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Applications for Generative AI in Banking and Finance: Opportunities, Risks, and Governance

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ABSTRACT

The research paper involves a thorough discussion of the how Generative AI (GenAI) has shifted the paradigm of banking and finance industry due to the use of artificial intelligence. In current times, the (GenAI) has become a new emerging force that hasn't been considered as a transformative one yet compared to the old methods of predictive analytics. This study analyzed the financial services ecosystem with its ability to provide new content, model scenarios, and personalized interactions. This research generalizes the exploration of GenAI as customer support services to other areas such as risk management, algorithmic trading, fraud detection, financial reporting, and regulation. This paper is based on the synthesis of the knowledge base on deep learning, multimodal systems, and ethical AI and creates a comprehensive system of GenAI application in finance. The important technologies forming the basis of GenAI including Large Language Models (LLMs), Generative Adversarial Networks (GANs), and diffusion models and how they are applied to financial services, including dynamic customer interaction and hyper-personalized creation of products to the creation of synthetic financial data to train and stress-test models. The article deals with such crucial implementation issues as the privacy of data, model hallucination, regulatory oversight, and ethical aspects of autonomous financial content creation. By comparing and assessing the performance of GenAI over conventional rule-based systems (such as IVR and simple chatbots) in terms of flexibility, knowledge of context, and value-generating interactions, we demonstrate that GenAI outperforms them. Nevertheless, to integrate successfully, there should be strong governance structures and explainability systems as well as human AI collaboration models. The article finds that GenAI is not just a minor upgrade, but a complete rethinking of how financial services is offered, and has the capability to streamline the offer process, make it more accessible, and more personal and offer new aspects of risk, which need to be carefully managed by responsible innovation.

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1. Introduction

The financial services sector is at a turning point where artificial intelligence is moving away from analysis augmentation and toward creative generation. While supervised machine learning and deep learning have revolutionized algorithmic trading, fraud detection, and credit scoring, Generative Artificial Intelligence (GenAI) offers features that drastically alter risk assessment, product development, and service delivery (Mohammed & Skibniewski, 2023). Otherwise, GenAI models produce new data instances that are similar to training data, such as text, code, photos, music, structured financial situations, etc., unlike discriminative models that categorize or forecast (Cano-Marin, 2024).

The application of GenAI is not limited to conversational interfaces to core banking functions. We apply a multimodal learning perspective Kumar (2020), an evolutionary optimization perspective, and a responsible AI framework to construct a complete taxonomy of GenAI applications and look at both potential opportunities and major issues that may arise because of the heavily regulated financial industry.

With its transformer architecture, GenAI models like GPT represent a quantum leap from the AI of the past, which was mostly concerned with comprehending and processing data. These models are now the creators of text, graphics, code, and more, ushering in a period of unprecedented banking innovation. The strategic use of GenAI is much more than a fad; it is a thorough rethinking of operations, product development, and risk management that enables banks to provide individualized services and creative solutions while simplifying routine activities (Bhattacharya et al., 2024).

Banks are rolling out AI chatbots that can help customers any time, day or night. These bots handle everything from basic questions about your balance to more complicated stuff, like financial advice. Take Commonwealth Bank, for example. Their AI system deals with around 50,000 inquiries every day, giving smart, personalized answers that keep customers happy and help the bank save money (Lau & Leimer, 2019).

Generative AI can scan large datasets to spot abnormalities that might signal fraudulent behaviors. It handles billions of transactions per year and identifies and prevents fraud in real-time, protecting customer funds as well as reputation.

1.2 Generative AI Technologies: Foundations for Financial Innovation

In finance, GenAI makes use of several sophisticated architectures (Shalini & Patil, 2021):

Large Language Models (LLMs) (e.g., GPT, Llama): They do well in generating text, text translation, text summarization and code synthesis trained on large corpora. They drive high-level chatbots and document inspection in finance as well as creating reports (Anand, 2022).

Generative Adversarial Networks (GANs): GANs produce realistic images on synthesis by having a discriminator and generator as part of adversarial training. They play a vital role in financial information augmentation and simulation of fraud and they are based on parallel concepts of Spatio-Convolutional GAIN that is used to impute missing data (Buche et al.).

Variational Autoencoders (VAEs) & Diffusion Models: Applicable to portfolio simulation and market scenario generation Used to generate complex data structures and synthetic market datasets of high fidelity (Wilenius, 2024).

Multimodal Generative Models: Multi data type (text, table, chart) processing and generating models are necessary to perform the holistic financial analysis, tackle problems presented by multimodal machine learning researchers (Sardesai et al., 2025).

1.3 Application Domains in Banking and Finance

1.3.1 Customer Experience and Engagement

In addition to the use of rule-based IVR and chatbots, GenAI can be used to (Puchakayala, 2024):

Hyper-Personalized Conversational AI: The LLMs can have context-driven conversations, which are understanding, that solve diverse queries, synthesizing data based on the transaction history, market-related news, and product-related documents of a buyer. This is a super leap of the conventional supervised learning methods that were revised to estimate student performance (Ghule et al., 2024).

Dynamic Content Creation: Personalized financial advice summary, investment report, and educational content generated automatically, according to the level of individual literacy and interests.

Omni-channel Experience Synthesis: Consistent and context-sensitive dialogues between web, mobile and voice interfaces through the generation of contextually correct responses and delivery of those responses to the correct channel.

1.3.2 Risk Management and Compliance (RegTech)

Synthetic Data Generation for Model Validation: Instead of having to expose sensitive customer data to risk, GANs can generate realistic and synthetic financial information (records of transactions, market, etc.) to train and test risk models. This resolves the issue of limited data and privacy that is comparable to medical imaging (Wang et al., 2023).

Automated Regulatory Reporting and Documentation: Writing the compliance report, tracking the regulatory changes, and creating audit trails LLMs can analyze the complicated legal documents, turning manual and mistake-ridden processes into automated ones.

Anti-Money Laundering (AML) and Fraud Detection: GenAI is capable of modeling advanced patterns of money laundering and synthesizing fake transactions of fraud to enhance detection systems to supplement deep learning methods of anomaly detection (Anand, 2022).

1.3.3 Investment and Trading

Algorithmic Strategy Generation**:** All to formulate, and to test, new dream trading signals and portfolio allocations under evolutionary algorithms (Almeida & Neves, 2022).

Market Scenario Simulation and Forecasting: Causally simulating future market conditions (including tail risks) in which portfolios are stressed, beyond the conventional time-series forecasting frameworks (Bhattacharya et al., 2024).

Earnings Call and Sentiment Analysis: LLMs can produce summaries and sentiment analysis reports based on earnings calls, analyst reports, and news based on the subtle notes and contradictions.

1.3.4 Product Development and Personalization

AI-First Financial Products: Creating tailored insurance documents, loan contracts, or investment portfolios under the input of risk profile, objectives, and behavioral information of an individual and applying tenets in artificial intelligence in behavioral economics (Aoujil et al., 2023).

Smart Contract Generation: In the case of blockchain-based finance, the LLMs will be able to write, audit, and interpret a complex smart contract code, minimizing errors and time spent on the code development.

1.3.5 Operational Efficiency

Code Generation for Financial Models: Automating quantitative model development, data pipeline development and analytics dashboards (Zeggaf, 2023).

Document Processing and Knowledge Management: Automated detection, summary, and connection of information across various sources (PDFs, emails, databases, etc.), and formation of dynamic organizational knowledge graph (Peddisetti, 2023).

This evolution is reflected in the wide range of AI applications already available, from automated knowledge management to investment research and personalized banking facilities proved to be a testament to the incredible advances and vast promise of GenAI. Major firms are early leaders during the innovation journey and have worked heavily with AI to create new pathways for talent and operational transparency. Their investment focuses on multiple applications, including upgrades to fraud detection and customer service bots. While obtaining vital AI processing hardware, such as NVIDIA chips, their investments focus on critical people and AI technology. The strategic shift is aimed at refining processes and coupled with the intent to analyze and tackle high-impact use cases, control and iterate the benefits and risks of innovative bleeding-edge prototypes and transform them into scalable operational solutions.

AI keeps changing fast, and honestly, the rules just can't keep up. Banks and other financial companies must make sure their AI tools follow the law, or they'll land in trouble. The Reserve Bank of India isn't just watching from the sidelines—they've already flagged real risks to financial stability as AI and machine learning become more common in finance.

A major improvement over conventional AI models is represented by generative AI. Generative models can produce, analyzing, and interpreting complex textual and contextual information, in contrast to earlier generations of artificial intelligence that were mainly concerned with pattern recognition and predictive analytics. This translates into previously unheard-of skills in legal document analysis, contract formulation, risk assessment, regulatory compliance, and contract comprehension in the BFSI industry.

Regardless of the financial efficiency of the AI and Banks integration, the current study tries to analyze the impact of the advancement of AI on Banks' financing efficiency. The current study attempts to analyze the empowerment effects of AI on different dimensions of the banking industry, including ownership, services offered, and region, and attempts to broaden the scope of research related to the economic impact of AI. The integration of AI and Banks financing efficiency into a single framework is a primary research attempt of this nature. This study aims to analyze the direct impact of the implementation of artificial intelligence on the financing efficiency of Banks in China.

2. Literature Review

The use of artificial intelligence in finance has created new ways to tackle funding challenges for the financial industry. Financial institutions use AI technologies to assess firms' creditworthiness and improve risk evaluation models (Faheem, 2021). This helps lower financing barriers. AI also helps banks simplify internal management processes. This improves operational efficiency and financial transparency Omokhoa et al. (2024), which boosts their ability to finance. However, some studies point out that implementing AI can lead to problems like inconsistent procedures, inaccurate information flow, and delays (Jangam & Karri, 2022). This adds to the complexity of the financing environment for banks. Therefore, figuring out how to make the most of AI's strengths to improve financing efficiency for banks has become an important research topic.

For Banks, financing operations constitute an essential economic behaviour, and the key to financing efficiency is for businesses to follow economic substantive principles (Beck, 2006). To maximize enterprise value and minimize capital acquisition expenses and related risks, it is necessary to optimize financing structures and fund management. Asymmetric knowledge between banks and businesses causes moral hazard and adverse selection, which are institutional barriers to banks funding from the outside (Wheelock & Kumbhakar, 1995).

Research from Kaluarachchi and Sedera (2024) showed that AI-driven solutions improve financial institutions' decision-making processes, lower costs, and increase operational efficiency. Personalization and client Engagement: AI's capacity to customize client experiences is among its most prominent effects in the financial sector. According to Accenture research (2019) AI-driven recommendation systems use consumer data to provide customized financial products, greatly increasing client engagement and happiness. Increased sales and client loyalty result from this customization.

Shaikh et al. (2024) dive into how AI shapes automated trading. They show that AI doesn't just make trading faster it sharpens accuracy, too. The result? Investors see stronger financial returns, and investment products sell better. Lee and the team (2022) look at what happens when you mix AI with blockchain in finance. Their research points out that this combo tightens up security and streamlines transactions. Plus, it helps push sales of blockchain-based financial products even higher.

In accounting, the accuracy of financial data is crucial. According to Alhazmi et al. (2025), the use of AI can improve the accuracy of financial reports from the Saudi stock exchange, as well as the accuracy of financial disclosures and the compliance of the report's regulations. This is primarily due to the ability of AI to analyze large amounts of data and recognize discrepancies that the human eye may miss. Moreover, the use of AI in accounting has also greatly augmented the efficiency and quality of financial data, resulting in improved outcomes in tax compliance and the detection of financial fraud. All of these studies confirm that AI has enhanced financial data accuracy. The use of accounting automation and artificial intelligence is also transforming the responsibilities of accounting professionals (Mengdie et al., 2025).

AI applications in finance have also been studied from an enterprise-side standpoint. On the one hand, using AI technology improves financing efficiency by streamlining SMEs' financing procedures and facilitating the quick completion of financing activities (Omokhoa et al., 2024). However, AI applications cause a number of intricate chain reactions in the operational models, external finance environments, and internal management of businesses, which have an indirect impact on financing efficiency (Li, 2023).

3. Research Methodology

3.1. Research Design

This study uses a survey research design to examine how GenAI affects banks' accounting decision-making and financial efficiency. A survey design is suitable because it enables the direct collection of primary data from respondents, guaranteeing a wide range of viewpoints on GenAI finance principles and their effect on efficiency (Şahin & Karayel, 2024). A cross-sectional approach is utilized, as data is collected at a single point in time to capture financial decision-making trends without requiring a longitudinal perspective (Alimohammadlou & Bonyani, 2018). The efficiency of data collection, cost-effectiveness, and capacity to generalize findings within the study's population make this design advantageous (Meyer et al., 2014). Nevertheless, it has drawbacks like response bias and the inability to determine. This design works well because it collects data efficiently, saves money, and lets us apply the results to the broader study group. Still, there are some drawbacks like response bias and the fact that we can't prove cause and effect. To handle these issues, we'll use solid statistical analysis and validation methods.

3.2. Population of the study

Bank employees, accountants, financial analysts, and corporate decision makers in the financial industry make up the study's target population. These individuals are selected due to their direct engagement with accounting decision-making processes influenced by GenAI finance principles.

3.3. Sampling technique

The study adopts a probability sampling method, specifically stratified random sampling, to ensure representation across different professional backgrounds and organizational sizes (Burger & Silima, 2006). This method lessens selection bias while improving the findings' generalizability.

3.4. Sample size

Figuring out the right sample size starts with a power analysis. The goal is to make sure the results mean something. Based on Lakens and Ravenzwaaij (2022), at least 300 respondents work well. That number isn't random, it lines up with earlier research in GenAI finance and accounting, so you get enough statistical power to run solid inferential analysis.

3.5. Data Collection Method

The method used in the research is self-administrated online survey. It includes structured questionnaires to test how GenAI finance principles, namely Return on Equity (ROE), Financing cost, Financing risk and anchoring impact accounting decision making. Questions are developed in terms of Likert scale (1-5) to note the level of agreement/disagreement with the finance constructs defined by Taylor (2020).

3.6. Reliability and Validity

Cronbach's alpha is used to test internal consistency in order to guarantee reliability; a threshold of 0.7 and above is deemed acceptable (Izah et al., 2023). Exploratory and confirmatory factor analysis are used to validate construct validity. Expert reviews and pre-testing of the survey instrument establish content validity (Ghazali & Fauzi, 2025).

3.7. Data Analysis Techniques

We analyzed the data using a 5-point Likert scale, and calculated the mean to tackle the study's main objective. For this research, we built a composite financing efficiency index, following the method Zhang and Zhao introduced in 2015. This maintains a close connection to the three-part theoretical framework of the study. In essence, this method incorporates the theory directly into the calculations, making it evident how financing risk, returns, and expenses change over time. This is the formula that we employed:

$$FE_R = FI\ X\ [\ 1 - FC\ X\ (\ 1 + FR\ )]\ X\ 100\%$$

Where ROE represents financing return, DC represents financing cost, and DFL represents financing risk. To reduce skewness in the variable's distribution, the financing efficiency measure (FE_R) is log-transformed to create the variable FE. Additionally, to confirm the validity of the findings, this study adds a financing efficiency measurement method based on DEA as a further robustness check.

4. Empirical Analysis

4.1 Descriptive statistics

Table 1 shows the descriptive statistics. To reduce significant skewness in the distribution, the dependent variable, finance efficiency (FE), is a logarithmic transformation of the original measure (FE_R). While the sample firms demonstrate some financing efficiency overall, there are still notable differences among the enterprises. The degree of AI application, the main independent variable, has a mean of 0.7391, a median of 0, and a maximum value of 5.5094. This indicates that some enterprises have reached a high level of AI adoption, even though most firms in the sample are still using AI at a relatively low level.

Table 1.
Descriptive Statistics

Var Name	Obs	Mean	SD	Min	Median	Max
FE_R	11056	9.4683	7.9595	0.0077	7.9983	231.3723
FE	11056	1.9119	0.9346	-4.8687	2.0792	5.444
AI	11056	0.7391	1.0943	0	0	5.5094
ASY	11056	-0.1484	0.4301	-6.2328	-0.0857	1.0898
FC	11056	0.545	0.0858	0.2941	0.5294	0.8824
Innovation	11056	2.8494	1.5336	0	2.9957	8.2404
Size	11056	0.5105	1.4487	0.0218	0.2496	71.7168
ROA	11056	0.061	0.0506	-0.0056	0.0506	0.8796
Growth	11056	0.2663	1.5318	-0.9132	0.1474	84.992
Top1	11056	32.7702	13.9107	2.12	30.75	89.99
Indsize	11056	37.6185	5.4422	0	33.33	75
Lev	11056	0.3537	0.1795	0.0075	0.339	0.9755
Cash	11056	0.0532	0.0691	-0.6702	0.0508	0.6641

4.2 Baseline Regression Analysis

The foundational regression results regarding the impact of AI on the banking sector's financing efficiency are shown in Table 2. To validate the robustness of these findings, control variables, year fixed effects, and firm fixed effects are incorporated in a sequential manner. Concerning the primary explanatory variable, the coefficient for AI consistently remains significantly positive at the 1% level across all model specifications, suggesting that AI exerts a substantial positive impact on the efficiency of banking sector. AI helps businesses obtain capital at lower risks and expenses while maximizing capital use to increase returns.

Table 2.
Baseline Regression Results

Variable	(1) FE	(2) FE	(3) FE	(4) FE	(5) PSM
AI	0.0359*** (2.8999)	0.0291*** (4.7336)	0.0356*** (5.4510)	0.0280*** (2.6405)	0.0320** (2.0053)
Size		0.0026*** (3.3860)	0.0433*** (3.3382)	0.0294** (2.4525)	0.0558** (2.2486)
ROA			15.372*** (24.796)	14.521*** (24.4897)	13.374*** (18.396)
Growth			0.0083** (2.5431)	0.0080** (2.4544)	0.0246* (1.5305)
Top1			0.0029*** (4.2131)	0.0026*** (3.6222)	0.0043* (1.9572)
Indsize			-0.0051*** (-3.1607)	-0.0047*** (-2.8641)	-0.0041 (-1.3191)
Lev			0.815*** (10.8651)	0.824*** (10.8034)	0.557*** (3.7728)
Cash			-0.585*** (-4.2059)	-0.501*** (-3.4348)	-0.518** (-1.7103)
_cons	1.8854*** (92.380)	0.7918*** (9.1336)	0.7762*** (8.9197)	0.8013*** (7.7064)	0.8968*** (6.1145)
Year-fixed	N	N	Y	Y	Y
Firm-fixed	N	N	N	Y	Y
N	11056	11056	11056	11056	10963
Adj. R^2	0.0077	0.0696	0.051	0.0971	0.7175

Note: *, **, and *** denote significance levels at 10 %, 5 %, and 1 %, respectively. Robust standard errors clustered at the firm level are used, with t-values reported in parentheses.

The regression analysis conducted with this instrumental variable strategy demonstrates that artificial intelligence markedly enhances financing efficiency, thereby affirming the strength and dependability of our conclusions. These findings indicate that companies utilizing AI are more effectively equipped to handle financing expenses, refine risk evaluations, and attain superior financial returns, underscoring important ramifications for the management strategies of small and medium-sized enterprises as well as for policy development.

5. Conclusion

Based on a sample of experts from China's listed financial banks, this study methodically examines the impact and underlying mechanisms of GenAI application on bank financing efficiency. The study finds a strong positive relationship between the use of GenAI and the banking industry's financing efficiency through thorough theoretical analysis and empirical testing; in particular, the incorporation of AI technologies results in improvements in financing efficiency. AI impacts financing efficiency through three primary mechanisms: it reduces information asymmetry, mitigates financing constraints, and encourages technological innovation. The effect of AI on financing efficiency differs among various types of financial services in China. This demonstrates a greater capacity to effectively absorb and implement AI technologies to improve their financing efficiency.

6. Policy Implication

Banks need to start using generative AI in their financial management and innovation plans. This makes information clearer and helps tackle financing problems head-on.

On top of that, financial institutions should upgrade how they serve customers. Big data and machine learning can make credit checks more accurate. Smart platforms can offer solutions tailored to each client. And expanding digital channels means more people get access to these services.

The government plays a big role here, too. It should step up policy support—think tax breaks and funding for AI research and development. Speeding up tech transfers through partnerships between businesses, universities, and research groups will help. Plus, putting more money into AI infrastructure, especially in central and western regions, pushes for growth that includes everyone.

Conflict of Interests/Disclosures

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