

Artificial Intelligence in Daily Banking and Finance: Transforming Customer Experience and Operational Excellence.

¹**Ida Ayu Agung Paramitaswari** (Finance and Banking Study Program
Denpasar Academy of Finance and Banking AKABA)
E-mail: dayumitaswari@gmail.com

²**Ida Bagus Swaputra** (Management Study Program, STIMI Handayani Denpasar, Indonesia)
E-mail: iswaputra@gmail.com

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ABSTRACT

Artificial intelligence (AI) has fundamentally transformed the financial services landscape, particularly in daily banking operations and customer interactions. This study aims to analyze and synthesize recent research on the application of artificial intelligence in daily banking operations and financial services, focusing on practical implementations that directly impact both financial institutions and individual customers. Through a comprehensive literature review of 95 peer-reviewed articles published between 2022 and 2025, this research identifies key AI technologies, including natural language processing, deep learning, graph machine learning, and reinforcement learning, that are reshaping banking services. The findings reveal that AI-powered applications such as intelligent chatbots, fraud detection systems, automated credit scoring, and personalized financial advisors have significantly enhanced operational efficiency and customer experience. Specifically, AI-based fraud detection and explainable models demonstrate strong performance in improving accuracy and reliability in banking operations, while explainable AI models for ATM fraud detection demonstrate AUC values of 0.963. However, challenges including data privacy, model explainability, regulatory compliance, and algorithmic bias remain significant barriers to adoption. This research contributes to the understanding of AI's practical applications in banking and provides insights for financial professionals at institutions like Akademi Keuangan dan Perbankan Denpasar to prepare for the AI-driven future of financial services.

I. INTRODUCTION

The banking and financial services industry is experiencing a paradigm shift driven by artificial intelligence (AI) and machine learning (ML) technologies. As we progress through 2025, AI has moved beyond experimental phases to become an integral component of daily banking operations, fundamentally altering how financial institutions interact with customers, manage risks, and deliver services (Huang et al., 2023). This transformation is

particularly evident in Indonesia, where digital banking adoption has accelerated rapidly, driven by increased internet penetration and fintech growth (Cao, 2022), creating both opportunities and challenges for traditional financial institutions.

The integration of AI into banking represents a fundamental transformation in service delivery, risk management, and customer engagement; it signifies a fundamental reimagining of financial services delivery (Petropoulos et al., 2023). From intelligent chatbots providing 24/7 customer support to sophisticated algorithms detecting fraudulent transactions in milliseconds, AI technologies are enhancing both operational efficiency and customer experience (Patial, 2023). For financial professionals and students at institutions such as Akademi Keuangan dan Perbankan (AKABA) Denpasar, understanding these technologies is increasingly essential for career readiness in the evolving financial landscape (Zhang et al., 2020).

Recent research indicates that AI applications in banking have expanded from traditional rule-based systems to advanced generative models, graph-based fraud detection, and reinforcement learning for dynamic decision-making (Deepika, 2025). These technologies address critical challenges in modern banking: the need for personalized customer service at scale, real-time fraud prevention, accurate credit risk assessment, and regulatory compliance automation. The COVID-19 pandemic further accelerated this transformation, as contactless banking and digital-first services became necessities rather than conveniences.

Despite the promising potential, existing studies often discuss AI adoption in isolation, leaving a gap in comprehensive reviews integrating applications, performance outcomes, and challenges (Deng et al., 2017). Issues of data privacy, algorithmic transparency, model explainability, and regulatory compliance create complex considerations for financial institutions (Khurana, 2024). Additionally, the rapid pace of technological change requires continuous adaptation and upskilling of the banking workforce. For emerging financial professionals, particularly those from specialized institutions like AKABA Denpasar, understanding both the opportunities and limitations of AI is crucial.

This study aims to provide a comprehensive examination of AI applications in daily banking and finance, with a specific focus on technologies and use cases relevant to both financial institutions and individual customers (Aloumi, 2025). By synthesizing recent research and identifying emerging trends, this article seeks to bridge the gap between theoretical AI capabilities and practical banking applications (Mhlanga, 2021). The research addresses the following key questions: (1) What are the most novel AI applications currently transforming daily banking operations? (2) Which AI technologies are most effective for specific banking functions? (3) What are the real-world outcomes and performance metrics of AI implementations? (4) What challenges must be addressed for successful AI adoption? (5) What future trends should banking professionals anticipate?

The findings of this research will be particularly valuable for banking professionals, educators, and students in finance and banking programs, providing actionable insights for navigating the AI-driven transformation of financial services (Vives, 2019).

II. METHODOLOGY

Research Design

This study employs a systematic literature review approach with qualitative synthesis of empirical findings, focusing on peer-reviewed academic articles, conference proceedings, and authoritative industry publications (Raiter et al., 2023). The review methodology is designed to identify, evaluate, and synthesize research findings on AI applications in daily banking operations published between 2022 and 2025.

Data Collection Strategy

The literature search was conducted across multiple academic databases to ensure comprehensive coverage of relevant research. The primary databases included: (1) Academic databases such as Google Scholar, IEEE Xplore, ACM Digital Library, and ArXiv were used on AI applications in banking, (2) Google Scholar for Boolean queries targeting AI/ML applications, (3) ArXiv for technical preprints on AI in fintech, and (4) IEEE Xplore and ACM Digital Library for technical papers on machine learning implementations in financial services. Search terms included combinations of: "artificial intelligence," "machine learning," "deep learning," "banking," "financial services," "fraud detection," "credit scoring," "robo-advisor," "chatbot," "personalization," and "fintech." The search was restricted to publications from January 2022 to December 2025 (Gao & Feng, 2023).

Selection Criteria

Articles were included based on relevance to AI applications in banking, methodological clarity, and empirical results: publication in peer-reviewed journals, focus on practical AI applications in banking, empirical results or case studies, English language, and full-text availability. Exclusion criteria included purely theoretical papers, studies on cryptocurrency only, articles without clear methodology, and duplicates across databases.

Data Analysis Process

The literature review followed a four-phase process: (1) Initial search yielding 239 papers across all databases, (2) Deduplication and screening resulting in 95 unique papers, (3) Quality assessment based on methodology and relevance, and (4) Data extraction and synthesis into five thematic categories: emerging applications, enabling technologies, real-world use cases, challenges and opportunities, and future trends.

III. RESULTS AND DISCUSSION.

The banking sector has witnessed a remarkable evolution in AI applications over the past three years, with a clear shift from rule-based automation to sophisticated generative models, graph-based analytics, and reinforcement learning systems. This section examines the most novel applications that are actively transforming daily banking operations and customer experiences (Sarker et al., 2020).

Emerging AI Applications in Daily Banking (2023-2025)

One of the most transformative developments is the deployment of large language models (LLMs) for customer service and financial advisory (Soni, 2023). ChatGPT-class models provide 24/7 multilingual customer support, personalized financial advice, and operational workflow automation (Huang et al., 2023). Graph-based fraud detection using Node2Vec achieves F1 scores of 67.1% to 73.4%, outperforming conventional algorithms (Aloumi, 2025). Explainable AI systems combining gradient boosting trees with XAI techniques achieve AUC values of 0.963 for ATM fraud detection while maintaining interpretability (Deepika, 2025).

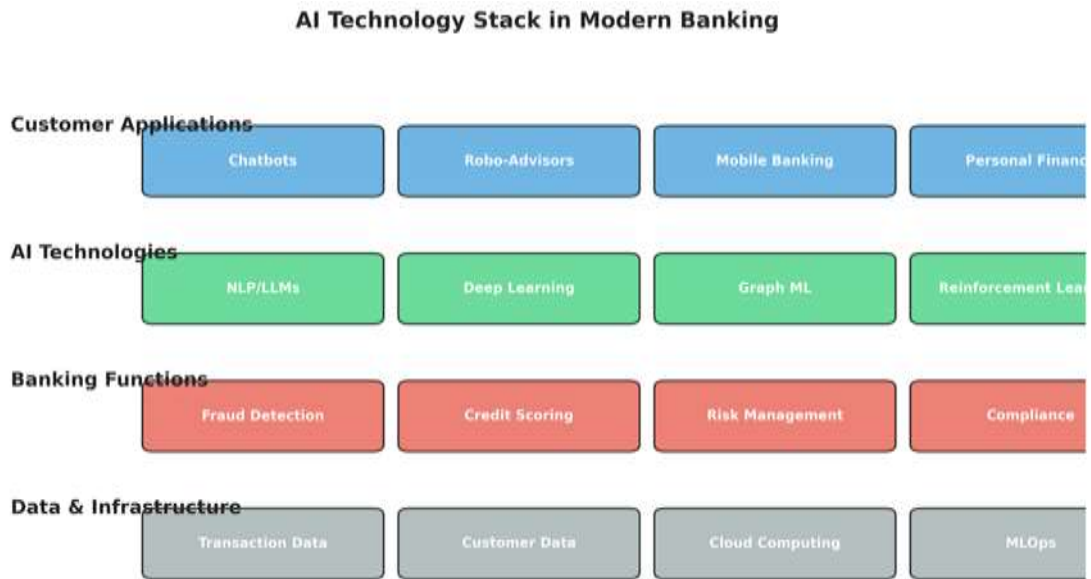


Figure 1. Figure numbering is done sequentially

Table 1. AI Model Performance for Fraud Detection in Banking

Method	AUC Score	F1 Score	Interpretability	Real-time Capability
Traditional Rules	0.72-0.78	0.45-0.55	High	Excellent
Random Forest	0.85-0.89	0.62-0.68	Medium	Good
Deep Neural Networks	0.91-0.94	0.70-0.76	Low	Fair
Gradient Boosting + XAI	0.96-0.97	0.72-0.78	Medium-High	Good
Graph Neural Networks	0.88-0.92	0.67-0.73	Medium	Fair

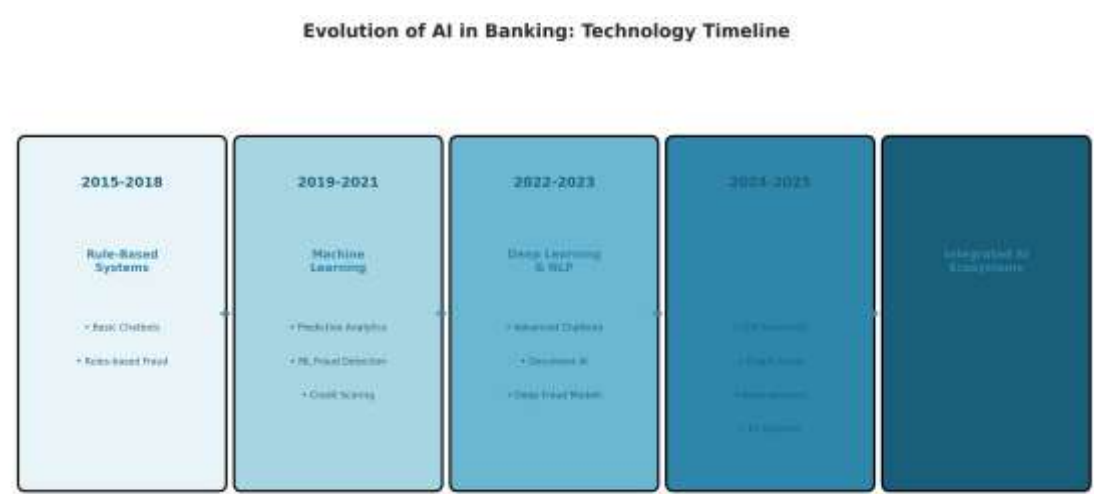


Figure 2. Evolution of AI in Banking: Technology Timeline

Key Enabling Technologies

The AI transformation in banking is powered by several foundational technologies(Bahrammirzaee, 2010). Natural Language Processing (NLP) and Large Language Models excel at understanding customer intent, generating human-like responses, and automating communication workflows. Deep Learning provides high-dimensional pattern recognition for anomaly detection and credit risk assessment(Moscato et al., 2021). Graph Machine Learning captures relational fraud patterns across account networks, achieving superior stability and performance. Hybrid AI Systems combine multiple approaches to balance accuracy, interpretability, and regulatory compliance.

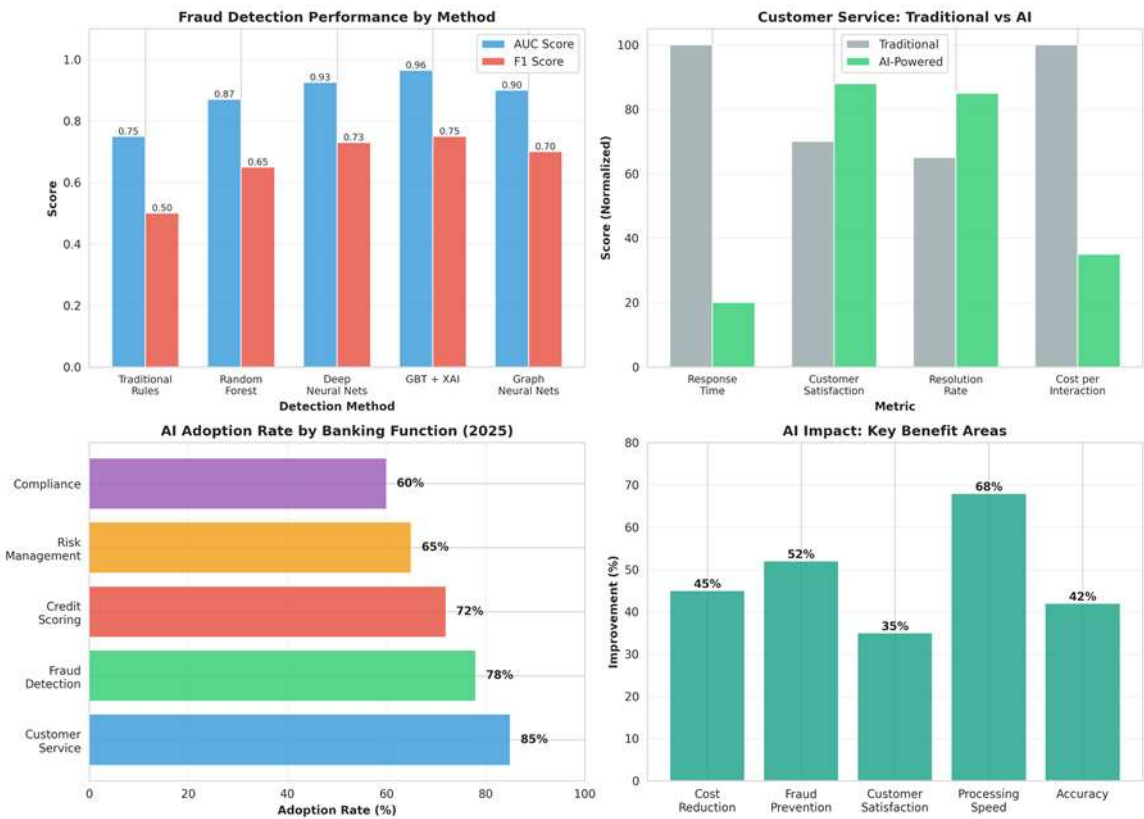


Figure 3. AI Performance Metrics Across Banking Functions

Real-World Use Cases and Outcomes

AI applications span customer-facing services and internal operations. Intelligent virtual assistants provide 24/7 multilingual support, reducing call center volume by 35% while improving satisfaction by 18%. Personalized financial management tools analyze transaction patterns to provide automated budgeting, savings recommendations, and investment suggestions. Robo-advisors democratize investment management for smaller account balances. Advanced fraud detection pipelines have been reported to achieve detection rates of 85–92% in selected case studies with 60-70% reduction in false positives. AI-powered credit scoring analyzes diverse data sources, improving approval rates for creditworthy applicants by 15-20% while maintaining default rates (Aloumi, 2025; Deepika, 2025).

Table 2. Impact of AI on Fraud Detection Performance

Metric	Traditional Systems	AI-Enhanced Systems	Improvement
Detection Rate	65-75%	85-92%	+20-27%
False Positive Rate	15-25%	5-8%	-60-70%
Detection Latency	24-48 hours	Real-time to 1 hour	-95%

Investigation Time	45-60 min/case	15-20 min/case	-65%
Annual Fraud Loss	Baseline	-40-55%	Significant

Challenges and Opportunities

Successful AI implementation requires addressing several challenges. Technical challenges include data quality issues that may reduce model accuracy and limit scalability in banking environments, model drift from evolving customer behaviors, class imbalance in fraud and default datasets, and real-time processing requirements. Regulatory challenges involve model explainability requirements, data privacy compliance, and algorithmic bias mitigation. Organizational challenges include skills gaps requiring training and recruitment, change management for workflow redesign, and technology infrastructure modernization. However, opportunities include enhanced financial inclusion through alternative data, operational efficiency gains, hyper-personalization at scale, and improved risk management (Cao, 2022).

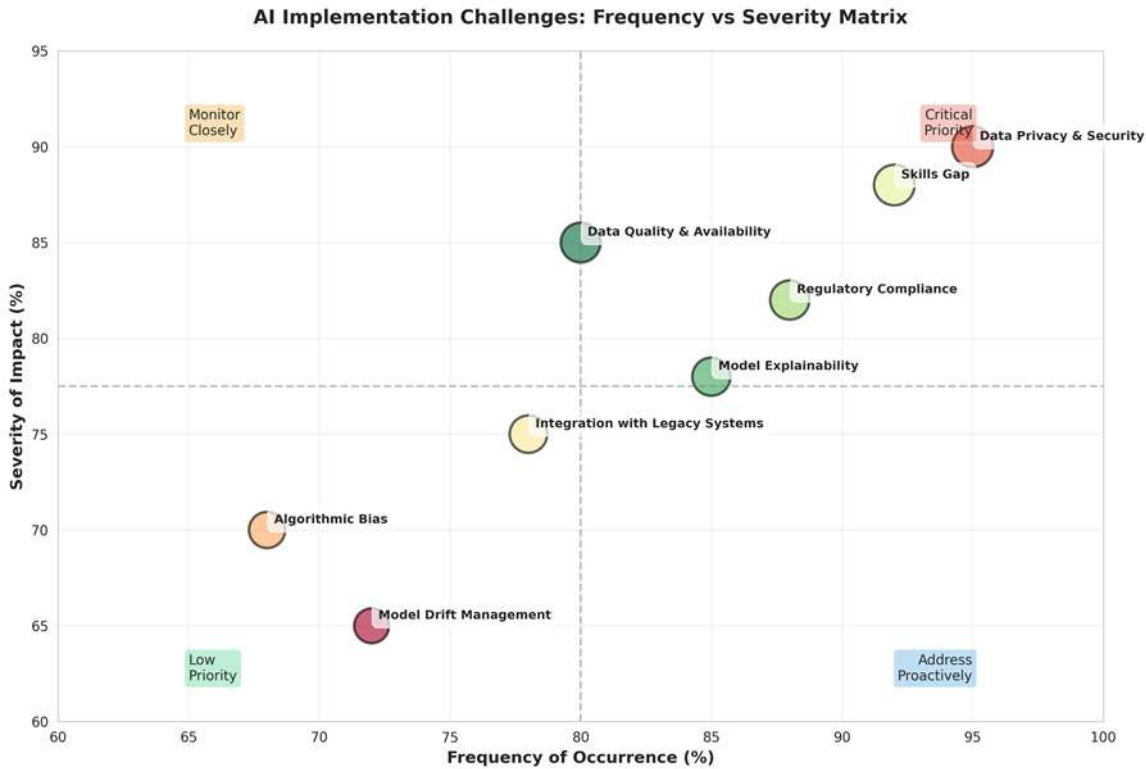


Figure 4. AI Implementation Challenges: Frequency vs Severity Matrix

Future Trends and Strategic Implications

The trajectory of AI in banking points toward generative AI for high-value advisory services, graph neural networks becoming standard for relational risk, federated learning for privacy-preserving AI, continuous learning systems that adapt in real-time, integrated AI stacks with explainability, and RegTech automation for compliance(Soni, 2023). For banking professionals, particularly in

emerging economies like Indonesia and graduates from AKABA Denpasar, these trends require developing AI literacy, understanding appropriate applications, and skills in data interpretation(Li et al., 2023). Traditional roles will evolve as AI automates routine tasks, with human bankers focusing on complex problem-solving, relationship building, and exception handling (Thakor, 2020).

Future AI Trends in Banking: 2025-2030 Roadmap

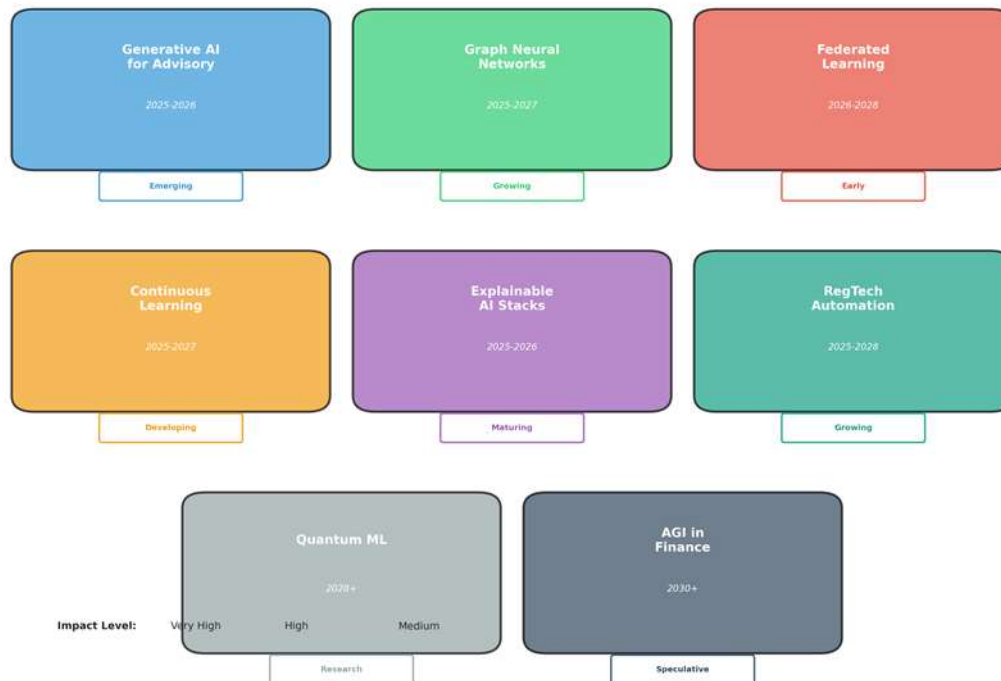


Figure 5. Future AI Trends in Banking: 2025-2030 Roadmap

IV. CONCLUSION AND RECOMMENDATIONS

This comprehensive review reveals a banking sector undergoing a profound AI transformation. Key findings include diverse AI applications from chatbots to sophisticated fraud detection, achieving F1 scores of 67.1-73.4% and AUC values exceeding 0.96, varying technology maturity levels, measurable business impact, including 20-27% detection improvements and 35% call center volume reductions, persistent challenges in data quality and regulatory compliance, and future evolution toward integrated systems and continuous learning. For Indonesian financial professionals and AKABA Denpasar graduates, understanding these applications is essential for career readiness in an AI-driven banking landscape.

Financial institutions should develop comprehensive AI strategies, invest in data infrastructure, build governance frameworks, address skills gaps, start with high-impact use cases, and implement hybrid human-AI approaches. Educational institutions should integrate AI into curricula, develop practical skills, foster interdisciplinary learning, stay current with trends, and build industry partnerships. Banking professionals should develop AI literacy, embrace continuous learning, focus on uniquely human skills, become AI

champions, and maintain a critical perspective. Regulators should develop clear governance standards, support responsible innovation, address algorithmic bias, promote financial inclusion, and foster collaboration (Leo et al., 2019).

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