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Decentralized to Centralized Organizational Strategies for AI Integration in Finance

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Abstract: ***This article explores the burgeoning intersection of artificial intelligence (AI) and the financial sector, focusing on the transformative impact of large models and generative AI technologies. Amidst the ongoing digital revolution in finance, these technologies are revolutionizing traditional operational frameworks across banks, insurance firms, and securities brokers. The paper examines key applications such as risk management, fraud detection, personalized financial recommendations, and automated customer service, highlighting their potential to enhance operational efficiency and customer satisfaction. Drawing on McKinsey's projections of substantial economic value creation, the study also analyzes organizational structures adopted by financial institutions for AI integration, ranging from highly centralized to decentralized models. Ultimately, the research underscores the pivotal role of AI-driven innovations in reshaping financial services and outlines future directions for research and implementation in this dynamic field.***

Keywords: Artificial Intelligence in Finance; Generative AI; Financial Technology; Digital Transformation.

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1. Introduction

During the financial industry's digital transformation, artificial intelligence (AI) powered by large models and generative technologies has emerged as a pivotal force driving unprecedented change. This technological evolution revolutionizes operational paradigms across banks, insurance firms, and securities brokers and redefines customer experiences profoundly [1]. From enhancing risk management and fraud detection to delivering personalized financial recommendations and streamlining automated customer service, AI's application scenarios in finance are vast and transformative. McKinsey estimates that generative AI alone could unlock annual values ranging from $200 billion to $340 billion in the banking sector, underscoring its pivotal role in driving operational efficiency and profitability across the industry.

As financial institutions increasingly integrate generative AI into their operational frameworks, the organizational structures for deploying these technologies vary widely[2]. From highly centralized models facilitating rapid technological advancements to decentralized structures enabling tailored implementations across diverse business functions, institutions are navigating a dynamic landscape to harness AI's full potential. This article explores the multifaceted applications of large models and generative AI in finance, highlighting significant use cases, implementation strategies, and the transformative impact on industry dynamics and regulatory landscapes.

2. Background and Related Work

2.1 Artificial Intelligence and Finance

In the wave of digital transformation in the financial industry, large models and generative artificial intelligence are becoming the new engines driving change. Not only are they revolutionizing the way financial services operate, but they are also playing a key role in significantly enhancing the customer experience. [3-5]Whether banks, insurance companies or securities brokers, financial institutions of all kinds are actively exploring and

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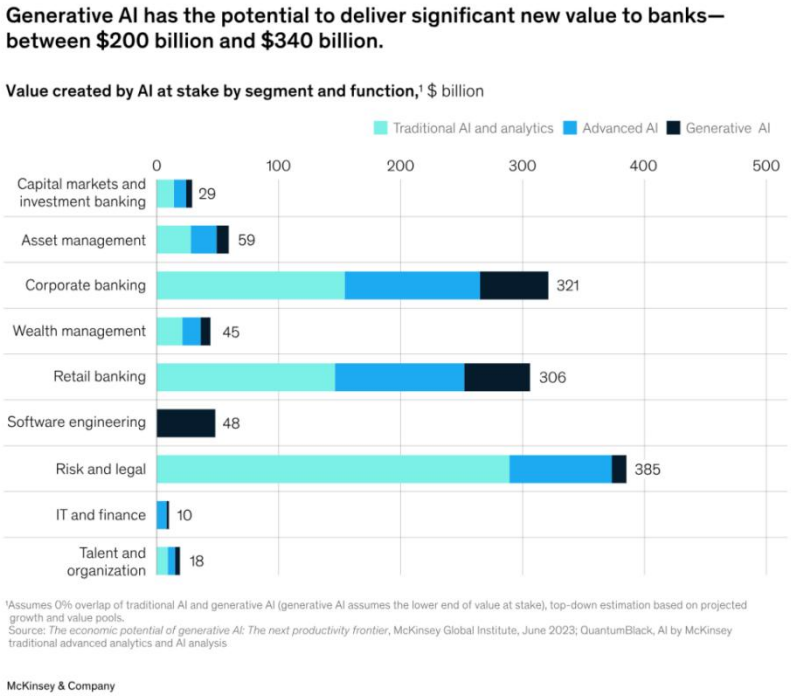
implementing these cutting-edge technologies to capture new opportunities brought about by changes in the industry.

In this process, the application scenarios of AI are broad and deep, covering many aspects such as risk management, fraud detection, personalized financial product recommendations, intelligent investment advisers, and automated customer service.

The impact of generative AI on the financial industry

1) Generative AI will significantly improve the work efficiency of financial institutions

According to the McKinsey Global Institute (MGI), the potential value of generative AI technology in various industries worldwide is as high as $2.6 trillion to $4.4 trillion per year. [6] Among industries, banking is expected to see a huge opportunity, with a potential annual value of $200 billion to $340 billion, representing 2.8 to 4.7 percent of total industry revenue and 9 to 15 percent of operating profit, mainly due to significant improvements in industry efficiency.



Since last year, leading financial companies have been closely implementing generative AI in business scenarios. For example, Citigroup's risk and compliance teams began using generative AI technology last year to analyze and assess the impact of new capital rules issued by federal regulators. [7-9] the Wall Street Journal recently reported that Goldman Sachs plans to roll out its first generative AI tool for code generation to thousands of developers across the company by the end of June.

Financial institutions that have successfully implemented and leveraged Gen AI are working to develop an appropriate, customized operating model that carefully considers the characteristics and risks of new technologies rather than simply embedding Gen AI technology into existing operational processes.

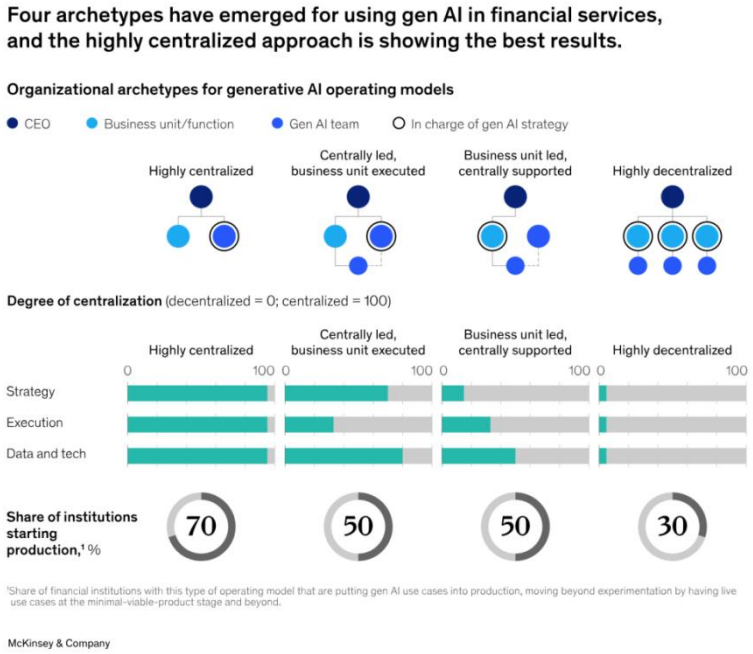
2) The four organizational forms of financial institutions' landing generation style AI[10]

McKinsey examined the use of general AI at 16 of the largest financial institutions in Europe and the United States, which collectively have assets of nearly $26 trillion. [11]The results show that more than 50% of research organizations have adopted a more centralized organizational structure to implement general AI technologies.

However, this centralization may be temporary, and as the application of AI technology continues to mature, the structure of financial institutions will become more decentralized. Ultimately, financial institutions may find it

beneficial to have individual functions prioritize general AI activities according to their needs.

In McKinsey's study, although the way financial enterprises implement generative AI is different, it can be summarized as the following four main forms of implementation organization[12].



(1) Highly centralized

In this highly centralized organizational structure, a core team is solely responsible for the design and implementation of Gen AI solutions. This team is independent within the enterprise and is able to quickly provide the latest skills and capabilities related to AI[13]. In addition, the team has autonomy in the decision-making process and is not directly influenced by other business units or functional units.

(2) Centralized decision-making by the leadership and implementation by the business departments

This architecture optimizes communication between leadership and the Gen AI team, significantly reduces friction in collaboration, and ensures effective integration of new technology application processes within the enterprise. But this collaborative model can also cause some delays in the pace of technology implementation by AI teams, as each project must be reviewed and approved by leadership before moving forward.

(3) Led by the business department and supported by the leadership

Based on this model, as Gen AI's strategy is endorsed from the bottom up, the relevant teams are able to quickly gain support from business units and functions. [14]However, the adoption of Gen AI across different business units may be challenging, as each department may have differences in maturity in the development and application of Gen AI capabilities.

(4) Highly decentralized

In this model, cross-functional or cross-functional teams communicate and collaborate more smoothly, can quickly produce valuable insights, and can effectively promote internal integration. [15]However, when business units undertake Gen AI projects independently, they may face some risks, such as a lack of the wealth of knowledge and industry best practices that centralized management can provide. This lack can make it difficult for companies to fully tap into the potential of AI technology, which in turn affects the chances of achieving major innovative breakthroughs.

2.2 Major Application Scenarios and Cases of Large Models and Gen AI in the Financial Industry

1) Major application scenarios of large models and Gen in the financial industry

Shenqing Technology believes that AI is helping financial institutions achieve "intensification" and "refinement" of service models in retail business, significantly improving operational efficiency and effectiveness.

The "intensive" service model is aimed at a large number of long-tail customer groups with dispersed and diversified needs. Through artificial intelligence technology, centralized and large-scale business strategies are adopted to optimize resource allocation and improve operation management efficiency[16-17]. In conclusion, artificial intelligence technology can be used at a lower cost to cover the artificial energy to cover the long tail customer group and to provide customers with 70 points of service quality.

The "fine" service model is based on the customer's asset size, transaction characteristics, financial needs, family conditions, and other portrait information; the customer group is deeply subdivided. Limited by the bottleneck of service capacity, under traditional technical conditions, financial institutions are difficult to provide refined and differentiated services for segmented customer groups. Artificial intelligence technology allows financial institutions to provide personalized products and services tailored to each customer. This includes providing personalized content services based on the customer's investment life cycle, transaction cycle, and important time points to meet customers' individual needs.

A South China head brokerage executive believes that large models and generative AI usually have the following main application scenarios in the financial industry:

(1) Intelligent question and answer scenario

Users can ask questions and get answers quickly through a single channel by building a centralized question-and-answer system based on large model technology. [18]This system not only promotes the basic knowledge of the business but also enables front-line account managers to deal with customers' common problems more efficiently, significantly improving work efficiency.

(2) Consulting scenario

Due to the limited resources of investment advisers, the traditional diagnostic analysis services for individual stocks often only cover important clients in large branches. The use of large model technology, combined with regular reports and professional materials such as research reports and prospectuses, can effectively improve the efficiency of investment advisers, and expand the coverage of services, so that more clients can enjoy professional stock diagnosis services, help them quickly grasp investment opportunities and risks, and make wise investment decisions.

(3) Diagnosis scenario of individual stocks

Investment advisers often face the challenge of rapidly changing markets when refining market dynamics and hot news to form an investment opinion. The use of large model technology can assist investment advisers to quickly capture market hot spots, stimulate creativity, transform complex information into a form that is easy for customers to understand, and effectively promote customer conversion. [19]At the same time, this method also helps to extend the ability of professional investment advisers to front-line account managers and cultivate more talents with professional investment advisory skills.

(4) Fund diagnosis scenario

When making fund diagnosis, investment advisers need to analyze the market environment in depth, which requires solid investment research ability. [20-22]Through large model technology, we can provide comprehensive fund research and diagnostic support for professional investment advisers, help them improve their investment research capabilities, and optimize fund portfolio management.

(5) Account diagnosis scenario

Account comprehensive diagnosis is one of the important responsibilities of investment advisers. Using large

model technology, we hope to provide professional investment advisers with comprehensive account diagnostic capabilities, support them to analyze clients' portfolios, assess risks and returns, and provide clients with objective and professional diagnostic reports to improve investment research capabilities.

2.3 The Financial Industry has the Following Typical Application Scenarios

(1) Fraud detection and prevention

Data in the financial sector, such as credit card information, personal records, and bank account details, make it a prime target for cyber-attacks. [23]Combined with fraud detection algorithms, generative AI improves data protection capabilities.

Traditional fraud detection algorithms using machine learning (ML) [24]are self-trained from historical data, making it difficult to keep up with new fraud methods. Generative AI, on the other hand, can optimize detection algorithms to stay ahead of fraudsters by creating synthetic "anomaly" patterns. [25]This reduces the need for surveillance and enables greater automation and more efficient identification of cyber-attack attempts.

(2) Personalized financial services and support

Personalized service and support are key factors for companies to increase their competitiveness and are estimated to increase annual revenue by up to 10%. Personalization is a challenge in finance because of the large amount of customer data that needs to be processed, such as transaction history, spending preferences, and savings goals.

Generative artificial intelligence (GenAI) [26]is important in quickly leveraging this data to generate customized recommendations and offers that improve customer satisfaction, facilitate cross-selling, and enhance business competitiveness. In addition, GenAI provides efficient self-service through intelligent virtual assistants and automated form submission, helping financial institutions reduce costs and increase customer engagement. It is also a key tool for optimizing service efficiency and customer experience.

(3) Risk assessment and credit scoring

In loan approval, financial institutions must evaluate customers' credit status and potential risks, and credit score is the core link of this process. Traditional credit scoring relies on historical data and fixed rules, but this approach can be inflexible and difficult to adapt to the complexity and variability of credit risk[27]. In addition, these methods require constant monitoring and in-depth analysis, which is time-consuming.

Generative Artificial Intelligence (GenAI) offers a new solution in this area. It trains more accurate predictive analytics tools by creating synthetic data that closely resembles real data and combining it with real data to build richer training datasets. GenAI's ability to efficiently process large amounts of dynamic data reduces the reliance on manual operations, making the credit scoring process more reliable and efficient.

(4) Compliance and regulatory challenges

Regulatory compliance is critical in banking and is closely linked to risk assessment and human error. Financial institutions must comply with various regulations covering operations, confidentiality, security, and more, requiring exhaustive data collection, analysis, and reporting, which are time-consuming and error prone[28].

Generative artificial intelligence (GenAI) can effectively handle these tasks. GenAI generates high-quality synthetic data to enhance compliance control and quality assurance accuracy, ensuring compliance reporting is fast, consistent, and error-free. [29]In addition, GenAI can monitor compliance continuously, automatically notify violations, and take timely action.

(5) Market and investment analysis

Financial analysis involves processing large amounts of data such as market trends, company reports, financial estimates, etc. Analysts must constantly monitor this data, which consumes much time and energy.

Generative artificial intelligence (GenAI) plays an important role here. It can quickly scan and analyze vast

amounts of historical data, identifying patterns and anomalies humans might miss[30]. GenAI's automated analysis process generates insights and creates trading parameters such as the best time to buy or sell, stop loss points, and position size.

This data-driven approach gives banks a significant competitive advantage, enabling them to understand market conditions better and develop more precise and effective strategies. GenAI is becoming a useful tool for financial analysts who are navigating complex data.

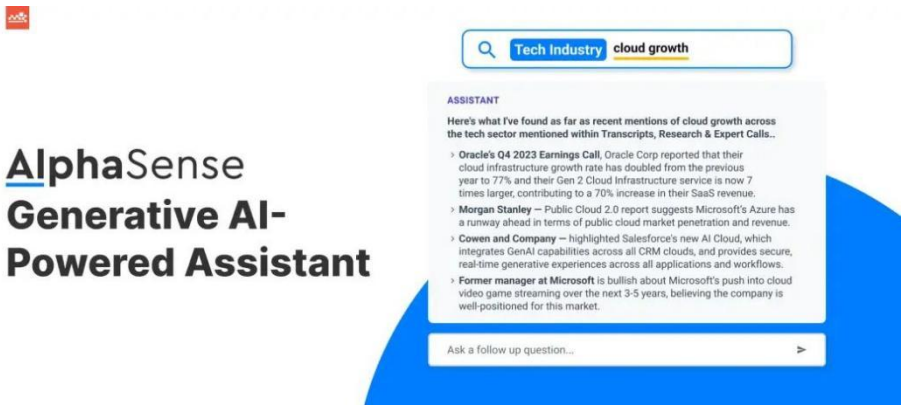
(6) Document processing/report generation

Jobs in the financial industry involve much information processing, especially when dealing with documents and information from different sources, which are often heterogeneous[31-32]. For example, when analyzing various financial reports, deciding whether to grant a loan to a financial client requires a combination of legal disputes, financial statements, ownership structures, and articles of association. Therefore, one of the most direct and effective application scenarios for AI today is to handle these multi-source heterogeneous report generation tasks, which are more expensive and of lower quality if you rely on manual processing of these reports.

The main purpose of the financial industry to process these reports is to identify and assess risks. When the quality of reporting is poor, it often means increased risk and high risk can lead to higher non-performing loan ratios. Therefore, improving the quality of reporting processing is crucial for the financial industry.

3. A Typical Example of Gen AI in the Financial Industry

3.1 AlphaSense Introduces Generative AI Assistant -AlphaSense Assistant



AlphaSense, a leading platform for financial market intelligence and search, has launched AlphaSense Assistant, an innovative generative AI chat tool designed to change how finance practitioners extract industry insights from millions of business and financial documents. In addition, AlphaSense has launched Enterprise Intelligence services that securely integrate its AI-powered search, digest, and chat capabilities into customers' proprietary organizational knowledge and AlphaSense's extensive content library.

AlphaSense Assistant is powered by AlphaSense's Large Language Model (ASLLM) [33]tailored for market intelligence, based on AlphaSense's industry-leading content library, and provides a conversational chat interface that greatly improves research efficiency for business and finance professionals. Users can easily consult investment opportunities or competitor analysis in specific areas and get accurate answers immediately. The answers also have built-in auditability, allowing users to return to the source material for contextual and validation checks.

3.2 FeatureSpace Unveils TallierLTM™ Financial Vertical Mega Model

FeatureSpace, a leading global enterprise-class fraud prevention technology provider, has launched TallierLTM™, the world's first Large Transaction Model[34].

TallierLTM™ uses a self-supervised, pre-training approach that provides an in-depth analysis of transaction behavior across jurisdictions and market segments, enabling it to reflect real-world consumer transaction behavior

truly. TallierLTM™ improves fraud detection accuracy by up to 71% compared to the industry standard model, which operates at a typical 5:1 false positive rate.

By analyzing billions of transactions, TallierLTM™ can reveal hidden transaction patterns and predict consumer behavior, providing data scientists with key insights that distinguish legitimate from criminal activity. Financial institutions can interact with TallierLTM™ through an embedded API that converts transaction history into a machine-readable feature vector, creating a unique "behavioral barcode" that fully represents the consumer's transaction behavior while protecting personal privacy.

3.3 Visa Launches Generative AI-based Fraud Solution

Based on generative AI technology, Visa launched its Account Attack Intelligence (VAAI) scoring tool for U.S. financial institutions in May to identify and prevent enumeration attacks in financial transactions. The tool detects suspicious activity in real-time and provides a risk score for financial institutions to help customers pinpoint when to block transactions, thereby preventing potential fraud.

By learning cardholders' trading habits, the AI tool can automatically assess transaction risk within four milliseconds, distinguish between normal consumption and abnormal behavior, and quickly identify possible offensive transactions[35]. It has been trained on more than 15 billion transaction data to generate a risk score by comparing historical enumeration attack patterns to predict whether a transaction is an enumeration attack. Compared to existing risk assessment models, VAAI tools showed significant progress in reducing false positives, with an 85% reduction in false positives[36].

3.4 LAN Code Technology Report Agent Case

A Chinese bank has launched an inclusive loan service to provide convenient loan services to small and medium-sized enterprises to support the development and innovation of the real economy. However, when granting inclusive loans, it is difficult for banks to fully understand the information status and repayment ability of borrowing enterprises, especially in the face of small and medium-sized enterprises and individual industrial and commercial households that lack perfect financial records.

Therefore, bank account managers often spend a lot of time collecting and analyzing all kinds of information, conducting due diligence on the applicant enterprises, and writing due diligence reports, including customer situation analysis, financial data analysis, due diligence audit analysis, and so on.

However, the level of business analysis of first-line account managers in banks is uneven, resulting in the quality of due diligence and due diligence reports. At the same time, the report templates in the system are often rigid and cannot be used directly, so first-line account managers have to spend a lot of time on report writing.

Based on this requirement, LANCa builds a due diligence report Agent based on a large language model for customers, which can automatically provide analysis conclusions and generate reports to assist the work of first-line bank account managers. [37]It can save 80% of the time for first-line account managers to write reports and comprehensively review customer information to help them manually find some difficult points or omissions. Reduce error rates.

3.5 The Key Capabilities of Gen AI in the Financial Industry

Although the implementation of Gen AI in the financial industry will face challenges such as data privacy and security, technology and resource thresholds, model interpretation and transparency, and regulatory compliance, the difficulty of implementation will be lower than that of traditional AI projects, and the implementation path is more direct.

Sweet New Technology believes that Gen AI in the financial industry needs to cross the following seven dimensions of key capabilities:

1) Define transformation objectives and strategies:

Financial institutions must first clarify their digital transformation goals and strategies and determine the role and

positioning of AI technology in it. An effective Gen AI scaling strategy must include the following key elements: vision, consistency, and commitment from senior leadership, as well as business unit-level responsibility for delivering results, clear application scenarios and goals, and a comprehensive operational plan.

2) Select the application scenario:

After defining the transformation goals, financial institutions must select the application scenarios of AI technology. These scenarios should be pain points in the business process or potential areas of value creation. For example, AI technology can be used in risk assessment, credit approval, intelligent investment advisory, customer service, etc.

3) Accumulation of data and technology[38]:

Financial institutions need to accumulate large amounts of data and related technical capabilities. Data is the foundation of AI technology, and technical capabilities determine the competitiveness of financial institutions in the field of AI. This includes the construction of a data warehouse, data mining, machine learning, deep learning, and other technical capabilities.

Financial organizations need to integrate large models with their existing systems, workflows, enterprise applications, and data sources when deploying large models. This is a critical and complex task. McKinsey believes that effective integration and model maintenance will rely on multiple architectural components: context management and caching, policy management, model hubs, hint libraries, MLOps [39-40] platforms, risk management engines, large language model (LLM) operations, and more [41-42].

4. Conclusion

In summary, although generative artificial intelligence has attracted much attention in the current industries, it still faces many challenges in the application of the financial industry. Zhou Jian, CEO of Lanlan Technology, pointed out that the main difficulties include the lack of accuracy of large-scale models and the certainty of the matching path between the technology and a specific scenario. Solving these core challenges requires careful selection or development of suitable large models and solutions and ensure their superior performance in specific application scenarios. In addition, common misunderstandings include over-reliance on the ideal path and high expectations for the universal applicability of the technology, while in practice, the lack of professional knowledge of the business personnel may affect the effective application of the technology.

In addition, to overcome these challenges, the financial industry needs to innovate and improve the way human computer interaction enables businesspeople to express requirements more effectively, enabling end-to-end support of large models in business processes. However, to achieve the idea of technology adapting to users, rather than users adapting to technology, financial institutions need to explore and innovate deeply in how technology responds to user interaction and understanding of needs. Therefore, promoting the landing of large-scale models and generative AI in the financial sector requires not only technological upgrades, but also a transformation of corporate culture to promote innovation and address potential challenges.

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advanced AI technologies in optimizing supply chain operations and mitigating risks, thereby contributing to both theoretical advancements and practical implications in the field.

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