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Agentic Artificial Intelligence in financial and banking operations: A comprehensive reviWew

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Abstract. The purpose of the study was to review of academic and industry literature, with the goal of clarifying the concept of agentic Artificial Intelligence, explaining its architectural workings, and exploring its applications in the financial and banking sectors. The rising use of Artificial Intelligence in the financial services sector had been pushing into a stage of financial automation that was not focused on rules but on systems able to reason, adapt, and act autonomously and goal-focused. This transition had led to what was currently referred to as agentic Artificial Intelligence – a category of intelligent systems that worked independently to a certain extent, which was missing in conventional Artificial Intelligence applications. The research was based on the systematic review methodology, which summarised the evidence related to the use of agentic Artificial Intelligence in autonomous trading, dynamic risk assessment, algorithmic underwriting, fraud detection, customised customer interaction, and regulatory compliance. As the analysis showed, it increased operational proactivity, situational awareness, and multi-step decision-making, allowing financial institutions to be more responsive to complex and fast-changing environments. In addition, the review outlined that there were persistent issues in regard to explainability, accountability, integration with legacy infrastructures, ethical protection, and preparedness to regulatory issues. Results suggested that agentic Artificial Intelligence had the potential ability to transform operational and strategic activities in the financial sector, but only by means of responsible governance and strict supervision, its advantages can become actual. The contribution of this review to the literature was an evidence-based integrated evaluation of the modern trends and an outline of the most prominent opportunities and limitations that will define the future of autonomous intelligent systems in the financial services

Keywords: artificial agents; autonomous finance; digital banking; financial innovations; financial algorithm

Introduction

The field of Artificial Intelligence (AI) had been a foundation of the financial field with the first applications of expert systems and rule-based decision support systems in the 1990s. However, the nature of AI-based interventions had been radically transformed in 2020s. Beginning in 2020, machine learning, reinforcement learning, and large language models have enabled a new type of intelligent system to emerge, often referred to as agentic AI, a novel type of intelligent system that was characterised by autonomy, adaptive reasoning, and goal-orientated behaviour. These systems were not merely qualitatively different to their predecessors in that they offered assistive decision-making support by offering pre-coded rules, but in that they were multi-step, context-dependent tasks that were sensitive to dynamic financial conditions. This had been summarised in the academic enquiry. D.B. Vuković *et al.* (2025) pointed out on how agentic AI changes financial services to make real-time decisions, dynamically rebalanced portfolios, and constantly monitor risk levels, in addition to raising substantial regulatory and systemic risks. Similarly, I.A. Elgendy *et al.* (2025) argued that agentic systems played

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the role of catalysts of innovation in FinTech, enabling adaptive investment systems, autonomous compliance processes, and scalable advisory systems, which changed in line with the market environment. In the perspective of banking business, M. Mucsková (2024) recorded how smart automation contributed to improving the fundamental banking processes, such as customer onboarding, compliance procedures, and back-office tasks, thereby improving latency and eliminating human error compared to the conventional support solutions. R. Sapkota *et al.* (2026) provided a taxonomy simultaneously marking agentic AI versus the legacy rule-based systems and foregrounding autonomy, proactivity, and goal-oriented optimisation as its salient features. In addition to these contributions, contemporary empirical research showed the use of agentic AI in particular financial environments.

C. Dutta *et al.* (2023) discussed the use of autonomous algorithms in high-frequency trading and suggested that contemporary trading platforms were becoming more and more dependent on agents that can self-adjust positions, assess liquidity, and implement trades under minimum human involvement a trend that highlighted the growing operational dependence on agentic architectures. B. Vyas (2023) also illustrated that intelligent agents with behavioural analytics were significantly more successful in fraud-prevention compared to classical rule-based detection models because they can learn the patterns of individual users and even update detection thresholds in real time. H.K. Sriram & B. Somu (2025) argued that autonomous agents together with continuous anomaly detection can be used to strengthen credit risk assessment and fraud surveillance, which can reduce false positives with an increase in the sensitivity of the detection. Furthermore, A.Y. Topraklı (2025) examined agentic AI-driven algorithmic underwriting systems that found that these systems expedited the loan-approval process, enhanced the accuracy of credit decisions, and reduced bias by applying risk models in the large applicant populations in a consistent manner. Taken together, these studies pointed to the fact that the shift to purely autonomous, adaptive, and goal-oriented systems as an extension of the conventional, rule-based approach to automation was not only an evolutionary one but also a reorganisation of financial and banking processes. The capabilities in agentic AI (such as situation awareness, lifelong learning, proactive decision-making, and multi-step action execution) were beyond the assistance paradigm. These features will guarantee improvements in the trading performance, optimisation in underwriting, fraud detection, compliance automation, and real-time customer interaction. However, as the academic discourse was becoming more and more aware, this change presented significant challenges in substance. The ability to interoperate with legacy infrastructures, data governance, ethical alignment, and cross-institutional interoperability were still daunting challenges. Besides, the empirical literature was not complete as few studies synthesised agentic AI uses, the risks involved, and the prerequisites of governance across domains.

Given the rapid technological advancements since 2020 and the growing body of distributed literature, there was a strong need for a systemic, integrative review. The purpose of the study was to provide such a review, which will present a systematic and extensive evaluation of agentic AI, its conceptual basis, practical implementation, its limitations, and opportunities in the future research and practice. The systematic literature review methodology used in this study will be aimed at synthesising and critically evaluating the academic and corporate literature related to agentic AI in the financial and banking sectors. The review followed three major steps: the process of a broad literature search and selection, the purposeful retrieval of relevant information, and the thematic framework of extracted data. The systematic approach to research allowed identifying general conceptual frameworks, defining practical application, and sorting empirical data into fundamental thematic groups, i.e., conceptual foundations, applications, and challenges or opportunities, in that way producing a consistent yet detailed view on the subject.

Conceptualising agentic AI in the financial context

To understand the impact of agentic AI on finance, it is important to define the concept of "agency" in relation to AI. According to B. Somu (2024), agentic AI was AI that had "the ability to act on its own in an environment to achieve given goals". This definition evolved from prior AI definitions, which were systems that passively analysed data or executed human instructions and commands. The process of moving from automation to autonomy was essentially a realignment of the role of technology in finance. Traditional automation was for automating repetitive and rules-based tasks at high scale. G. Jindal (2024) noted that an example can be data entry or a standard transaction. Machine learning models allowed using predictive analytics to find patterns in data for uses such as credit scoring or fraud detection. V. Garg (2025) explained that agentic AI, however, moved beyond prediction to action, referring to a machine that can sense its environment, made decisions on its own, planned multi-step action, and executed those actions with the goal of changing its environment. Z. Yordanova & Y. Hristozov (2025) identified the key characteristics of agentic AI as proactivity, goal directedness, and adaptability. Proactivity meant the agent can act without waiting for an external trigger or explicit command. Goal directedness meant its actions were not random but were coherent to achieve a predefined often complex objective. Adaptability was the most important feature; an agentic system can learn from its interactions and outcomes and modify its future behaviour to improve performance in dynamic and uncertain environments like volatile financial markets. I.A. Elgendy (2025) argued that this ability to operate autonomously was what made agentic AI a catalyst for innovation especially in FinTech, where new agents were being developed to reimagine financial services.

Agentic AI's capabilities were the result of a combination of several specialised AI fields. The theoretical foundations were diverse and largely based on reinforcement learning, large language models, and classical AI planners. R. Sapkota *et al.* (2026) stated that reinforcement learning provided the mechanism for agents to learn optimal behaviours through trial and error, receiving rewards or penalties based on their actions. This was especially valid in financial applications like trading or portfolio management. An agent learnt to maximise returns over a period of time. Over a hundred billion parameter large language models had emerged as a building block that endowed agents with sophisticated understanding, reasoning, and communication abilities. Large language models (LLMs) functioned as the reasoning engine or brain for a number of contemporary agentic architectures, which assisted the systems in processing non-structured information (e.g., news reports or financial filings) or complex user requests and producing logical plans. A typical agentic system's architecture usually consisted of a number of interacting components. There was a perception module that helped in fetching data from the environment. Then there was a memory module that held information about the past. Further, reasoning and planning engine (usually based on LLM) facilitated decision-making. M. Luqman *et al.* (2025) described an action module that helped in carrying out actions through the respective tools or application programming interfaces (APIs). Frameworks often utilised an action-perception cycle. An agent may first take the user's question and the relevant market information before performing the financial analysis. After creating the prompt, the planning module was utilised to break it down into sub-goals. Like fetching historical stock data, discounted cash flow analysis, judging valuation, and summarising key findings. Ultimately, these sub-goals were carried out by interacting with financial data APIs and creating a detailed report. The multi-tasking modular architecture can complete a series of steps on its own. This was far from the capabilities of single-tasking ones. The architectural frameworks were continuously researched and great strides have been made since 2020 (Joshi, 2025).

It was important to understand the difference between agentic AI and the typical AI systems being used in finance. Algorithmic systems and ML models have been around since the 1990s to serve financial institutions. But these systems were not typically autonomous agents. The new paradigm's disruptive potential was evident when the differences were clarified. First, typical AI in finance was often reactive and task-oriented. Fraud detection model was a good example of machine learning. The system learnt from past information where fraud was usually detected. Then, suspicious transactions were identified for frauds. It performed a specific task well-defined in advance in response to new data but did not take it upon itself to investigate root cause of fraud, decide on new rules to stop fraud, or interact with other systems to block a user's account. The fraud detection system, which was agency-based, not only detected suspicious fraudulent transfers, but could also independently freeze accounts and use a communication robot to communicate with customers to determine whether such transactions were similar to legitimate past transactions. H.K. Sriram & B. Somu (2025) noted that it could also analyse for more suspicious transactions in the user's past history and adjust its parameters based on the result.

Conventional systems cannot communicate over a wider link spectrum. It meant algorithmic trading systems that were either speedy or complicated but essentially heavy trading had been allowed to happen in its own magic. Automating trading systems responded to market data in the context of a defined strategy, but did not themselves develop entirely new trading strategies based on macroeconomic research analysis or dynamic reallocation. An agentic trading system could be assigned a high-level objective, such as "maximise alpha for this portfolio, while locking in a particular risk profile". Classic AI systems aimed to boost human decisions through a "human-in-the-loop" approach. The machine analysed or alerted the user and a human finalised the decision. AI that was agentic still required governance or oversight but it was built to work in a "human-on-the-loop" or "human-over-the-loop" mode. The agent does everything from start to finish. The human sets the goals and constraints only intervening in exceptional cases. This change had a major impact on the way work was performed and the skills and roles needed in the financial industry. K. Huang (2025) observed that there was an ever-growing number of innovative FinTech companies utilising these autonomous methods, which was already showing promise in opening up access to complex financial services that had traditionally been costly and labour-intensive. Consequently, the integration of agentic capabilities signified a fundamental shift in financial operational models, moving from static automation to dynamic, autonomous interaction. This evolution necessitated a re-evaluation of operational oversight and the integration of adaptive technologies within the banking sector.

Applications of agentic AI in financial operations

Due to a major paradigm shift in financial operations, a transition was occurring from rules-based AI to agentic AI. Z. Yordanova & Y. Hristozov (2025) noted that AI systems such as Artificial General Intelligence and Artificial Super Intelligence, characterised by autonomy and goal-directedness, were moving past automation into undertaking works previously reserved for human experts. The space of trading and investment had long been an area for sophisticated computational techniques, from early quantitative models to high-frequency trading algorithms. C. Dutta *et al.* (2023) discussed the use of autonomous algorithms in high-frequency trading, suggesting that agentic AI was positioned to usher in the next evolutionary phase by providing traders with autonomy beyond the conventional set of pre-defined rules for trading. Unlike classic algo trading, which was programmed to trade when reaching certain price levels or technical signals, agentic AI systems were able to devise and adapt their own trades. The ability of these autonomous agents to analyse multiple data sources such as market data, news sentiment, macroeconomic data, and social media data, allowed the systems to spot trading opportunities. M.S. Amin *et al.* (2024) demonstrated that these models can create hypotheses, test them on both historical and simulated data, and deploy cash automatically without human involvement. An example of agentic AI could be an AI system assigned the task of managing a portfolio. It may decide autonomously to move money out of equities and into bonds, based on reasoning regarding rising inflation and central bank signalling. A lot of autonomous trading agents relied on reinforcement learning as a foundational technology.

Alpha agents took actions (buying, selling or holding on to an asset) in a simulated market environment by trial and error. They learnt an optimal policy that maximised the cumulative reward signal (for example, profit). The reward can also be an indicator of risk-adjusted return (like the Sharpe ratio). As a result of this, the systems were able to discover patterns and relations that were complex and non-linear. The role of agentic AI was particularly apparent in derivatives trading and arbitrage: markets that relied on speed and the rapid calculation of multi-variable information. These intermediaries enabled complex multiple trades in various exchanges and assets to take place instantly to benefit from price inefficiencies. R. Inala (2023) emphasised that a key application domain was the ability to offer autonomous investment and advisory services. But fully autonomous trading agents bring new challenges. Multiple independent agents could create emergent, herd-like behaviour and amplify market volatility or trigger flash crashes. To ensure these agents operate within risk parameters and the firm's overall investment thesis, robust governance frameworks, real-time monitoring, circuit breakers, and "human-in-the-loop" oversight were required. Table 1 illustrated high performance of agentic AI systems in trading applications, specifically analysing data regarding market share and return rates.

Table 1. *Algorithmic trading performance metrics and financial market penetration*

Metric	Conventional algorithms	Agentic AI systems	Improvement (%)
Market share of total trading, %	65	75	15.4
Average annual returns, %	12-18	25-35	82
Success rate, %	60-70	85-97	35
Risk-adjusted returns (Sharpe ratio)	0.8-1.2	1.5-2.1	65
Trade execution speed (milliseconds)	50-100	10-25	75

Source: *Grand View Research (n.d.), Quantified Strategies (n.d.)*

The 82% improvement in average annual returns and 35% increase in success rates demonstrated the transformative potential of autonomous trading agents. The significant enhancement in risk-adjusted returns, as measured by the Sharpe ratio, indicated that agentic systems not only generate higher returns but do so with more efficient risk management. Sharpe ratio was important for evaluate the portfolio's performance by adjusting the return for the level of risk taken. The foundational block of the financial system was effective risk management. Conventional risk management techniques utilised static models like Value-at-Risk, which were calculated periodically, and may fail to capture the rapidly changing dynamics of the financial market. R. Gangavarapu (2025) stated that agentic AI was changing this field by allowing dynamic, proactive risk assessment, making the shift from reactive monitoring to predictive and preventative control. AI systems can function as independent risk management watchdogs that monitor a firm's whole portfolio and market exposure constantly and in real-time. These agents can simultaneously ingest information streams from thousands of sources, including trading positions, counterparty credit information, market liquidity indicators, and geopolitical information streams. Through sophisticated machine learning models, subtle anomalies can be identified, emerging concentrations of risk spotted, and possible market shocks forecast before tipping over. For instance, an agent might identify a growing correlation between two assets in a portfolio, alerting a human risk manager to a hidden exposure that models might overlook. M. Luqman *et al.* (2025) highlighted that an important ability of agentic AI in this space was a real time evaluation and metering of risk scores. These systems can provide a more real-time, flexible, or dynamic view of risk instead of the end of day reports.

An agentic system can quickly assess the credit risk of a sovereign bond issuer following an abrupt political event. In the same manner, it was possible to reassess the counterparty risk of the bank upstream or downstream. Moreover, it was possible to estimate the impact of the political event on the overall capital sufficiency of the firm. This ability made risk mitigation efforts significantly more agile. R. Inala (2023) pointed out that by emphasising intelligent risk control, financial institutions can prepare for worst-case scenarios instead of using past events as a reference. Agentic AI can run advanced stress tests and scenario analyses autonomously. The firm's portfolio can be tested by thousands of market situations ranging from a rise in interest rates to a disruption in the supplies. By using this tool, gaps can be identified, and suggestions provided to hedge and change the portfolio. Analysis of the impact of cyber security and emerging technology developments on financial stability was gaining momentum since 2020 among policymakers and financial authorities. A. Dodda (2024) observed that the combination of such advanced risk assessment tools allowed for deeper analysis of complex risk management issues. Underwriting and lending were always done manually based on data analysis and heuristic methods. Agentic AI transformed this landscape by introducing autonomous systems that can handle the entire lending lifecycle from application to approval to monitoring. N. Chitturi (2025) indicated this was most evident in the mortgage lending space, where operational challenges and paperwork had always created friction. In algorithmic underwriting, agentic AI systems act as autonomous decision makers. They can collect and verify applicant data from multiple sources including credit bureaus, bank statements, employment records, and even alternative data sets where permitted.

Using advanced machine learning algorithms, these agents can assess a borrower's creditworthiness with a level of granularity and predictive accuracy that surpassed conventional credit scoring models. Complex patterns in an applicant's financial history can be analysed to better predict the likelihood of default and enable lenders to make more informed and consistent decisions. The autonomy of these agents goes beyond a simple "approve" or "deny" decision. Loan terms such as interest rates, loan to value ratios, and repayment schedules can be dynamically structured to personalise the offer to the applicant's risk profile and financial situation. For example, an agent might identify a self-employed applicant with fluctuating income but strong cash reserves and offer a mortgage product with features that accommodate income volatility. Agentic AI can also speed up the lending process, reducing time from application to close from weeks to days or even hours. A.Y. Topraklı (2025) explained that by automating document verification, property appraisals (using automated valuation models) and compliance checks, these systems reduced manual overhead and minimised human error. AI agents can monitor transactions and data throughout the mortgage lifecycle and ensure compliance, identifying potential issues early on. This improved the customer experience and reduced operational costs for financial institutions. The goal was to create a more streamlined, data driven, and accessible lending ecosystem.

Financial analysis and reporting were the foundation of investment decisions, corporate strategy, and regulatory compliance. These tasks involved sifting through vast amounts of structured and unstructured data – financial statements, earnings call transcripts, industry reports, regulatory filings – to extract insights. Agentic AI was automating and augmenting these processes so analysts can get deeper, faster, and more accurate insights. Agentic AI can be an autonomous financial analyst. It can be given a high-level goal such as "evaluate Company X" or "what are the growth drivers in the semiconductor industry". The agent would then devise and execute a plan to achieve that goal. This could involve automatically retrieving and parsing 10-K and 10-Q filings from the SEC database, extracting key financial metrics, doing ratio analysis, and benchmarking the company against its peers. It is important that these agents used natural language processing (NLP) and generation (NLG) to understand unstructured text and synthesise findings into human readable reports. R. Inala (2023) noted that an agent could analyse the sentiment of an earnings call transcript, identify the key themes discussed by management, and cross reference statements with the quantitative data from the financial statements. It could then generate a summary report with charts, tables, and a narrative of conclusions. This ability to author quality content for these analytical tasks frees human analysts from data gathering and allows focusing on higher level strategic interpretation and client communication. By analysing historical data and identifying leading indicators from alternative data sources, these systems can generate more accurate and dynamic forecasts for revenues, earnings, and cash flows. Simulations can be run to model the impact of different economic scenarios on a company's performance. For regulators and compliance departments, these autonomous systems can continuously monitor corporate disclosures and market activity to flag potential instances of accounting fraud, insider trading, or other forms of misconduct, thereby helping to strengthen market integrity.

Applications of agentic AI in banking operations

While financial operations focused on markets and investments, banking operations concentrated on serving customers, managing transactions, and maintaining the core banking system. Agentic AI was shifting these functions from a reactive, product-centric model to a proactive, customer-centric one. B. Somu (2024) observed that as financial institutions and FinTech companies developed new agents, the presence of these systems was becoming ubiquitous across the sector. The following analysis examined agentic AI in personalised customer service, fraud detection, regulatory compliance, and the modernisation of core banking infrastructure. The modern banking customer expected personalised, seamless, and instant services. Agentic AI enabled banks to deliver these capabilities at scale. This technology transcended simple chatbots and rule-based virtual assistants, offering truly autonomous financial assistants capable of understanding context, anticipating needs, and executing complex tasks on the customer's behalf. S. Brohi *et al.* (2025) emphasised that these systems were designed with trustworthiness as a core principle to foster strong customer relationships. Autonomous customer service agents powered by large language models (LLMs) and conversational AI can handle a wide range of inquiries and transactions without human intervention. For instance, a customer might request to pay a credit card bill, dispute a recent transaction, and inquire about better interest rates on a savings account simultaneously.

An agentic AI system can process this multi-part request, authenticate the user, execute the payment, initiate the dispute process by requesting relevant details, and analyse the customer's account history to proactively offer a higher-yield savings product. This level of interaction and task execution reduced the load on human call centres and improved customer satisfaction. The substantial capability of agentic AI lay in the provision of proactive and hyper-personalised financial guidance. By analysing transaction history, income patterns, and financial goals, an autonomous agent can function as a personal financial advisor. For example, the system might identify a large cash balance yielding minimal interest and, based on the user's risk profile, suggest investing a portion in a low-cost index fund, accompanied by a simulation of potential returns. The system can assist customers in creating budgets, setting savings goals, and automatically optimising financial decisions, such as sweeping excess cash into higher-interest accounts or suggesting efficient debt repayment strategies. K. Huang *et al.* (2025) noted that the objective was to democratise access to sophisticated financial services that were previously available exclusively to high-net-worth individuals. Although these systems offer significant advantages, M. Mucsková (2024) argued that seamless handovers to human agents remained essential, when complex or sensitive issues requiring human empathy and judgment arise. Table 2 demonstrated the substantial performance advantages of agentic AI systems over traditional chatbot implementations.

Table 2. *AI customer service performance metrics in banking*

Performance indicator	Traditional chatbots	Agentic AI systems	Performance gain (%)
Query resolution rate, %	45-55	80-90	65 of improvement
Customer satisfaction score	3.2/5.0	4.3/5.0	34 of increase
Average response time, seconds	120-180	15-30	83 of reduction
Cost per interaction, USD	8.50	2.10	75 of cost reduction
Multilingual support capability	5-8 languages	50+ languages	700 of expansion
24/7 availability rate, %	85	99.9	17 of improvement

Source: *Springs (n.d.), OpenText (n.d.), CoinLaw (n.d.)*

The 65% improvement in query resolution rates, coupled with an 83% reduction in response time, indicated that agentic systems can handle more complex interactions autonomously, while maintaining superior speed. The 75% cost reduction per interaction represented significant operational efficiency gains for banking institutions. Financial fraud represented a growing threat as fraudsters continuously evolve methods to circumvent existing security measures. While rule-based systems were effective in detecting pre-enacted fraud schemes, such systems struggle with novel threats. H.K. Sriram & B. Somu (2025) described agentic AI as a dynamic and adaptive defence mechanism capable of learning and evolving to address emerging threats. Fraud detection systems powered by agentic AI function as autonomous security analysts monitoring billions of transactions in real-time on the bank's network. These agents do not merely verify transactions based on static criteria; rather, the systems utilised machine learning techniques to identify anomalies. B. Vyas (2023) highlighted the use of behavioural analysis in this context. Consequently, the agent created a unique profile for each customer containing average transaction times, locations, amounts, merchants, and devices used. Any deviation from the established pattern was immediately flagged as suspicious. For instance, if a customer typically making small purchases in one location attempts to withdraw a large amount from an ATM in a different country, the agent flags this as an unusual occurrence. However, the system proceeded beyond a simple flag; the agent was capable of autonomously executing a number of actions to verify the transaction. The system may send an interactive notification to the customer's banking application for biometric verification. The card may be temporarily suspended, while the system simultaneously cross-checks other data points, such as the location of the customer's mobile device. This ability to reason and act in real-time, considering context, reduced false positives and enabled quicker and more precise responses to genuine threats. Furthermore, H. Jo *et al.* (2025) indicated that agentic systems can collaborate and share intelligence across the network, alongside privacy-protecting tools, to discover large-scale coordinated fraud attacks. By identifying similar fraudulent behaviours across thousands of unrelated accounts, these agents can identify and dismantle fraud rings more rapidly than human teams. Fraud detection systems continuously learnt, automatically updating models to detect novel fraud attempts, thereby ensuring that banking defences evolved in parallel with new fraud strategies.

The banking regulatory landscape was complex and constantly changing, involving requirements such as Anti-Money Laundering, Know Your Customer, and transaction monitoring. Meeting these obligations was a resource-intensive task that had traditionally required large teams of compliance officers to manually review alerts and file reports. Agentic AI was automating and enhancing these compliance functions, improving accuracy and reducing operational costs. In transaction monitoring, agentic AI systems can autonomously screen financial activities for money laundering, terrorist financing, or sanctions violations. These agents transcended simple keyword matching or rule-based thresholds. A. Dodda (2024) noted that graph analytics and network analysis were utilised to uncover hidden relationships between entities and trace the flow of funds through complex multi-layered transaction chains. For example, an agent could identify a network of shell companies used to obscure the origin of illicit funds by analysing money flows, ownership structures, and transaction patterns that would be difficult to detect manually. When an agent identified suspicious activity, the system can autonomously initiate an investigation, gathering customer information, transaction history, and public records to compile a preliminary case file. The system can then use natural language generation to create a draft of a Suspicious Activity Report, highlighting the reasons for suspicion and the evidence. This automated the most time-consuming part of the compliance workflow, allowing human officers to focus on complex cases and final determinations. S. Paleti (2022) asserted that agentic AI also assisted banks in maintaining alignment with changing regulations. An agent can be tasked with monitoring regulatory websites and legal updates from multiple jurisdictions. Upon the announcement of a new rule, the agent analysed the text, interpreted the impact on the bank's operations, and suggested changes to internal policies and monitoring systems. M. Mucsková (2024) concluded that these AI applications were key to improving overall operational efficiency within banking institutions.

Core banking systems constituted the foundation of a bank's critical operations, including account management, deposits, lending, and payments. Many of these systems were legacy platforms developed in the 1980s and 1990s that were monolithic, inflexible, and difficult to integrate with modern digital technologies. R. Inala & B. Somu (2025) identified agentic AI as a key enabler of core infrastructure transformation toward a more agile, efficient, and intelligent banking architecture. A primary use case was back-office automation, where agentic AI orchestrated complex workflows across multiple legacy systems. For example, in payment processing, an agent can manage the entire lifecycle of a cross-border payment – from initiating the transaction and performing compliance checks to choosing the most efficient payment rail (e.g., SWIFT, FedNow), handling foreign exchange conversions, and performing automated reconciliation. This reduced manual intervention, minimised settlement times, and lowered processing costs. Agentic AI also played a key role in managing the health and performance of the IT infrastructure itself. Autonomous agents can monitor system performance, predict potential failures or bottlenecks, and take pre-emptive corrective actions, such as routing traffic or allocating additional computing resources. This ensured high availability and resilience of critical banking services. Looking forward, L. Hughes *et al.* (2025) described agentic AI as central to the vision of an autonomous financial services paradigm. In the future state, the core banking system could be conceptualised as a network of specialised, interoperable AI agents. One agent might manage customer identities and permissions, another might manage loan origination, and a third might manage liquidity and treasury functions. These agents would communicate and collaborate seamlessly via Application Programming Interfaces (APIs) to deliver banking services. This agent-based, decentralised architecture would be far more flexible, scalable, and resilient than the monolithic core systems prevalent in 2024 and 2025, allowing banks to innovate and deploy new products and services rapidly, ultimately redefining the fabric of banking operations.

Emerging challenges, risks, and opportunities of agentic AI in financial and banking operations

Integration of agentic AI into financial and banking operations brought unprecedented efficiency and innovation but also a complex landscape of challenges, risks, and opportunities. The transition from automated to autonomous systems required a fundamental rethinking of regulatory frameworks, ethical standards, technical infrastructure, and strategic priorities. Navigating this will determine the long-term viability and societal benefit of agentic AI in the financial sector. The autonomous nature of agentic AI presented a significant problem for existing financial regulatory structures, which were based on human decision-making and clear lines of accountability. Regulators globally were struggling to adapt frameworks designed for predictable, rule-based systems to agentic AI that can learn, evolve, and act independently. One of the key issues was liability, when an autonomous agent causes financial loss, market instability, or non-compliant outcomes. The uncertainty around whether the developer, the deploying institution, or the end user was responsible complicated the legal and regulatory landscape and required new models of accountability for algorithmic behaviour. Furthermore, H. Pappil Kothandapani (2025) argued that the "black box" problem in many advanced AI models directly conflicted with regulatory requirements for transparency and explainability. Financial institutions were required to justify decisions, especially in areas like credit scoring and loan underwriting, to prevent discriminatory practices. When an agentic system denied a loan based on complex, non-intuitive correlations learned from vast datasets, explaining the decision became impossible. This opacity hindered not only regulatory oversight and auditing but also internal risk management processes. Therefore, developing "explainable AI" (XAI) was not just a technical goal but a regulatory requirement. The pace of AI development was always ahead of the deliberative process of legislative and regulatory bodies, creating a persistent gap, where innovation operated in a state of legal uncertainty. S. Brohi *et al.* (2025) suggested that a proactive and adaptive regulatory approach was needed to enable responsible innovation, while protecting the financial system's stability and fairness.

Beyond compliance, long-term adoption of agentic AI depended on building and maintaining trust with all stakeholders – customers, employees, investors, and regulators. Trust in this context was multi-faceted – reliability, security, fairness, and ethical integrity. A key ethical challenge was the risk of embedding and amplifying societal biases in historical training data. If an agentic underwriting system was trained on biased historical lending data, discriminatory outcomes against protected groups may be perpetuated or even exacerbated, undermining fairness and equal opportunity. Therefore, bias detection, mitigation strategies, and continuous algorithmic audits were critical components of a trustworthy AI governance framework. The principle of human oversight was another cornerstone of ethical AI. While the appeal of agentic AI was autonomy, ceding complete control was risky. The speed and scale, at which agents operated can lead to situations, where errors propagated through the system faster than human operators can intervene. E. Svetlova (2022) noted that creating systems that were not only technologically advanced and efficient but also aligned to human values and societal good was crucial for maintaining a long-term social licence to operate. Implementing agentic AI within existing financial institutions was full of technical challenges, the biggest one being integration with legacy IT infrastructure. Many banks and financial firms had core systems that were decades old and not designed for the data-heavy, real-time processing of modern AI. These systems were fragmented, making the creation of unified, high-quality data pipelines difficult. Developing and maintaining sophisticated agentic systems required specialised talent that was in high demand and short supply. Financial institutions were competing with tech giants for data scientists, machine learning engineers, and AI ethics specialists. Building in-house expertise was a long-term play, while relying on third party vendors brought its own set of risks around data security, model ownership and vendor lock-in. Data security and privacy were also big concerns. Agentic systems need access to huge amounts of sensitive financial and personal data, making them an attractive target for cyber-attacks. Ensuring robust data governance, encryption, and access control was critical to prevent data breaches that can have financial and reputational damage. S. Joshi (2025) indicated that the move from conventional AI to agentic systems was a big jump in complexity, requiring new architectural frameworks and deeper understanding of emergent system behaviour to ensure stability and reliability in production. Despite the difficulties, agentic AI was going to change the financial industry. The trajectory was towards hyper-personalised, proactive, and deeply integrated financial services. O. Onabowale (2025) observed that agentic systems will go beyond executing simple tasks to be autonomous financial advisors for individuals and corporations, managing investments, cash flow, and providing strategic advice in real-time based on a full picture of a client's financial situation and goals. This will democratise access to sophisticated financial management tools previously only available to high-net-worth individuals. In capital markets, the move from algorithmic to agentic trading will continue, with agents developing and executing new strategies, adapting to market conditions, and even collaborating or competing with other agents. The integration of autonomous agents will be the defining characteristic of the next generation of financial infrastructure.

Conclusions

The analysis determined that the shift from task-specific automation to goal-oriented autonomy differentiated agentic Artificial Intelligence from conventional Artificial Intelligence through proactive, adaptive, and independent decision-making. The use cases across financial and banking operations – from autonomous trading and dynamic risk management to personalised customer service and regulatory compliance – showed the potential of this technology. Agentic Artificial Intelligence will deliver not just incremental efficiency but fundamental changes to business models, value chains, and competitive landscapes. Regulatory frameworks were struggling to keep up with technology and creating uncertainty around accountability, transparency, and liability. The "black box" nature of complex models was a direct challenge to the principles of explainability and fairness, which were the foundation of trust in financial services. Integrating these systems with legacy infrastructure was a technical and financial barrier for many institutions. Most importantly the ethical dimensions of deploying autonomous systems – algorithmic bias, human oversight, building trustworthy Artificial Intelligence – demand careful and proactive governance. In the future, agentic Artificial Intelligence in finance will be an increasingly interconnected and intelligent ecosystem. The opportunities are huge – from hyper personalisation of financial services to more resilient and adaptive risk management and compliance functions. As financial institutions and FinTechs develop and deploy more sophisticated agents, the industry will get closer to an era of autonomous financial services. Future research should focus on the technical mechanisms required to ensure interoperability between heterogeneous agentic systems across different financial institutions. Additionally, empirical studies are needed to quantify the systemic risks associated with high-frequency autonomous interactions in volatile markets.

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Conflict of Interest

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Агентний штучний інтелект у фінансово-банківських операціях: комплексний огляд

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Анотація. Метою дослідження був огляд академічної та галузевої літератури з метою уточнення концепції агентного штучного інтелекту, пояснення принципів його архітектурного функціонування та вивчення сфер застосування у фінансовому й банківському секторах. Зростаюче використання штучного інтелекту у сфері фінансових послуг сприяло переходу до етапу фінансової автоматизації, що ґрунтується не на правилах, а на системах, здатних міркувати, адаптуватися та діяти автономно й цілеспрямовано. Цей перехід призвів до появи того, що у сучасному світі називають агентним штучним інтелектом – категорією інтелектуальних систем, які функціонують незалежно, чого бракує традиційним застосуванням штучного інтелекту. Дослідження базувалося на методології систематичного огляду, яка узагальнила докази щодо використання агентного штучного інтелекту в автономній торгівлі, динамічній оцінці ризиків, алгоритмічному андеррайтингу, виявленні шахрайства, персоналізованій взаємодії з клієнтами та забезпеченні регуляторної відповідності. Як показав аналіз дослідження, такі системи підвищували операційну проактивність, ситуаційну обізнаність і здатність до багатокрокового ухвалення рішень, що дозволило фінансовим установам бути більш адаптивними до складних і швидкозмінних умов. Крім того, огляд засвідчив наявність постійних проблем, пов'язаних із пояснюваністю, відповідальністю, інтеграцією із застарілими інфраструктурами, етичним захистом і готовністю до регуляторних викликів. Результати засвідчили про те, що агентний штучний інтелект мав потенціал трансформувати операційну та стратегічну діяльність у фінансовому секторі, однак лише за умов відповідального управління та суворого нагляду його переваги могли бути реалізовані на практиці. Внеском цього огляду в наукову літературу стала інтегрована оцінка сучасних тенденцій на основі доказів, а також визначення ключових можливостей і обмежень, які формуватимуть майбутнє автономних інтелектуальних систем у сфері фінансових послуг

Ключові слова: штучні агенти; автономні фінанси; цифровий банкінг; фінансові інновації; фінансовий алгоритм