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ЗАСТОСУВАННЯ ТЕХНОЛОГІЙ ШТУЧНОГО ІНТЕЛЕКТУ В КОРПОРАТИВНОМУ ФІНАНСОВОМУ МЕНЕДЖМЕНТІ: ПРИКЛАДНИЙ АСПЕКТ

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Анотація. У статті досліджено проблематику інтеграції технологій штучного інтелекту (ШІ) та алгоритмів машинного навчання (МН) у системи корпоративного фінансового менеджменту підприємств реального сектора економіки. В умовах макроекономічної нестабільності та високої волатильності ринків традиційні інструменти фінансового контролінгу й планування, зокрема електронні таблиці та базові модулі ERP-систем, поступово стають недостатніми для своєчасного ухвалення обґрунтованих управлінських рішень. Ці традиційні підходи переважно спираються на ретроспективний аналіз і детерміновану лінійну екстраполяцію, що може обмежувати здатність корпоративного менеджменту обробляти значні масиви неструктурованої інформації (Big Data) та виявляти приховані нелінійні взаємозв’язки. Відповідно, зростає наукова і практична потреба в переході від реактивного фінансового моніторингу до проактивного предиктивного управління. Основною метою дослідження є обґрунтування практичної корисності інструментів ШІ та визначення можливостей їх застосування в операційній діяльності фінансових менеджерів.

Методологічну основу дослідження становлять методи аналізу і синтезу, систематизації, порівняльного аналізу, якісного контент-аналізу та вивчення корпоративних кейсів, представлених у відкритих джерелах.

Установлено, що практична цінність штучного інтелекту в корпоративних фінансах може проявлятися насамперед у 3 ключових напрямах. Першим є прогнозування ліквідності та запобігання касовим розривам. Використання таких архітектур нейронних мереж, як довга короткочасна пам’ять (LSTM), дає підприємствам змогу аналізувати грошові потоки як складні часові ряди та адаптувати фінансові прогнози до макроекономічних коливань і внутрішніх виробничих циклів, що сприяє виявленню ризиків ліквідності до виникнення касового розриву. Іншим напрямом є управління дебіторською заборгованістю та скоринг контрагентів. Інтеграція технологій обробки природної мови (NLP) і машинного навчання забезпечує інтелектуальний скоринг у режимі реального часу, безперервний моніторинг інформаційного середовища та адаптивне управління кредитними лімітами, сприяючи зниженню ризику виникнення безнадійної заборгованості. Ще одним напрямом є фрод-моніторинг і внутрішній аудит. ШІ може посилювати аудиторську функцію завдяки забезпеченню безперервного аудиту та використанню алгоритмів виявлення аномалій і нейронних мереж-автокодувальників для ідентифікації багатовимірних відхилень і зниження ймовірності фінансових втрат, спричинених внутрішніми загрозами або фішинговими атаками.

Незважаючи на значний потенціал ШІ, підтверджений сучасними дослідженнями, у статті окреслено суттєві інфраструктурні виклики, які можуть перешкоджати його широкому

впровадженню в корпоративному секторі. До таких бар'єрів належать низька якість первинних історичних даних, що описується принципом «сміття на вході – сміття на виході», психологічні та управлінські труднощі, пов'язані з проблемою «чорного ящика», а також значні інвестиційні обмеження щодо розвитку IT-інфраструктури та залучення фахівців із data science.

Подальші дослідження доцільно спрямувати на розроблення доступних та адаптивних моделей машинного навчання для підприємств малого і середнього бізнесу, а також на підвищення пояснюваності фінансових рішень, ухвалених із використанням ШІ.

Ключові слова: фінансовий менеджмент, штучний інтелект, машинне навчання, предиктивна аналітика, касовий розрив, скоринг контрагентів, фрод-моніторинг, управління ліквідністю.

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APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN CORPORATE FINANCIAL MANAGEMENT: AN APPLIED ASPECT

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Abstract. The article explores the issue of integrating artificial intelligence (AI) technologies and machine learning (ML) algorithms into corporate financial management systems of real-sector enterprises. In the context of macroeconomic instability and high market volatility, traditional tools for financial control and planning, including spreadsheets and basic ERP modules, are gradually becoming insufficient to support timely and well-grounded managerial decisions. These conventional approaches rely primarily on retrospective analysis and deterministic linear extrapolation, which may limit the ability of corporate management to process large arrays of unstructured information (Big Data) and identify hidden, non-linear relationships. Accordingly, there is a growing scientific and practical need to move from reactive financial monitoring toward proactive predictive management. The primary aim of the research is to substantiate the practical utility of AI instruments and demonstrate how these technologies can be applied in the operational activities of financial managers.

The methodological framework combines analysis and synthesis, systematisation, comparative analysis, qualitative content analysis, and the case study method applied to publicly available corporate implementation cases.

The study highlights that the practical value of artificial intelligence in corporate finance may be manifested primarily in three key domains. First, predictive liquidity forecasting and the prevention of cash gaps. By using neural network architectures such as Long Short-Term Memory (LSTM), enterprises can analyse cash flows as complex time series and adapt financial forecasts to macroeconomic fluctuations and internal production cycles, which may help identify liquidity risks before a cash gap occurs. Second, accounts receivable management and counterparty scoring. The integration of Natural Language Processing (NLP) and machine learning enables real-time intelligent scoring, continuous monitoring of the information environment, and adaptive credit limit management, thereby contributing to the reduction of bad debt risks. Third, fraud monitoring and internal auditing. AI can strengthen the audit function by supporting continuous auditing, applying anomaly detection algorithms and autoencoders to identify multidimensional deviations and reduce the probability of financial losses caused by internal threats or phishing attacks.

Despite the considerable potential of AI identified in recent studies, the article outlines significant infrastructural challenges that may hinder its widespread corporate adoption. These barriers include the poor quality of primary historical data, commonly described by the "garbage in, garbage out" principle, the psychological and managerial difficulty associated with the "Black Box Problem", and substantial investment constraints related to IT infrastructure and data science expertise.

Future research should focus on developing accessible and adaptive ML models for small and medium-sized enterprises (SMEs), improving the explainability of AI-based financial decisions.
Keywords: corporate financial management, artificial intelligence, machine learning, predictive analytics, cash gap, counterparty scoring, fraud monitoring, liquidity management.

Introduction. In the context of macroeconomic instability and high market volatility, corporate financial management faces unprecedented challenges. Rapid changes in market conditions, supply chain disruptions, and fluctuations in demand require corporate management to respond to threats immediately. Today, successful business operations and solvency depend less on recording the current financial position than on the ability to forecast cash flows and continuously mitigate financial risks in advance.

The problem is that traditional financial controlling and planning tools (spreadsheets and basic ERP modules) are gradually becoming less effective in a rapidly changing environment. They rely primarily on retrospective analysis; that is, they process historical data and record events after the fact. Such approaches limit the capacity to promptly process vast amounts of unstructured information (Big Data) and make it difficult to identify hidden, non-linear relationships between economic factors. This results in delayed managerial decisions, unexpected cash gaps, and an increase in bad accounts receivable.

Consequently, the transition from reactive to proactive management is an essential scientific and practical objective of contemporary corporate financial management. Achieving it is directly associated with introducing advanced digital technologies, particularly artificial intelligence (AI) and machine learning algorithms. The practical objective is to identify and substantiate the use of predictive AI tools capable not only of analysing historical data but also of supporting financial flexibility and business resilience under persistent uncertainty.

The digital transformation of the economy and the introduction of innovative technologies into financial management have been examined by many contemporary Ukrainian and international researchers. Fundamental aspects of economic digitalisation and the impact of innovation on the financial sector have been thoroughly investigated by Ukrainian scholars [1-5], including N. A. Mazur, V. P. Vyshnevskyi, O. M. Harkushenko, S. I. Kniaziev, D. V. Lypnytskyi, V. D. Chekina, A. V. Cherep, I. M. Dashko, Yu. O. Ohrenych, O. H. Cherep, V. M. Helman, L. V. Nechyporuk, and others. Their studies address the mechanisms of transition to a digital economy and the use of financial technologies (FinTech) by Ukrainian enterprises. The literature also extensively discusses the automation of accounting processes, the use of Big Data in financial analysis, and the integration of information systems into corporate governance. Leading global consulting companies, including McKinsey [6], Deloitte [7], and PwC [8], devote considerable attention to the potential of neural networks and machine learning, regularly reporting on the effectiveness of algorithms in optimising financial business processes.

Despite the substantial theoretical foundation, most contemporary publications focus on applying artificial intelligence primarily in specialised segments of the financial sector, including banks, insurance companies, investment funds, and algorithmic trading. AI is frequently considered either as a global macroeconomic trend or as a purely mathematical model.

At the same time, the integration of artificial intelligence algorithms directly into the operations of financial departments at real-sector enterprises remains insufficiently explored. The literature lacks a comprehensive approach that clearly demonstrates the usefulness of AI in addressing the daily applied tasks of corporate financial managers. A considerable gap currently exists between recognition of the theoretical potential of intelligent systems and the shortage of methodological recommendations for using them to manage working capital, forecast cash gaps, and minimise accounts receivable risks at the level of an individual non-financial company. The need to bridge this gap and shift AI research towards practical application in corporate financial management constitutes the previously unresolved aspect of the broader problem addressed in this article.

Task statement. The purpose of the article is to investigate and substantiate the applied utility of artificial intelligence tools in corporate financial management. To achieve this purpose, the study seeks to identify the limitations of traditional retrospective approaches to financial analysis and systematise the AI technologies most relevant to the activities of corporate finance departments. Particular attention is paid to the mechanisms through which machine learning and predictive analytics can support cash flow forecasting and early identification of cash gaps, counterparty scoring and accounts receivable management, as well as fraud monitoring and internal auditing.

The methodological framework of the study combines general scientific and applied research methods. The methods of analysis and synthesis were used to examine the theoretical foundations and technological capabilities of artificial intelligence in corporate finance. Systematisation and generalisation were applied to distinguish the principal areas, instruments, potential effects, implementation barriers, and organisational conditions associated with AI adoption. Comparative analysis was used to contrast traditional financial management procedures with AI-supported approaches. The case study method and qualitative content analysis were employed to examine publicly available corporate implementation cases and identify the technologies used, the financial processes affected, the role of finance professionals, and the reported operational results.

The information base of the study consists of scientific publications on machine learning, predictive financial management, credit scoring, anomaly detection, and continuous auditing, as well as official corporate case studies published by technology providers and companies implementing AI-based solutions. Corporate cases were selected according to their relevance to the three areas examined in the article, the availability of a clear description of the implementation mechanism, and the presence of measurable financial or operational results. Since the respective companies or technology providers report the quantitative effects presented in corporate case studies, they are interpreted as evidence of practical application rather than as independently verified causal estimates of AI effectiveness.

Results. The evolution of corporate financial management demonstrates a steady transition from traditional retrospective analysis to predictive management systems. Conventional models based on the linear extrapolation of historical data are vulnerable to unexpected market shocks. By contrast, artificial intelligence enables financial managers to use probabilistic models capable of identifying hidden patterns in unstructured datasets. Research indicates that the practical benefits of AI for enterprises may be manifested primarily in three key areas:

1. Liquidity forecasting and cash gap prevention.

Working capital management is fundamental to the operational stability of any enterprise. In a turbulent environment, a company’s ability to accurately forecast and maintain the required liquidity level has a substantial effect on its operational resilience. A cash gap - a critical timing mismatch between cash inflows and outflows - may occur even in highly profitable companies [9].

Traditional approaches to liquidity management rely mainly on deterministic methods and linear extrapolation embedded in conventional ERP systems and based on fixed payment and contract schedules. Although these models are effective under stable conditions, they cannot adapt when external factors or internal disruptions disturb established operating patterns. A linear model disregards the probabilistic nature of financial flows [10; 11].

Artificial intelligence may significantly change this paradigm by shifting it from static planning to dynamic modelling. Long Short-Term Memory (LSTM) neural network architectures make it possible to analyse cash flows as complex time series containing hidden non-linear dependencies [10; 12].

The key advantages of AI models in liquidity and cash flow forecasting include:

- dynamic adaptation to macroeconomic fluctuations: AI systems incorporate a broad range of macroeconomic indicators into financial models, including inflation expectations, changes in central bank policy rates, and exchange-rate movements. Unlike static systems, neural networks automatically adjust their forecasts when these external parameters change, thereby maintaining the relevance of financial planning [11; 12];
- in-depth analysis of internal production cycles: machine learning algorithms can identify hidden relationships among production volumes, the duration of logistics operations, and the intensity of working capital utilisation. This supports modelling the impact of seasonal demand peaks or supply chain delays on the closing cash balance, which is difficult to implement fully using conventional spreadsheet tools [9; 12];
- processing multidimensional datasets: AI can integrate information from disparate corporate subsystems, ranging from tax payment and payroll schedules to data on current energy and repair costs. By processing vast amounts of unstructured data, the system develops complex models of future liquidity that account even for minor operating expenses, which, taken together, may materially affect the overall balance [10; 13; 14].

The practical experience of international corporations confirms the gradual integration of artificial intelligence into liquidity management, financial planning, and forecasting. In particular, the consulting company Accenture uses the “Intelligent Cash” tool, developed on the SAP platform, to manage operating cash across more than 50 countries. The solution consolidates financial and operational data within an integrated information environment. It applies machine learning algorithms to determine an appropriate level of cash reserves and generate recommendations for financial managers. According to SAP’s corporate case study, the use of this tool enabled Accenture to release approximately 20% of temporarily idle cash and redirect it towards financing acquisitions and strategic development [15]. Other companies are integrating AI into broader financial planning systems. Hearst, for example, uses tools embedded in Oracle Fusion Applications for cash management, variance analysis, automated reconciliations, and the generation of explanations for financial statements [16]. At the same time, Avis Budget Group applies Oracle Cloud ERP and EPM to consolidate financial data, update forecasts, and automate selected accounting procedures. These solutions are implemented as part of a comprehensive digital transformation of the finance function; therefore, the effect is determined by a combination of AI, automation, data standardisation, and the integration of ERP and EPM systems [17].

Hypothetical example. At a manufacturing enterprise, the traditional ERP system indicates that in November the company is expected to receive UAH 1 million from a key customer and pay UAH 800 thousand to suppliers; according to the linear plan, no cash gap is anticipated. However, after analysing the available data, the AI model identifies hidden risks: historical payment data indicate that the customer’s payments are delayed by an average of ten days during the fourth quarter each year, while the supplier of imported raw materials may require payment earlier than scheduled because of seasonal congestion at customs. The AI model may detect an elevated probability of a cash gap weeks or months before it occurs. The company can therefore arrange short-term financing in advance at a lower cost and avoid emergency borrowing on unfavourable terms.

2. Accounts receivable management and counterparty scoring.

Accounts receivable management is a strategic lever of financial stability. Since the solvency of business partners may change dynamically under the influence of macroeconomic and microeconomic shocks, an enterprise’s ability to assess credit risk accurately determines the turnover rate of its capital. Funds tied up in unpaid invoices and the emergence of bad debt directly undermine liquidity, making continuous counterparty scoring a priority in financial management [18].

Conventional methods of assessing customer creditworthiness are labour-intensive and frequently lack timeliness, thereby limiting the ability to respond rapidly to a deterioration in a counterparty's payment discipline. Modern intelligent systems transform this process by enabling real-time scoring. Machine learning algorithms and Natural Language Processing (NLP) technologies can synthesise both structured financial indicators and unstructured information, allowing warning signals to be detected long before they appear in official financial statements [18; 19].

The key advantages of AI-based scoring models include:

- dynamic monitoring of the information environment: NLP modules continuously scan thousands of sources, from news feeds and industry analytical reports to litigation and tax registers. This enables the system to respond immediately to unusual events, such as payroll delays, changes in senior management, or the emergence of numerous lawsuits against a counterparty [18; 19];
- identification of hidden correlations: machine learning algorithms detect relationships between a company's behavioural characteristics (for example, unusual changes in the frequency of requests for payment deferrals) and the probability of default. This enables models to identify high-risk debtors even when a company appears to meet standard profitability criteria [18; 20];
- adaptive credit limit management: AI systems enable the dynamic recalculation of recommended credit limits for each customer. Based on continuous risk assessment, the system may recommend an adjustment to the existing limit, while the final decision should remain with an authorised financial manager [18; 19].

An example of AI implementation in accounts receivable management and payment document processing is the "PowerMatch" solution developed by Ernst & Young's (EY) Global Finance team. The solution is based on Microsoft Power Platform and AI Builder and is integrated with SAP systems. It extracts the required data from payment documents, identifies relationships between received payments and open invoices, and automatically processes transactions with a high level of algorithmic confidence. As a result, the proportion of payments that are automatically matched and cleared increased from 30% to 80%. A further 15% of transactions are automatically matched to invoices but require final employee confirmation, while the proportion of transactions requiring fully manual processing decreased to 5%. According to EY estimates, the solution saves approximately 230,000 working hours annually [21].

A similar approach has been implemented by Concentrix, which uses Microsoft Power Platform, AI Builder, and multimodal generative AI models to automatically recognise, extract, and standardise data from invoices in various formats. The solution processes approximately 100,000 invoices per month and achieves an average data extraction accuracy of more than 96%, while non-standard cases are referred to employees for additional review [22]. These examples demonstrate that AI not only reduces the labour intensity of accounts receivable and payment processing but also supports a human-in-the-loop model, in which finance professionals retain final control over ambiguous transactions.

Hypothetical example. A B2B distributor receives a request from a large retail chain to supply a substantial quantity of goods with extended payment terms. According to the customer's latest financial statements, the company remains profitable and solvent. However, an AI-powered analytics module processes authorised internal payment-history data and publicly available information, identifying several early warning signals, including an increase in requests for payment deferrals, reports of delayed payroll payments, and newly initiated legal proceedings involving logistics partners. Based on these indicators, the system assigns the transaction a higher risk score and recommends that the finance manager review the customer's credit limit and payment terms. Following additional verification, the authorised manager may reduce the available credit limit, request partial advance payment, or retain the existing terms if the warning signals are not confirmed. This approach enables the distributor to respond to a possible deterioration in the counterparty's payment capacity while preserving professional judgement and avoiding fully automated adverse decisions.

3. Fraud monitoring and internal auditing.

Ensuring financial security and protecting assets against fraud are critical aspects of corporate governance. As corporate transaction volumes continue to grow and abusive practices become increasingly sophisticated, the ability to identify anomalies in real time helps companies minimise financial losses. Internal threats, including the substitution of bank account details, phishing, and the abuse of delegated authority, may harm even companies with robust compliance systems. The transition to continuous intelligent fraud monitoring is therefore a priority for internal audit [23].

Control procedures have traditionally relied primarily on preventive rule-based algorithms embedded in ERP workflows. These mechanisms operate based on rigid thresholds (for example, mandatory approval of payments exceeding a specified amount) and checklists. Although effective in detecting typical errors, such methods are inadequate against technologically sophisticated schemes because static algorithms cannot recognise hidden malicious behaviour that does not formally breach established limits [24; 25].

Artificial intelligence may transform internal audit by shifting it from discrete sample-based reviews to continuous auditing. Contemporary machine learning techniques, particularly anomaly detection algorithms and autoencoder neural networks, enable a system not merely to record deviations but also to dynamically determine normal behavioural patterns for users and counterparties [23; 24].

The key advantages of AI models in fraud monitoring include:

- comprehensive transaction screening: AI systems can automatically examine a large number of payments at the time they are initiated, substantially reducing the limitations inherent in traditional audit sampling. Unlike static systems, algorithms can analyse transaction records across a broader set of parameters, enabling the detection of even minor systematic abuses that may result in substantial cumulative losses [24; 25];
- detection of multidimensional anomalies: machine learning algorithms can identify hidden deviations from the digital profile of normal operations. This provides a basis for modelling transaction risk through a comprehensive analysis of the initiation time, geographical location, technical device parameters, and history of previous interactions, thereby enabling potentially fraudulent transactions to be flagged for additional verification before funds are debited [23];
- cross-system data integration: AI can compare information from disparate corporate sources, ranging from ERP access logs to HR databases. This facilitates the detection of complex conflicts of interest or compromised employee accounts while reducing the effects of human error and abuse of authority [24].

Practical examples of AI implementation in internal financial control, anomaly detection, and reconciliation automation can be observed in the practices of IBM and U.S. Venture. As part of the "Jobotx" initiative, IBM's internal finance function combined IBM watsonx.ai, watsonx Orchestrate, Apptio, and robotic process automation. The system validates input data against general ledger information, performs root-cause analysis of variances, prepares journal entry data, and applies real-time anomaly detection mechanisms. The resulting transactions are not posted automatically to the general ledger but are first reviewed and approved by a finance manager. According to IBM estimates, this automation may reduce the duration of selected financial close and reconciliation procedures by more than 90% and generate potential annual savings of approximately USD 600,000 [26]. U.S. Venture and its business unit U.S. AutoForce use Microsoft Copilot for Finance to reconcile bank statements and corporate payment card transactions. According to Microsoft's corporate case study, the system saves the finance team more than 30 working hours per month and has reduced the time required for selected bank reconciliations by approximately 80% [27]. Thus, the practical role of AI in internal control primarily involves continuous transaction analysis, exception identification, and referral of potentially risky cases for professional review, rather than fully autonomous decision-making regarding transaction blocking.

Hypothetical example. A company's finance department receives an invoice from a regular contractor for an amount below the threshold requiring mandatory manual approval. Under conventional rule-based controls, the transaction does not formally violate any established condition and may therefore be prepared for execution. However, an AI-based anomaly detection model identifies an unusual combination of indicators: the document was uploaded at 2 a.m. on a Sunday, the IBAN differs slightly from the account details previously used by the contractor, and the initiator's IP address does not correspond to the corporate network. The system flags the transaction as potentially suspicious, temporarily suspends its processing, and refers it to an authorised finance or compliance specialist for additional verification. If the review confirms that the invoice or payment details have been compromised, the transaction is rejected, thereby preventing a potentially unauthorised transfer that a conventional control system might not have detected because no formal payment threshold was breached.

Table 1

Comparative assessment of the potential effects of applying AI in corporate financial management

Area of application	Traditional approach	AI tools	Potential effect of AI application
Cash flow forecasting and liquidity management	Extrapolation of past trends, expert adjustments, and periodic analysis of the payment calendar	LSTM, machine learning, predictive analytics	Improved forecast accuracy, early detection of cash gaps, and enhanced financial resilience
Counterparty scoring and accounts receivable management	Analysis of financial statements and credit history, and manual monitoring of payment deadlines	ML-based scoring, NLP-based document analysis, and overdue payment prediction models	Early identification of non-payment risk, faster counterparty assessment, and lower overdue accounts receivable
Fraud monitoring and internal auditing	Sample-based rule-driven reviews conducted mainly after transactions	Anomaly detection algorithms, neural networks, and real-time analysis	Broader audit coverage, prompt identification of high-risk transactions, and reduced potential financial losses

Source: compiled by the author.

Despite the potential effects identified in contemporary research and reported in corporate cases, the integration of AI into financial management involves several interrelated risks:

- data and model risks: the reliability of AI-generated forecasts and recommendations depends directly on the quality, completeness, consistency, and relevance of corporate data. Inaccurate, outdated, distorted, or incompatible information may result in unreliable liquidity forecasts, incorrect counterparty risk scores, and excessive numbers of false transaction alerts. Changes in market conditions, customer behaviour, supply chains, or internal business processes may also cause model drift, which requires regular validation, performance monitoring, recalibration, and retraining of AI models;
- explainability and managerial risks: the limited transparency of complex machine learning models may prevent financial managers from clearly understanding why a system recommends reducing a counterparty's credit limit, suspending a payment, or classifying a transaction as anomalous. Historical data may also contain implicit biases that are reproduced in subsequent assessments. Therefore, AI-generated outputs should be treated as analytical recommendations rather than autonomous decisions, while responsibility for their interpretation and approval should remain with authorised finance, audit, risk-management, or compliance professionals;
- operational, cybersecurity, and confidentiality risks: the integration of AI with ERP, EPM, banking, accounting, and document-management systems expands the range of potential threats to commercially sensitive financial information. Unauthorised access, data leakage, manipulation of input data, compromised user accounts, system failures, or incorrect integration may affect the integrity of forecasts and control procedures. Dependence on external software providers may additionally create technological lock-in and operational disruption, requiring differentiated access rights, encryption, audit trails, cybersecurity testing, backup mechanisms, and manual fallback procedures;
- financial and organisational risks: the costs of acquiring software, preparing and standardising data, integrating information systems, strengthening cybersecurity, and training employees may exceed the expected operational benefits, particularly for small and medium-sized enterprises. The shortage of specialists who combine expertise in corporate finance, data analytics, and information technology may increase dependence on external providers. Another risk is excessive reliance on algorithmic recommendations, which may weaken independent professional judgement. To mitigate these risks, AI should be introduced gradually through pilot projects, measurable performance indicators, regular model reviews, employee training, and formal procedures for human oversight.

Thus, the use of AI does not negate the classical fundamental principles of financial management but serves as a tool for multiplying efficiency. The technology can gradually transform the role of the corporate finance department from a recorder of past events into a forward-looking strategic navigator.

Conclusions. The study demonstrates that the applied value of artificial intelligence in corporate financial management is most evident in three areas: cash flow forecasting and liquidity management, counterparty scoring and accounts receivable management, and fraud monitoring and internal auditing. In these areas, AI and machine learning tools extend the analytical capabilities of finance departments by processing large volumes of structured and unstructured data, identifying non-linear relationships, detecting early warning signals, and supporting more timely managerial decisions.

The analysis of corporate implementation cases confirms that AI is already being integrated into operational financial processes. The practical results reported by Accenture, EY, Concentrix, IBM, U.S. Venture, Hearst, and Avis Budget Group include the release of temporarily idle cash, higher levels of automated payment matching, reduced manual document processing, faster financial reconciliations, and improved identification of anomalous transactions. These cases indicate that the most mature applications of AI are currently found in standardised, repetitive, and data-intensive financial procedures. At the same time, the reported effects should be interpreted as the combined result of AI technologies, process automation, data standardisation, and the integration of ERP, EPM, and analytical systems rather than as the isolated effect of individual algorithms.

AI should therefore be regarded as a decision-support instrument rather than as a complete substitute for conventional financial management methods or professional judgement. The human-in-the-loop principle remains particularly important when changing counterparty credit limits, suspending payments, assessing potentially fraudulent transactions, and approving accounting entries. The effectiveness of AI-based financial management depends on the quality and consistency of corporate data, the digital maturity of the enterprise, the transparency of algorithmic outputs, the integration of financial and operational information systems, and the availability of employees with competencies in both finance and data analytics.

The implementation of AI should follow a phased approach, beginning with clearly defined financial procedures for which results can be measured using specific operational and financial indicators. Such indicators may include forecast accuracy, the frequency of cash gaps, the duration of payment allocation and reconciliation, the level of overdue accounts receivable, the proportion of automatically processed documents, and losses prevented through the timely identification of anomalous transactions.

An important limitation of the study is that it relies on publicly available corporate cases and does not provide comparable estimates of return on investment or payback periods, since implementation costs are not disclosed consistently across the cases analysed.

Future research should focus on developing accessible and adaptive machine learning models for small and medium-sized enterprises, which do not always have sufficient resources to establish their own data science teams. Promising avenues also include developing methodological approaches to assessing the economic effects of introducing AI into financial management, designing explainable artificial intelligence models for corporate finance, and exploring opportunities to combine predictive analytics with sustainable development principles and ESG-oriented financial management.

References

1. Mazur, N. A., editor. *Digital Transformation of the Economy: Micro- and Macro-Aspects.* Chernivetskyi natsionalnyi universytet imeni Yuriia Fedkovycha, 2022.
2. Vyshnevskyi, V. P., et al. *Digitalization of Ukraine's Economy: Transformational Potential.* Akademperiodyka, 2020.
3. Dziamulych, M. I., et al. "Business Transformation in the Conditions of Information and Network Economy." *Ekonomichnyi chasopys Volynskoho natsionalnoho universytetu imeni Lesi Ukrainky*, vol. 35, no. 4, 2023, pp. 26–33.
4. Cherep, A. V., et al., editors. *Digital Transformation of Ukraine's Economy through the Integration of European Experience during the War and Post-War Recovery.* Baltija Publishing, 2025.
5. Nechyporuk, L. V. "Digitalization as a Factor of Modernization of the Financial System in the Context of Sustainable Development." *Stalyi rozvytok ekonomiky*, no. 4 (55), 2025, pp. 142–47, https://doi.org/10.32782/2308-1988/2025-55-20.
6. McKinsey & Company. "Tech & AI Insights." *McKinsey & Company*, www.mckinsey.com/capabilities/tech-and-ai/our-insights. Accessed 24 May 2026.
7. "The State of AI in the Enterprise." *Deloitte*, www.deloitte.com/us/en/what-we-do/capabilities/applied-artificial-intelligence/content/state-of-ai-in-the-enterprise.html. Accessed 24 May 2026.
8. "Artificial Intelligence Services." *PwC*, www.pwc.com/gx/en/services/ai.html. Accessed 24 May 2026.
9. Roy, Soumit, et al. "Harnessing AI and Machine Learning for Improved Cash Flow Forecasting." *Proceedings of the 2024 Sixth Doctoral Symposium on Intelligence Enabled Research (DoSIER 2024), CEUR Workshop Proceedings*, vol. 3900, 2025, pp. 211–22, ceur-ws.org/Vol-3900/Paper17.pdf. Accessed 24 May 2026.

10. Novandi, Muhammad Ananta Arya, et al. "Cash Flow Prediction System of PT Gudang Garam Using ERP-Integrated LSTM." *Electronic Journal of Education, Social Economics and Technology*, vol. 6, no. 2, 2025, article 1235, https://doi.org/10.33122/ejeset.v6i2.1235.
11. Yang, A. "Big Data-Driven Corporate Financial Forecasting and Decision Support: A Study of CNN-LSTM Machine Learning Models." *Frontiers in Applied Mathematics and Statistics*, vol. 11, 2025, article 1566078, https://doi.org/10.3389/fams.2025.1566078.
12. Kumar, Atul, and Vinit Kumar Sharma. "Using AI for Predictive Financial Management: Opportunities and Risks in Corporate Finance." *International Journal of Science, Architecture, Technology, and Environment*, vol. 2, no. 8, 2025, pp. 259–67.ю https://doi.org/10.63680/ijsate0725020.19.
13. Bondaruk, Vladyslav. "Digital Technologies in Ensuring the Financial Performance of Business Entities in Foreign Economic Activities." *Ekonomika ta suspilstvo*, no. 71, 2025, https://doi.org/10.32782/2524-0072/2025-71-144.
14. Uhodnikova, O. I., et al. "Digital Transformation of Financial Management, Analysis and Audit: Conceptual Foundations and Implementation Tools." *Efektyvna ekonomika*, no. 7, 2025,https://doi.org/10.32702/2307-2105.2025.7.64.
15. Bown, B. "AI Road Map: How Accenture Uses AI as a Growth Engine." *SAP News Center*, 31 Mar. 2026, news.sap.com/2026/03/how-accenture-uses-ai-as-growth-engine/. Accessed 31 July 2026.
16. "Hearst Gives Finance Teams Faster, Broader Insight with Oracle." *Oracle*, www.oracle.com/customers/hearst-erp/. Accessed 31 July 2026.
17. "Avis Budget Group Gains AI-Powered Automation with Oracle Cloud ERP." *Oracle*, www.oracle.com/customers/avis-budget-group/. Accessed 31 July 2026.
18. Huang, A. H., et al. "FinBERT: A Large Language Model for Extracting Information from Financial Text." *Contemporary Accounting Research*, vol. 40, no. 2, 2023, pp. 806–41, https://doi.org/10.1111/1911-3846.12832.
19. Dumitrescu, E., et al. "Machine Learning for Credit Scoring: Improving Logistic Regression with Non-Linear Decision-Tree Effects." *European Journal of Operational Research*, vol. 297, no. 3, 2022, pp. 1178–92, https://doi.org/10.1016/j.ejor.2021.06.053.
20. Bücker, M., et al. "Transparency in Machine Learning for Credit Scoring." *Journal of the Operational Research Society*, vol. 73, no. 1, 2022, pp. 70–90, https://doi.org/10.1080/01605682.2021.1922098.
21. "EY Uses Power Platform to Automate Customer Payment Processing." *Microsoft Learn*, Microsoft, 12 Feb. 2025, learn.microsoft.com/en-us/power-platform/guidance/case-studies/global-finance. Accessed 31 July 2026.
22. "Concentrix Innovates with Intelligent Document Processing at Scale Using Power Platform and AI Hub." *Microsoft Customer Stories*, Microsoft, 14 Apr. 2026, www.microsoft.com/en/customers/story/26378-concentrix-microsoft-power-platform. Accessed 31 July 2026.
23. Schreyer, M., et al. "Detection of Accounting Anomalies in the Latent Space Using Adversarial Autoencoder Neural Networks." *KDD 2019 Workshop on Anomaly Detection in Finance*, 2019, https://doi.org/10.48550/arXiv.1908.00734.
24. Hasan, A. R. "Artificial Intelligence (AI) in Accounting and Auditing: A Literature Review." *Open Journal of Business and Management*, vol. 10, 2022, pp. 440–65, https://doi.org/10.4236/ojbm.2022.101026.
25. Hilal, W., et al. "Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances." *Expert Systems with Applications*, vol. 193, 2022, article 116429, https://doi.org/10.1016/j.eswa.2021.116429.
26. "IBM Finance: Transform Team Productivity with Ease." *IBM*, www.ibm.com/case-studies/ibm-finance. Accessed 31 July 2026.
27. "U.S. Venture Gains Efficiencies and Insights with Dynamics 365 and Microsoft 365 Copilot for Finance." *Microsoft Customer Stories*, Microsoft, 28 Jan. 2025, www.microsoft.com/en/customers/story/20600-us-venture-microsoft-365-copilot-for-finance. Accessed 31 July 2026.

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