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A Comparative Assessment of AI-Driven Risk Management Governance: Evidence from Major US and UK Banks

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ABSTRACT

Risk management has a key role in securing the strength and execution of financial institutions. As of late, there have been growing levels of complexity in banking systems and financial markets. These complexities include regulatory pressures, market unpredictability, and advancement in the field of technology. As a result, banks have consistently evolved their risk management practices to comprehend and deter any financial risks.

***Keywords**: Risk Management, Financial Institutions, Financial Markets, Market Unpredictability, Financial Risks.*

Introduction

The embracement of artificial intelligence and complex statistics/analytics has crucially altered the processes of risk management in the banking sector. Ai-driven tools are progressively utilized for fraud detection, credit risk assessment, compliance with regulations, and risk supervision. These technologies and tools do improve validity and coherence, basically anything that manages risk better. However these tools can also make it harder to keep things under control. Although ai is a tool that one can use for their benefit someone has to control it and take accountability if anything goes wrong.

So far there have been many studies that have evaluated traditional risk management and market behaviour. However there are only a few researches examining how banks control AI-based risk management systems. This study extensively compares how major bank firms in the US and UK contrastingly manage and regulate risk management that is AI driven.

Review of Literature

Dhumal and Jha (2018), investigated the stake of structured risk management customs in financial markets. Credit risk, market risk, operational risk, and liquidity risks were all key risks that the study identified. The study points out the use of tools like stress testing, hedging, Value-at-Risk (VaR), and diversification, finalizing that to ensure market stability and to minimize losses it is crucial that effective management is implemented.

Singh and Verma (2012), carried out a study focusing on developing markets. The study conducts an investigative assessment on advanced portfolio risk management strategies while highlighting the need for diversity and constant monitoring in reducing downside risks and volatility in trading portfolios.

Bhowmik and Wang (2020), assessed multiple GARCH models in their systematic analysis. These models were utilized to forecast stock market volatility. The study examined practical evidence from both developing and already developed economies and finalized that advanced econometric models substantially improve investment decisions and enhance return forecasting accuracy.

Lamont (2019), reviewed the productiveness of risk management strategies when it comes to market volatility and inflation risk. The findings showed that diversification and disciplined investment strategies can reduce uncertainty even though there are certain market risks that are inescapable.

Kumar and Bansal (2021), inspected the relationship between portfolio performance and investor risk tolerance. Their study explored the psychological and demographic factors which influenced investment decisions and found that higher risk tolerance is connected with better risk-adjusted returns despite the fact that behavioral biases may impair outcomes.

Healy and Palepu (2023), reviewed and studied how stock price behavior can be influenced by disclosure and transparency practices. The research winded up by finding that investor confidence, the diminishing of information asymmetry, and contribution to market efficiency can all be enhanced by improved risk disclosures.

Marrone and Spagnolo (2011), reviewed the role of governance mechanisms in the course of financial stress. The findings of this study indicates that risk committees, strong board oversight, and internal controls can very much improve sustainability and reduce credit risk during moments of crisis.

Rahman, Hossain, and Ahmed (2022), carried out empirical research that explores the connection amid stock performance in the banking industry and formal risk management implementations. Employing regression analysis throughout publicly recorded banking institutions, the study established that structured enterprise risk management frameworks were interrelated with developments in stock returns spanning from 8–12%. The findings further cover that reinforced credit risk controls gave measurable improvement in enhanced market confidence and return on equity. These results presuppose that effective institutional risk governance promptly affects capital efficiency and financial performance, augmenting the significance of efficient supervision mechanisms in banking industries.

Chen, Liu, and Zhao (2024), in their research, inspected machine learning in financial risk management and the application of artificial intelligence. The findings determined that accurate real-time risk predictions can be provided by AI-driven systems compared to traditional models especially in volatile market conditions.

Sang (2024), scrutinized recent developments in banking risk management, as well as the inclusion of ESG considerations, sustainable finance, and artificial intelligence. The study found that although advanced risk management structures can refine long-term elasticity, they can also introduce regulatory, ethical, and governance challenges.

Research Gap

The literature we have looked at discusses risk management in stock markets and banks. It covers topics like traditional tools to handle risks, ways to predict volatility, how people behave in these situations, what gets disclosed, governance setups, and now more on AI and smart systems taking over. All that together shows why good risk management really matters for keeping things stable and performing well in finance.

But there are some big holes that we noticed. For one, most studies stick to looking at markets or whole portfolios, not so much at single institutions. For example, they mention governance and risk etc, but they don't dig deep into how a big commercial bank actually fits advanced tools into its own internal structure.

Another thing that seems to be lacking is how there is the talk about corporate governance helping during crises, which makes sense, but it raises a question about how these frameworks change to handle overseeing AI-driven risks? That interaction between old school governance and new tech risks, seems underexplored. Which seems highly essential, however is not yet looked at.

There was some interest in intelligent systems and sustainability, but still there wasn’t much information evaluating if banks are really ready governance wise to oversee these in practice. For instance, the capacity for real world oversight, limited research there.

The biggest gap though, is how there is no real comparison at the bank level across different countries. Hardly any empirical work on how major banks govern advanced risk systems under various regulations. For example, comparing US banks like JPMorgan Chase and Co. and Bank of America to

UK banks like HSBC and Barclays. The studies that we have looked over, don't quite cover this. Without those institution specific looks, it's hard to see how rules and structures affect AI risk management effectiveness in different places.

The existing literature has thoroughly examined traditional risk management tools, market volatility models, governance mechanisms, and disclosure frameworks in banking and financial markets. Yet despite all this, we still don't have enough empirical research analyzing how major commercial banks actually manage, validate, and oversee AI-powered risk management systems as part of their enterprise risk frameworks. Even though AI is becoming an integral part in credit risk modeling, fraud analytics, and financial crime monitoring, surprisingly few studies examine how institutions across different countries are organizing and managing their oversight of AI-related model risk across jurisdictions. This study aims to fill that gap by making a structured comparison of AI-driven risk management governance in major U.S. and U.K. banks running under specific regulatory environments.

Objectives of Study

- To examine the AI-driven risk management practices adopted by leading commercial banks in the US and the UK
- To evaluate the effectiveness of AI-based risk management frameworks in mitigating financial risks.
- To compare the governance structures overseeing AI-driven risk management in major banks in the United States and the United Kingdom.

Research Methodology

Research Design

This study conducts a comparative and qualitative research that is designed to go over ai-driven risk management control in major banks from the United States and the United Kingdom. The research is based on secondary data, as it depends on pre published information rather than primary data collections such as surveys or interviews.

Research Approach

The study is descriptive as well as analytical and its aim is to analyse, evaluate, and compare how artificial intelligence is combined into risk management control structure in an organizational environment. To identify the correlation and contrast between US and UK banking institutions in terms of, AI adoption, risk oversight mechanisms, and governance structures, a comparative approach is used.

Sample Selection (Banks)

For this study, four major banks were selected: From the US we selected JpMorgan Chase & Co and Bank Of America, whilst for the UK we chose HSBC and Barclays. These banks were chosen because of their advanced use of ai in risk management, large size, global operations, and because of the amount of detailed public disclosures that are available for access. Since both the US and the UK are leading countries, selecting leading banks from these two countries allows us for a relevant comparison of ai-driven risk management governance under opposing regulatory frameworks.

JPMorgan Chase & Co. (USA)

JPMorgan Chase & Co. is one of the biggest banks in not only the US but in the whole world. The bank is well recognized for utilizing modern technology in their banking system. The bank actively uses artificial intelligence for fraud detection, supervision of credit risk, and handling functioning risks. Since the bank publishes intricate reports, it makes it useful to us for studying how AI risks are controlled within the bank.

Bank of America (USA)

Bank of America is a major US bank that has a strong background when it comes to digital banking and risk management. The bank uses Ai for fraud preventing, monitoring risk, and conformity. The Bank of America has accessible reports that work as a clear help in understanding risk management control and how it works.

HSBC (UK)

Is an internationally operating, leading UK bank that has previously invested a lot in digital risk management as well as ai. The bank concentrates on any proper inaccuracies and control that comes with using AI. The bank has public disclosures that we can use to compare with US banks with regard to control and practicing regulations.

Barclays (UK)

Barclays is another leading UK bank that has also put money into AI and digital risk management. The bank pays close attention while using advanced technologies. Barclays also releases public disclosures allowing us to compare Ai risk management control with US banks.

The study depends on disclosures that were self-reported by the bank itself, which often paints unduly positive picture. This study only examined 4 banks, which confines how extensively you can infer the outcomes. No primary data like surveys or interviews were conducted so no verification can be made about the claims made by the banks versus what actually goes down in their practice.

Risk Management in Banks

This portion offers a constructive analysis of AI-driven risk management governance in the four selected banking firms from the U.S and U.K. Making use of regulatory disclosures, secondary academic literature, and annual reports, the analysis encompasses the integration of artificial intelligence technologies inside enterprise risk management frameworks. The discourse is organized to evaluate individual bank-level risk management practices, accompanied by an assessment regarding the measurable effectiveness of AI, and lastly a comparative examination of governance structures through jurisdictions. This framework permits a thorough and orderly judgement of how AI augments risk identification, validation, monitoring, and board-level oversight.

Risk management in banks is the approach where bank establishments meticulously measure, identify, control, and monitor risks that may hinder its capital, reputation, and earnings. Risk management brings about several factors like credit risk which is a type of risk that occurs when borrowers can't keep up with their obligations. Market risk, which are casualties brought by changes in interest rates, equity prices, exchange rates or commodities. Liquidity risk which is what occurs when banks aren’t able to fulfil their payment obligations. And operational risk which are losses from inadequate people, processes, systems and external events.

There are several key elements that can tell apart a good risk management framework in banging. These elements are risk measurement and assessment, risk identification, risk mitigation and control, and ongoing risk monitoring. This is organized through a formal governance framework, where board of directors determine the overall risk appetite, management then turns this into limits, risk policies, and procedures, as well as independent risk and internal audit functions that give insight and challenge. Most banks also turn to enterprise-wide risk management frameworks like ERM, COSO, or ISO-based risk management standards to make sure that the awareness of risks in a harmonized and consistent manner are carried out by all business units.

In the past few years, artificial intelligence and digitalization have appeared as fundamental considerations in banking risk management. Big data analytics as well as AI-based models are hugely being utilized in fields like credit risk assessment, fraud detection, transaction monitoring, and stress testing, allowing banks to inspect big sums of data in real time and go to more predictive risk assessments from prior purely backward-looking risk assessment. However, rises have still been identified in new risks because of these technologies. These risks include operational risk, model risk, and data risk which all need to be handled within occurring risk management frameworks of the bank that already exist.

Risks are distinguished through scenario analysis as well as data analytics, it is evaluated based on models like stress tests and VaR, and observed through simultaneous dashboards and suppresses any issues at hand. Conventional systems depend on knowledge based models and analytical models, whereas AI-driven approaches utilize machine learning for credit scoring and predictive fraud detection, contributing swiftness but demanding governing for transparency and bias.

Risks are eminent through data analytics as well as scenario analysis which have been reviewed on the basis of stress tests and VaR models, and gone through by simultaneous dashboards that can suppress any issues at hand. Ordinal systems rely on knowledge based models and analytical models, while AI-driven advances use machine learning for predictive fraud detection and credit score. This contributes to swiftness even though governing for bias and transparency is still being demanded.

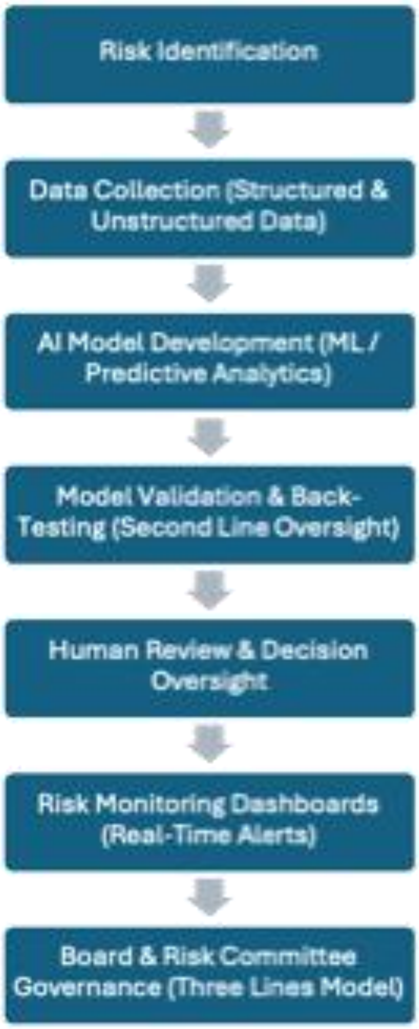

Figure 1: AI-Integrated Risk Governance Framework

Need for Risk Management in Banks

Risk management works as a pillar for the whole financial system thus it is essential for banks to have them, especially considering a bank's job is already inherently risky. They take short term deposits from customers, issue long term loans, and overall use a great deal of borrowed funds to operate, all of these aspects can cause serious problems if not managed thoroughly. Additionally, banks are unified with other financial markets and institutes, so if one bank has a fragile risk management system, it can work as a domino effect and create heavy loss, bank failure, and cause economical damage throughout the entire financial system. Implementing risk management effectively helps guarantee financial balance by confining unanticipated casualties, maintaining trust amongst depositors, investors and regulators, while protecting their capital.

From a regulatory standpoint, strong risk management is critical to conform with sensible frameworks for example liquidity, capital adequacy, and supervised stress testing. It is vital for banks to prove that they are able to distinguish material risks, carry out any possible consequences under harmful scenarios, and execute plausible agendas to stay solvent and liquid even under immense stress.

Risk management at the business level really helps with making smarter decisions and getting better returns after accounting for risks. Banks can set up a clear idea of how much risk they are okay with, and then measure things carefully to price loans right or handle other products. That way, they allocate capital where it makes sense across different parts of the business, and they try to steer clear of piling up too much in one area or getting overexposed somewhere. This makes a difference in how things run day to day. A strong culture around risks, plus being open about what the risk profile looks like, can build up reputation and make investors feel more confident. Those things matter a lot for staying competitive over the long haul.

Significance of AI Driven Risk Management

Now, as AI and all these complex analytics get more built into front office work and risk handling, it seems like the push for solid risk management has to ramp up even more. AI does a good job boosting accuracy and speed, especially in spotting fraud or checking credit or keeping an eye on transactions. But it also brings in bigger issues with model risks, worries about data quality, biases in algorithms, and vulnerabilities to cyber stuff. Banks have to weave AI into their governance setups and controls that already exist, making sure the advanced models can be explained somehow, that they get validated properly, and that someone is clearly accountable for them. If not handled correctly this part could get messy, however there isn’t much information on how banks are approaching this situation yet.

The process of embedding technologies like machine learning algorithms, predictive analytics, natural language processing, pattern recognition mechanisms, and automated decision making systems into conventional enterprise risk management models is AI-driven risk management. These systems process large amounts of structured and unstructured data in real time, helping institutions check defaults, suspicious transactions, keep eye on liquidity pressures, and mark unusual behavioral patterns. What makes these systems different from conventional rule-based systems is the ability of AI-driven models to consistently learn and evolve through training data and pattern identification, improving predictive precision while introducing a new layer of governance responsibilities around validating models, ensuring if their decisions can be understood and explained, rooting out bias, maintaining cybersecurity, and keeping meaningful human oversight.

Basel-Style Risk Management Foundations

International principles state that it is essential that banks manage risk on an enterprise-wide basis, essentially referring to risk management and how it should be implemented throughout all major risk types. The Basel Core Principles for Effective Banking Supervision clarify that the board of directions as well as the senior management are in charge of endorsing risk policies, and a clear risk appetite, as well as ensuring that risk management shields market risk, operational risk, credit risk, liquidity risk, and any other material risks consistent with merged framework. Basel guidance on credit risk additionally establishes that banks are required to have vigorous processes for measuring, identifying, controlling, and monitoring credit exposures. These processes need to have clear stress testing, limits, and independent reviews to guarantee appropriate control and oversight.

These supervisory expectancies can be reflected in the public disclosures of the four case banks. Each bank clarifies that group-wide risk frameworks, via board oversight, along with well defined risk appetite, and risk management processes that are applicable to diverse business lines, are very much present. This gives us the idea that when AI-based tools are implemented by banks, those technologies aren't quite functioning in isolation or independently. Rather they are unified into an already existing risk management architecture already aligned with Basel principles, particularly in regions such as capital protection, risk control, and governance.

The practice of global governance in banking has converged on the “three lines” approach, which allocates responsibilities for risk management and oversight. The Institute of Internal Auditors' revised Three Lines Model defines the first line (management) as responsible for and in control of risk, the second line (risk and compliance) as providing oversight and challenge, and the third line (internal audit) as providing independent assurance on the effectiveness of governance and controls. This framework is commonly used in financial institutions and provides a common point of reference for supervisors and boards in assessing risk management in banks.

The annual reports of the case banks are consistent with this framework. JPMorgan's 2023 annual report presents risk governance through its board risk committee and management risk committees, with independent risk and control functions and internal audit, which together form a three-lines structure. The annual report of Bank of America and its Basel III disclosure also present an enterprise risk management framework in which risk is owned by businesses, overseen by risk functions, and reviewed by audit. The 2024 Annual Report and Accounts of HSBC Bank describes risk governance with board and group risk committee oversight, global risk and compliance teams, and internal audit conducting independent reviews. Barclays' 2023 Annual Report describes its risk governance framework, key risks, and the three lines approach, which focuses on board risk committee oversight and dedicated control functions. On AI risk management, this framework suggests that AI models and systems should be allocated to these lines, which are owned by first- or second-line functions, overseen by risk committees, and reviewed by internal audit, rather than being treated as “tech” that is separate and ungoverned.

Evaluation of the Selected Banks’ Risk Management

JPMorgan Chase & Co. (United States)

- **Background and Institutional Scale**

JPMorgan Chase & Co., primarily located in New york, dating back to 1799, has an approximation of $4.4 trillion in reported total consolidated assets since December 2024. The organization functions throughout 100 jurisdictions globally and sustains a standard average loan portfolio surpassing $1.5 trillion. For the full year of 2025, the bank stated a net income of about $57.0 billion and a return on tangible common equity (ROTCE) of nearly 20%, alongside a revealed net charge off rate of 3.14 percent.

- **AI Systems and Risk Architecture**

JPMorgan combines incline amplifying credit models and probabilistic default modeling systems internally through its credit portfolio monitoring and credit underwriting frameworks. Recurrent neural network based fraud classification engines work within concurrent transaction filtering architectures which filter high-volume payment flows in a widespread manner. Behavioral anomaly detection systems examine trade trends by employing adaptive machine learning in order to identify deviations from confirmed guidelines.

These AI petitions operate under a proper Model Risk Governance Framework integrating back-testing controls and model validation, documentation standards, independent second-line review, and explainable AI (XAI) regulative mechanisms. Human-in-the-loop governance frames secure supervision of model outputs in advance of material risk decisions, aligning with administrative standards and Basel III capital capability arrangement standards.

At the application level, JPMorgan's payments and fraud publication and an AWS case study discuss real-time AI-driven fraud filtering that analyzes payment traffic at a very large scale to reduce fraud and false positives while maintaining a positive customer experience. This example demonstrates the use of AI to improve predictive accuracy and accelerate and scale existing fraud risk processes, all within a very closely governed governance framework.

Within the Basel-compliant, three-lines-based frameworks, the four banks utilize artificial intelligence (AI) in a way that supports and enhances existing risk management processes. JPMorgan’s 2023 Annual Report and its audited financial statements highlight model risk as a separate risk type, together with policies on model development, validation, and monitoring. The company’s public discussion on “AI and Model Risk Governance” further emphasizes the integration of AI and machine learning models into this model risk framework, with cross-functional teams working to ensure model integrity, explainability, and ongoing human review. At the application level, JPMorgan’s payments and fraud publication and an AWS case study discuss real-time AI-driven fraud filtering that analyzes payment traffic at a very large scale to reduce fraud and false positives while maintaining a positive customer experience. This example demonstrates the use of AI to improve predictive accuracy and accelerate and scale existing fraud risk processes, all within a very closely governed governance framework.

Bank of America

- **Background and Institutional Scale**

Bank of America Corporation was established in Charlotte in 1904, with over $3.2 trillion consolidated assets at the end of 2024. There are currently 4000 branches that the institution operates over, with about 213,000 individuals working for them. Its business risk management structure combines board-approved risk appetite statements that cover credit, as well as market, operational, liquidity, strategic, and compliance risks.

- **AI Systems and Risk Architecture**

There are more than 270 machine learning and AI models currently deployed by the bank. These models (Gradient boosting and neural network classification tools) go over cybersecurity, fraud prevention, operation risk, and credit analytics domains. Bank of America makes functions of 2 types of AI models that immediately aid in monitoring and flagging any suspected frauds detected through real-time transaction monitoring. These same AI abilities are additionally utilized to calculate the probability of a borrower unable to settle a debt through probabilistic default modeling, this overall assists banks to manage their overall lending risk and credit exposure management. Moreover, AI's robotic process automation (RPA) integrates with automated stress-testing simulations and compliance analytics.

AI models work under systematic validation and compliance review that are inserted into detection systems that attempt to damage computer network. Explainable AI (XAI) acquiescence frameworks assure of decisions that are deemed to be high-impact, whereas human-in-the-loop governance frames go over model outputs before lending and capital actions.

Bank of America's 2023 Annual Report and Basel III disclosure offers an enterprise risk management framework that addresses credit, market, liquidity, operational, and compliance risks within a board-approved risk appetite. In this context, the company's publications on machine learning and cybersecurity describe the use of AI to detect anomalies, improve threat detection, and help prevent fraud by continuously analyzing network and transaction activity. Reuters reports that a large number of Bank of America's recent patents have been in the area of AI and information security, reflecting the company's ongoing focus on AI for risk and cyber-control applications. These sources together confirm that AI is used to improve operational and cyber-risk resilience, with its development processfully integrated into the company's overall risk and technology strategies rather than as a separate innovation effort.

HSBC Holdings plc (United Kingdom)

- **Background and Institutional Scale**

HSBC was formed in 1865, with its headquarters being in London. This establishment is currently active in 62 countries and possesses assets of approximately $3 trillion. It operates under Prudential Regulation Authority supervision and international Basel III standards as it is a Global Systemically Important Bank (G-SIB).

- **AI Systems and Risk Architecture**

For its financial crime and anti-money laundering functions, machine learning-driven Dynamic Risk Assessment systems are used by this establishment. HSBC uses machine learning–based dynamic risk assessment systems in its financial crime and anti–money laundering operations. In collaboration with Google Cloud, it employs real-time transaction monitoring systems that use probabilistic modeling and behavioral anomaly detection to evaluate suspicious activity.

AI systems operate under Model Risk Management Framework that is dedicated to them and one that includes model validation and back-testing procedures, bias evaluation, explainable AI (XAI) compliance, and structured independent review processes. Automated stress-testing models strengthen capital scenario analysis, helping ensure alignment with Basel III capital adequacy requirements across global portfolios.

The case study with Google Cloud illustrates that the AI-based solution can process a massive amount of data in near real-time and has improved the quality of alerts for monitoring transactions, with fewer false positives and pointing investigators to truly high-risk cases.

The 2024 Annual Report and Accounts of HSBC contains a thorough analysis of key risks and risk management, including financial crime risk and operational risk. At the same time, the public press release by HSBC on "Harnessing the Power of AI to Fight Financial Crime" introduces the bank's Dynamic Risk Assessment tool, which uses artificial intelligence and analytics to track customers' transactions and behavior for signs of money laundering. The case study with Google Cloud illustrates that the AI-based solution can process a massive amount of data in near real-time and has improved the quality of alerts for monitoring transactions, with fewer false positives and pointing investigators to truly high-risk cases. According to the report by Reuters, HSBC's overall AI plan includes collaborations with AI companies to help develop generative AI for the bank's internal use, described in the context of the bank's efforts to optimize efficiency and risk management. These sources together suggest that AI is thoroughly embedded in HSBC's management of financial crime and operational risk, as described by the oversight mechanisms outlined in the bank's annual report.

Barclays plc (United Kingdom)

- **Background and Institutional Scale**

Barclays plc, stationed in London was implemented in 1690, operating around 40 countries with approximately $1.7 trillion of total assets. Its enterprise-wide risk management framework that is supervised by the Board Risk Committee, is governed with a structured three-lines-of-defense architecture.

- **AI Systems and Risk Architecture**

Barclays embraces a rooted AI governance techniques in which, behavior anomaly detection tools, neural network based fraud classification systems, and predictive analytics engines work within current operational risk and model risk frameworks. Up to date deal filtering structures assist cybersecurity flexibility and fraud monitoring.

AI applications fall within the scope of back testing controls that are steady with traditional risk models and model validation. Explainable AI (XAI) conformity secures clarity within statutory reviews, while human-in-the-loop governance frames manage automated decisions that are very demanding. These systems work in coordination with PRA supervisory expectations and Basel III capital adequacy conditions.

The 2023 Annual Report of Barclays Bank explains its risk governance and major risks, including credit risk, market risk, treasury risk, operational risk, and conduct risk, in an enterprise-wide framework and three lines of defense approach. In a public insights article, Barclays Bank claims, "Fraudsters are getting smarter – but so are we," emphasizing the application of advanced analytics and machine learning techniques to detect unusual patterns and prevent fraud in customer accounts. Evidence presented by Barclays to a parliamentary committee in the UK also suggests the bank's use of big-data analytics in fraud detection and cyber risk, combining data from multiple channels to track suspicious activity. Moreover, the bank's policy statement on financial crime describes its overarching strategy for sanctions and AML compliance, with a focus on governance and risk controls for financial crime risk, even if not all underlying tools are specifically identified as "AI."

Effectiveness of AI-Based Risk Management Frameworks

- **JPMorgan Chase & Co. – Measured Impact**

Throughout the 2024-2025 during the period under review, AI-enhanced predictive analytics endorsed firm portfolio performance, taken into account of sustained profitability and charge-off levels. Improved fraud-prevention architectures diminished any false alarms while fortifying detection precision, aiding risk reduction and operational effectiveness across digital payment systems. External launches further stated no substantial cybersecurity occurrences, which entails potent inclusion of AI within enterprise cyber and risk resilience frameworks.

- **Bank of America – Measured Impact**

Throughout 2024-2025, AI-enabled fraud detection systems fundamentally decreased exposure caused by digital fraud, with industry reports suggesting decreases nearing 50% in particular classes. Behavior anomaly detection systems furthermore boosted cyber resilience and lowered assistance inadequacies. These discernable improvements results prove tangible risk reduction stemmed from AI incorporation within business governance frameworks.

- **HSBC Holdings plc – Measured Impact**

AI-powered AML monitoring helped cut down false positive alerts and improved accuracy in spotting high-risk cases during the 2024 reporting period. Predictive modeling that had been enhanced, also led to more efficient capital allocation and stronger financial crime prevention, even within a highly regulated environment.

- **Barclays plc – Measured Impact**

AI-driven anomaly detection systems upgraded the speed of fraud detection and amplified the effectiveness of operations across channels throughout 2024-2025. Inserting AI within already present governance structures upholds extensible stationing while continuing needed discipline and institutional stability.

To exemplify the measurable outcomes throughout the chosen establishments:

Throughout the four establishments, AI execution has shown quantitative and perceptible risk developments.

JPMorgan Chase has decreased false positives related to fraud by approximately 20% using its AI-driven fraud detection systems. These systems not only help reduce false positives but also enhance persistent profitability adjacent to enhanced AI-based risk governance.

In 2024, **Bank of America** recorded a net income of $27.1 billion in which they also dispensed machine learning models and 270 AI across credit analytics, cybersecurity, and fraud detection functions. In the industry case studies, it is stated that due to these AI-enabled systems, there have been substantial reductions in digital fraud exposure and enhanced predictive monitoring.

HSBC reported $32.3 billion in profit before tax in the year 2024. False positive alerts were reduced to an approximation of 60% with the help of their AI-powered anti-money laundering (AML) monitoring systems. This permitted investigators to improve operational efficiency while concentrating on genuinely high-risk transactions.

A group income of £26.8 billion was recorded in group income in 2024 by **Barclays**. Barclays reinforced cyber resilience while also improving real-time risk response capabilities with the help of their AI-based anomaly detection systems which lowered fraud investigation by about 60%.

These quantifiable results establish that AI-based frameworks improve scalability, responsiveness, and accuracy in risk governance when fixed within oversight mechanisms and organized model validation.

In all four banks, the use of artificial intelligence is reported to improve risk management by increasing predictability, speed, and scalability, with a focus on fraud, financial crime, and operational risk. This is still contained within the risk and model risk management frameworks, which directly corresponds to the aim of assessing the effectiveness of AI risk frameworks in managing financial risks.

Comparative Governance of AI-Driven Risk Management in the U.S. and U.K.

When looking at both bank-level disclosures and regulatory principles, it gives us the opportunity to compare between UK and US banks. The Basel standards produce general expectations for risk governance, implying that all major banks should follow high-level rules that are equivalent to them. Despite that, national supervisors and different market contexts provoke banks to prioritize separate risk priorities. For instance Bank of America and JPMorgan Chase, which are large US-based banks, position firm attention on market risk, liquidity risk, credit, as well as compliance risk and operational, in their annual reports. This shows that they manage huge wholesale and retail portfolios. When mentioning AI, their official papers, like JPMorgan's AI and model-risk governance article and Bank of America's machine learning in cyber security materials, demonstrate that they utilize AI in order to control important operations in areas like credit, cyber-threat detection, and payments. They showcase AI as a device to improve both productivity and risk control.

On the other hand, Barclays and HSBC, which are both UK based and function across many countries with extensive cross-border operations, depict AI contrarily. They link AI more towards financial crime compliance, operational resilience, and sanctions. For instance, the Google Cloud case study by HSBC and its Dynamic Risk Assessment illustrate how the bank uses AI to combat money laundering and improve its transaction monitoring capabilities. It highlights the importance of compliance and financial crime detection. In the same way, Barclays' parliamentary evidence and its fraud prevention insight underline the utilization of big data analytics and machine learning in order to track down any cyber threats and fraud. Correspondingly, Barclays external summaries of sanctions related enforcement actions and their financial crime policy statement both emphasise the need for robust controls and financial crime governance. These documents display that analytics based tools are being incorporated into this governance framework.

In the context of the regulatory environment, the US and UK banking institutions have different approaches, with the US focusing more on disclosures with the Securities and Exchange Commission (SEC), while the UK has focused more on the concept of resilience with the Prudential Regulation Authority (PRA), with the regulatory environment in both countries evolving in the context of the anticipated influence of the EU AI Act.

Despite the fact that banks draw attention to different risk areas, all four banks act under frameworks that are persistent with the three lines model and the Basel Core Principles. All four banks detail comparable risk governance frames, including internal audit, board oversight, and independent risk functions. Consequently, their AI-driven risk systems are becoming alike in how they are controlled in both UK and US banks. AI isn't isolated from the primary system, it is however embedded into model-risk frameworks and enterprise risk management. It is governed by risk commitess and applied as decision-support inside the three-lines structure. Having this standpoint on the four banks permits us to immediately meet our objectives, our objectives being to compare the governance structures which oversees AI-driven risk management in major US and UK banks.

Overview of Institutional Scale, AI Applications, and Measured Impact Across Selected Banks

Bank	Established	Assets (2024)	Net Income	AI Application	Measurable Impact
JPMorgan	1799 roots	$4.4T	$58.5 Billion (Net Income)	ML fraud & credit risk	3.14% charge-off rate
Bank of America	1904	$3.2T	$27.1 Billion (Net Income)	270 AI models	Fraud losses reduced
HSBC	1865	~$3T	$32.3 Billion (Profit Before Tax)	ML AML Monitoring	Fewer false positives
Barclays	1690	~$1.7T	£26.8 Billion (Group Income)	Embedded AI	Fasted anomaly detection

Note: HSBC reports Profit Before Tax (PBT) and Barclays reports Group Income; terminology differs across jurisdictions.

Findings and Conclusion

This research examines AI-based risk management practices in the top commercial banks in the United States and the United Kingdom, evaluates the efficacy of AI-based risk management frameworks, and compares the governance frameworks overseeing AI-based systems in both countries. From a comparative study of JPMorgan Chase, Bank of America, HSBC, and Barclays, a number of key findings are determined.

First, AI-based risk management is no longer a pilot project in the top global commercial banks. Each of the four banks has incorporated artificial intelligence into their core risk management processes, such as credit risk modeling, fraud analysis, anti-money laundering screening, stress testing, and cybersecurity monitoring. Machine learning-based credit analysis, behavioral anomaly detection, probabilistic default analysis, and real-time transaction monitoring have been incorporated into the enterprise-wide risk management framework rather than being used as separate applications.

Second, AI-based risk management frameworks have proven to be effective. In the four sampled banks, the implementation of AI has led to improvements in the accuracy of fraud analysis, a reduction in false positives, improved predictive models, improved cyber resilience, and optimized capital allocation. The findings show that AI improves speed, scalability, and predictability while maintaining alignment with traditional model validation and governance principles. More importantly, the findings show that AI is effective not because of automation but because of the structured oversight framework, including model validation, back-testing, explainable AI, and human-in-the-loop governance frameworks.

Third, while both U.S. and U.K. banks are subject to Basel-compliant and three lines of defense models, there are differences in terms of priorities. U.S. banks seem to prioritize the integration of AI solutions with overall enterprise risk and innovation strategies, which are often centered on operational efficiency and digital scale. By contrast, U.K. banks tend to have a relatively stronger priority on financial crime compliance, operational resilience, and regulatory alignment under PRA regulation. However, despite these differences in priorities, there is a convergence in governance. In all four banks, AI solutions are integrated into formal model risk management structures, which are monitored by board-level risk committees and independently audited.

In conclusion, the research study finds that AI-based risk management in major U.S. and U.K. banks is a process of evolution rather than revolution in the traditional risk management systems. Artificial intelligence improves risk identification, monitoring, and mitigation processes, but it is still subject to institutional safeguards. The integration of AI solutions with overall enterprise risk management systems aligned with Basel enterprise suggests that there is a possibility for advanced analytics to exist alongside regulatory discipline and stability within the institution.

In the future, studies need to carry out primary research consisting of interviews with risk officers to verify information found through secondary research. Expansion of the sample should also be considered to include banks residing in other regions like Europe or Asia. Adding longitudinal studies that track AI governance maturity over time would add value to this type of study.

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