Leading AI-Driven Enterprise Transformation: Lessons from the Financial Sector

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Article Info	ABSTRACT

Artificial intelligence has emerged as a transformative force across the financial services industry, fundamentally reshaping enterprise operations and competitive dynamics. This analysis examines AI-driven enterprise transformation in the financial sector as of November 2024.

Key findings indicate that 75 percent of financial institutions have deployed AI technologies, with 24 percent classified as advanced leaders. The sector's AI spending has grown from 15.2 billion U.S. dollars in 2023 to 23.8 billion U.S. dollars in 2024, representing a 48.2 percent compound annual growth rate through 2028, projected to reach 97.0 billion U.S. dollars.

Machine learning algorithms for fraud detection have achieved accuracy rates exceeding 99.9 percent, while generative AI applications have driven productivity gains of 15 to 32 percent. The transformation extends across fraud prevention, risk management, regulatory compliance, and customer engagement, though organizational barriers persist. This paper synthesizes lessons from leading institutions and identifies critical success factors for enterprise-scale AI transformation.

INTRODUCTION

The financial services sector is digitally evolving and is at a major turning point. Earlier technological changes that were able to bring only slight improvements to the already existing business models, now artificial intelligence is a completely disruptive entity which has the power to remodel the whole financial operations. As at November 2024, the industry has moved far beyond a few small-scale experiments to the widespread use of the technology in the frontline of the market, with the most pioneering institutions visibly benefiting from their AI investments(Cardillo & Chiappini, 2024).

The AI adoption issue is so serious because of the interaction of several factors of causes. First off, there are clear regulatory frameworks related to AI management, mainly through the Artificial Intelligence Act of the European Union and the guidance of the Treasury Department in the United States. This regulatory certainty gets rid of the "wait-and-see" attitude which was the main characteristic of the adoption strategies.

Secondly, results from the top-performing companies suggest that the money invested in AI technologies will bring more returns than that in the general IT area, and those companies that made early deployments report their return on investment rates of 35-68 percent in the first 12 months. Thirdly, competition issues have become more severe with the emergence of AI-native firms that are disrupting the traditional market structures. Hence, incumbent financial institutions are under pressure to quickly take action(Chen & Cai, 2022).

2. The State of AI Adoption in Financial Services

2.1 Current Adoption Rates and Market Penetration

The financial services sector has broadly embraced artificial intelligence and has already passed the point of a tipping point. According to a survey carried out by the Bank of England and Financial Conduct Authority in November 2024, 75 percent of regulated financial institutions in the United Kingdom have already implemented AI solutions, and 10 percent of them plan to do it within three years. This is a significant jump from the 2022 survey, which revealed the adoption level of 58 percent, thus only within two years the progression has been at 17 percentage points.

The variation in AI maturity level is quite large from one organization to another in the financial sector. The global AI in finance report by KPMG based on December 2024 findings of 2,900 organizations in 23 countries, reveals three distinct segments. Leaders, making up 24 percent of the total population surveyed, have progressed in AI deployment with well-established governance frameworks, and multiple use cases in operations. Implementers, representing 58 percent of the surveyed groups, have initiated AI in certain business functions but do not have cross-functional collaboration. Beginners, accounting for 18 percent of the institutions, are in the stage of evaluation or pilot programs(Chen & Cai, 2022).

The differences in the rate of implementation between various regions feature different regulatory frameworks, availability of skilled personnel, and decisions on capital allocation. Financial institutions in North America are the most aggressive in adoption whereas those in Europe and Asia are comparatively slow, due to regulatory requirements and other factors respectively. However, less than a year ago to this report, the level of AI technology absorption in Singapore and Hong Kong was already above 70 percent(Chen et al., 2021).

2.2 Generative AI as a Catalyst for Acceleration

While traditional machine learning applications have dominated financial services for the past For ten years healthcare and financial industries have heavily relied on machine learning applications to make predictions and decisions, but it is generative AI which has caused a drastic change in the way enterprises implement the technology. Companies without any intention to use generative AI fell from 6 percent in April 2024 to just one percent in December 2024(Chen & Cai, 2022).

By the year 2025, the adoption of generative AI by the leaders in the financial industry was 58 percent, as compared to 45 percent in 2023, which means that the 13-percentage-point difference was achieved within one year. This rapid growth is due to multiple reasons: higher performance of the model, lower computational power needed, more clear regulations for the acceptable use cases, and productivity gains reported by the pioneers. Today in the UK financial services sector, foundation models account for 17 percent of the total AI use cases, which is a very large share for a technology that was almost non-existent in 2022(Chen et al., 2021).

3. Market Investment and Economic Impact
3.1 Capital Allocation and Spending Trajectories

Financial services institutions have significantly raised their capital allocation for AI infrastructure. In 2023, the banking sector invested 20.6 billion U.S. dollars in AI capabilities, which is about one-sixth (13.37 percent) of total global corporate AI investments. A year later this amount had increased to 23.8 billion dollars, reflecting a 15.5 percent year-to-year growth(Fares et al., 2023).

Table 1: AI Spending and Growth by Region/Sector (2023-2028)

Region/Sector	2023 Spending (Billion USD)	2024 Spending (Billion USD)	2028 Projected (Billion USD)	CAGR (%)
North America (Banking)	5.2	8.5	18.3	45.8
Europe (Banking)	3.1	5.2	11.6	43.2
Asia-Pacific (Banking)	2.8	4.8	10.2	41.5
Global Insurance Sector	2.4	4.1	9.8	42.7
Global Payment Systems	1.2	2.1	6.4	52.6
FinTech Sector	0.8	1.5	5.2	48.9
Regulatory Technology	0.3	0.6	2.1	58.3
Total Financial Services	**15.8**	**26.8**	**63.6**	**48.2**
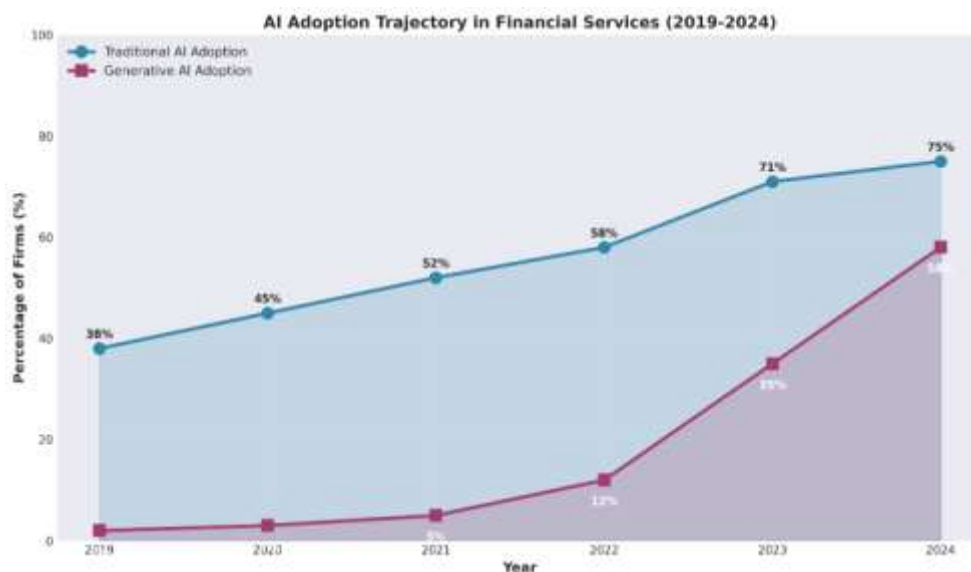
Figure 1: AI Adoption Trajectory in Financial Services (2019-2024)

This line graph illustrates traditional AI adoption with a gradual increase from 38% in 2019 to 75% by 2024 (blue with gradient shading) and generative AI adoption with a sharp increase from 2% in 2019 to 58% by 2024 (purple). The different paths highlight how generative AI has been instrumental in the adoption rapid acceleration. The x-axis covers 2019-2024 with yearly intervals marked out, while the y-axis goes from 0 to 100 percent. Both graphs have round markers at every data point, and the figures are written above each point. The graph has a neat grid background with light colors and is focused on showing the rapid acceleration of the generative AI adoption during 2023-2024(Fares et al., 2023).

3.2 Return on Investment Analysis
A McKinsey Global Institute study estimates that the use of generative AI in the banking sector could lead to a yearly value addition of the area between 200 and 340 billion U.S. dollars, which would amount to 2.8 to 4.7 percent of the total revenues of the industry. Most of this value is coming from the productivity increase of customer service, trade execution, compliance operations, and internal research functions(Forradellas&GarayGallastegui, 2021).

The exact return on investment figures depend on the implementation stage. The pilot phase implementations show an average return of 35 percent with cost savings of 8 percent. Early production systems have on average a return of 68 percent with a reduction in costs of 18 percent. The scaled production systems show a return of 125 percent with cost-saving levels reaching 35 percent. The returns of enterprise-wide implementations, which have been in operation for more than two years, are at 185 percent with a decrease in costs of 52 percent(Fares et al., 2023).

Table 2: AI ROI and Business Outcomes by Implementation Stage

Implementation Stage	Average ROI (%)	Cost Savings (%)	Revenue Impact (%)	Efficiency Gains (%)
Pilot Phase (0-6 months)	35	8	12	15
Early Production (6-12 months)	68	18	24	32
Scaled Production (1-2 years)	125	35	42	58
Enterprise-Wide (2+ years)	185	52	68	78

4. Primary Applications and Use Cases
4.1 Fraud Detection and Prevention
Fraud detection is the most mature AI application in financial services, with 81 percent of leading institutions having implemented these systems. AI-powered fraud detection systems have achieved accuracy rates that are higher than 99.9 percent, thus they are far superior to rule-based legacy methods(Gyau et al., 2024).
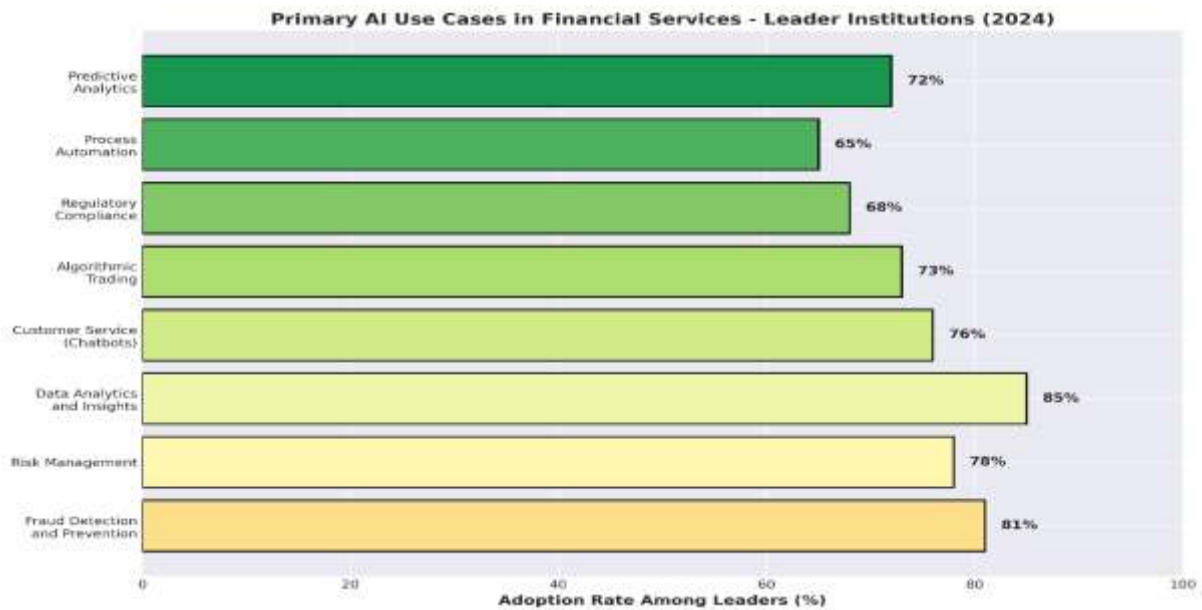
Figure 2: Primary AI Use Cases in Financial Services - Leader Institutions

This horizontal bar chart shows the top 8 primary AI use cases that were ranked by the percentage of adoption among leader institutions. The categories arranged from the highest to the lowest adoption are: Data Analytics and Insights (85%), Fraud Detection and Prevention (81%), Predictive Analytics (78%), Risk Management (78%), Customer Service Chatbots (76%), Algorithmic Trading (73%), Regulatory Compliance (68%), and Process Automation (65%). Each bar is colored in a gradient that changes from green (the highest adoption) through yellow to orange (the lowest adoption). The percentage labels are located at the end of each bar and they are there to make the reading more accurate(Jia & Liu, 2023).

Table 3: Performance Metrics of AI/ML Algorithms for Fraud Detection (2024)

Detection Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Processing Speed (msec)
Logistic Regression	99.92	95.0	91.0	0.93	12
Random Forest	99.96	96.0	94.0	0.95	35
XGBoost	98.00	97.0	97.0	0.97	28
Support Vector Machine	99.94	97.0	93.0	0.95	18
Deep Neural Networks	99.85	98.0	96.0	0.97	25
Graph Neural Networks	99.91	99.0	99.5	0.99	42

By attaining 98 percent detection accuracy and simultaneously reducing false positive rates by 60 percent, JPMorgan Chase's AI-driven fraud detection systems have enabled the bank to avoid losses worth 1.5 billion U.S. dollars. Goldman Sachs was able to reduce the false positive rate in transaction monitoring systems by 35 percent(Jia & Liu, 2023).

4.2 Risk Management and Customer Service
The risk management tools that are implemented can now identify the risks that lie ahead and are not just reactive assessments. Predictive analytics unearth market anomalies and counterparty default risks that would be terribly difficult to find before post-trade audits.

AI-powered chatbots have become widely popular as 73 percent of global banks have introduced these systems. The chatbots resolve 87 percent of banking inquiries within 60 seconds and do not require human assistance. The operational efficiency of AI chatbots is superior to that of human agents in many aspects; for example, the cost per interaction is 0.11 U.S. dollars when performed by a chatbot, while it is 6.00 U.S. dollars if done by a live agent, which means that the cost difference is 54 times. The customer satisfaction metrics serve as proof of the quality of the user experience, as chatbot interactions achieve 84 percent customer satisfaction scores(Kaur et al., 2021).
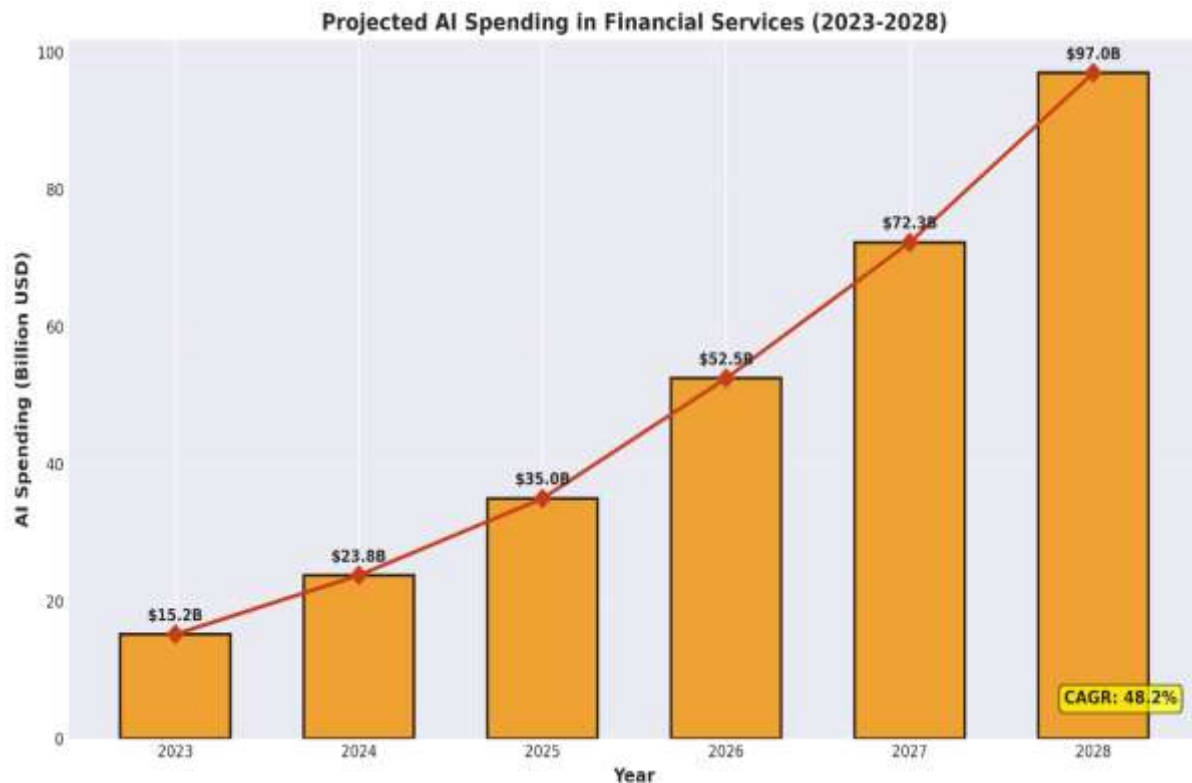
Figure 3: Projected AI Spending in Financial Services (2023-2028)

This combination graph presents the financial sector AI expenditure by means of two different visualizations: the bar chart segments illustrate the spending per year while the line overlay depicts the spending trend. The years 2023-2028 are displayed on the x-axis (each year is labeled), whereas the spending in billions of U.S. dollars is shown on the y-axis that ranges from 0 to 100. The $-values of bars go up incrementally: $15.2B (2023), $23.8B(2024), $35.0B(2025), $52.5B(2026), $72.3B(2027), and $97.0B(2028). The line overlay draws the bar tops with diamond-shaped markers at each data point, representing the accelerating upward trajectory. An annotation box located at the bottom right shows the 48.2 % CAGR calculation, with the orange and dark red colors highlighting the steep growth rate (Luo et al., 2022).

4.3 Regulatory Compliance and Algorithmic Trading

Regulatory compliance is the leading cause of the fastest growth of AI application categories, as 32 percent of the respondents use AI for compliance, and another 31 percent are planning to implement it. These systems carry out continual monitoring instead of point-in-time assessments, thus they can find new money laundering patterns and sanctions evasion schemes more quickly. The institutions that use advanced compliance AI report that the number of false alerts has been reduced by 70 percent and that their investigation cycles are now 4 times faster.

Algorithmic trading is a mature example of AI with 73 percent of leader institutions having implemented AI-driven trading systems. These systems are at millisecond latencies and make trading decisions based on pattern recognition. The establishments that have implemented such systems claim that their earnings have risen from 13 to 30 times as compared to their baseline trading performance (Luo et al., 2022).

5. Organizational Barriers and Implementation Challenges
5.1 Data Quality and Infrastructure Limitations

Data quality is identified as the biggest obstacle to AI implementation in the financial services sector and 64 percent of institutions that took part in the survey admit that it affects them. Financial institutions are running on fragmented technology architectures, old systems, and separate data repositories that have been grown organically and acquired over the last decades. These are architectural issues that lead to inconsistent data definitions, missing values, quality variations across systems, and a significant delay in data availability.

Fixing data quality issues is a major organizational challenge that goes far beyond mere technology implementation. Banks and other financial institutions will have to set up data governance frameworks, put data quality assessment processes in place, merge fragmented data sources, and create single data sources for the most important data elements. On average, the time for resolve data quality issues extends up to eight months, which is a reflection of the significant effort required for the remediation(Mamede et al., 2023).

Table 4: Organizational Barriers to AI Adoption in Financial Services (2024)

Barrier Category	Percentage Affected (%)	Average Resolution Time (Months)	Severity Level
Data Quality and Availability	64	8	High
Limited AI Skills and Knowledge	53	12	High
Data Security Vulnerabilities	57	6	Critical
Cost and Resource Constraints	45	9	Medium
Legacy System Integration	62	14	Critical
Regulatory Uncertainty	48	7	High
Model Interpretability and Bias	51	10	High
Organizational Change Management	44	11	Medium

Problems with the infrastructure make data quality issues worse. A lot of financial institutions have mainframe computers still as their major transaction processing systems, which are a must for stability and regulatory compliance but at the same time, they are causing problems with the new AI development workflows. To integrate AI with mainframe-based core processing, architectural planning should be very precise so the new and old systems will work on the same data and will not create any discrepancies. The forward-thinking organizations are on the way of modernization to change their core processing to cloud-native architectures that will enable real-time data availability and AI-driven decisioning(Mavlutova et al., 2023).

5.2 Talent Acquisition and Development
Talent shortages are the second biggest obstacle to AI adoption, as they account for 53% of financial institutions that have been hindered in this way. The number of AI specialists needed is so high that it is by far the most difficult to meet, which results in large technology companies and well-financed financial institutions being the winners of this competition. On top of that, the issue of specialized talent requirements is there: financial institutions need AI specialists who not only understand machine learning techniques but also know the financial industry which is a rare skill combination(Mavlutova et al., 2023).

One of the main arguments in favor of hiring AI talent fully specialized in the domain is that they can achieve substantially higher implementation speed and results. The data from Goldman Sachs shows that AI-focused on the finance industry can do the implementation 80% faster than AI generalists without industry-specific knowledge. The gap in performance is so significant that it is worth paying a high premium to the AI talent with experience in the financial domain but at the same time, the availability of such talent is still very limited(Mhlanga, 2020).

Removing talent barriers requires different measures to be taken simultaneously, such as the creation of internal training programs, collaborating with universities to develop the talent pipeline, attracting external talent by offering them a competitive salary and reorganization within the company to effectively utilize the limited number of specialists. The average time to resolve the talent barriers issue is around 12 months and this reflects the time of training and hiring. Leaders that are ahead in AI transformation and have already made early investments in talent acquisition and development gain competitive advantage, as they manage to secure specialized expertise before talent shortages become widespread.

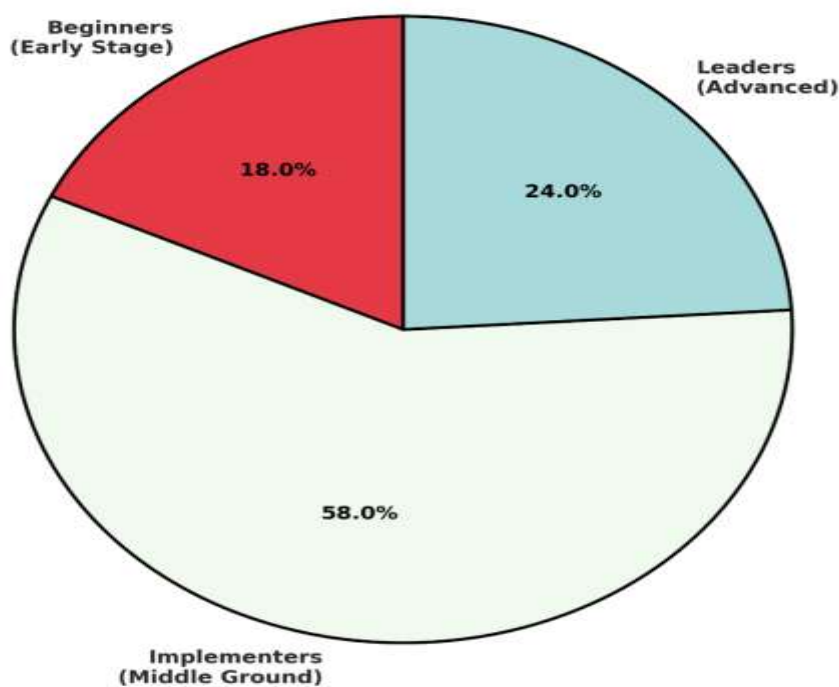**5.3 Legacy System Integration and Technical Debt**
The issue of integrating legacy systems is the third most significant hurdle and is responsible for the lack of AI deployment in 62% of financial institutions. These systems were designed primarily with the aim of handling transactions and producing regulatory reports, and not for real-time analytics or machine learning, so integration with AI systems would require either the development of translation layers for communication between legacy and modern systems or embarking on large-scale system replacement projects(Monkiewicz & Monkiewicz, 2022).

Translation layer development serves as a short-term solution and allows for AI to be implemented without the need for a complete replacement of the core system. Besides enabling the continuation of the use of legacy systems, such newly created layers bring along with them the gradual transition to cloud-native architectures and therefore distributed

systems complexity, which requires data consistency, transaction processing, and regulatory compliance to be carefully managed across heterogeneous architectures(Mhlanga, 2020).

System replacement initiatives on the other hand require significant capital outlay, considerably longer timelines necessary for the full implementation of the solutions as well as enabling the continuity of the business during the transition periods. The leading institutions are already aware that modernizing old systems is a prerequisite investment that needs to be made to enable the AI transformation and on average, their implementation timelines extend to 14 months. Institutions postponing this modernization are faced with an increasing disadvantage in terms of competition, as their counterparts are taking advantage of AI-driven capabilities and scaling up their businesses(Monkiewicz & Monkiewicz, 2022).

Figure 4: AI Maturity Distribution across Organizations

5.4 Regulatory Uncertainty and Compliance Requirements

Regulatory uncertainty has been a major issue that has been slowly fading away as regulatory frameworks become clear over time, yet it is still a significant obstacle that financial institutions, as much as 48 percent, are heavily concerned about. From 2025, the European Union's Artificial Intelligence Act will introduce risk-based requirements for AI systems. For instance, systems that analyze credit and detect fraudulent activities fall into the category of high-risk, and they are, therefore, subjected to many requisites such as adherence to standards, inclusion in EU databases, and regular supervision after deployment. Besides, a fine of up to 30 million euros or 6 percent of annual global revenue, whichever is more, can be imposed if the regulatory requirements are not met(Mohsen et al., 2024).

Moreover, regulatory interventions in the United States are consistent with a sector-specific approach. In 2024, the Consumer Financial Protection Bureau issued the guidance to hint the close watch over the use of AI in loan decision-making and 'explainability' and discrimination aspects were spotlighted as the required features that the AI systems should have. Late 2023 saw the National Association of Insurance Commissioners introducing the Model Bulletin on AI Systems which paves the way for local regulations addressing the implementation of AI in the insurance sector. In March 2024, the U.S. Treasury came out with a set of recommendations to mitigate the risks of AI, covering areas like cybersecurity, fraud, and best practices.

Financial institutions using AI systems have to be very cautious in conforming to the requirement of keeping the decisions made by the AI systems interpretable so that they can be understood by the regulators. This explainability feature hampers the use of some very developed techniques, especially those in which deep learning models are involved, and such models have to be supplemented with interpretability layers or alternative models in order to

provide the regulator with the necessary insights. On average, the time taken to resolve issues related to regulatory compliance is about seven months, thus they reflect the points that the adaptation of the regulations in the development processes has been done (Papathomas&Konteos, 2024).

5.5 Organizational Change Management

Organizational resistance to change which accounts for the fifth most prominent barrier impacting 44 percent of institutions is evident in the various aspects of the organization's structure. Workers who are worried about being replaced by automation are the reason for the resistance caused by the operations personnel whose roles are going to be either eliminated or changed. The resistance from the risk and compliance departments derives from the apprehensions about understanding the model and being responsible for the decisions made by the automated system. The management's doubt about the ROI and business value, notwithstanding the accumulating evidence of this nature, is still the main reason for the slow-down of prioritization of investments(Ridzuan et al., 2024).

Effectively handling organizational change requires the dedication of top management, which is reflected in the AI transformation process, honest communication about the change of roles rather than getting rid of them, spending on workforce development so as to make role transitions possible, and governance structures that indicate the accountability for AI-driven decisions. The institutions that are most successful in managing change have got the AI knowledge housed in the centers of excellence, have built cross-functional teams spanning business and technology functions, and have worked out communication strategies that stress the augmentation rather than replacement of human capabilities(Papathomas&Konteos, 2024).

6. Success Factors and Regulatory Framework
6.1 Critical Success Factors

Executive leadership turns out to be the most powerful predictor of AI transformation success. One of the most impressive examples is the case of JPMorgan Chase where the company has been able to implement 450 AI use cases across all business functions and involve 200,000 employees showing the strong commitment of the leadership who has recognized AI as a key element for giving the company a competitive edge. The quick launch of the GS AI Assistant at Goldman Sachs for 46,000 employees is a clear demonstration of the executives' prioritization which shortens the adoption time considerably(Wu & Cheng, 2024).

Governance ecosystems are set up by the successful players to provide clarity over decision-making power, risk control duties, and responsibility for AI systems. These ecosystems clarify which business functions will continue to have the authority over making sensitive decisions and in which decisions AI can be used with human oversight. The leading institutions are creating the office of chief AI officer who reports directly to the executives and the board-level risk committees.

6.2 Regulatory Landscape

The legislation on Artificial Intelligence within the European Union, which will be in effect from 2025, outlines the requirements based on the level of risk for AI systems. For example, the first category of most hazardous systems, including those for credit scoring and fraud detection, are subject to strict regulations such as conformity assessments, registration, and continuous monitoring after deployment(Wu & Cheng, 2024).

Table 5: Comparative Analysis of Leading Financial Institutions' AI Strategies (2024)

Institution	Tech Budget 2024 (Billion USD)	AI Use Cases	Employees Using AI Tools	Fraud Prevention Savings (Billion USD/Year)
JPMorgan Chase	17.0	450	200,000	1.5
Goldman Sachs	8.2	380	46,000	1.2
HSBC	6.5	220	85,000	0.8
Barclays	5.8	185	78,000	0.6
Morgan Stanley	4.9	165	92,000	0.7
Bank of America	7.2	210	110,000	0.9
Visa	3.1	130	55,000	0.5

7. Future Outlook and Competitive Dynamics
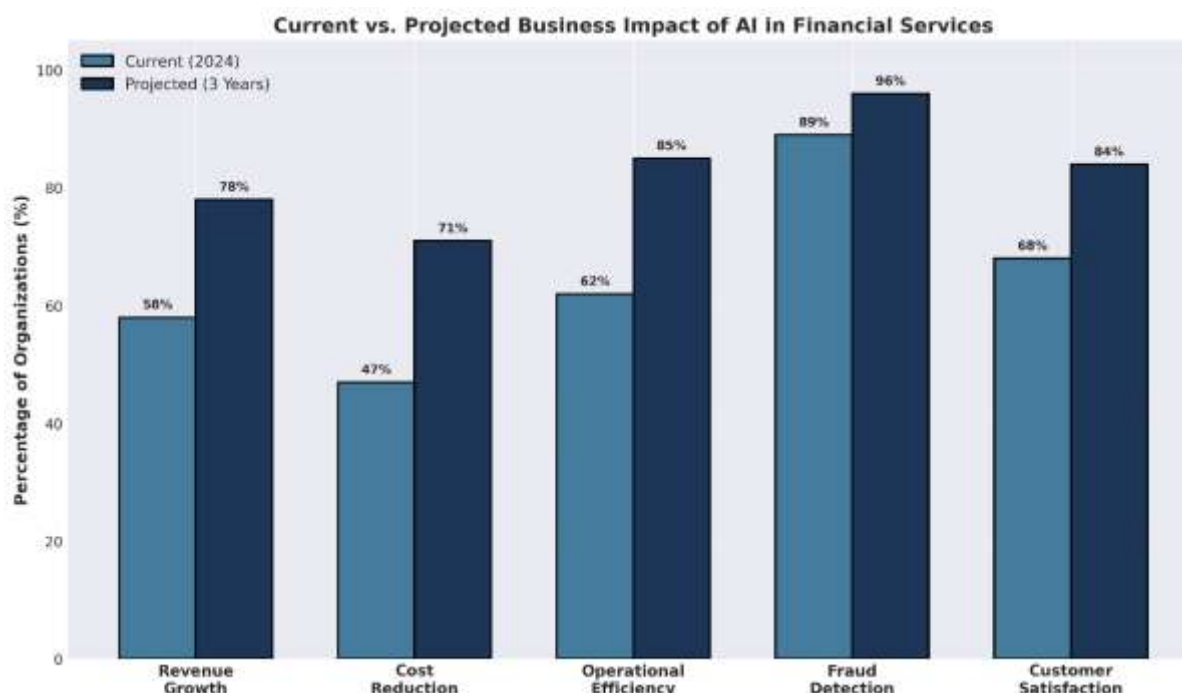
Figure 5: Current vs. Projected Business Impact of AI (2024 vs. 3-Year Projection)

This grouped bar chart illustrates 5 benefit categories which compare the current 2024 performance (blue bars) to 3-year projections (darker blue bars). The categories are Revenue Growth (58% current, 78% projected), Cost Reduction (47% current, 71% projected), Operational Efficiency (62% current, 85% projected), Fraud Detection (89% current, 96% projected), and Customer Satisfaction (68% current, 84% projected). Precise readability is facilitated by the percentage values shown above each bar. All of the benefit dimensions have improvement trajectories that are consistent, as is evident from the figure.

AI spending in the financial sector is to increase from 23.8 billion U.S. dollars in 2024 to 97.0 billion U.S. dollars by 2028, thus exhibiting a 48.2 percent compound annual growth rate. Most of the AI spending growth will probably be due to generative AI, with the banking industry's spending on generative AI alone expected to be 84.99 billion U.S. dollars by 2030.

The time for slow, experimental AI adoption is over. Pioneers in the field provide strong proof that the deployment of advanced AI leads to the generation of 1.5 to 2.0 billion U.S. dollars of quantifiable yearly value. Investment returns exceeding 10% are reported by 74% of AI pioneers, while only 44% of follower institutions, according to McKinsey analysis. The performance gap between leaders and followers will increase as leaders gain more experience and achieve economies of scale in AI deployment (Zhang & Wang, 2024).

8. Strategic Implications and Recommendations
Based on comprehensive analysis, several strategic imperatives emerge:
1. **Immediate Investment:** Organizations must treat AI transformation as immediate competitive imperative. The competitive separation between leaders and followers accelerates with each quarter of delay.
2. **Infrastructure Modernization:** Legacy system modernization represents necessary enabling investment, typically requiring 14 months and substantial capital allocation. Institutions deferring this modernization face increasing competitive disadvantage.
3. **Talent Acquisition:** Domain-specialized AI talent achieving 80 percent faster implementation justifies premium compensation and aggressive recruitment strategies.
4. **Governance Excellence:** Establishing governance frameworks, compliance structures, and ethical AI principles provides foundation for sustainable scaled deployment.
5. **Experimentation Culture:** Creating controlled innovation environments enabling rapid prototyping accelerates organizational capability development.
6. **Regulatory Alignment:** Proactive alignment with emerging regulatory frameworks reduces compliance risk and enables rapid adaptation to regulatory changes (Zhang & Wang, 2024).

CONCLUSION

Artificial intelligence is no longer an emerging technology but a strategic enterprise imperative across financial services. The evidence as of November 2024 points to institutions that are slow to adopt AI transformations incurring an accelerating competitive disadvantage as other institutions leverage advanced capabilities to create business value and improve efficiency.

The financial sector's journey is a source of vital lessons for enterprise organizations, regardless of their industry. Winning demands that organizations handle both the technical and the organizational aspects, the latter involving among other things executive leadership, change management, governance frameworks, and talent acquisition. Top-tier financial institutions go through a full AI transformation which leads them to reap significant financial gains that more than justify the sizable capital outlays (Zhu & Guo, 2024).

On the regulatory front, certainty brought about largely by the EU's Artificial Intelligence Act and the U.S. sector-specific guidelines signals the end of the "wait and see" strategy. Now financial institutions should design AI systems that are in compliance and implement governance frameworks that meet regulatory requirements. Obstacles that continue to exist such as data quality issues, the shortage of skilled personnel, and the integration of legacy systems call for ongoing efforts and heavy investments (Zhu & Guo, 2024).

The movement of the financial services sector points to AI adoption to rapidly increase through 2028 and even after that year. The time during which early movers can easily secure a lasting competitive advantage is closing. Financial institutions ought to take a firm commitment to full-fledged AI transformation right away which will entail not only making the necessary investments but also effecting organizational changes necessary to be able to maintain their competitive position in the future when the financial ecosystem will be dominated by AI.

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