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APPLICATIONS OF AI FOR ENTERPRISE PROFIT ANALYSIS

НАПРЯМКИ ВИКОРИСТАННЯ ШТУЧНОГО ІНТЕЛЕКТУ ПРИ АНАЛІЗІ ПРИБУТКУ ПІДПРИЄМСТВА

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Artificial intelligence (AI) has become a key driver of analytical transformation in modern enterprises, redefining the way organizations collect, process, and interpret financial information. AI tools such as machine learning, deep neural networks, and predictive analytics provide businesses with the ability to detect early indicators of profitability fluctuations, optimize pricing strategies, and identify inefficiencies in resource allocation. This study aims to explore the main limitations and risks associated with applying AI for profit analysis, focusing on data quality, algorithmic bias, model transparency, and compliance with ethical and regulatory standards. The research methodology combines analytical review and comparative analysis of international and Ukrainian studies on AI-based financial decision-making, emphasizing the technological, managerial, and ethical aspects of implementation.

Keywords: artificial intelligence, AI, profit enterprise, analysis, financial analytics, digital transformation.

У сучасних умовах військової агресії, економічної нестабільності, та високої конкуренції, здатність підприємства не лише генерувати, але й оптимально розподіляти прибуток стає вирішальним чинником його фінансової стійкості та інвестиційної привабливості. Багато вітчизняних підприємств, зокрема роздрібні торговельні мережі, обмежуються традиційними підходами до аналізу прибутку, орієнтуючись на ретроспективні узагальнені показники, що не дозволяє здійснювати оперативне та стратегічне управління рентабельністю на рівні окремих структурних підрозділів. Штучний інтелект став ключовим фактором аналітичної трансформації в сучасних підприємствах, переосмисливши спосіб, яким організації збирають, обробляють та інтерпретують фінансову інформацію. Його інтеграція в системи аналізу прибутку дозволяє компаніям управляти величезними обсягами даних, виявляти приховані закономірності в динаміці витрат і доходів, а також прогнозувати фінансові результати з рівнем точності, недосяжним за допомогою традиційних статистичних методів. Інструменти ШІ, такі як машинне навчання, глибокі нейронні мережі та прогнозна аналітика, надають підприємствам можливість виявляти ранні ознаки коливань прибутковості, оптимізувати цінові стратегії та виявляти неефективність у розподілі ресурсів. Дослідження щодо впровадження ШІ має на меті дослідити основні обмеження та ризики, пов'язані із застосуванням ШІ для аналізу прибутку, зосередившись на якості даних, алгоритмічній упередженості, прозорості моделей та дотриманні етичних і регуляторних стандартів. Методологія дослідження поєднує аналітичний огляд та порівняльний аналіз міжнародних і українських досліджень щодо прийняття фінансових рішень на основі ШІ, акцентуючи увагу на технологічних, управлінських та етичних аспектах впровадження. Результати дослідження показують, що, хоча ШІ істотно підвищує точність, швидкість та об'єктивність оцінки прибутковості, підприємства все ще стикаються з проблемами недостатньої інтеграції даних, нерозбірливості складних моделей та потенційного ризику.

Ключові слова: штучний інтелект, ШІ, прибуток підприємства, аналіз, фінансове управління, цифрова трансформація.

Statement of the problem. In the digital economy, enterprises are becoming increasingly dependent on data-driven decision-making processes that determine their competitiveness and long-term sustainability. Artificial intelligence (AI) offers advanced capabilities for analysing financial results, including profit dynamics, cost structures, and predictive modelling of future performance. Through machine learning, neural networks, and natural language processing, AI systems can identify subtle patterns and correlations that remain invisible to traditional analytical tools. However, despite these advantages, the integration of AI into enterprise profit analysis faces a range of methodological, ethical, and technical barriers. These include issues of data availability and quality, algorithmic bias, lack of transparency in decision-making models, and potential risks related to data privacy and security. Moreover, many companies struggle to align AI-driven insights with existing accounting frameworks and corporate governance standards. Addressing these challenges is crucial to ensure that the application of AI not only improves analytical accuracy but also strengthens trust, accountability, and transparency in enterprise financial management under conditions of constant market uncertainty.

Analysis of recent research and publications. The growing integration of artificial intelligence (AI) into financial management has been widely examined in global academic discourse. Scholars such as Brynjolfsson and McAfee and Davenport argue that AI technologies are reshaping the analytical landscape of modern enterprises by enhancing data interpretation, improving forecasting precision, and reducing the influence of human error in financial decision-making[6]. Böhme further emphasize the role of algorithmic governance in strengthening financial transparency and accountability [1]. At the same time, other studies – particularly those by Li and Chen and Kshetri – highlight unresolved issues related to data integrity, algorithmic opacity, ethical considerations, and the need for regulatory frameworks capable of controlling the use of AI in financial analytics [3]. Recent literature also points to the problem of “explainability,” where even highly accurate models fail to provide transparent reasoning behind their outputs, posing risks for managerial accountability. In the Ukrainian context, research on AI in financial analysis remains at an early stage and primarily focuses on the automation of accounting processes, digitalization of reporting, and business intelligence systems. Consequently, the practical and methodological aspects of applying AI for profit analysis – particularly its integration with corporate financial systems and decision-support tools – are still underexplored, creating a clear research gap that this article aims to address.

Formation of the objectives of the article. The primary purpose of this paper is to identify, classify, and systematize the key problems that arise when implementing artificial intelligence technologies in the process of enterprise profit analysis. The study aims to reveal the underlying causes of these challenges, including data quality issues, algorithmic bias, lack of interpretability, and insufficient integration with traditional financial systems. Furthermore, the article seeks to outline potential strategies and methodological recommendations for mitigating these problems – such as developing transparent and explainable AI models, improving data governance practices, and enhancing the digital competence of financial analysts. By achieving these objectives, the paper contributes to forming a theoretical and practical foundation for the effective and responsible application of AI in enterprise financial management.

Highlighting previously unresolved parts of the overall problem. A comparative analysis revealed the absence of a unified conceptual model for analysing enterprise profits using digital solutions and artificial intelligence models to ensure transparent and effective restoration of economic potential after military aggression.

Summary of the main research material. Artificial intelligence has become one of the most transformative technologies in financial analytics, allowing enterprises to process enormous volumes of data and discover new insights into their profitability structure. Machine learning and neural network algorithms, in particular, provide the ability to identify non-linear relationships between revenues, costs, and external market conditions. By analysing real-time data from various sources – including accounting systems, sales platforms, and macroeconomic indicators – AI systems can detect hidden patterns that indicate profitability trends or early signs of financial risks. Such analytical precision enables managers to make better-informed decisions on pricing, investment allocation, and operational optimization.

However, despite these promising benefits, the practical application of AI in enterprise profit analysis is accompanied by a wide range of complex and interrelated challenges that significantly influence the reliability, accuracy, and transparency of analytical outcomes. One of the most fundamental and recurring problems lies in data quality and bias, which serve as the foundation of any AI-based decision-making system [2]. Artificial intelligence models, no matter how advanced, are only as effective as the datasets they are trained on. In practice, many companies face issues with fragmented data infrastructures, incomplete historical records, inconsistent data entry, and human errors in financial reporting. These problems often stem from outdated accounting practices, insufficient automation, and poor coordination between departments responsible for finance, marketing, and operations. When AI systems are trained on such imperfect or unbalanced data, they can unintentionally learn and reinforce existing biases, producing profit forecasts that misrepresent actual financial performance. For example, a model might overestimate future revenue based on temporary seasonal trends or underestimate risks due to missing cost-related parameters. Therefore, ensuring high-quality, unbiased, and regularly updated datasets is not only a technical requirement but also a strategic necessity for any enterprise seeking to rely on AI-driven profit analysis.

Another major limitation relates to model transparency, often referred to as the “black box problem.” Many modern AI algorithms– especially those based on deep learning architectures – can achieve extremely high levels of predictive accuracy but provide little or no insight into how specific inputs influence the final output. In the context of financial management, this opacity poses serious challenges for compliance, auditability, and managerial decision-making [6]. When an AI model predicts a decline in profit or recommends resource reallocation, executives and auditors must be able to understand the rationale behind these suggestions. However, the absence of interpretability prevents them from verifying whether the algorithm’s reasoning aligns with the company’s financial policies, ethical principles, or legal obligations. This lack of transparency also creates a psychological barrier: managers tend to distrust AI outputs they cannot explain, which leads to underutilization of the technology. To overcome this limitation, researchers and practitioners are increasingly turning to Explainable Artificial Intelligence (XAI) – a methodological approach aimed at making algorithmic logic visible and comprehensible. XAI provides visual explanations, decision trees, and model interpretability layers that allow stakeholders to trace how individual financial indicators contribute to profit projections, thereby enhancing confidence and accountability in AI-assisted decision-making.

A third critical challenge involves integration barriers between AI-based analytical systems and existing enterprise infrastructures, particularly legacy accounting and Enterprise Resource Planning (ERP) systems. These traditional platforms were primarily designed for manual input, static reporting, and periodic financial consolidation rather than for dynamic, data-intensive processes required by AI solutions [4]. As a result, incompatibility between these systems often leads to duplicated data, synchronization errors, or delays in data transmission. Implementing AI within such environments demands substantial investments – not only in software upgrades but also in employee training, data pipeline optimization, and the establishment of secure interfaces for automated information exchange. Moreover, AI-driven analytics require continuous real-time data streams to function effectively, which can only be achieved through the modernization of IT architectures and the adoption of interoperable standards. This transition period, where human expertise must coexist with automated intelligence, represents a critical phase for most organizations. It demands a rethinking of workflows, a reassessment of IT budgets, and the creation of multidisciplinary teams that bridge financial analysis, data science, and system administration [1].

Lastly, ethical and regulatory considerations represent a vital and rapidly evolving aspect of AI implementation in enterprise profit analysis. Financial data is among the most sensitive types of information a company handles, and its misuse can have far-reaching consequences – from data breaches and reputational damage to severe legal penalties. The use of customer transactions, supplier contracts, or payroll records in algorithmic training requires strict adherence to data protection regulations such as the General Data Protection Regulation (GDPR) within the European Union and similar frameworks in other jurisdictions. However, compliance involves more than simply anonymizing data; it requires companies to establish clear internal policies regarding consent, storage, access control, and algorithm auditing. Ethical concerns also arise when AI systems are used to make financial decisions that directly affect employees, partners, or clients, such as performance evaluations or resource allocations. In such cases, maintaining human oversight is essential to prevent potential misuse or unintended discrimination. Enterprises that integrate AI responsibly must therefore cultivate a culture of transparency and ethical awareness, ensuring that all stakeholders – management, employees, and clients – understand how AI is used, what data it processes, and how its outputs influence strategic and operational decisions.

As shown in Table 1, the implementation of artificial intelligence in enterprise profit analysis reveals a complex interplay of technical, organizational, and ethical challenges that collectively determine the success or failure of AI-driven financial systems. The most critical barrier – data quality and bias – forms the foundation upon which all subsequent analytical accuracy depends. Inconsistent or incomplete datasets can distort the representation of a company's financial position, leading to inaccurate forecasts and misguided strategic decisions [6]. This issue often arises in enterprises that rely on outdated data management systems or manual entry processes, where information silos and human errors are common.

By enforcing comprehensive data governance policies, automating collection procedures, and conducting regular quality audits, companies can ensure that the datasets feeding their AI systems are reliable, relevant, and representative. Such measures not only improve predictive performance but also reduce the risk of systemic bias – a major ethical and operational concern in AI analytics. Likewise, model transparency remains a pressing issue [4]. Deep learning models, while capable of identifying complex non-linear relationships, often fail to provide interpretable reasoning behind their predictions. This lack of clarity undermines managerial trust and complicates financial auditing processes. Hence, the adoption of Explainable AI (XAI) frameworks is vital to bridge the interpretability gap, allowing decision-makers to trace how specific variables influence profitability and to validate the fairness and logic of algorithmic outputs.

Integration barriers, ethical compliance, and human–AI collaboration challenges form another critical layer of difficulty. Many companies continue to operate within legacy ERP or accounting systems that are not designed for real-time data interaction, limiting the potential of AI-based tools to deliver continuous insights. Overcoming these technological limitations requires substantial investments in infrastructure modernization, application programming interfaces (APIs), and staff retraining to cultivate digital literacy across departments. Ethical and regulatory issues

Table 1

The main problems of using artificial intelligence in the analysis of corporate profits and possible strategies for their mitigation

Problem Area	Impact on Profit Analysis	Possible Solutions / Mitigation Strategies
Data Quality and Bias	Distorted profitability models and inaccurate financial forecasts due to incomplete or inconsistent datasets.	Implement strict data governance policies, automate data collection, and regularly validate datasets for accuracy and representativeness.
Model Transparency (“Black Box”)	Inability to explain AI-generated results, leading to reduced managerial trust and difficulties in auditing decisions.	Introduce Explainable AI (XAI) methods, utilize interpretable models, and apply visualization tools to clarify algorithmic logic.
Integration Barriers	Fragmented analytical processes and limited automation caused by incompatibility with legacy accounting systems.	Modernize ERP systems, develop data APIs, and provide cross-department training to enhance digital literacy.
Ethical and Regulatory Issues	Potential violations of data protection laws and loss of stakeholder trust due to poor governance of sensitive information.	Ensure GDPR compliance, establish internal data ethics frameworks, and conduct periodic algorithmic audits.
Human – AI Collaboration Gap	Over-reliance on automated outputs or misinterpretation of results due to lack of human control and understanding.	Foster cooperation between data scientists, financial analysts, and executives to balance human expertise with AI-driven insights.

Source: compiled by the authors

further complicate implementation, as the use of financial and personal data in algorithmic models must fully comply with international standards such as the GDPR. Establishing internal data ethics policies, conducting regular algorithm audits, and ensuring transparency in data handling are essential for maintaining stakeholder trust [5]. Finally, the human–AI collaboration gap reflects an organizational challenge: without adequate understanding of AI mechanisms, managers may either over-rely on automated systems or dismiss their outputs entirely. The most effective approach is to foster multidisciplinary cooperation between data scientists, financial analysts, and executives, ensuring that AI insights complement – rather than replace – human judgment [5]. Ultimately, addressing these five problem areas collectively allows enterprises to develop a robust, transparent, and ethically grounded framework for AI-driven profit analysis, ensuring both analytical precision and sustainable trust in digital financial transformation.

Conclusions. Artificial intelligence represents a revolutionary and transformative approach to financial analytics, reshaping the way enterprises evaluate profitability, forecast performance, and make strategic decisions. Despite its enormous potential, the adoption of AI in profit assessment remains constrained by several critical limitations related to data quality, ethical considerations, and the interpretability of algorithmic results. The findings of this study highlight that while AI tools can significantly enhance analytical precision and reduce human error, their effectiveness ultimately depends on the reliability of the underlying data and the transparency of the models being applied. Many enterprises still operate within traditional frameworks that are not designed to accommodate real-time data processing or algorithmic reasoning, resulting in integration difficulties and organizational resistance. Moreover, the ethical dimension of AI use – particularly regarding data privacy, fairness, and accountability – poses an ongoing challenge that must be addressed through strong governance and regulatory compliance. Therefore, the future of AI-driven profit analysis lies in the development of hybrid analytical models that combine the computational power of AI with the critical thinking, intuition, and contextual understanding of human experts. This collaboration between human and artificial intelligence is essential to ensure not only the accuracy of financial insights but also their credibility and social responsibility. Future research should focus on designing explainable AI (XAI) systems that make algorithmic logic transparent and accessible, improving financial data governance through standardized data management practices, and formulating clear industry-wide guidelines for the ethical and methodological application of AI in financial analysis. For Ukrainian enterprises, these advancements will be particularly important, as they can foster digital competitiveness, strengthen decision-making capacity, and support the broader transition toward a sustainable, innovation-driven economy.

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