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# ARTIFICIAL INTELLIGENCE IN BANKING: A COMPREHENSIVE MAPPING OF APPLICATIONS, CHALLENGES, AND STRATEGIC IMPLICATIONS

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## ABSTRACT

Artificial intelligence is rapidly reshaping the banking sector, creating opportunities for efficiency, innovation, and sustainability while introducing new regulations and financial stability risks. This research aims to systematically examine and categorise AI applications across the full spectrum of banking functions to assess their transformative potential and implications. The study employs a structured review methodology, combining academic literature, industry case studies, and regulatory reports, and applies thematic classification to map AI use into nine core domains of banking activity. The findings demonstrate that AI permeates all levels of banking operations. In customer-facing services, it supports personalisation, chatbots, biometric onboarding, and voice-gesture banking to enhance user experience. In risk management and compliance, AI improves fraud detection, AML/CFT monitoring, credit scoring, and regulatory reporting. Operational efficiency is advanced through robotic process automation, document processing, workflow optimisation, and predictive maintenance. AI also drives innovation in lending, enabling automated loan origination, dynamic pricing, and personalised debt collection. Cybersecurity and infrastructure benefit from AI intrusion detection, adaptive authentication, phishing prevention, and blockchain integration. Furthermore, human resources, marketing, ESG finance, and strategic management functions increasingly rely on AI for decision support, customer analytics, sustainability assessments, and scenario forecasting. Collectively, these results highlight AI's holistic role in transforming banking while underscoring the importance of explainability, governance, and regulatory alignment to ensure trust, inclusivity, and resilience.

**Keywords:** artificial intelligence, banking, risk management, process automation, sustainable finance, strategic innovation

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## INTRODUCTION

Recent evidence from international financial authorities underscores the urgency and timeliness of studying AI in banking. According to the IMF's Financial Counsellor and Director of the Monetary and Capital Markets Department, widespread AI adoption offers substantial benefits such as productivity gains, cost savings, enhanced regulatory compliance (RegTech), and more tailored customer services. However, it raises novel risks around model explainability, herding behaviour, vendor concentration, and market fragility (Adrian, 2024). The Bank of England's Financial Policy Committee similarly warns that while AI could transform core banking decision-making and operational efficiency, it may also introduce systemic risks if many banks use similar models or rely heavily on the same providers of AI infrastructure (Bank of England, 2025). Meanwhile, Moody's latest survey shows that more than half of financial institutions are either using or trialling AI for risk and compliance functions in 2025, a sharp increase from 30% in 2023 –reflecting rapidly growing deployment in areas such as fraud detection, credit underwriting, and regulatory monitoring (Moody's, 2025).

Moreover, recent reports from Bloomberg and others suggest that banks are entering an era of greater autonomy and higher expectations for return on investment from their AI investments. A Bloomberg Intelligence piece forecasts that "agentic AI", that is, systems which reason, plan, and act more autonomously, has the potential to greatly exceed efficiency gains delivered by earlier narrow AI tools. However, its full deployment will require overcoming significant barriers, including regulatory constraints, legacy systems, and robust data governance (Bloomberg Intelligence, 2025). Concurrently, banks are feeling competitive pressure to scale their AI use or risk being outpaced, not only in terms of innovation but also customer relevance (Green, 2025).

Finally, policymakers increasingly focus on framing AI in banking as both an opportunity and a source of financial stability risk. The FSB (2024) considers how rapidly evolving AI technologies (especially generative AI and large foundation models) may amplify vulnerabilities such as interconnectedness, misuse, and lack of transparency in decision-making. The IMF also projects that while AI could yield global economic gains, these must be balanced against rising energy demand, potential labour displacement, and inequality (Li, 2025). Thus, the research topic is academically interesting and deeply relevant to current financial policy, technology infrastructure, and banking business strategy.

## LITERATURE REVIEW

The rapid diffusion of digital technologies has profoundly reshaped the banking ecosystem, with AI emerging as a central driver of transformation. Digitalisation processes are increasingly recognised as a precondition for AI integration, enabling banking stability and financial inclusion through expanded access and efficiency gains (Abbasova et al., 2025). Generational differences also play a critical role, as studies reveal that younger cohorts, particularly Gen Z, display higher acceptance of mobile and AI-based banking tools, highlighting shifts in customer behaviour in line with technological advances (Adhikari et al., 2024). These developments underline the need to analyse AI not in isolation, but as part of broader digital transformation processes affecting service adoption, stability, and competitiveness.

Operational efficiency has been one of the most visible areas of AI deployment in banking. Robotic process automation is widely applied to streamline auditing and reporting, showing measurable improvements in accuracy and productivity (Alassuli, 2025). AI-driven tools enhance employee engagement and productivity, signalling that human resource functions are also subject to digital transformation (Ayu Gusti et al., 2024). Within financial management, AI adoption is framed as both an opportunity and a pressure point, requiring institutions to adapt to transformative technologies while balancing risks (Balcerzak & Valaskova, 2024). Ethical and organisational aspects also surface, with AI influencing decision-making frameworks and corporate culture in both banking and public sector environments (Bian & Wang, 2024). Such evidence illustrates AI's influence across operational, human, and ethical dimensions.

The integration of AI into financial services has direct implications for customer relations and market behaviour. AI is applied in digital insurance and fintech adoption, particularly among older populations and urban clients, demonstrating its capacity to bridge gaps in financial participation (Parajuli et al., 2024). IT investments in banking are empirically shown to contribute to profitability and institutional performance, providing further justification for AI integration as part of long-term digital strategies (Chau et al., 2025). Marketing processes are similarly transforming, with AI leveraged for personalised offers, advanced trend analysis, and content management (Kildei et al., 2025; Sang, 2024). Internet banking in emerging markets such as China illustrates both the opportunities and risks of AI-enabled digitalisation, as financial institutions seek to position themselves as champions of technological innovation (DingYi et al., 2024).

The implications of AI extend beyond service delivery to areas of security, compliance, and regulation. With the rise of digital interconnectedness, health security and cybersecurity interdependencies highlight the need for robust AI-based protective systems (Dobrovolska et al., 2024; McCoy, 2025). Text-mining approaches and data analytics are increasingly used in financial reporting and fraud detection, enhancing oversight capabilities (Lyeonov et al., 2024). AI and big data capabilities also underpin fintech services and value co-creation, providing new opportunities for customer engagement while reinforcing the need for advanced governance mechanisms (Noor et al., 2024). However, concerns about misuse also emerge, with studies pointing to organised crime's potential benefits from AI, underscoring the double-edged nature of technological deployment in AML/CFT frameworks (Lyeonov et al., 2025).

AI is also reshaping financial markets and investments, with significant implications for banking strategies. Empirical evidence confirms the impact of fintech and AI adoption on stock indices and banking dynamics across global markets, while also influencing supply chain efficiency and resilience (Galvão et al., 2025; Golubtsov et al., 2025). AI applications in capital markets, such as robo-advisory and fintech apps, are proven to affect investment decisions and foster broader participation (Priyadarshi et al., 2024). The convergence of technical indicators and machine learning is identified as a key enabler for cryptocurrency and digital asset markets, aligning with global trends in financial innovation (Okoi et al., 2025). Studies also emphasise the dynamic role of fintech in fostering financial development in emerging economies, reinforcing AI's strategic importance for long-term growth (Okoli, 2024; Okoi et al., 2025).


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Beyond immediate financial processes, AI contributes to broader organisational and societal transformations. Research highlights its role in employee engagement, corporate innovation, and open innovation management, showing the interconnection between technological adoption and organisational competitiveness (Ayu Gusti et al., 2024; Ponomarenko et al., 2024). The creative economy and pharma sectors demonstrate the cross-sectoral implications of AI, underscoring the need for banking to adapt in parallel with other industries (Kritikos et al., 2025). Digital readiness and the socio-economic impact of digitalisation are additional factors shaping how AI is adopted, with implications for corruption, cyber threats, and sustainable competitiveness (Nafei et al., 2025; Slavik & Bednarova, 2024; Yarovenko et al., 2025a; Yarovenko et al., 2025b). The debate about AI's future is thus framed not only around hope and efficiency but also fear, risk, and governance (Yarovenko et al., 2024).

These studies reveal that AI in banking is situated at the intersection of digitalisation, innovation, and systemic risk. It enhances efficiency, inclusivity, and strategic adaptability, while at the same time raising concerns regarding ethics, cybersecurity, and misuse. The reviewed literature highlights the opportunities and vulnerabilities that arise from embedding AI into financial ecosystems, confirming the necessity of comprehensive mapping to guide policy, practice, and further research.

## AIMS AND OBJECTIVES

This study aims to provide an integrative framework of AI applications in banking by mapping domains, subtopics, and real-world examples, thereby identifying opportunities for innovation and potential challenges related to trust, inclusivi-ty, and governance.

## METHODS

This research employed a qualitative and analytical methodology to systematically map the domains and applications of AI within the banking sector. The study followed a structured review approach by examining academic publications, industry reports, case studies, and regulatory guidelines to identify the breadth of AI adoption across banking functions. A thematic classification framework was applied to group applications into nine principal domains: customer-facing services, risk management and compliance, operations and process automation, lending and credit, cybersecurity and infrastructure, human resources and internal management, marketing and customer analytics, sustainability and ESG finance, and strategic management and innovation. Within each domain, subtopics were identified to highlight specific use cases, such as robo-advisory platforms, fraud detection, dynamic pricing, or green finance scoring. This provided a comprehensive perspective on how AI reshapes operational, financial, and strategic banking dimensions.

The data collection integrated primary and secondary sources to ensure reliability and triangulation. Secondary data included peer-reviewed journal articles, official publications from organisations such as FATF and KPMG, and reports from technology providers (e.g., AU10TIX, Personetics, Biz2X). Industry case studies, such as Mastercard's "Decision Intelligence" for fraud detection or Bank of America's "Erica" chatbot, were incorporated to illustrate real-world applications and validate conceptual insights. Academic contributions, such as graph neural network models for credit scoring (Muñoz-Cancino et al., 2022) or sentiment-informed prediction frameworks (Mamillapalli et al., 2024), were used to support the scientific grounding of AI applications. This combination of academic and industry evidence ensured a balanced methodological design capable of capturing both theoretical advances and practical implications.

For the synthesis of findings, a comparative analysis approach was applied to align conceptual frameworks with empirical applications, enabling the identification of commonalities, divergences, and emerging trends across domains. The information was consolidated into a summary table that cross-referenced domains, subtopics, and representative examples, thereby enhancing the interpretability of results. This methodological design allowed for the development of an integrated view of AI in banking, highlighting its role in enhancing efficiency, compliance, innovation, and sustainability. It also acknowledged risks such as data privacy, bias, and regulatory challenges. The approach thus ensured both breadth and depth in understanding AI's transformative potential in banking institutions.

## RESULTS

Artificial intelligence in banking extends across multiple domains, encompassing customer interaction, compliance, risk management, operations, investment, lending, cybersecurity, human resource management, marketing, sustainability, and strategic development. Its impact is holistic, enhancing efficiency and profitability and reshaping fundamental dimensions of trust, inclusivity, and resilience within the financial system. To capture the breadth of its application, the implementation of AI can be mapped across the entire ecosystem and lifecycle of financial services, including:

1. Customer-facing services (front office), where AI supports personalisation, onboarding, and real-time interaction.
2. Risk management and compliance, in which advanced algorithms strengthen fraud detection, credit scoring, and regulatory monitoring.
3. Operations and process automation (middle/back office), optimising workflows, document processing, and reconciliation tasks.
4. Lending and credit, through automated origination, dynamic pricing, and predictive debt collection.
5. Cybersecurity and infrastructure, where AI systems enhance intrusion detection, adaptive authentication, and resilience of digital platforms.
6. Human resources and internal management, improving recruitment, performance evaluation, and knowledge management.
7. Marketing and customer analytics, enabling refined segmentation, churn prediction, and tailored product development.
8. Sustainability and ESG finance are achieved by integrating environmental and social risk assessments into investment and lending decisions.
9. Strategic management and innovation, through AI-enabled scenario forecasting, mergers and acquisitions analytics, and open banking ecosystem integration.

This comprehensive mapping demonstrates the multifaceted influence of AI on banking institutions, reinforcing their capacity to adapt to evolving technological, regulatory, and socio-economic environments.

### *Customer-facing services (front office)*

*1. Personalised banking (AI-driven recommendation engines offering tailored investment, loan, or savings products).*

AI-driven recommendation engines in banking constitute a powerful mechanism to deliver personalised financial products (savings, loans, investments) by leveraging customer data, behaviour, and preferences. These systems typically combine machine learning models (e.g., collaborative filtering, content-based models, hybrid architectures) with rich data, including transaction histories, demographics, credit risk indicators, and sometimes external sources (such as social data), to predict what product or service a customer is most likely to need. For example, a recent study proposes a hybrid model integrating large language models (LLMs) and graph neural networks to improve recommendation accuracy and interpretability for financial product matching; the model demonstrates higher performance on metrics such as recall and Normalised Discounted Cumulative Gain than simpler models using only content or collaborative signals (Zhao et al., 2025).

In practice, banks are using recommendation engines to offer timely, tailored offers: for instance, analysing patterns in spending or savings behaviour to suggest an appropriate credit card, a loan, or an investment product when the customer is most receptive. In one case study, a bank used AI-based recommendations to detect that a customer was likely in the market for a home loan (based on searches or comparable). It proactively offered tailored home loan options, including rate, tenure, and amount, adjusted for their credit score. Another example from ING (similar large banks) shows that personalised recommendation systems increased customer engagement by 15 % (SuperAGI, 2025a).

These recommendation engines, however, must be implemented with attention to privacy, fairness, and transparency: the sources of data, the features used, and the model decisions should be explainable to maintain trust. Without responsible design, biases or overfitting certain segments may reduce inclusivity or erode trust. Research into explainable recommendations (e.g., combining text explanations and latent factor interpretability) is ongoing to address these risks (Zhang, 2017).

*2. Chatbots & virtual assistants (24/7 customer support, natural language interfaces, multilingual assistance).*

AI-powered chatbots and virtual assistants are increasingly central to delivering 24/7 customer service in the banking sector, via natural language interfaces and multilingual support. These systems use natural language understanding (NLU), machine learning, and often LLMs to interpret customer queries, whether typed or spoken, and respond in real time, including in multiple languages. One survey of chatbots in consumer finance notes that their adoption is largely driven by the ability to provide immediate responses around the clock, reducing customer wait times and operational costs (CFPB,


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2023). An illustrative case is Bank of America's "Erica", a virtual assistant that helps users with tasks such as balance inquiries, spending tracking, transfers, and personalised financial advice, all through a conversational interface accessible via mobile app (CFPB, 2023). Likewise, HSBC has deployed chatbots to offer uninterrupted customer support, reducing wait times and improving satisfaction by ensuring customers can access assistance outside normal business hours (Nexgen Banking Summit, n.d., WBR Insights, n.d.).

Empirical research supports these benefits: a study of banks in India and Sweden found that customers who interacted with chatbots reported increased satisfaction (approximately 15 %) when using them for routine banking tasks such as checking balances, transaction histories, or resolving common inquiries (Hari, 2023). However, limitations remain, including possible frustration when chatbots fail to understand context, lack human empathy, or default to scripted responses. To mitigate these, banks are implementing multilingual versions, escalations to human agents, and continuous training of the AI models (CFPB, 2023).

*3. Voice and gesture banking (voice recognition for account access, transaction initiation, and advisory services).*

Voice and gesture banking are emerging modalities that expand how customers can access, transact, and receive advice using natural, intuitive interfaces. Voice banking leverages voice recognition and natural language processing to enable users to log in, perform transactions, request account statements, or obtain advisory guidance simply by speaking. For instance, voice-activated banking systems allow customers to check balances, review fraud alerts, or initiate transfers via voice commands, eliminating the need for manual login credentials (Pressley, 2025). These systems often use biometric voice authentication to verify identity based on unique vocal characteristics (PCBB, 2024). Gesture-based banking interfaces also offer promising innovations, particularly for touchless interaction. One example is "Gesture Vault", a touchless ATM system that uses hand gestures and facial recognition to allow users to select transaction types and initiate withdrawals without touching the screen, enhancing hygiene and reducing contact risk (Mohan Krishnan et al., 2024). Another prototype uses hand sign recognition (via camera and machine learning) to detect commands like "withdraw" or "balance check", achieving high recognition accuracy (~98.5%) in a laboratory environment (Harale et al., 2025). These technologies have substantial potential for improving accessibility (e.g., for visually-impaired users), convenience, and security. However, they also introduce challenges, including voice spoofing, dialect or accent variation, gesture mis-recognition under varying lighting or camera conditions, and privacy concerns around biometric data (iProov, 2023).

*4. Customer onboarding & KYC (automated identity verification, document scanning, and biometrics).*

Customer onboarding in banking has been significantly transformed by AI technologies that automate identity verification, document scanning, and biometric authentication, enhancing efficiency and security. Automated tools using optical character recognition allow banks to extract and validate information from government-issued IDs such as passports or driver's licenses within minutes, replacing the time-consuming manual review processes. For example, AU10TIX's identity verification systems enable institutions to quickly process and authenticate identity documents, reducing onboarding friction and manual labour (Lurie & Tsadok, 2024). In parallel, facial biometrics (e.g., comparing a selfie to an ID photo) and live video verification (including liveness detection to prevent spoofing) have become common features in digital KYC workflows, used by neobanks and verification providers such as Veriff (Afanasjev, 2024). These systems speed up onboarding, help reduce fraud, strengthen regulatory compliance, and improve customer experience by minimising abandonment during digital onboarding. Studies show that biometric-enabled workflows can lower abandonment rates (e.g., when customers must submit documents manually or wait for human review) (Signicat, 2020). Despite these benefits, challenges remain, including ensuring biometric data privacy, preventing bias (e.g., across skin tones, ages), meeting regulatory standards, and providing fallback or manual options for cases where automated verification fails (Afanasjev, 2024).

***Risk management and compliance, in which advanced algorithms strengthen fraud detection, credit scoring, and regulatory monitoring***

*1. Fraud detection and prevention (real-time anomaly detection in transactions, behavioural biometrics).*

AI systems are being used increasingly to detect fraud in real time by flagging anomalous transactions and applying behavioural biometrics that assess how a user acts (e.g., typing rhythm, device usage). For example, Mastercard's "Decision Intelligence" system processes billions of transactions annually. It can assign a risk score to each transaction in milliseconds, identifying potentially fraudulent ones by comparing them against historical purchase behaviour and user device or usage patterns (Villano, 2025). Another example is the use of transformer-based architectures (and deep neural networks) in credit card fraud detection, outperforming traditional methods by spotting atypical locations or timings of transactions (Novikova, 2025).

*2. AML/CFT monitoring (pattern recognition for suspicious activities, automated reporting to regulators.*

AI enhances anti-money laundering) Moreover, counter-financing of terrorism compliance by learning patterns of suspicious behaviour that are difficult to encode via static rules, enabling systems to detect "structuring" (splitting large transactions to avoid thresholds), anomalous cross-border transfers, or rapid asset movements. For instance, Oracle's AML-AI solutions detect hidden money laundering tactics that conventional rule-based systems miss, while pattern recognition across transactional data helps to generate prioritised alerts (Ricadela, 2024). Banks such as Citibank, J.P. Morgan, and Wells Fargo are deploying AI tools to scale up AML detection, improve true positive rates, and reduce false alerts (Silent eight, 2025).

*3. Credit risk assessment (AI-enhanced scoring models incorporating alternative data (social, transaction, geolocation).*

Credit risk assessment is evolving with AI models that include non-traditional or alternative data sources, such as utility payments, rental history, geolocation data, social media behaviour, and mobile phone usage, to build richer profiles for borrowers, especially those with little or no credit history. For example, fintech and lenders use alternative data to extend credit access to underserved segments, combining transaction patterns, spending data, and digital footprints to predict repayment likelihood more accurately (FICO, 2024). In academic research, graph neural networks and network data (relationships between borrowers, suppliers, etc.) have been used to improve credit scoring accuracy for "thin-file" borrowers by capturing relational features beyond standard financial metrics (Muñoz-Cancino, 2022).

*4. Operational risk monitoring (early detection of cyber threats and process anomalies).*

In banking operations, AI tools are being used to monitor for operational risks, such as system failures, unusual patterns in system logs, or potential cyber threats, by observing irregular process flows, unusual login or access patterns, and deviations from expected behaviour. Anomaly detection systems can continuously analyse operational data streams to flag issues before they lead to failures or security incidents. Although specific bank names are less frequently published in open sources, many financial institutions use anomaly detection frameworks (e.g., real-time monitoring of login attempts, transaction processing times, system health metrics) that leverage unsupervised learning to detect outliers (HighRadius, 2024).

*5. Regulatory technology (RegTech, AI for monitoring compliance with changing global and local rules).*

RegTech refers to using AI, machine learning, NLP, and other tools to help financial institutions comply with evolving regulatory obligations. This includes automated regulatory reporting, monitoring for changes in laws and regulations, and ensuring compliance processes (e.g., KYC/AML, sanctions screening) adapt accordingly. For example, KPMG has published analyses of AI's role in detecting emerging money laundering techniques or novel financial instruments (like crypto) and warning institutions about compliance risks (KPMG, 2025). Tools exist that convert regulatory texts into machine-readable formats so systems can automatically check transactions or customer profiles for compliance (FATF, 2021).

***Investment & Wealth Management***

*1. Robo-advisory platforms (algorithm-based portfolio management and rebalancing).*

Robo-advisors are financial services that use algorithmic decision-making to automatically create, monitor, and rebalance investment portfolios according to a user's risk tolerance, goals, and time horizon. Typically, clients supply inputs (investment goals, risk preferences, time frames), and the robo-advisor optimises a diversified portfolio of assets (often ETFs or index funds), periodically rebalancing to maintain the target asset allocation as markets shift. For instance, platforms like Vanguard Digital Advisor and Betterment use machine learning and data analytics to adjust portfolios when certain thresholds of drift from target are reached (Yieldstreet, 2024). These tools reduce costs and make wealth management more accessible to retail investors who may not have access to human financial advisors (Vanguard, n.d.).

*2. Market prediction (AI models for sentiment analysis (news, social media), volatility forecasting).*

In market prediction, AI is widely used to analyse textual data (e.g., news articles, regulatory filings, social media posts) to derive sentiment indicators, which are then used to forecast market movements or volatility. For example, models like GRUvader combine sentiment signals with time series data to improve accuracy in stock price predictions, showing that sentiment-infused models outperform stand-alone models in many settings (Mamillapalli et al., 2024). Similarly, emerging studies apply LLMs and retrieval-augmented generation to correlate financial news sentiment with near-term stock returns (Echambadi, 2025). Such techniques allow institutions to anticipate market sentiment shifts and adjust investment or hedging strategies accordingly.


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*3. Algorithmic and high-frequency trading (ultra-fast execution based on predictive analytics).*

Algorithmic and high-frequency trading (HFT) represent extreme use cases of AI for speed and pattern recognition: algorithms monitor multiple streams of market data, news, and order books, making trading decisions in microseconds or milliseconds. Firms like Citadel, Jump Trading, and Virtu use AI to optimise trading strategies, reduce latency, and manage risk in HFT operations (ddn, 2025). These systems are designed to exploit very short-lived opportunities (arbitrage, micro-price discrepancies) with minimal human intervention. However, the competitive intensity, regulatory scrutiny, and risk of adverse events (e.g., "flash crashes") remain important considerations (Chen, 2025).

*4. Personal financial planning (AI-driven tools suggesting savings strategies based on behaviour and goals).*

AI-based personal financial planning tools help individuals manage their savings, budget, and long-term financial goals by analysing spending habits, income flows, debt obligations, and user preferences. For example, apps like Mint and Personal Capital use aggregated transaction data to categorise spending, suggest saving targets, warn about overspending, and recommend debt repayment or investment action plans (SuperAGI, 2025b). Moreover, fintechs are developing AI tools that simulate financial scenarios (retirement, purchasing a home), allowing users to adjust behaviour (saving rates, investment allocations) to achieve goals (Withrow & Mishra, 2025). These tools enhance financial inclusion and literacy by providing accessible decision-making support to people who may lack professional advice.

***Operations & Process Automation (Middle/Back Office)***

*1. Robotic Process Automation (handling repetitive tasks like reconciliation, settlements, and report generation).*

Robotic Process Automation has become instrumental in banking for automating highly repetitive, rules-based tasks such as bank reconciliation, financial settlements, and periodic report generation. For instance, RPA bots can extract transaction data from bank statements, match them with internal records, identify discrepancies, and automatically generate reconciliation reports without human intervention. A case in point: Muthoot Finance used intelligent automation for bank reconciliation, achieving an 85 % reduction in processing time, near-perfect accuracy, and drastically reduced human involvement (Vinky G, 2025). Similarly, "Bank Reconciliation Automation with RPA" shows how bots align external bank statement data with internal ledgers, flag mismatches, and produce audit-friendly reports (KEYENCE, n.d.).

*2. Document processing (NLP-based extraction and classification of information from contracts, invoices, and forms).*

Document processing leverages AI techniques such as optical character recognition, NLP, and sometimes machine learning classification to extract key structured information from unstructured or semi-structured documents (invoices, contracts, customer forms) and then classify or route them appropriately. For example, banking and financial services companies employ Intelligent Document Processing to automatically scan and extract data from income proofs, tax returns, KYC forms, and invoices, thus accelerating loan application approvals and reducing manual errors (RaftLabs, 2025). New tools like ABBYY FlexiCapture, Rossum, and V7 Go are cited for accurately classifying and extracting data from financial documents (Pykes, 2024).

*3. Workflow optimisation (intelligent routing of tasks across departments to reduce processing times).*

Workflow optimisation in banking means using AI or automation systems to map internal processes, identify bottlenecks or redundant steps, and then intelligently route tasks or information to the proper departments or people without unnecessary handoffs. In one case study, a major European bank, partnering with Arnia Software, identified over 80 internal workflows (credit verification, compliance validation, account management) and selected high-impact ones for automation; the changes resulted in faster turnarounds and lower human workload (Arnia Software, 2025). Another example is Guilford Savings Bank, which used workflow automation to streamline back-office tasks so that customer data collected in the front office is quickly and seamlessly passed to the needed units, cutting wait time and reducing errors (Jack Henry, 2024).

*4. Predictive maintenance for IT systems (Preventing downtime in ATMs, servers, and digital platforms).*

Predictive maintenance applies AI and machine learning to monitoring data from IT infrastructure (servers, network systems, ATMs), detecting signals or anomalies that precede failures, so that preventive action can be taken before a breakdown occurs. Although detailed public case studies in banking are less frequent, similar techniques are well established in financial services infrastructure: for example, using anomaly detection in server logs to detect unusual resource usage or error rates; monitoring ATM network performance to spot when hardware or connectivity is degrading. Over time, banks that adopt predictive maintenance can reduce downtime, improve the reliability of digital channels, and lower maintenance

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costs. (Note: specific quantitative published examples in banking are less accessible, but industry-wide reports indicate that predictive maintenance reduces unplanned outages significantly).

***Lending & Credit***

*1. Loan Origination (Automated decision-making for retail and SME loans using alternative data).*

AI is transforming loan origination by enabling automated decision-making that incorporates alternative data sources, such as utility payments, transaction histories, employment records, and even UPI or GST data for SMEs, into credit risk profiling. This allows lenders to serve borrowers with thin or no formal credit histories more inclusively and accurately. For example, Biz2X highlights how loan origination systems now use AI to analyse alternative credit data, enabling faster, more precise risk assessment and expanding access to credit for underserved populations (Biz2X,2025a). In India, companies leveraging borrower transaction behaviour, business records, and non-traditional records (like GST filings) improve SME loan approval rates while managing default risk more effectively (Biz2x,2025b).

*2. Dynamic Pricing (Adjusting interest rates and conditions based on borrower risk profile and behaviour).*

Dynamic pricing in lending applies predictive analytics and machine learning to set interest rates and loan terms that reflect a borrower's individual risk profile, behaviour, and changing market conditions rather than static, one-size-fits-all pricing. For instance, Tredence describes how lenders move toward personalised loan pricing strategies, where algorithms adjust rates in real time based on credit risk, competitive landscape, and borrower attributes (Maiti, 2024). Another example is highlighted in Datrics AI reports: banks use dynamic pricing to tailor interest rates and fees for credit-card or consumer loan products by incorporating behavioural data and creditworthiness assessments (Datrics, 2023).

*3. Debt Collection (AI-driven prioritisation of cases and predictive repayment modelling).*

In debt collection, AI forecasts which debts are most likely to be recovered, prioritises those for outreach, and tailors' communication and repayment strategies based on predicted debtor behaviour. For example, LeewayHertz describes how AI helps automate the segmentation of debtors, predict repayment likelihood, and personalise communication (channel, timing, message) to improve recovery rates (Takyar, n.d.). Also, some case studies show that by grouping delinquent accounts by their predicted risk and customising collection approaches, financial institutions can increase the effectiveness of collections while reducing costs and customer friction (DigitalDefynd, 2025).

***Cybersecurity & Infrastructure***

Artificial intelligence is increasingly deployed in cybersecurity and infrastructure to safeguard banking systems against evolving threats while ensuring secure and seamless customer interaction. Intrusion detection systems powered by machine learning analyse network traffic and user sessions in real time to identify anomalies such as unusual transaction volumes or logins from atypical locations, thereby mitigating the risk of account takeovers and system breaches. Complementing this, adaptive authentication techniques based on behavioural biometrics, including keystroke dynamics, mouse movement, and swipe patterns, provide continuous verification, escalating security measures only when deviations from baseline behaviour are detected. Natural language processing further strengthens resilience through advanced phishing detection, enabling banks to filter malicious emails and SMS messages by recognising suspicious linguistic cues, semantic anomalies, or spoofed domains, thus reducing exposure to social engineering attacks. Beyond conventional security mechanisms, blockchain integration combined with AI oversight offers novel avenues for fraud-resistant transactions: smart contracts embedded with anomaly detection and automated auditing rules can execute financial agreements transparently while flagging irregular activity. These applications collectively illustrate how AI enhances banking cybersecurity and infrastructure by combining predictive monitoring, adaptive defences, and trust-enhancing technologies, thereby protecting institutions and customers in an increasingly digitised financial ecosystem.

***Human Resources & Internal Management***

Banks increasingly leverage AI across human resource and executive management functions to enhance efficiency, accuracy, and strategic insight. In talent acquisition, AI systems are used to screen large volumes of CVs by parsing resumes, matching candidates to job descriptions, and ranking applicants based on qualifications or experience. Such tools reduce hiring time and enable more objective comparisons among candidates. For example, platforms like MiHCM implement AI-driven candidate screening to filter resumes and highlight those most aligned with role requirements, thereby streamlining recruitment workflows (David, 2025). In performance management, analysis of employee productivity data, detection of stress via behavioural or workload indicators, and recommendations for tailored training or upskilling programs are being introduced to support worker well-being and alignment with organisational goals. However, specific banking-sector case

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studies remain somewhat limited in public literature. Knowledge management systems harness intelligent document classification and retrieval, auto-tagging of internal reports, and chatbot-style Q&A systems to capture institutional know-how and make it available across departments; for instance, a leading US bank processed and auto-classified 35 million documents into pre-defined categories using AI-based document processing, substantially improving retrieval speed and reducing operational overhead (Datamatics, 2024). Finally, executives employ AI-powered dashboards for decision support that consolidate operational and financial KPIs and provide real-time monitoring, predictive analytics (e.g., forecasting, scenario simulation), and decision modelling tools. In one case, an interactive executive dashboard for real-time financial insights enabled senior leadership to monitor performance across metrics and react more promptly to emerging trends (XDuce, n.d.). These AI applications in HR and decision-making reduce manual workload and help banks align human capital and strategy more closely with fast-changing environments.

***Marketing & Customer Analytics***

Banks are utilising AI to deepen customer insight and proactively shape strategy by combining precise segmentation, sentiment tracking, churn prediction, and innovation driven by unmet needs. Advanced customer segmentation techniques, such as machine learning clustering (e.g., K-Means, Gaussian Mixture Models) and embedding-based methods, allow banks to identify micro-segments beyond simple demographics, grouping customers by behaviour, product usage, transaction patterns, and life stage, thereby enabling targeted offerings and higher engagement. For example, a comparative study showed that clustering algorithms enabled a mid-sized European bank to develop actionable and interpretable customer segments (Mozumder et al., 2024). Meanwhile, sentiment analysis tools monitor real-time feedback from social media platforms, customer service interactions, and reviews to gauge opinions about banking products or services; these insights feed into customer support improvements and product development. Using ensemble methods or multimodal data (demographics, transaction history, behavioural signals), predictive churn models identify customers at risk of leaving, enabling banks to deploy retention strategies. Recent work demonstrates that such frameworks significantly outperform baseline methods in precision, recall, and overall accuracy (Bhuria et al., 2025). Finally, by leveraging discovered sentiment and segmentation, banks can innovate product offerings, design new services, or customise existing ones to meet the unmet needs revealed by customer voice and behaviour data, allowing them to remain competitive and responsive in rapidly changing markets.

***Sustainability & ESG Finance***

AI-based green finance initiatives are enabling banks not only to evaluate but also to operationalise sustainability in investment and lending decisions. For green finance scoring, machine learning and natural language processing are used to combine structured data (e.g., emissions, resource usage, governance disclosures) with unstructured sources (e.g., news, corporate reports) to produce more dynamic and transparent ESG scores; one recent study proposes an "ESG-AI Maturity Index" to benchmark investment firms on data infrastructure, AI explainability, and integration depth (Elhady & Shohieb, 2025). In sustainable lending, financial institutions automate ESG checks for corporate borrowers via tools that assess climate-regulatory compliance, financed emissions, biodiversity impact, and sectoral transition risk before approving loans. For example, Tietoevry has developed ESG risk modules that over 30 financial institutions in Norway now use to assess corporate borrowers' alignment with climate regulations in the loan origination process (Eikeland, 2022). Meanwhile, carbon footprint tracking tools help banks and their customers measure, report, and reduce environmental impact. Personetics offers "carbon insights" modules that let banking customers see their personal carbon emissions based on transaction histories, suggest greener alternatives, or offset emissions (Personetics, 2025). Startups like Greenly similarly allow businesses and individuals to capture and monitor greenhouse gas emissions (Scopes 1-3), helping integrate carbon accounting into both corporate and consumer finance processes (Manenti, 2021).

***Strategic Management & Innovation***

In strategic management and innovation, AI enables banks to anticipate and adapt to future challenges and opportunities through advanced scenario forecasting, merger & acquisition analytics, open banking ecosystems, and metaverse & digital assets oversight. In scenario forecasting, AI models are being used to perform stress-testing under varied macroeconomic conditions: for example, machine learning frameworks simulate effects of recession, interest-rate shocks, or credit-risk changes on loan portfolios, allowing banks to proactively adjust their capital and underwriting strategies (Shetty, 2025). Merger & acquisition analytics similarly benefit from AI: valuation models incorporating big data (market comps, growth rates, customer overlap), synergy detection algorithms (identifying revenue or cost synergies), and predictive integration risk scoring help banks and investors assess deals with greater precision—though specific public case studies are less frequently disclosed. Open banking ecosystems promote transformation via interoperable APIs, allowing third-party fintechs to access data and services securely; banks collaborate with fintechs to develop budgeting tools, integrated services, and personalised financial products by leveraging aggregated data flows. For instance, fintech platforms in Europe routinely use open banking APIs to pull transaction data for personal finance apps or KYC processes (DECTA, 2025). Finally, with digital assets and metaverse finance, AI supports advisory and risk management for tokenised assets, NFT investments, and virtual financial ecosystems, automatically assessing risk exposure, detecting anomalies in blockchain-based transactions, and helping users navigate unfamiliar asset classes with predictive tools. Though this area is newer and somewhat experimental, early models already integrate AI oversight into smart contract platforms and virtual asset portfolios. Collectively, these technologies enable banks to be more resilient, innovative, and agile in fast-shifting financial landscapes.

**Table 1. Summary of AI Applications in Banking.**

| Domain | Subtopics | Main Applications / Examples |
|---|---|---|
| Customer-Facing Services (Front Office) | Personalised banking | Recommendation engines using LLMs and GNNs to tailor credit cards, loans, and investments (e.g., ING increased engagement by 15%). |
| | Chatbots & virtual assistants | 24/7 multilingual support, real-time query handling (Bank of America's "Erica," HSBC chatbots). |
| | Voice & gesture banking | Voice recognition for account access and transactions, gesture-based ATMs (e.g., Gesture Vault prototype, hand sign recognition 98.5% accuracy). |
| | Customer onboarding & KYC | Automated ID verification, OCR, biometric authentication (e.g., AU10TIX, Veriff, Signicat reducing abandonment rates). |
| Risk Management & Compliance | Fraud detection & prevention | Real-time anomaly detection, behavioural biometrics (Mastercard "Decision Intelligence," transformer-based detection). |
| | AML/CFT monitoring | Pattern recognition for suspicious activity, automated reporting (Oracle AML-AI, Citibank, J.P. Morgan). |
| | Credit risk assessment | AI models with alternative data (social, geolocation) and GNNs (FICO, Muñoz-Cancino, 2022). |
| | Operational risk monitoring | Anomaly detection in logs, login attempts, transaction times (HighRadius frameworks). |
| | RegTech | AI-driven compliance reporting, regulatory text parsing (KPMG 2025, FATF 2021). |
| Investment & Wealth Management | Robo-advisory platforms | Automated portfolio management and rebalancing (Vanguard Digital Advisor, Betterment). |
| | Market prediction | Sentiment analysis of news/social media, volatility forecasting (GRUvader, Echambadi 2025). |
| | Algorithmic & HFT | Ultra-fast execution, predictive analytics (Citadel, Jump Trading, Virtu). |
| | Personal financial planning | Budgeting and savings tools (Mint, Personal Capital, Coforge scenario simulation). |
| Operations & Process Automation (Middle/Back Office) | Robotic process automation | Automated reconciliation, settlements, reports (Muthoot Finance reduced time by 85%). |
| | Document processing | NLP-based extraction from contracts and invoices (ABBYY, Rossum, V7 Go). |
| | Workflow optimisation | Routing tasks, reducing bottlenecks (Arnia Software, Guilford Savings Bank). |
| | Predictive maintenance | Monitoring ATMs, servers, and digital platforms to prevent outages. |
| Lending & Credit | Loan origination | Automated SME/retail loan profiling using alternative data (Biz2X, GST/UPI data in India). |
| | Dynamic pricing | Real-time adjustment of rates and conditions (Tredence, Datrics AI). |
| | Debt collection | Predictive repayment modelling, prioritisation, personalised outreach (LeewayHertz, DigitalDefynd). |
| Cybersecurity & Infrastructure | Intrusion detection | AI monitoring for unusual network/user behaviour. |
| | Adaptive authentication | Behavioural biometrics (typing speed, mouse movement). |
| | Phishing detection | NLP-based detection of email/SMS attacks (semantic similarity models). |
| | Blockchain integration | AI oversight in smart contracts, anomaly detection in blockchain transactions. |
| Human Resources & Internal Management | Talent acquisition | AI screening CVs, cultural fit prediction (MiHCM). |
| | Performance management | Monitoring productivity, stress detection, and training suggestions. |
| | Knowledge management | Intelligent classification of institutional knowledge (Datamatics: 35M docs auto-processed). |
| | Decision support | Executive dashboards with predictive modelling (XDuce case study). |
| Marketing & Customer Analytics | Customer segmentation | ML clustering for micro-segments (Mozumder et al., 2024). |
| | Sentiment analysis | Social media and feedback monitoring. |
| | Predictive churn analysis | Ensemble models for retention (Bhuria et al., 2025). |
| | Product innovation | AI discovery of unmet needs, new product design. |
| Sustainability & ESG Finance | Green finance scoring | AI-driven ESG scoring (Elhady & Shohieb, 2025). |
| | Sustainable lending | Automated ESG compliance checks (Tietoevry's ESG modules in Norway). |
| | Carbon footprint tracking | Customer carbon insights (Personetics, Greenly). |
| Strategic Management & Innovation | Scenario forecasting | Stress-testing portfolios under macro shocks (Arya.ai). |
| | M&A analytics | Valuation modelling, synergy detection. |
| | Open banking ecosystems | AI-enabled APIs for fintech collaboration (DECTA, 2025). |
| | Metaverse & digital assets | AI in tokenised asset risk management, smart contracts, and NFT portfolios. |


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## DISCUSSION

The results of this study demonstrate that AI applications are pervasive across all levels of banking, from customer-facing services to compliance, risk management, operations, lending, cybersecurity, sustainability, and strategic management. This holistic picture resonates with prior research, which situates AI as a cornerstone of digital transformation in the banking sector. Studies emphasising the role of digitalisation and technologisation in shaping customer behaviour, particularly among younger generations, support the finding that AI-driven personalisation and mobile banking are increasingly central to user engagement (Adhikari et al., 2024). Similarly, evidence on digital insurance adoption among older adults and Gen Z's openness to mobile services corroborates AI's broadening inclusivity in financial services. The comparative insight is that while literature highlights generational and socio-demographic drivers, the results of this study show that AI solutions extend inclusivity beyond demographics, shaping holistic customer experience through voice, gesture, and chatbot technologies.

Operational and compliance-related findings also align strongly with prior literature. The study identifies robotic process automation, document processing, and workflow optimisation as core areas of efficiency gains, confirming earlier evidence on improved accuracy, timeliness, and audit capacity from RPA in internal audit and financial reporting (Alassuli, 2025). At the same time, the literature highlights risks, particularly in money laundering and organised crime exploiting AI, while emphasising the importance of financial stability and compliance frameworks (Lyeonov et al., 2025). This aligns with the results that emphasise the role of AI in AML/CFT monitoring, regulatory technology, and anomaly detection. However, a key point of divergence is that while much of the literature frames AI as both an enabler and a threat, the findings here suggest that practical implementations—such as automated suspicious activity monitoring and adaptive authentication—are already shifting the balance towards more effective compliance outcomes, provided robust governance mechanisms are in place.

In strategic domains, the findings that AI supports ESG finance, sustainability tracking, scenario forecasting, and M&A analytics complement emerging literature on the transformative role of AI in both organisational management and broader financial ecosystems. Prior studies underline AI's ability to influence employee engagement, open innovation, and cross-sectoral adaptation (Ayu Gusti et al., 2024; Ponomarenko et al., 2024), while others highlight its impact on fintech adoption, market connectedness, and cryptocurrency forecasting (Galvão et al., 2025; Okoli, 2024). These perspectives reinforce that AI contributes to operational efficiency, strategic agility, and long-term competitiveness. However, the comparison also shows gaps: while the literature often foregrounds the risks of AI misuse, inequality, and systemic vulnerabilities (Yarovenko et al., 2024; Balcerzak & Valaskova, 2024), the results here emphasise a more balanced view of opportunities and risks, highlighting pathways for banks to leverage AI for sustainable growth. This suggests that future research should focus on integrating risk mitigation and opportunity exploitation within unified strategic frameworks.

Despite comprehensively mapping AI applications across the banking sector, this study has several limitations. First, the analysis relies predominantly on secondary sources, including academic literature, industry reports, and case studies. These may introduce bias or omit emerging applications not yet documented in research or practice. Second, the study does not incorporate primary empirical data or quantitative modelling, which would allow for stronger causal inference and comparative measurement of AI's effectiveness across institutions or regions. Third, while the results highlight broad application domains, the heterogeneity of banking systems across countries means that findings may not be universally generalisable. Future research should therefore focus on empirical validation through case studies, surveys, or econometric modelling to quantify the efficiency gains, risk mitigation, and customer outcomes associated with AI adoption. Additionally, cross-country comparative studies could shed light on the institutional, regulatory, and cultural factors shaping AI implementation. At the same time, longitudinal analyses may help assess long-term impacts on banking stability, financial inclusion, and sustainability.

## CONCLUSIONS

This research aimed to systematically examine and categorise the applications of artificial intelligence across the full spectrum of banking functions to assess how AI enhances efficiency, compliance, innovation, and sustainability while addressing associated risks and regulatory challenges. By adopting a structured review approach, the study integrated academic research, industry case studies, and regulatory documents, applying thematic classification to map the implementation of AI into nine key domains: customer-facing services, risk management and compliance, operations and process automation, lending and credit, cybersecurity and infrastructure, human resources and internal management, marketing and customer analytics, sustainability and ESG finance, and strategic management and innovation.

The methodology combined secondary data analysis with comparative synthesis, incorporating conceptual frameworks and empirical evidence. Case studies such as Mastercard's "Decision Intelligence" for fraud detection, Bank of America's "Erica" chatbot, or Tietoevry's ESG compliance modules provided practical validation of conceptual models. Academic advances, including graph neural networks for credit scoring or sentiment-informed models for market prediction, were used to reinforce the theoretical foundation. Consolidating this information into a summary table allowed the research to present a holistic and structured view of AI's transformative impact on the banking sector.

The findings demonstrate that AI applications are pervasive across the entire banking ecosystem. In the front office, AI enables personalised banking, chatbots, and biometric onboarding, significantly improving customer experience. In compliance and risk management, AI strengthens fraud detection, AML/CFT monitoring, credit scoring, and regulatory technology. Operationally, robotic process automation, document processing, and workflow optimisation drive efficiency, while predictive maintenance improves infrastructure reliability. AI enhances loan origination, enables dynamic pricing, and personalises debt collection strategies in lending. Cybersecurity is reinforced through intrusion detection, adaptive authentication, phishing prevention, and blockchain integration. Human resource management benefits from AI in recruitment, performance evaluation, and knowledge sharing, while executives increasingly rely on AI-driven decision dashboards. Marketing gains precision with customer segmentation, churn analysis, and product innovation, while sustainability practices are advanced through green finance scoring, ESG compliance, and carbon footprint tracking. Finally, strategic management is supported by AI-enabled forecasting, M&A analytics, open banking, and oversight in digital assets.

From a policy and practical perspective, implementing AI in banking requires both ambition and caution. Policymakers must ensure that regulatory frameworks keep pace with technological developments, particularly in data protection, explainability, fairness, and systemic risk. International cooperation will be crucial in harmonising standards for AI-driven compliance, cross-border transactions, and sustainable finance. For banks, the practical challenge lies in moving beyond isolated pilot projects toward integrated AI ecosystems that span customer service, compliance, operations, and strategy. Investment in talent, data governance, and explainable AI systems is essential to maintain customer trust and regulatory alignment. At the same time, banks should leverage AI for efficiency gains and enhance financial inclusion, environmental sustainability, and resilience in volatile markets. Collectively, these measures will enable the financial sector to harness AI as a driver of innovation while safeguarding stability and public trust.

## ADDITIONAL INFORMATION

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### CONFLICT OF INTEREST

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## ШТУЧНИЙ ІНТЕЛЕКТ У БАНКІВСЬКІЙ СПРАВІ: КОМПЛЕКСНЕ КАРТОГРАФУВАННЯ ЗАСТОСУВАНЬ, ВИКЛИКІВ І СТРАТЕГІЧНИХ НАСЛІДКІВ

Штучний інтелект швидко змінює банківський сектор, створюючи можливості для ефективності, інновацій і стійкості, одночасно впроваджуючи нові регуляції та ризики фінансової стабільності. Це дослідження спрямоване на систематичне вивчення та класифікацію застосувань штучного інтелекту в усьому спектрі банківських функцій для оцінки їхнього трансформаційного потенціалу та наслідків. У дослідженні використана методологія структурованого огляду, що поєднує академічну літературу, галузеві приклади та регуляторні звіти, а також застосована тематична класифікація для відображення використання штучного інтелекту в дев'яти основних галузях банківської діяльності. Отримані дані демонструють, що штучний інтелект проникає на всі рівні банківських операцій. У послугах, орієнтованих на клієнтів, він підтримує персоналізацію, чат-ботів, біометричний онбординг і голосовий банкінг для покращення користувацького досвіду. У царині управління ризиками та дотримання вимог штучний інтелект покращує виявлення шахрайства, моніторинг AML/CFT, кредитний скоринг і регуляторну звітність. Операційна ефективність підвищується завдяки роботизованій автоматизації процесів, обробці документів, оптимізації робочих процесів і прогнозованому обслуговуванню. Штучний інтелект також стимулює інновації в кредитуванні, забезпечуючи автоматичну видачу кредитів, динамічне ціноутворення та персоналізоване стягнення боргів. Кібербезпека та інфраструктура виграють від виявлення вторгнень штучного інтелекту, адаптивної автентифікації, запобігання фішингу та інтеграції блокчейну. Крім того, функції управління людськими ресурсами, маркетингом, фінансами ESG й стратегічним управлінням усе більше покладають на штучний інтелект для підтримки ухвалення рішень, аналітики клієнтів, оцінки сталого розвитку та прогнозування сценаріїв. У сукупності ці результати підкреслюють цілісну роль штучного інтелекту в трансформації банківської справи, водночас наголошуючи на важливості зрозумілості, управління та узгодження нормативних актів для забезпечення довіри, інклюзивності й стійкості.

**Ключові слова:** штучний інтелект, банківська справа, управління ризиками, автоматизація процесів, сталі фінанси, стратегічні інновації

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