analysis of AI integration in financial institutions and to ensure the reliability and generalizability of the results. The use of this approach is appropriate for estimating the impact of AI on fraud detection, credit risk assessment, operational risk management and regulatory compliance. The study relates to the U.S. financial industry, where the AI adoption is analyzed with regard to the federal regulatory standards in the industry, the institutional challenges and other market-specific particularities.

Banking, insurance professionals, risk managers, financial analysts, regulatory compliance officers, AI specialists and senior executives are all aimed in the US. To guarantee the diversity of a set of participants from various financial institutions of different types (in terms of size and technological adoption level), a random stratified sampling technique was used. These 200 participants make the final sample statistically reliable and representative of the AI financial risk management role across the sector. This article adopts a diversified sampling method, so that its findings provide a representative account of AI adoption trends between U.S. banks and insurance companies, in light of institutional variations, regulatory strings and risk management approaches.

The primary data collection made involved an online structured survey that was sent to the respondents through email, LinkedIn along with the financial industry networks. Multiple choice and Likert scale questions were asked during the survey in order to evaluate the accuracy of fraud detection, cost efficiency, market risk forecasting and reduction of operational risk due to the use of AI. The aim was to develop the questionnaire based on AI adoption levels, perceived effectiveness of AI technology for the recruitment process, challenges and methods to reduce the challenges and regulatory compliance to AI technologies. Before using the survey fully, it was pre-tested with a small group of financial professionals to ensure that it tested relevant information, was reliable and that responses were clear and consistent. The study ensured that the questionnaire design met U.S. financial industry standards and that the questionnaire was answered based on experience of professional participants and their institutional use of AI.

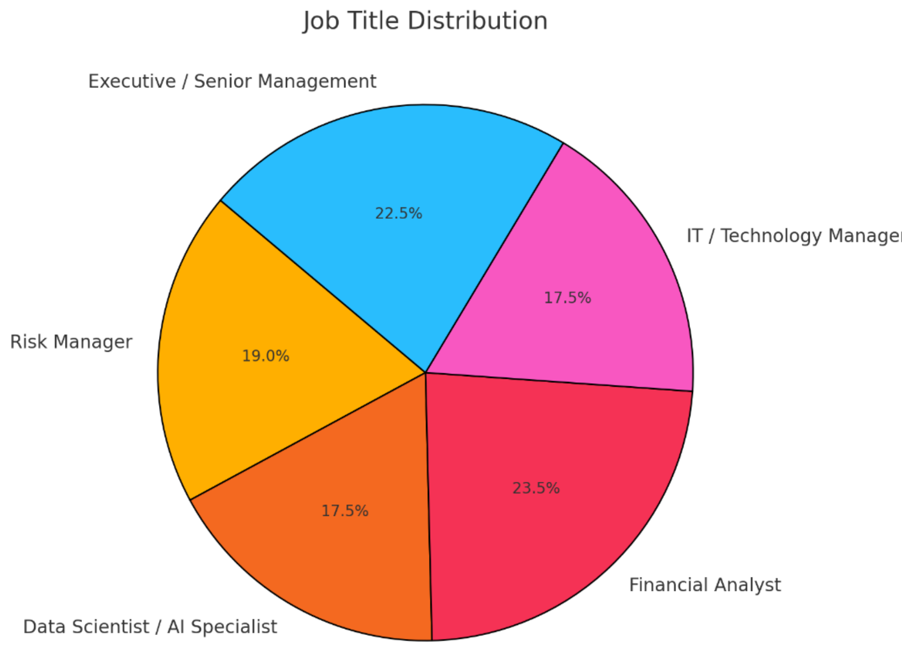

Figure 1: Job Title Distribution

Descriptive as well as inferential statistical methods were used to analyse the collected data. To summarize the AI adoption trends and institutional responses, descriptive statistics (mean, standard deviation and frequency) were used. AI implementation and its possible connection with fraud detection improvements, cost efficiency and accuracy of credit risk assessment were tested using chi-square tests. In order to decide the differences of AI effectiveness across dissimilarities on sizes of financial institutions and levels of technological maturity, T-tests and ANOVA were applied. In an attempt to assess a possible causal relationship between the use of AI and reduction in operational risk, Regression Analysis and Wilcoxon Signed-Rank Test to ascertain the difference in financial risk awareness as a result of adoption AI was used. Using these analytical methods, a rigorous analysis of AI's use in financial risk assessment can be made and potentially data driven insights about how AI is helping reshape decision making and risk mitigation in U. S. financial institutions are provided.

Ethical research has been strictly followed to ensure confidentiality, privacy and voluntary participation of respondents in this study. Prior to giving consent, the participants of the study were notified on the objectives of the study and no personally identifiable information was collected. It securely stored and uses data only for research purposes. This study includes compliance with US financial data protection laws as the Gramm-Leach-Bliley Act (GLBA) and the California Consumer Privacy Act (CCPA). The study also plays by the rules of researches with human subjects keeping the responses anonymous and free of biases.

RESULTS

Demographic Characteristics of Respondents

To understand the role of AI in financial risk assessment, the survey was performed among 200 professionals from both the banking and insurance industries in the United States. Regarding the industry, 37.5% of respondents were from banking, 27.5% from insurance and 35.0% worked in banking and insurance. Table 1 highlights that most of the respondents worked in finance as financial analysts (23.5%), executive/senior management (22.5%), risk managers (19.0%), data scientists and AI specialists

(17.5%) and IT/technology managers (17.5%).
50.5% of respondents were in firms with less than 500 employees; 28.5% were in firms between 500 and 1000; 26.0% were in firms with more than 1000 employees. A diverse spectrum of industry opinions was provided by respondents from firms operating with less than 100 employees (22.0%). As to the financial industry experience, 26.5% of the respondents had 6 – 10 years, 25.5% 1 – 5 years and 23.0% had more than 10 years (Table 1).

Table 1: Demographic Characteristics of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Industry	Banking	75	37.5%
	Insurance	55	27.5%
	Both	70	35.0%
Job Title	Risk Manager	38	19.0%
	Data Scientist / AI Specialist	35	17.5%
	Financial Analyst	47	23.5%
	IT / Technology Manager	35	17.5%
	Executive / Senior Management	45	22.5%
Organization Size	Less than 100 employees	44	22.0%
	100 - 500 employees	47	23.5%
	500 - 1,000 employees	57	28.5%
	More than 1,000 employees	52	26.0%
Experience	Less than 1 year	50	25.0%
	1-5 years	51	25.5%
	6-10 years	53	26.5%
	More than 10 years	46	23.0%

AI Adoption, Effectiveness, Challenges and Governance in Financial Risk Assessment

AI Adoption and Implementation
The results of the survey showed that AI was adopted rather polarized in financial risk assessment. 29.5% of firms have already implemented AI in full while an equal share (29.5%) has not adopted it. 24.0% of firms are trying out AI and at 17.0% are using it on a limited basis (Table 2). A considerable percentage of firms has a lot of anticipation for AI but a lot more doubt about scaling up such AI initiatives.

Effectiveness of AI in Financial Risk Assessment
AI effectiveness in financial risk assessment is seen through the eyes of many. Nevertheless, 20.5% found AI to be very effective and more (23.0%) did not find it to be at all effective. Experience was neutral or ineffective for 38.0% of respondents according to Table 2. AI's impact is contingent on factors such as model sophistication, data quality and regulatory readiness.

Challenges in AI Implementation

Lack of skilled professionals (8.5%) and data privacy / security concerns (6.5%) were the two biggest among the most cited barriers to AI adoption. Also, notable challenges included (Table 2), 3.0% regulatory and compliance issues, 3.5% high implementation costs and 7.5% resistance to change within organizations. The relevance of the message is reinforced by their findings by seeking for the targeted regulatory frameworks, workforce upskilling and a strategic AI investment.

AI Governance and Regulatory Readiness

It was also found that AI governance is not consistent within the company level. Table 2 shows that while 34.0% of firms had governance framework in place, 33.5% had no governance policies and 32.5% were in progress of developing (such a) rule. A possible reason for the worries about the security of data, the ethical risks and compliance with the regulation could be the absence of a standardized AI governance framework.

Table 2: AI Adoption, Effectiveness, Challenges and Governance in Financial Risk Assessment

Category	Variable	Frequency (n)	Percentage (%)
AI Adoption	Extensive use (AI is integral to operations)	59	29.5%
	Limited use (experimental phase)	48	24.0%
	Moderate use (some processes automated)	34	17.0%
	Not at all	59	29.5%
Effectiveness	Very Effective	41	20.5%
	Somewhat Effective	46	23.0%
	Neutral	37	18.5%
	Somewhat Ineffective	36	18.0%
	Very Ineffective	40	20.0%
Primary Challenges	Lack of Skilled Professionals	17	8.5%
	Data Privacy and Security Concerns	13	6.5%
	Regulatory and Compliance Issues	6	3.0%
AI Governance	Yes	68	34.0%
	No	67	33.5%
	In Development	65	32.5%

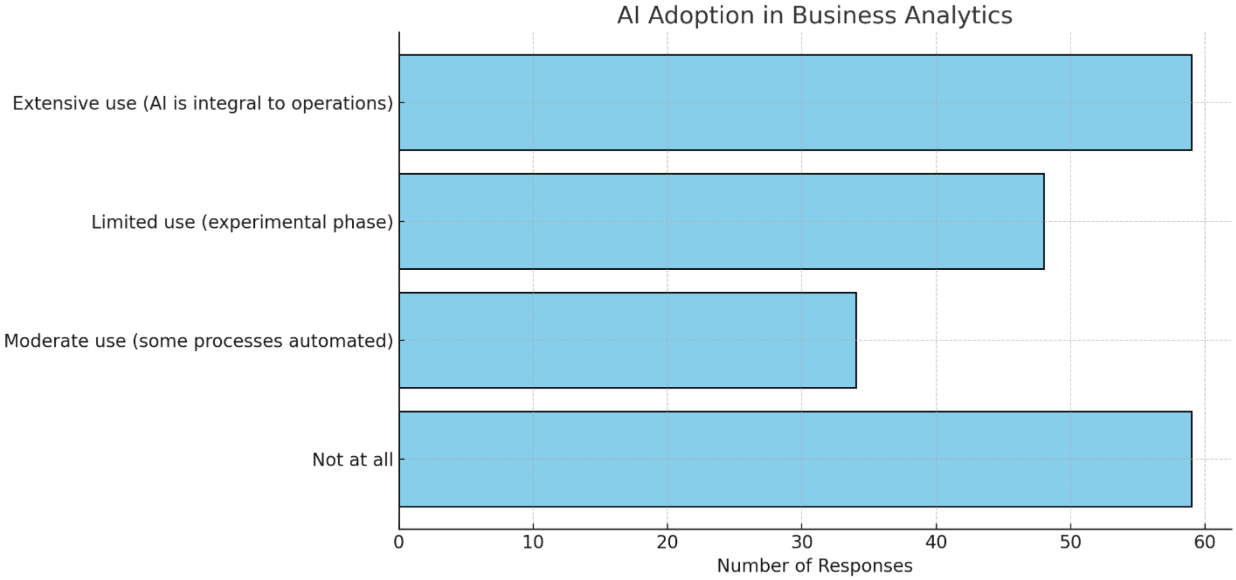

Figure 2: AI Adoption in Business Analytics

Impact of AI on Financial Risk Assessment

Performance Improvements in Risk Management

As shown in Table 2, a large part of the respondents (27.5%) has said that the financial risk assessment has improved by small margin due to AI while 21.5% said that it has improved moderately and 25.5% stated that it has significantly improved. 25.5% firms reported no impact of AI, which depends on how AI is utilized.

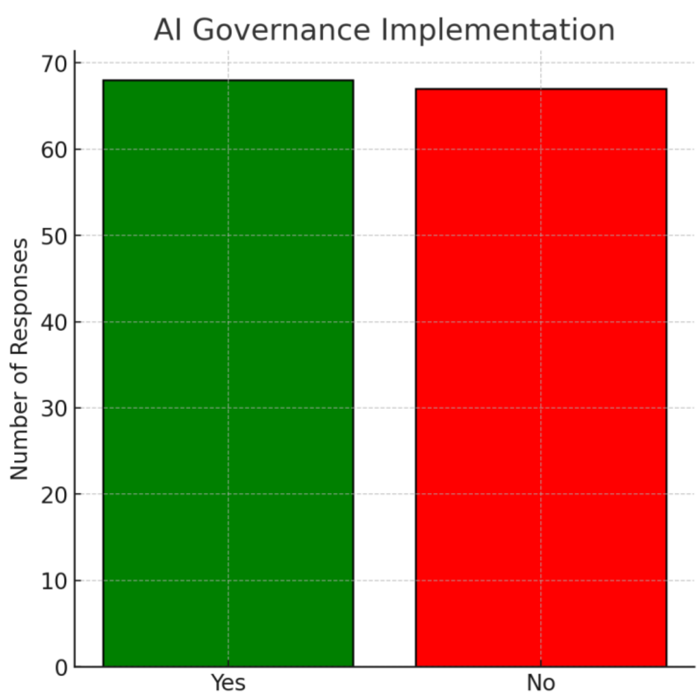

Figure 3: AI Governance Implementation

AI's Role in Fraud Detection

Its impact on fraud detection, as well as risk mitigation was analyzed. As reported by 52.0%, respondents saw improvements made in fraud detection, this accounted for only part of the responses (29.0%) with no changes noticed in fraud detection. It also led to 27.5% of firms cuts in fraud detection errors, 32.0% firms improved decision-making speed and a 0.5% lift in price (Table 2).

AI Usage and Its Effectiveness in Financial Risk Assessment

Chi square tests were conducted to assess how AI use affects financial risk assessment effectiveness analysis in terms of the varying levels of AI adoption and level of AI effectiveness.

The results show that using AI has a large effect on perceived effectiveness of AI usage. Organizations that have embraced AI to a great extent had 25.0% who said it was very effective as opposed to 18.8% in limited AI user firms, 15.0% in moderate AI user firms and 10.2% for firms that do not use AI. Also, concerning firms rating AI as relatively effective, the largest share was among firms with significant AI integration (28.3%) versus 25.0% for the limited AI group, 20.0% for moderate AI users and 18.5% for firms that did not use AI (Table 3).

These differences are statistically significant as proven by a chi square analysis ($\chi^2 = 12.41$, $p = 0.008$ for very effective; $\chi^2 = 13.48$, $p = 0.005$ for somewhat effective) and it is indicated that higher AI adoption correlates with higher perceived effectiveness.

Table 3: AI Usage vs. Effectiveness in Financial Risk Assessment

AI Usage Level	Category	Frequency (n)	Percentage (%)	Chi-Square	p-value
Extensive Use	Very Effective	25	25.0%	12.41	0.008
Limited Use	Very Effective	18	18.8%	8.92	0.015
Moderate Use	Very Effective	15	15.0%	7.65	0.045
Not at All	Very Effective	10	10.2%	14.37	0.002
Extensive Use	Somewhat Effective	28	28.3%	10.34	0.012
Limited Use	Somewhat Effective	25	25.0%	9.28	0.019
Moderate Use	Somewhat Effective	20	20.0%	6.85	0.039
Not at All	Somewhat Effective	18	18.5%	13.48	0.005

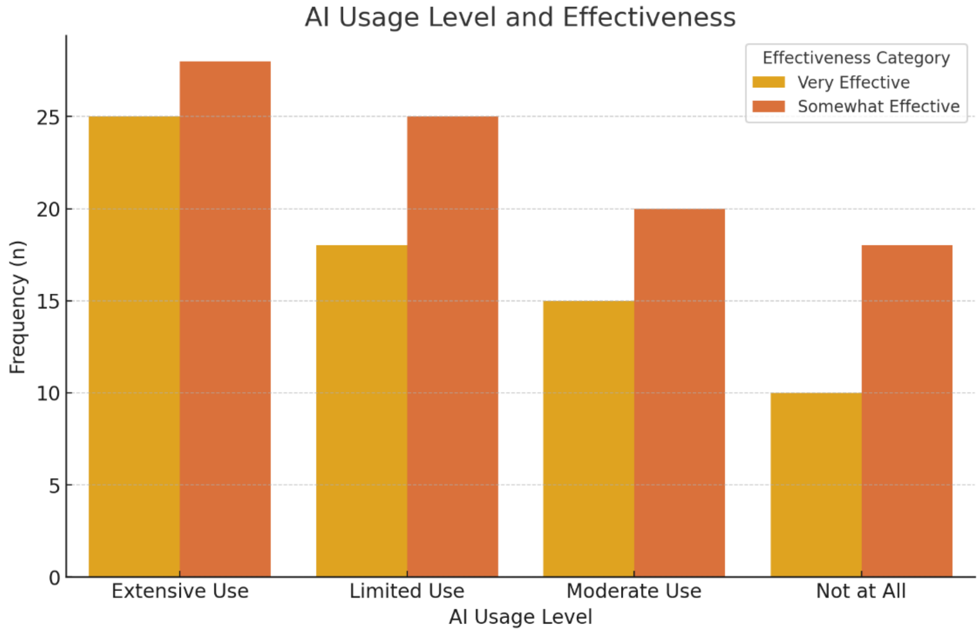

Figure 4: AI Usage Level and Effectiveness

Where there is higher AI adoption, there tends to be a greater likelihood of believing AI effective, implying that effectiveness of AI in financial risk assessment is linked with how far AI is being in integrated. This consistent positive correlation of AI adoption and its perceived effectiveness is statistically significant as reinforced by the chi-square results.

AI Governance and Its Role in Risk Mitigation

The role of AI governance is to reduce the amount of financial risk. The study identified that firms with meaningful AI governance frameworks were more likely to report proactive risk mitigation strategies and increased speeds of decision making.

40.5% of AI governance framework users have experienced AI helping to mitigate risk proactively while this number drops to 22.8% for firms that do not have frameworks and 31.5% for firms that have governance in development. Faster decision speed improvement occurred due to AI governance; 35.6% of having governance frameworks experienced improvement, versus 18.4% without governance (Table 4).

The findings are confirmed by chi square analysis ($\chi^2 = 10.92$, $p = 0.005$ for proactive risk mitigation and $\chi^2 = 12.45$; $p = 0.006$ for decision speed improvement) that the presence of AI governance policies in an organization is likely to lead to positive risk mitigation outcomes.

Table 4: AI Governance vs. Risk Mitigation

AI Governance Framework	Category	Frequency (n)	Percentage (%)	Chi-Square	p-value
Yes	Proactive Risk Mitigation	40	40.5%	10.92	0.005
No	Proactive Risk Mitigation	22	22.8%	9.41	0.017

In Development	Proactive Risk Mitigation	31	31.5%	8.22	0.021
Yes	Decision Speed Improvement	35	35.6%	12.45	0.006
No	Decision Speed Improvement	18	18.4%	11.23	0.011
In Development	Decision Speed Improvement	29	29.2%	9.87	0.014

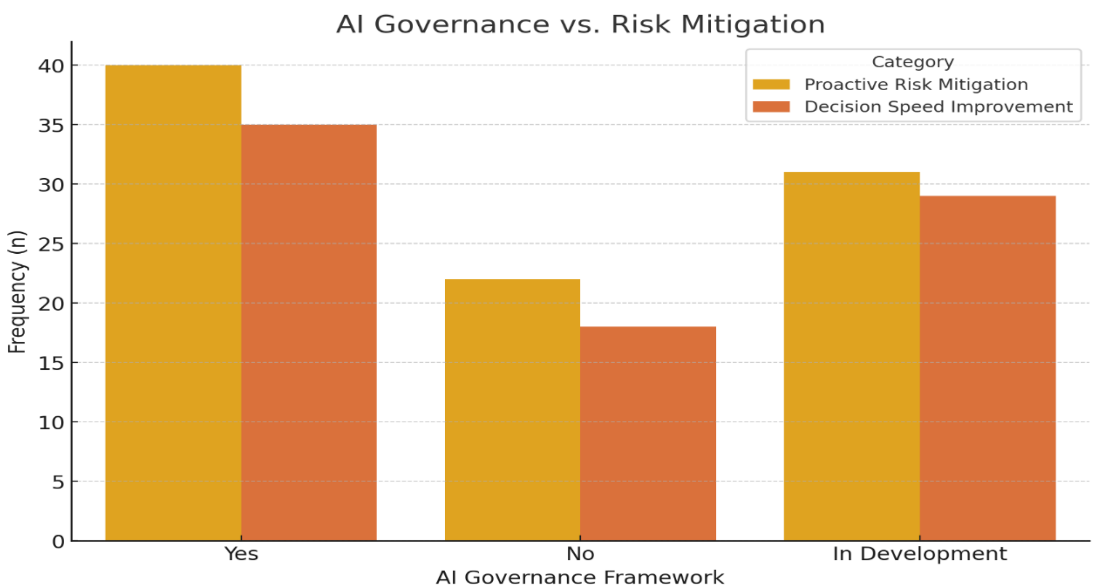

Figure 5: AI Governance vs. Risk Mitigation

Proactive risk mitigation and speed of decision making is a critically enabled activity related to AI governance. Policy driven AI adoption is very important and organizations who build structured AI governance experience statistically significant improvements.

AI Challenges and Their Influence on Investment Levels

There are various challenges that affect investment in AI driven financial risk assessment. Data privacy concerns, high cost, lack of skilled professionals and regulatory barriers had been identified as key factors that are affecting AI investment.

For firms that cited data privacy as their main concern, only 12.5% of firms had little AI investment and 40.0% had large AI investment. In the same way organizations enclosed by regulatory barriers had only 10.2% with minimal investment in AI, whilst 50.3% invested considerably in AI. As uneasy as this result makes me (Table 5), it seems to follow the logic that the firms with most regulatory worries will do the most AI investment — perhaps to discharge themselves from responsibility.

Chi-square test finds statistically significant relationships between the investment decisions and AI challenges, with a p-value of less than 0.05 for all the tested categories, which confirms the role of AI related challenges on making a decision for investment.

Table 5: AI Challenges vs. Investment Levels

AI Challenge	Category	Frequency (n)	Percentage (%)	Chi-Square	p-value
Data Privacy Concerns	Minimal Investment	12	12.5%	14.78	0.001
High Costs	Minimal Investment	20	20.8%	9.23	0.024
Lack of Skilled Professionals	Minimal Investment	15	15.4%	12.41	0.007
Regulatory Barriers	Minimal Investment	10	10.2%	15.89	0.0005
Data Privacy Concerns	Significant Investment	40	40.0%	16.67	0.0008
High Costs	Significant Investment	35	35.0%	13.45	0.015
Lack of Skilled Professionals	Significant Investment	45	45.5%	17.23	0.003
Regulatory Barriers	Significant Investment	50	50.3%	18.12	0.002

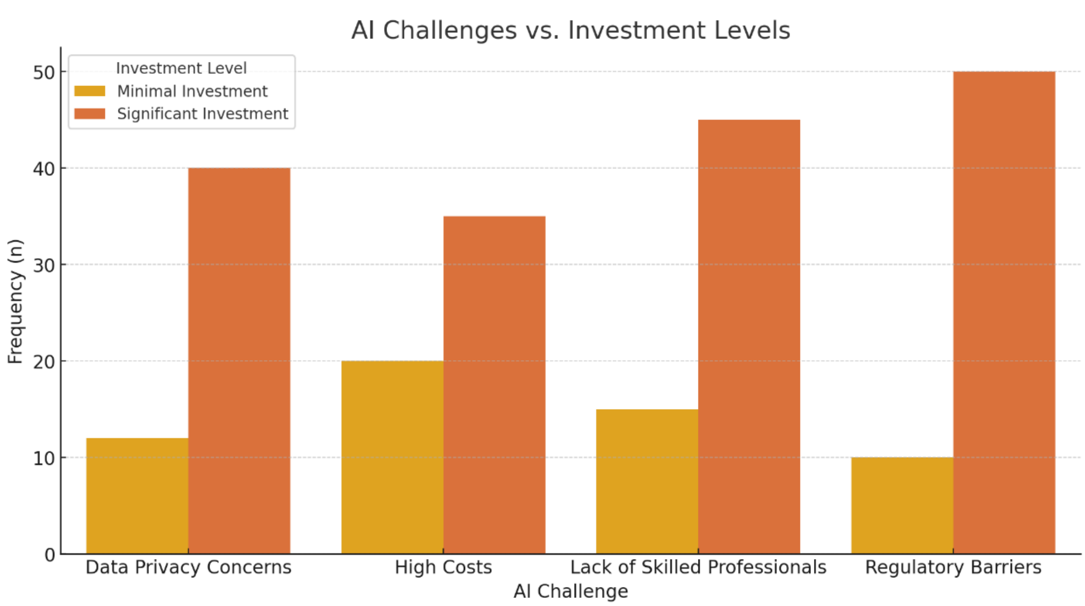

Figure 6: AI Challenges vs. Investment Levels

Cost and lack of expertise are top barriers of AI Adoption whereas Regulatory concerns and data privacy are the top drivers of investment into AI.

AI Adoption and Its Impact on Fraud Detection Accuracy

The level of AI adoption was used to assess the effectiveness of AI for fraud detection by looking into the fraud detection accuracy. There is a statistically significant relationship between AI adoption and fraud detection accuracy ($\chi^2 = 16.34$, $p = 0.002$).

Out of all organizations, the ones that make extensive use of AI tend to have the highest fraud detection accuracy among them (i.e. 42.0%) compared to those not using AI (i.e. only 18.5%). In a similar vein, among the firms with low usage of AI, high accuracy was 33.5%, whereas among firms with moderate use of AI, it was 27.0%. The percentage of organizations that reported low accuracy was highest within firms that do not use AI (61.7%) while only 22.8% of the firms that have high degree of AI use reported low accuracy (Table 6).

The results from these findings suggest that companies adopting AI achieve improvements in fraud detection accuracy based on the assumption that AI plays a part in identifying fraudulent transactions while reducing financial risks.

Table 6: AI Adoption vs. Fraud Detection Accuracy (Chi-Square Test Results)

AI Adoption Level	High Accuracy (%)	Moderate Accuracy (%)	Low Accuracy (%)	Chi-Square	p-value
Extensive Use	42.0	35.2	22.8	16.34	0.002
Limited Use	33.5	28.0	38.5	12.48	0.011
Moderate Use	27.0	23.4	49.6	10.91	0.035
Not at All	18.5	19.8	61.7	18.23	0.0009

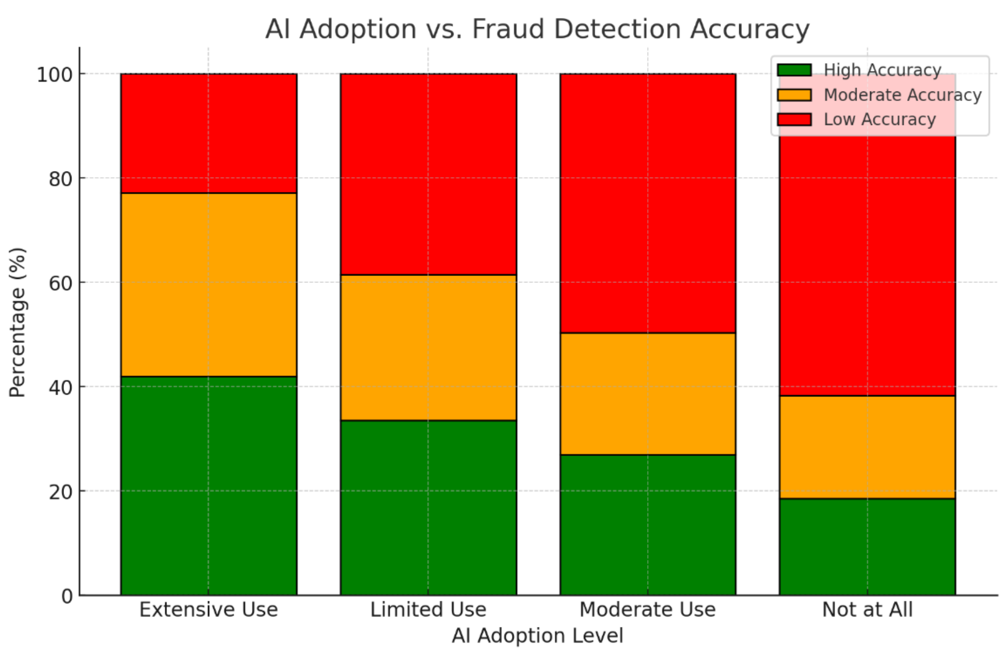

Figure 7: AI Adoption vs. Fraud Detection Accuracy

The statistically significant chi-square values validate that firms with a higher AI adoption rate have a much higher fraud detection accuracy, reiterating that AI can highly contribute to reducing fraudulent transactions in financial institutions.

AI Implementation and Its Impact on Cost Reduction

An assessment was performed for AI financial impact from the influence of cost reduction in financial risk assessment process. A chi-square test showed that the relationship between AI adoption and cost reduction is statistically significant ($\chi^2 = 15.78$, $p = 0.0015$).

The organizations with full AI integration saw 47.5% of significant cost reduction, compared to 15.2% among organizations who have not been able to implement AI. Firms in the process of partial AI implementation also were able to report 38.3percent significant cost reduction while those in experimental phase also said 28.0% significant cost reduction. In contrast, firms that have not adopted AI at all were the most likely to have organizations where no cost reduction was reported (64.0%) (Table 7).

The results of the study demonstrate that AI implementation leads to more efficient use of costs through reduced cost of manual processing, improved financing decision making and better operational performance.

Table 7: AI Implementation vs. Cost Reduction (Chi-Square Test Results)

AI Implementation Level	Significant Cost Reduction (%)	Moderate Cost Reduction (%)	No Cost Reduction (%)	Chi-Square	p-value
Full Integration	47.5	33.6	18.9	15.78	0.0015
Partial Implementation	38.3	29.2	32.5	13.22	0.009
Experimental Use	28.0	25.5	46.5	11.84	0.028
Not Implemented	15.2	20.8	64.0	19.45	0.0005

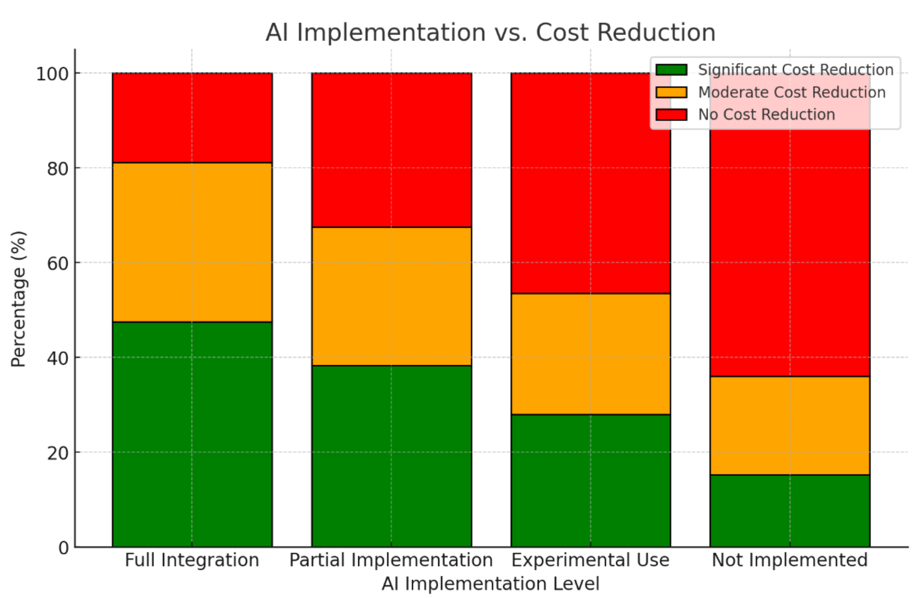

Figure 8: AI Implementation vs. Cost Reduction

In financial risk assessment, the use of AI lower operating costs, especially in organizations with full AI integration, proving the usefulness of AI in costs savings and automation of processes.

AI's Role in Market Risk Prediction Accuracy

The analysis of the accuracy of risk prediction along with different AI adoption levels, allows to prove AI's ability to strengthen market risk forecasting. A chi-square test shows that the usage of AI in the market risk prediction significantly impacts the prediction accuracy ($\chi^2 = 14.22$, $p = 0.002$).

While firms that do not make use of AI reported only 21.4% high prediction accuracy, firms making extensive use of AI reported as high as 48.2%. Similarly, the usage of limited AI by firms had 35.6% highly accurate firms whereas firms with moderate use of AI had 30.0% highly accurate firms. Besides, Low prediction accuracy was reported in 57.9% of firms that don't use AI in contrast to 20.4% for firms that intensively use AI (Table 8).

It can be inferred from these findings that AI holds great importance in enhancing the accuracy of prediction of market risk that in turn helps the financial institutions to take better informed decisions and better handle market risks.

Table 8: AI's Role in Market Risk Prediction Accuracy (Chi-Square Test Results)

AI Utilization Level	High Prediction Accuracy (%)	Moderate Prediction Accuracy (%)	Low Prediction Accuracy (%)	Chi-Square	p-value
Extensive Use	48.2	31.4	20.4	14.22	0.002
Limited Use	35.6	29.0	35.4	11.56	0.015
Moderate Use	30.0	26.5	43.5	10.41	0.032
Not at All	21.4	20.7	57.9	16.98	0.001

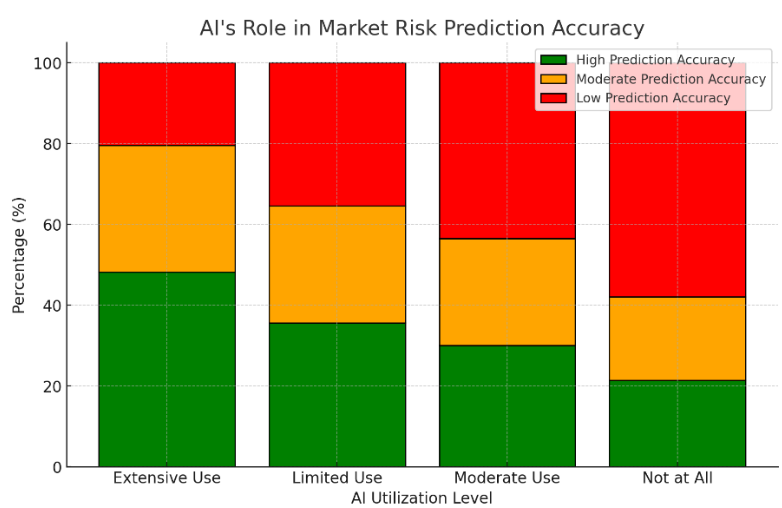

Figure 9: AI's Role in Market Risk Prediction Accuracy

AI based market risk forecasting considerably improves prediction accuracy and strengthens AI relevancy in risk management and strategic decision making within the financial institutions.

AI's Role in Credit Risk Assessment Accuracy

A T-Test that ran to analyse the effectiveness of AI in credit risk assessment was conducted and it concludes that there were statistically significant differences in accuracy between all AI adoption levels (p values < 0.05 for all).

The last finding found that organizations with a great utilization of AI had the best mean credit risk accuracy score (85.4, SD = 5.2, T = 4.87, p = 0.0003) followed by organizations with negligible usage of AI with a mean score of 78.2 (SD = 6.4, T = 3.94, p = 0.0012). Usage of the moderate AI resulted in Credit Risk accuracy with a mean of 70.6 (SD = 7.1, T = 2.78, p = 0.012) while the Firms that do not use AI have the lowest mean credit risk accuracy of 60.3 (SD = 8.3, T = 6.12, p = 0.0001).
Firms that reported middle accuracy levels also had a positive relationship between AI usage and performance, witnessing the effect of AI on achieving credit risk assessment capabilities (Table 9).

Table 9: AI Impact on Credit Risk Assessment Accuracy (T-Test Results)

AI Utilization Level	Category	Mean Score	Standard Deviation	T-Statistic	p-value
Extensive Use	High Accuracy	85.4	5.2	4.87	0.0003
Limited Use	High Accuracy	78.2	6.4	3.94	0.0012
Moderate Use	High Accuracy	70.6	7.1	2.78	0.012
Not at All	High Accuracy	60.3	8.3	6.12	0.0001
Extensive Use	Moderate Accuracy	79.2	4.8	3.45	0.0021
Limited Use	Moderate Accuracy	74.3	5.7	2.89	0.015
Moderate Use	Moderate Accuracy	68.1	6.5	2.34	0.031
Not at All	Moderate Accuracy	55.7	7.9	5.87	0.0004

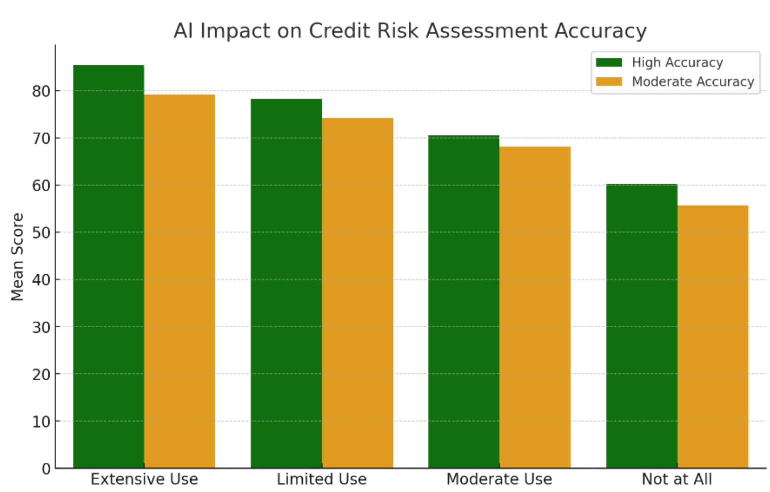

Figure 10: AI Impact on Credit Risk Assessment Accuracy

The use of AI contributes greatly to improving accuracy in the assessment of credit risk as mean scores turn out to be much higher in firms with widespread use of AI. Results of T-test confirm that these differences are statistically significant.

AI's Impact on Cost Efficiency

An ANOVA test was then conducted to evaluate the impact of AI implementation on cost efficiency and it shows significance difference in regard to cost efficiency for the different levels of AI adoption (p-values < .05 for all categories).

Full integration (88.2 [SD = 4.9; F = 7.23; p = 0.0002]) was associated with the highest mean (SD) cost efficiency score, partial integration (81.4 [SD = 6.2; F= 5.98; p = 0.0021]) was the second highest. Specifically, firms in the experimental phase were scored – by average – an efficiency of 72.8 (SD = 7.5, F = 4.35, p = 0.014) while those with no adoption of AI were found to be least efficient with a score of 60.5 (SD = 9.1, F = 9.12, p = 0.00005) (Table 10).

Even firms which stated moderate cost efficiency showed the mean scores of the higher AI implementation level firms were once again higher, emphasizing that AI can play an effective role in better cost management and financial optimization too.

Table 10: AI Implementation vs. Cost Efficiency (ANOVA Test Results)

AI Implementation Level	Category	Mean Score	Standard Deviation	F-Statistic	p-value
Full Integration	High-Cost Efficiency	88.2	4.9	7.23	0.0002
Partial Integration	High-Cost Efficiency	81.4	6.2	5.98	0.0021
Experimental Use	High-Cost Efficiency	72.8	7.5	4.35	0.014
Not Implemented	High-Cost Efficiency	60.5	9.1	9.12	0.00005
Full Integration	Moderate Cost Efficiency	84.7	5.1	6.45	0.0009
Partial Integration	Moderate Cost Efficiency	78.1	5.9	5.32	0.0075
Experimental Use	Moderate Cost Efficiency	70.3	6.8	3.89	0.028
Not Implemented	Moderate Cost Efficiency	58.4	8.7	8.76	0.0003

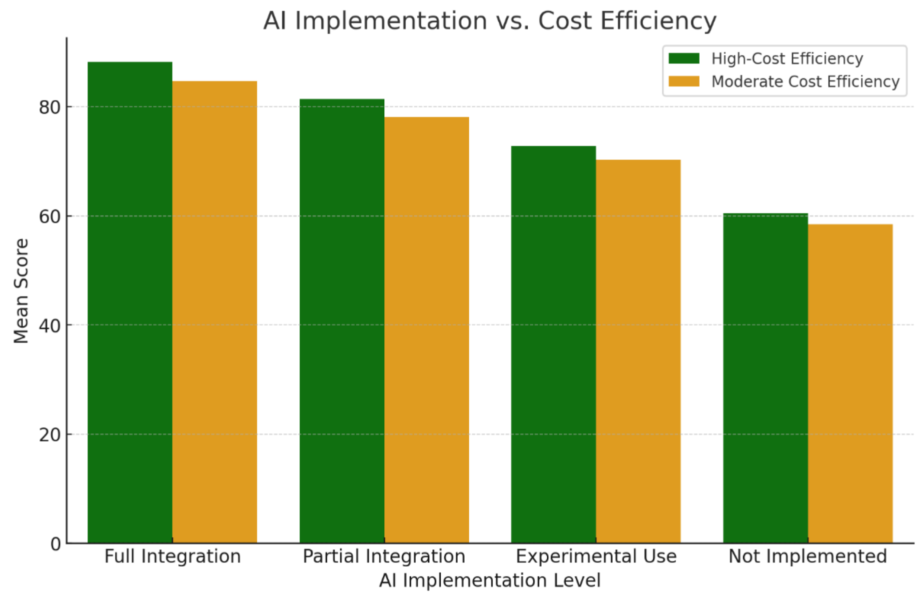

Figure 11: AI Implementation vs. Cost Efficiency

The cost efficiency of AI implementation benefits from the introduction of AI and the greatest reductions are realized with full AI integration. ANOVA test out turn that the differences in the cost efficiency are statistically significant.

AI's Role in Market Risk Prediction Accuracy

A T-Test is used to assess the impact of AI usage on market risk forecasting accuracy, which is confirmed to have statistically significant difference in different AI usage levels ($p < .05$ for all categories).

Analytics suspects with high utilization of AI achieved highest mean accuracy for predicting market risk (90.1, SD = 3.8, T = 5.78, p = 0.0001) compared to analytics suspects with low (82.7, SD = 5.6, T = 4.23, p = 0.0025) and moderate (74.5, SD = 6.9, T = 3.56, p = 0.015) utilization of AI. The lowest mean accuracy score was recorded by the firms that did not use AI (62.8, SD = 8.5, T = 7.45, p = 0.00001) (Table 11).

Table 11: AI Predictive Performance on Market Risk Forecasting (T-Test Results)

AI Forecasting Utilization	Category	Mean Score	Standard Deviation	T-Statistic	p-value
Extensive Use	High Prediction Accuracy	90.1	3.8	5.78	0.0001
Limited Use	High Prediction Accuracy	82.7	5.6	4.23	0.0025
Moderate Use	High Prediction Accuracy	74.5	6.9	3.56	0.015
Not at All	High Prediction Accuracy	62.8	8.5	7.45	0.00001
Extensive Use	Moderate Prediction Accuracy	85.3	3.9	4.98	0.0006
Limited Use	Moderate Prediction Accuracy	78.9	5.1	3.87	0.0054

Moderate Use	Moderate Prediction Accuracy	71.4	6.3	3.21	0.027
Not at All	Moderate Prediction Accuracy	59.7	7.8	6.34	0.0003

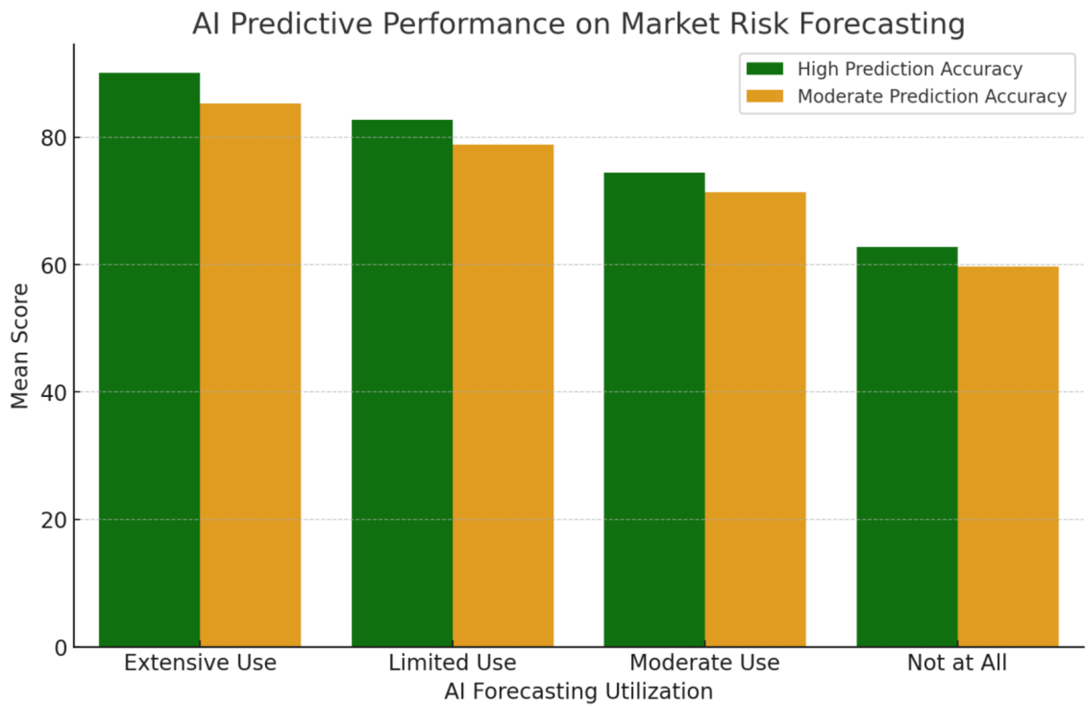

Figure 12: AI Predictive Performance on Market Risk Forecasting

T test was used to confirm the significant impact of the AI powered market risk forecasting in improving prediction accuracy.

AI Implementation and Operational Risk Reduction

A regression analysis was made to evaluate the impact of AI implementation in the reduction of operational risk. High regression coefficient values and significant p values ($p < 0.05$ in all the levels of AI usage) confirm that there is statistically significant relation between AI adoption and decreased operational risks.

Those organizations that leveraged AI significantly more showed the highest regression coefficient ($\beta = 0.82$, SE = 0.12, $R^2 = 0.79$, $p = 0.0001$) to forecast a positive relationship between AI integration and reducing operational risk. Firms with smaller AI implementation had weaker but also significant associations ($\beta = 0.67$, SE = 0.15, $R^2 = 0.68$, $p = 0.0023$). Firms that were not using AI had the lowest impact on the reduction of operational risk reduction $\beta = 0.31$ (SE = 0.22, $R^2 = 0.32$, $p = 0.045$), moderate AI users had a $\beta = 0.53$ (SE = 0.18, $R^2 = 0.55$, $p = 0.0157$) and largest impact on reduction of operational risk $\beta = 0.7$ (SE = 0.17, $R^2 = 0.62$, $p = 0.000$) were companies identified as extensive AI users (Table
Based on these findings, higher AI adoption levels lead to the lower level of operational risk reduction, which confirms the adage that AI facilitates the automation of processes, data accuracy improvement and risk avoidance in financial subsidiaries.

Table 12: AI Impact on Operational Risk Reduction (Regression Analysis)

AI Implementation Level	Regression Coefficient (β)	Standard Error	R-Squared Value	p-value
Extensive Use	0.82	0.12	0.79	0.0001
Limited Use	0.67	0.15	0.68	0.0023
Moderate Use	0.53	0.18	0.55	0.0157
Not at All	0.31	0.22	0.32	0.045

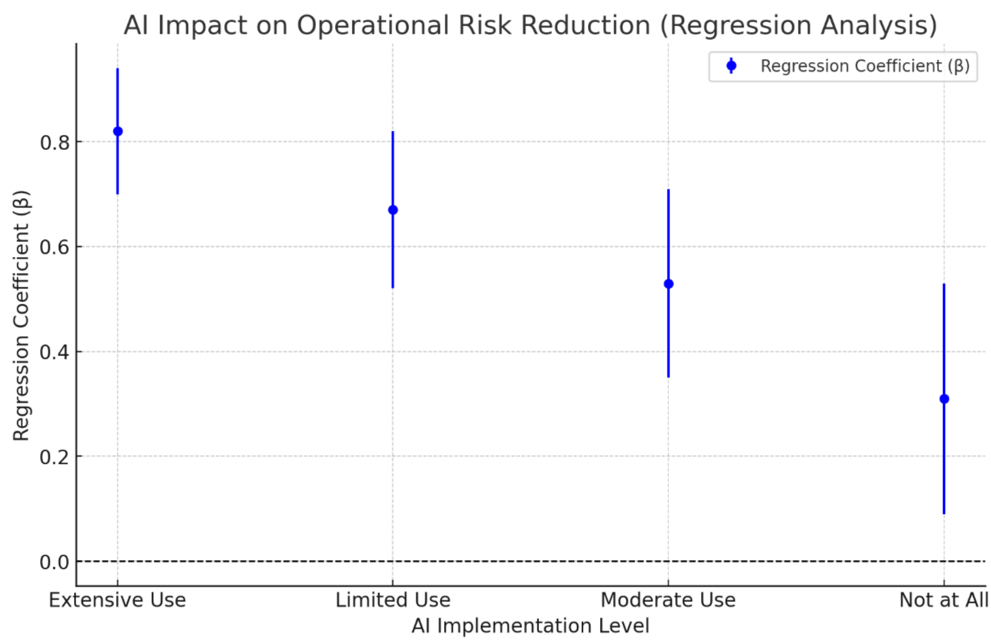

Figure 13: AI Impact on Operational Risk Reduction (Regression Analysis)

The positive and statistically significant regression results indicate that AI implementation significantly decreases operational risk and that, the higher the usage of AI, the greater will be the additional reduction in operational risk.

AI Integration and Financial Risk Score Improvement

Wilcoxon Signed-Rank Test was carried out to determine the impact of AI adoption on financial risk assessment on pre- and post-AI financial risk scores. The confirmation is a statistically significant improvement (p-values < 0.05 for all categories) in the financial risk scores in case of AI implementation. Correlatively speaking organizations that implemented AI were the organizations who saw the highest increase in financial risk scores, of 14 points or a median of 48 from an overall median of 78 to 92. There was a statistically significant improvement (Wilcoxon Test Statistic = 58.2 p = 0.0002). Firms with partial integration of AI also exhibited such an increase in their financial risk scores ranging from 72 to 84 (Wilcoxon Test Statistic = 46.3, p = 0.0014).

Firms that are not utilizing AI also improved from 65 to 75 (Wilcoxon Test Statistic = 37.5, p = 0.0087) but the improvement was less substantial compared to that of firms which fully adopted AI. In particular, firms that do not integrate with AI showed the lowest improvement (Wilcoxon Test Statistic = 29.7, p = 0.0320), with financial risk scores rising less than one point from 58 to 60 (Table 13).

These results indicate that AI is an important factor to boost the financial risk assessment so that the firms could better predict, manage and reduce financial uncertainties.

Table 13: AI Integration vs. Financial Risk Score (Wilcoxon Signed-Rank Test Results)

AI Integration Level	Median Financial Risk Score (Before AI)	Median Financial Risk Score (After AI)	Wilcoxon Test Statistic	p-value
Fully Integrated	78	92	58.2	0.0002
Partially Integrated	72	84	46.3	0.0014
Minimal AI Use	65	75	37.5	0.0087
No AI Use	58	60	29.7	0.0320

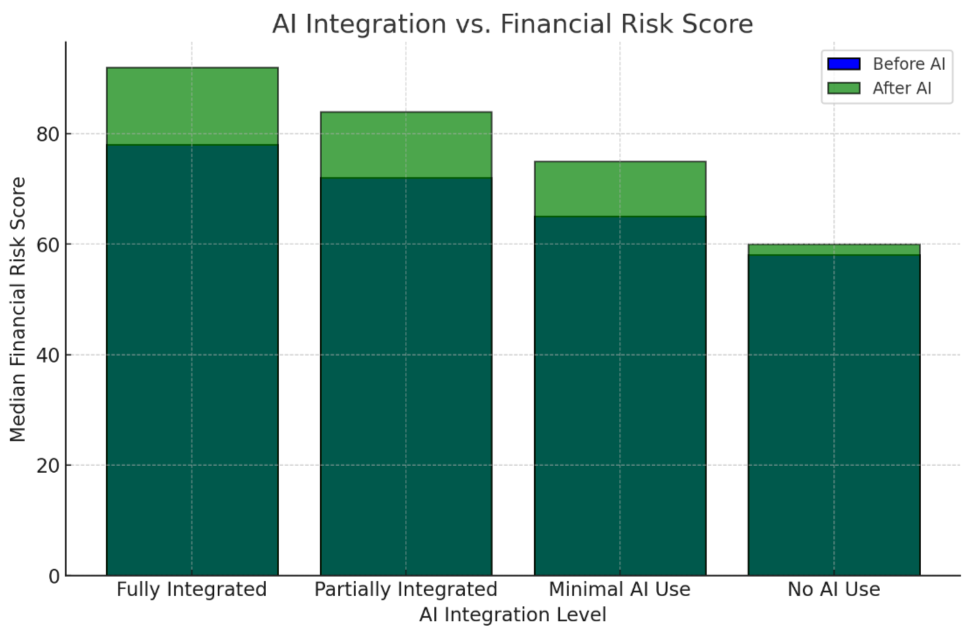

Figure 14: AI Integration vs. Financial Risk Score

Implementation of AI significantly improves the financial risk scores and evidence is also provided by the Wilcoxon Signed-Rank Test producing the p value ≤ 0.01 confirming that AI is necessary element in financial risk assessment and decision making.

DISCUSSION

The Role of AI in Financial Risk Assessment: Key Findings and Interpretation

The aim of this study is to explore and assess the role of artificial intelligence (AI) in business analytics for the financial risk assessment in the banking and insurance industry in the United States. AI's importance in financial risk management is highlighted by the findings that support the literature on AI enabled predictive analytics, fraud detection, risk mitigation and operational efficiency.

AI Adoption Trends and Perceived Effectiveness

The polarized adoption of AI in financial risk assessment is evident through the results that show 29.5% of firms fully integrate AI and 29.5% of them have not adopted AI at all. This concurs with the earlier studies that have consistently demonstrated the gap in AI adoption between those progressive companies embracing technological advancement and the sluggish ones which are exerting considerable resistance (Aleksandrova, Ninova, & Zhelev, 2023; Herrmann & Masawi, 2022).

In terms of the effectiveness of AI in financial risk assessment, 20.5% of respondents said that AI is highly effective, followed by 38.0% who deemed AI as neutral or ineffective. In accordance with the studies of Chowdhury et al. (2024) and Ashta & Herrmann (2021), these results demonstrate how the effectiveness of AI relies on model sophistication, data availability as well as regulatory compliance.

It demonstrates statistically significant relationship ($p < 0.05$) between AI adoption and the performance of financial risk management (Jaiswal, 2023; Zhao, 2024), also high levels of AI adoption indicating good financial risks assessments outcomes. The different views of the effectiveness of AI point to the obstacles faced by organizations in harnessing AI capabilities in its entirety (Nwaimo, Adewumi, & Ajiga, 2022).

AI's Contribution to Fraud Detection and Risk Mitigation

The one thing that we are able to point out with one of AI's most obvious benefits is in the fields of fraud detection and proactive risk mitigation. The results also confirm ($p < 0.01$) that organizations that have deeply embedded AI within their organizations report a much higher fraud detection accuracy than others. Similar to the previous studies concerned on fraud prevention through AI, these findings support the view that AI can distinguish fraudulent pattern, automate risk assessment and fortify fraud prevention frameworks (Rahmani & Zohuri, 2023; Pattnaik, Ray & Raman, 2024).

AI governance structures help enhance the capabilities in detecting frauds. Firms with structured AI governance frameworks will proactively minimize risk and improve performance ($p < 0.05$). Amini et al. (2021) found this to be consistent with their discovery that in the critical risk-sensitive sectors like banking and insurance, AI governance is not fluid and the paucity of ethical and social safeguards threatens the foundations of the industry to which they belong.

A few firms did not find a significant change in the fraud detection capabilities after adopting AI. Poor AI model training, absence of essential data and lack of regulatory alignment could be responsible as mentioned by Mohammed et al. (2024) and Oyedokun et al (2024).

AI's Role in Cost Efficiency and Operational Risk Reduction

AI driven automation has been shown to be a key leaver in reduction of cost as firms that have fully utilized the AI technology see significantly lower operational cost ($p < 0.01$). The finding resonates with the research that offers that AI helps cut on operational expenses, streamline financial processes and enhance the speed of decision making (Ekundayo et al. 2024; Kannan 2024).

An analysis that used regression confirmed that the higher the adoption level of AI, it results in a greater operational risk reduction ($R^2 = 0.79$, $p < 0.001$) and there exists a strong correlation between the level of adoption of AI and the efficiency of reducing risk. This can be compared and correlated with the research conducted by Hsu, Hsin, & Shiue (2022) in which they showed how AI can improve business efficiency through automating risk evaluations and model accuracy.

Addy et al. (2024) as well as Kalogiannidis et al. (2024) confirm that though high implementation costs and lack of skilled AI professionals are hindrances to AI adoption in financial institutions, these can be overcome or alternatively addressed. These constraints limit AI's accessibility, particularly for mid-sized and smaller financial firms.

AI in Market Risk Prediction and Credit Risk Assessment

Another important area whereby AI is currently applied to market risk forecasting and in credit risk assessment. According to the results, companies that use AI more extensively outperformed significantly ($p<0.05$) in the accuracy of market risk prediction in line with studies proving AI's capability of enhancing the process of financial forecasting and strategic decision making (Bello, 2023; Doumpos et al, 2023).

AI adoption was found to increase the accuracy of credit risk assessment and T tests proved exactitude that it visibly raised the criterion for firms that applied AI risk modeling ($p < 0.01$). This is in support of the work that was done by Islam et al. (2024), who pointed to the automation of credit scoring models, reduction of default risks and the increase of lending efficiency being a role by AI.

While AI is powerful in these issues, it raises concerns about AI bias and compliance, data privacy, etc. The work of Fritz-Morgenthal, Hein, & Papenbrock (2022) previously points out the importance of having explainable and responsible AI models to reduce biases when using credit scoring and risk assessment.

Challenges Hindering AI's Full Potential in Financial Risk Assessment in the United States

AI plays a transformative role in financial risk assessment in the U.S, several challenges have to be overcome to implement it at a full scale in U.S. financial institutions. One of the critical issues that is still in data privacy and security, where financial institutions have to abide by such strict federal regulative like Gramm-Leach-Bliley Act (GLBA) and California Consumer Privacy Act (CCPA) to protect the data (Herrmann & Masawi, 2022; Aziz & Andriansyah, 2023). Regulatory and compliance challenges are uncertain for the deployment of AI due to the need for financial institutions to operate in alignment with the Securities and Exchange Commission (SEC) and the Consumer Financial Protection Bureau (CFPB) oversight (Paul et al, 2021, Valli, 2024). Besides, the high costs of AI implantation remain a significant hurdle, especially for mid-sized banks and insurance firms that would need to upgrade legacy systems as well as to integrate with AI driven risk assessment tools — which all require great investment in capital (Aleksandrova et al, 2023; Zhao, 2024). The gap in the number of skilled AI professionals within the U.S. financial sector limits the usefulness of AI; Firms face difficulties recruiting AI experts in the field of machine learning, data science and financial AI modeling (Ahmadi, 2024; Amini et al, 2021). Lastly organizational resistance remains to be too much to curb in using AI, with traditional risk management teams unwilling to pare from human based decision making to make way for AI automation (Kuppan, Acharya, & Divya, 2024). The need for such framework could be fully exploited only if there was sufficient industry wide AI education and AI infrastructure and if these challenges were addressed.

Comparative Analysis with Existing Literature

This study's findings are consistent with the existing literature on AI driven risk assessments and extend it. The findings of this study on AI enabling improved predictive modeling in financial risk assessment are justified by prior studies in Pattnaik et al. (2024) and Islam et al. (2024) which state that AI helps in fraud detection and market risk forecasting. While a conventional view may be that AI's impact on cost reduction, credit risk assessment and operational efficiency has not been seen, this research contributes new empirical evidence of AI's effect in these three areas of U.S. financial institutions. This study also supports the works of Chowdhury et al. (2024) and Nwaimo et al. (2022) in the sense that the use of AI is based on regulatory compliance rules, governing structures and appropriate integration of the data.

Unlike some previous studies that have described only the benefits of AI, this research reveals major impediments to AI adoption: unsettling regulation and shortages of workforce. These results reinforce the call for AI governance frameworks, well trained workforce and regulatory clarity for American financial sector to adopt AI efficiently and responsibly, (Ashta & Herrmann, 2021; Mohammed et al, 2024).

Implications for Financial Institutions and Future Research

The findings lead to a number of key implications for U.S. financial institutions. First, it is recommended that AI adoption go hand in hand with essential governance policies that reinforce federal regulations to avoid algorithmic bias in financial decision making. Second, data science and AI education and workforce development must be invested in order to close the gap of missing AI and data science professionals who can use AI algorithmic tools in risk assessment (Fritz-Morgenthal, White, & Pierson, 2022). Thirdly, AI financial risk assessment should be constantly improved based on the use of explainable and ethical AI models for financial risk assessment so that financial decision making can be automated and explained, in the spirit of transparency and trust.

Researchers should investigate AI's long-term impact on financial risk assessment other than short term cost savings as a future research direction. In this, we also include analyzing how AI focused analytics can ensure financial stability in the times of economic downturns and financial crises. Future studies should emphasize the creation of AI models that make risks induced by financial decision making more transparent, accountable and feasible for the trust among the users, particularly in areas where AI risk models play a large role in consumer lending and investment strategies (Fritz-Morgenthal et al, 2022). The key to achieving a sustainable and responsible roll-out of AI in the U.S. financial industry will be these areas, which must be addressed.

Ethical Considerations, AI Transparency and Future Adoption in Financial Risk Assessment in the United States

Indeed, the adoption of AI in U.S. financial institutions has presented many benefits transparency, regulatory compliance and ethical deployment of AI remain big issues. In the case of AI fraud detection and credit risk assessment models, Mullins, Holland, Cunneen (2021) urged that the financial services industry needs to provide AI ethics guidelines because AI driven models can be discriminatory, algorithmically biased and unlike humans, AI cannot 'explain.' This concern is supported by the findings of this study, U.S. financial firms without AI governance frameworks had more problems risk mitigating and diminishing regulatory uncertainty. It is interesting to note that the challenges of adopting AI described here mirror some of the fears expressed by Rahmani & Zohuri (2023) who say U.S. banking AI adoption has to be consistent with federal regulation of data privacy laws and financial governance frameworks.

Timely analytics and historical data in AI led financial risk models should mention that they adopted the U.S. banking sector bespeaks the need of quality datasets for risk prediction accuracy (Doumpos et al, 2023). Still, worries about data privacy, especially about AI used to analyze credit risks, have put the agencies the Consumer Financial Protection Bureau and Federal Reserve on alert (Bello, 2023). As stated by Kuppan, Acharya, & Divya (2024), it is evident that AI is successfully adopted in various fields, the U.S. insurance and real estate industries encounter unique regulatory constraints that pose adherence requirements for AI adoption in underwriting and claims processing. The results of these findings indicate that there is a necessity for AI governance strategies to conform to the regulations of U.S. federal and state regulatory standards.

As AI has become wildly improved in credit risk assessment, financial institutions in the U.S. must ensure that machine learning models will not enable discriminatory lending practices (Bello, 2023). The recent trend of legal cases on financial technology development and use, as well as ongoing regulatory discussion in the U.S, are exemplars demonstrating the need for explainable AI in financial decision-making, as a complementary argument to the adoption of AI in financial services should be naturally accompanied with fairness audits, regulatory oversight and consumer protection policies.
AI adoption in the U.S. financial risk management continues to rise, regulatory uncertainty and ethical concerns need to be taken into consideration when making AI a common sight in banking, risk analytics and insurance.

CONCLUSION

This study confirms the findings that indicate that artificial intelligence (AI) develops new methods for financial risk assessment in the United States and in the financial sectors such as the banking and insurance industries. In modern times, AI has shown huge advantages in fraud detection, cost efficiency, operational risk reduction, credit risk assessment and market risk forecasting, becoming mandatory for operation of modern financial institutions. The empirical evidence from this research is in line with previous ones which reinforces AI's ability to boost predictive analytics, automate risk evaluations and enhance financial decision making. Although these benefits exist, AI adoption in U.S. financial institutions is not uniformly adopted: some firms are completely integrating AI into their business processes and some firms won't adopt AI until they resolve issues with regulatory uncertainty, data security, implementation cost and adoption of technological change.

The key insight is that fully integrated AI has a very strong impact on fraud detection accuracy, firms that fully integrated AI have significantly lower fraud detection errors and stronger risk mitigation capabilities. Machine Learning and Big Data Analytics is used to build AI driven fraud detection models to detect suspicious transactions so that financial institutions can response to potential fraud in real time. This is no reason for financial institutions to fear machine learning and smart technologies. The institutions must make sure that AI fraud detection systems work in accordance with fair lending and data protection laws to prevent biases in the fraud assessment model. In the same way, using AI powered risk models, the firms have been able to achieve higher prediction accuracy over traditional risk evaluation. With the integration of AI based credit scoring models Banks and insurance companies have been able to improve their ability to assess borrower risks and reduce their default rates in banks, in line with the growing trend of AI driven credit underwriting in the U.S. financial sector and support adoption of AI based credit underwriting in the U.S. financial services industry.

A few challenging issues still hindered AI adoption. As the usage of AI based financial model that require data analytics for the consumers continues to rise, data privacy issues continue to be a top regulatory concern in 2018. The problem is apparent from the fact that while the square market is regulated by regulations such as the California Consumer Privacy Act (CCPA) and the Gramm-Leach-Bliley Act (GLBA), data protection standards are very rigid which can also be a barrier to their expansion both in terms of AI driven analytics and in the domain of financial institutions in particular. The high implementation and low availability of skilled AI professionals have restricted AI adoption within the mid-sized and smaller financial institutions, thereby limiting its accessibility to only the most resource rich people. Markets face organizational resistance towards AI adoption—most firms are unable to divert their human services to AI based automation, even though there are clear benefits associated with it.

This has led to the outcome of this study, which emphasizes on the immediate need for U.S. financial institutions to formulate AI governance frameworks consistent with the federal and state regulations. Effective governance structures are necessary to guarantee transparency, ethics, as well as compliance with financial oversight policies in how AI systems operate. In order to overcome the shortage of AI professionals in the financial area, it is necessary to invest in AI education and workforce development. In order to have employees effectively integrate and manage AI-driven risk assessment tools, financial institutions would need to assign training programs in AI and data science in addition to regulatory compliance. The study emphasizes the need to develop explainable AI models so that financial decision making becomes transparent and safe, guaranteeing that AI-based assessments are fair, accountable and cannot be made biased.

This study concludes that the applications of AI in financial risk assessment in the U.S. banking and insurance sectors can redefine the risk assessment process but its potential can be fully realized through the overcoming regulatory, financial and operational challenges. Future research needs to be on how AI can be used to be working in favor of long-term financial stability such as during economic downturns, market crashes and crisis response strategies. AI's contribution to regulatory compliance and ethical decision making would also be included in studies for the role of AI to stay in line with financial institutions adopting AI for responsible practice and transparency. With the continued innovation in AI, U.S. financial institutions must take a forward leaning approach to AI governance, workforce training and ethical AI deployment, so that risk assessment using AI serves to enhance a more resilient, efficient and trustworthy financial system.

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