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СМАРТ-ЕКОНОМІКА, ПІДПРИЄМНИЦТВО ТА БЕЗПЕКА

Том 4, № 1, 2026

SMART ECONOMY, ENTREPRENEURSHIP AND SECURITY

Vol. 4, № 1, 2026



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ACCOUNTING METHODOLOGY FOR STABLECOIN TRANSACTIONS IN INTERNATIONAL TRADE: RECOGNITION AND VALUATION ISSUES

Abstract. *The growing use of stablecoins as a settlement instrument in cross-border trade creates a gap between the rapid evolution of digital financial instruments and the existing accounting framework, which lacks unified methodological approaches to their recognition, measurement, and disclosure. This study aims to develop theoretical foundations and practical recommendations for the accounting of stablecoin transactions in international trade, addressing the issues of identification, classification, valuation, and financial reporting presentation. The research employs a combination of general scientific and special methods: dialectical and abstraction methods to formulate the conceptual apparatus, systemic and structural analysis to construct a classification model, comparative legal analysis of IFRS and Ukrainian national standards, economic and statistical analysis of market dynamics including correlation analysis, and modelling to develop accounting procedures and chart of accounts correspondence. The study reveals that stablecoins cannot be unambiguously classified under existing IAS 38 or IAS 2 frameworks due to their hybrid nature as both a means of payment and a store of value. A classification algorithm is proposed based on the purpose of holding and the existence of an active market, which for leading stablecoins is confirmed by statistical data showing a 0.94 correlation between transaction volumes and capitalisation and a bid-ask spread of 0.08–0.12%. The comparative analysis of valuation models demonstrates that the cost model defers the recognition of impairment and precludes reflecting value increases, whereas the revaluation model provides more relevant information for users. A comprehensive chart of accounts correspondence for recording stablecoin acquisition, settlement, exchange differences, and impairment in international trade transactions is developed and substantiated. The study concludes that the current regulatory framework in Ukraine requires amendments at the by-law level, specifically to the Regulation on the Inventory of Assets and Liabilities and the Methodological Recommendations for the Accounting of Intangible Assets, to introduce provisions for virtual asset accounting and mandatory disclosure of information on accounting policies, fair value, and risk concentration. The proposed methodological approaches ensure faithful presentation of stablecoin transactions, minimise tax risks, and enhance the informational value of financial statements for stakeholders in the digital economy.*

Keywords: *accounting, digital assets, stablecoins, taxation, international trade.*

1. Introduction

The integration of digital assets into the system of international settlements is one of the most prominent trends in the development of the global financial infrastructure. Stablecoins — crypto-assets whose value is pegged to a reserve asset or a basket of assets — are increasingly being considered as an alternative to traditional payment instruments in cross-border trade. Their use makes it possible to reduce transaction costs, accelerate settlements, and minimise currency risks. At the same time, the rapid proliferation of stablecoins is outpacing the development



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of an adequate regulatory, accounting, and taxation framework, thereby creating a zone of methodological uncertainty for business entities.

The current accounting system does not offer a unified approach to the recognition, classification, and measurement of stablecoins. International Financial Reporting Standards (IFRS) do not contain a separate standard devoted to digital assets, which necessitates the analogical application of IAS 38 “Intangible Assets” or IAS 2 “Inventories”. However, stablecoins do not fully meet the criteria of either category: they may simultaneously function as a medium of exchange, a store of value, and an investment instrument.

A further issue concerns the measurement of stablecoins. While it is theoretically possible to apply fair value measurement to fiat-backed stablecoins (USDT, USDC), algorithmic stablecoins — whose stability is maintained through software mechanisms — lack both market quotations and established valuation methodologies. In the event of a de-pegging from the underlying asset, such instruments can depreciate rapidly, giving rise to risks of material misstatement in financial reporting.

In the field of international trade, the use of stablecoins generates additional accounting challenges. Transactions involving them entail currency conversion, the recognition of exchange differences, and the need for documentary evidence of settlements in the absence of unified requirements for electronic proof. The tax consequences of such transactions remain unregulated at both the national and international levels, creating conditions conducive to double taxation or, conversely, tax evasion.

Thus, the problem of developing a methodological framework for the accounting of stablecoin transactions in international trade is multifaceted. It encompasses theoretical issues concerning the identification of the nature of stablecoins as accounting objects, practical aspects of their measurement and presentation in financial statements, as well as the alignment of accounting procedures with the requirements of tax legislation.

The rapid development of the virtual asset market and its incursion into the sphere of international settlements have led to the emergence of a substantial body of scholarly work devoted to the methodological and applied aspects of accounting, taxation, and regulation of digital financial instruments. Particular attention has been paid to studies addressing stablecoins as a specific type of crypto-asset designed to ensure price stability and serve as a means of payment.

The theoretical and methodological foundations for the recognition and measurement of digital assets in the accounting system are examined in the works of Hedz *et al.* [3]. The authors systematised approaches to the classification of crypto-assets in accordance with IFRS, notably IAS 38 “Intangible Assets” and IAS 2 “Inventories”, and identified inconsistencies between IFRS and US GAAP regarding the valuation and presentation of such assets in financial statements. Emphasis is placed on the necessity of developing

a separate international standard, as current approaches fail to capture the specific nature of stablecoins as hybrid instruments exhibiting characteristics of both payment mechanisms and investment assets.

An important strand of research concerns the challenges of professional judgement in the absence of unified standards. Based on qualitative research, Kanu [4] identified key challenges for accounting and auditing professionals when dealing with digital currencies, including stablecoins, NFTs, and CBDCs. These include the absence of comprehensive and universal financial reporting standards, the non-authoritative nature of existing auditing standards, high litigation risks, and the rise of cybercrime. The author argues for urgent intervention by international regulatory bodies (IASB, FASB, IAASB) to develop coherent global standards.

The issue of legislative uncertainty in Ukraine is explored by Shram *et al.* [8]. The authors contend that the current regulatory framework does not permit unambiguous identification of cryptocurrency as an accounting object, and the absence of taxation mechanisms creates conditions conducive to a shadow market. Justification is provided for amending the National Accounting Regulations (Standards) to recognise digital assets and harmonise national approaches with IFRS. A similar position is advanced by Panasiuk *et al.* [12], who emphasise the need to establish a unified conceptual apparatus and to refine the Chart of Accounts for recording transactions involving virtual assets in accordance with the purpose for which they are held.

Chyzykhov [1] analyses the prospects for regulating the accounting and taxation of virtual assets in Ukraine, highlighting the country’s pioneering role in adopting the framework law “On Virtual Assets”. At the same time, the researcher identifies considerable gaps in ensuring a transparent and stable market, necessitating continuous updating of regulatory requirements and the implementation of international standards.

A distinct body of literature addresses the use of digital assets in international trade and payment systems. Kumar *et al.* [5], drawing on data from the Bank for International Settlements, the IMF, and the WTO, forecast the emergence of a hybrid model of international trade in which stablecoins and tokenised assets will play a pivotal role. A technical implementation of such solutions is proposed in the work of Jaffer *et al.* [10], which presents the architecture of the PACT digital carbon stablecoin on the Tezos blockchain, combining economic modelling, satellite data, and smart contracts to ensure transparency in issuance and circulation.

Statistical aspects of reflecting digital assets are investigated by Sato *et al.* [9], who propose a methodology for integrating stablecoins and CBDCs into the System of National Accounts (SNA). While acknowledging the difficulty of collecting primary data, the authors insist on the necessity of their consistent representation in financial statistics. Issues of international tax harmonisation are addressed by Sidik [11], who examines the challenges of implementing a digital

services tax as an instrument for the fair taxation of transnational digital corporations.

The transformation of accounting systems under the influence of digitalisation is analysed by Selvi and Antepi [2], who trace the evolution from traditional commerce to ecommerce and the corresponding shifts in accounting paradigms. The authors demonstrate that digitalisation is creating a new reality for accounting, characterised by flexible accounting models, automation, increased complexity in revenue recognition, and the emergence of new objects of taxation.

Selected aspects of taxation in the context of digital transformation are examined in the work of Kovtseniuk [6], which analyses the inconsistencies between national standards, IFRS, and Ukrainian tax legislation in determining the object of corporate income taxation. The US experience in organising accounting and taxation of trade activities, analysed by Sarakhman *et al.* [7], illustrates the complexity of a multitiered tax system and the necessity of adapting national accounting practices to international requirements, a matter of particular relevance in the context of integrating digital assets into crossborder settlements.

Despite the considerable volume of publications devoted to the accounting of crypto-assets, a number of important issues remain insufficiently addressed by researchers:

1. There is a lack of comprehensive studies elucidating the methodological foundations of accounting specifically for stablecoins as a distinct subtype of virtual assets possessing unique characteristics (pegging to fiat currencies or commodities, stability maintenance mechanisms, and various issuance models).

2. The problem of valuing stablecoins upon initial recognition and at subsequent reporting dates remains unresolved, particularly in the absence of an active market or where algorithmic value stabilisation mechanisms are employed.

3. The question of accounting for transactions involving stablecoins as a means of payment in international trade remains underexplored, especially with regard to currency conversion, the recognition of exchange differences, and the documentary formalisation of such transactions. The foregoing considerations determine the relevance of the present study, its aim, and its objectives.

2. Materials and Methods

The research methodology is constructed on a combination of general scientific and special methods of cognition that ensure the validity and reliability of the obtained results. The choice of methods is determined by the purpose and objectives of the study, as well as the specific nature of the research object — stablecoins as a subtype of virtual assets used in international trade settlements.

The theoretical foundation of the study rests on the dialectical method, which enabled the consideration of stablecoins in their development, the identification of contradictions between their economic substance

and existing forms of accounting recognition, and the substantiation of directions for the evolution of methodological approaches. The method of abstraction was applied to formulate the conceptual apparatus, delineate the essential characteristics of stablecoins, and distinguish them from other types of crypto-assets and traditional means of payment.

The systemic and structural method served as the basis for constructing a classification of stablecoins according to the purposes of their holding, the nature of collateral, and the existence of an active market. This method also made it possible to position the accounting of stablecoins within the overall system of enterprise asset accounting and to determine the interconnections between individual accounting objects and reporting indicators.

The comparative legal method was employed to analyse the provisions of International Financial Reporting Standards (IAS 2, IAS 7, IAS 21, IAS 36, IAS 38, IFRS 9, IFRS 13, IFRS 15) and National Accounting Regulations (Standards) of Ukraine, as well as to identify inconsistencies and gaps in the regulation of accounting for virtual assets. The comparative method was also applied in analysing the approaches of standard-setting bodies (IASB, FASB) and professional organisations (ACCA, PwC, AICPA) to the interpretation of the nature of digital assets.

The monographic method ensured an in-depth study of the scientific works of domestic and foreign scholars who have investigated the problems of accounting and taxation of crypto-assets, including stablecoins. The method of theoretical generalisation and systematisation was used to summarise the existing positions of scientists and practitioners and to identify unresolved issues that determined the direction of this research.

To substantiate the choice of the stablecoin valuation model, the method of modelling was applied, which allowed the development of an algorithm for selecting an accounting model depending on the business model of the enterprise and the characteristics of the stablecoin. In developing the proposed accounting methodology, the modelling method was combined with the normative method, ensuring the construction of accounting procedures in accordance with the requirements of current legislation and international standards.

The economic and statistical method, including the calculation of the Pearson correlation coefficient, was used to analyse the dynamics of stablecoin market capitalisation and transaction volumes. The use of statistical data from international organisations (Bank for International Settlements, IMF, WTO) and analytical platforms (Bloomberg, Artemis Analytics) provided an empirical basis for conclusions regarding the transformation of stablecoins into a means of payment and the indisputable existence of an active market for certain types of stablecoins.

The method of tabular and graphical presentation was employed to visualise the research results. The

comparative analysis of the impact of valuation models on financial indicators was systematised in tabular form, and the algorithm for selecting an accounting model and the dynamics of stablecoin market development were presented in graphical form. This contributed to the clarity of the proposed methodological approaches and facilitated the perception of analytical data.

The design method was used in developing the chart of accounts correspondence for recording transactions with stablecoins in international trade. When constructing the correspondence, the principles of double entry and the current Chart of Accounts for accounting assets, capital, liabilities, and economic operations of enterprises and organisations of Ukraine were observed.

The combination of the aforementioned methods ensured the comprehensiveness of the study, the reliability of its conclusions, and the practical applicability of the formulated recommendations for improving the methodology of accounting for stablecoins in international trade.

3. Results and Discussion

The problem of recognising stablecoins in financial statements is complex and resolved depending on the purpose of holding, the existence of an active market, and the legal nature of the holder's rights. According to the position of the IFRS Interpretations Committee, crypto-assets are generally not financial instruments as they do not grant the holder a contractual right to receive cash or another financial asset.

Based on the analysis of sources, the authors systematised approaches to the classification of stablecoins depending on the business model of the organization, which is presented in Fig. 1.

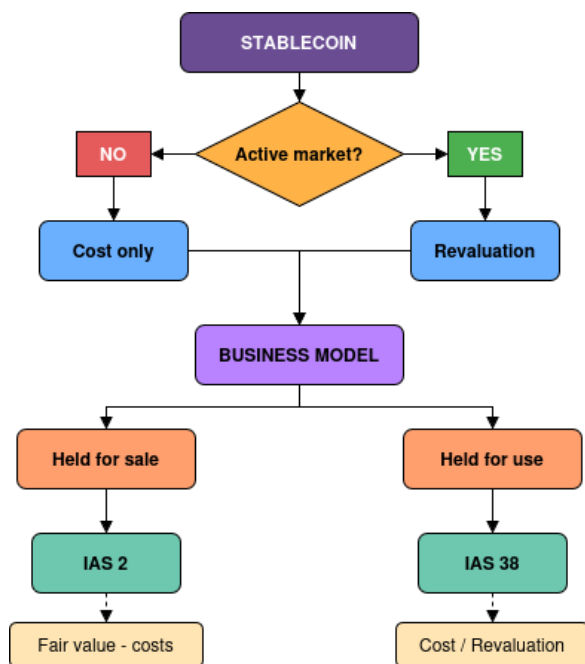


Fig. 1. Algorithm for Selecting an Accounting Model for Stablecoins under IFRS

Source: developed by the authors based on [1–19]

When applying IAS 38, the criterion of the existence of an active market is of fundamental importance. In the context of stablecoins, this means that for USDT and USDC, which are traded on over 300 exchanges with an average daily trading volume exceeding \$50 billion, an active market exists. For specialised or regional stablecoins, the application of the revaluation model is not possible.

The question of qualifying stablecoins as cash or cash equivalents requires separate consideration. According to IAS 7, cash equivalents must meet the following criteria: (1) short-term investments, (2) high liquidity, (3) insignificant risk of changes in value. Stablecoins do not meet these criteria due to the credit risk of the issuer, the risk of de-pegging, and the absence of government guarantees. Consequently, classifying stablecoins as cash is methodologically incorrect.

Initial recognition of stablecoins is carried out at cost, which includes the purchase price and directly attributable transaction costs (blockchain fees, wallet fees, exchange commissions). For stablecoins received as payment for goods sold (works, services), measurement is performed at fair value at the date of receipt in accordance with IFRS 15.

Subsequent measurement depends on the selected accounting policy. The authors conducted a comparative analysis of the impact of different valuation models on the financial indicators of a hypothetical enterprise conducting international settlements using USDC (Table 1).

The data in Table 1 demonstrate that the cost model results in the deferral of recognition of impairment losses and precludes the reflection of an increase in the asset's value. For stablecoins whose value is stable, the revaluation model or the inventory model (for traders) is more relevant, as it ensures a faithful representation of economic reality.

When using stablecoins denominated in foreign currency (USDT, USDC), business entities face a dual impact: (1) changes in the value of the stablecoin itself relative to the underlying asset (de-pegging) and (2) changes in the exchange rate between the entity's functional currency and the currency of the stablecoin denomination.

According to IAS 21, transactions in foreign currencies are initially recorded by applying the exchange rate at the date of the transaction. At each reporting date, non-monetary items that are measured at fair value in a foreign currency are translated using the exchange rate at the date when the fair value was determined. Exchange differences are recognised in profit or loss.

The authors has developed a chart of accounts correspondence for recording stablecoin transactions in international settlements in accordance with the Chart of Accounts of Ukraine (Table 2).

The proposed correspondence assumes that stablecoins are accounted for within intangible assets (sub-account 122). For trading enterprises that hold stablecoins exclusively for resale, it is advisable to

Table 1

Comparative Analysis of the Impact of Stablecoin Valuation Models on Enterprise Financial Indicators (as at 31.12.2025)

Indicator	Cost Model (IAS 38)	Revaluation Model (IAS 38)	Inventory Model (IAS 2)
Initial cost, thousand UAH	12,000	12,000	12,000
Fair value at reporting date, thousand UAH	11,880*	11,880	11,880
Carrying amount, thousand UAH	12,000	11,880	11,880
Financial result for the period, thousand UAH	0 (impairment loss not recognised until confirmed)	-120 (recognised in profit or loss)	-120 (recognised in profit or loss)
Comprehensive income, thousand UAH	0	-120	-120
Impact on equity	Decrease due to unrecognised loss (hidden)	Direct decrease	Direct decrease
Necessity of impairment testing	Mandatory, at least annually	Not applicable	Not applicable
Possibility of recognising revaluation gain	Not provided	Yes (through OCI)	Yes (through profit or loss)

*Note: minor deviation from par value (0.5%) due to temporary de-pegging in the market.

Source: calculated by the authors based on [13–19]

apply account 28 “Goods” with the introduction of a separate sub-account 286 “Crypto-assets (Stablecoins) in the Trading Portfolio”.

To substantiate methodological approaches to the valuation of stablecoins, a statistical analysis of the dynamics of their market capitalisation and transaction volumes was conducted. According to Bloomberg and Artemis Analytics, the total volume of stablecoin

transactions in 2025 reached \$33 trillion, representing a 72% increase compared to 2024. The growth dynamics are presented in Fig. 2 [13–19].

Pearson’s correlation coefficient between transaction volumes and stablecoin capitalisation is 0.94, indicating an extremely strong direct relationship. This confirms the hypothesis that stablecoins are transitioning from the category of speculative instruments to

Table 2

Chart of Accounts Correspondence for Accounting for Stablecoin Transactions in International Trade

No.	Content of Transaction	Debit	Credit	Measurement Basis
1	Purchase of USDC for hryvnia	122 “Intangible Assets” (analytical account “Stablecoins”)	311 “Current Accounts in National Currency”	NBU exchange rate at transaction date + commissions
2	Recognition of blockchain fee for transferring stablecoin to supplier	122 “Stablecoins”	122 “Stablecoins” (internal entry) or 685	Commission amount in hryvnia equivalent
3	Transfer of stablecoin as payment for imported goods	632 “Settlements with Foreign Suppliers”	122 “Stablecoins”	Fair value at transfer date
4	Recognition of exchange difference at transfer date (if accounted for at fair value)	945 “Expenses from Operating Exchange Differences”	122 “Stablecoins”	Difference between carrying amount and fair value at transaction date
5	Additional accrual of VAT tax credit (for imports)	641 VAT	632	Recognised after customs declaration processing
6	Capitalisation of goods from non-resident	281 “Goods”	632	Contract value according to customs declaration
7	Recognition of stablecoin impairment at reporting date	972 “Losses from Impairment of Intangible Assets”	133 “Accumulated Amortisation (Impairment) of Intangible Assets”	Excess of carrying amount over recoverable amount
8	Recognition of stablecoin revaluation gain (subject to active market existence and selection of revaluation model)	122 “Stablecoins”	423 “Revaluation of Intangible Assets” (OCI)	Difference between fair value and carrying amount
9	Receipt of stablecoin from foreign buyer	122 “Stablecoins”	362 “Settlements with Foreign Buyers”	Fair value at receipt date

Source: proposed by the authors

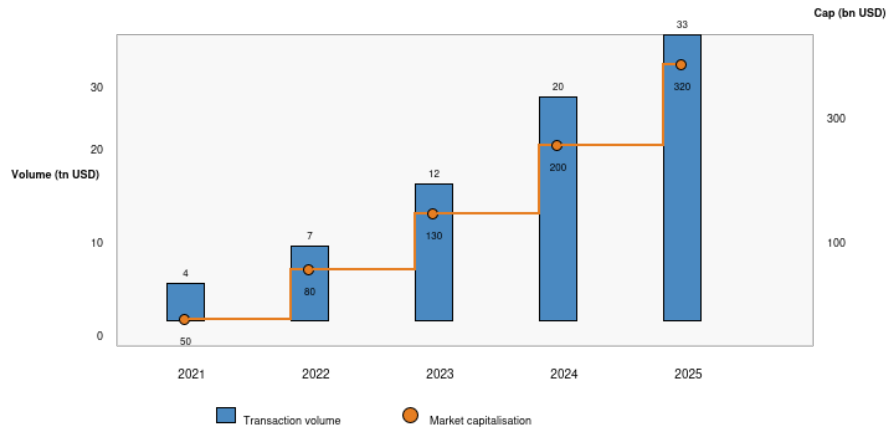


Fig. 2. Dynamics of Stablecoin Transaction Volumes and Market Capitalisation, 2021–2025

Source: constructed by the authors based on [13–19]

the category of payment instruments. For accounting purposes, this conclusion is of fundamental importance: the higher the share of payment transactions in the total volume, the greater the justification for applying the fair value model, since the existence of an active market is indisputable.

The weighted average bid-ask spread for USDC on major exchanges in 2025 was 0.08–0.12%, which is lower than the spread for the euro/dollar on the Forex market. This provides an additional argument in favour of recognising stablecoins as liquid assets, albeit without the status of cash equivalents [13–19].

A specific risk of stablecoins is the loss of peg to the underlying asset. An analysis of historical data indicates that even the largest stablecoins have periodically experienced temporary deviations (USDC in March 2023 to \$0.88) [13–19]. In the context of IAS 38, de-pegging is an event indicating the impairment of an asset. The following algorithm of accounting actions upon de-pegging is proposed:

1. Immediate impairment testing (IAS 36).
2. Recognition of an impairment loss in the amount by which the carrying amount exceeds the higher of: fair value less costs to sell or value in use.
3. If the stablecoin is accounted for under the revaluation model, the loss is applied to reduce the revaluation reserve, and any excess is recognised in profit or loss.
4. After the restoration of the peg, revaluation is possible only within the limits of previously recognised impairment losses (for the cost model prohibited; for the revaluation model through OCI).

The conducted analysis reveals significant gaps in the National Accounting Standards (NAS) concerning the regulation of virtual asset accounting. The following is proposed:

1. Amend the Regulation on the Inventory of Assets and Liabilities by supplementing it with a procedure for confirming the existence of stablecoins through blockchain verification mechanisms (verification of private keys, wallet addresses).
2. Supplement the Methodological Recommendations for the Accounting of Intangible Assets with

a separate section “Accounting for Virtual Assets”, defining the criteria for classifying stablecoins as intangible assets or inventories.

3. Implement a mandatory disclosure requirement in the notes to the financial statements of information on: the accounting policy regarding stablecoins; fair value with indication of quotation sources; concentration of risks (issuer, blockchain, geography of counterparties).

Thus, the proposed methodological approaches allow for the faithful and complete presentation of stablecoin transactions in international trade, minimise tax risks, and enhance the informational value of financial statements for users.

The findings obtained in this study provide grounds for a critical reassessment of established approaches to the accounting treatment of stablecoins and allow for their positioning as an independent object of accounting that cannot be reduced to either traditional intangible assets or inventories. The discussion of the results necessitates their correlation with the findings of other authors, the identification of points of agreement and divergence, and the substantiation of the contribution of this research to the development of the scientific problem.

The conclusion regarding the impossibility of recognising stablecoins as cash equivalents aligns with the position of Kanu [4], who emphasises that the absence of state guarantees and the presence of issuer credit risk preclude the classification of any crypto-assets, including stablecoins, as cash equivalents under IAS 7. At the same time, the results of the statistical analysis conducted in this paper (Pearson’s correlation coefficient of 0.94 between transaction volumes and capitalisation, bid-ask spread of 0.08–0.12%) indicate a qualitatively new state of the stablecoin market, which has transformed from a speculative segment into a full-fledged payment infrastructure. This finding allows us to question the categorical nature of the prohibition on recognising stablecoins as highly liquid assets. In our view, for fiat-backed stablecoins with transparent reserve structures and independent audit

confirmations, exceptions to the general rule may be permissible. This thesis requires further discussion and empirical verification.

The systematisation of approaches to the classification of stablecoins depending on the business model of the enterprise, presented in Fig. 1, develops the ideas of Hedz *et al.* [3] regarding the expediency of applying IAS 2 exclusively for traders and brokers. However, unlike the cited authors, who consider such an approach to be universal, this study substantiates that even for trading enterprises, the application of the inventory model is not always methodologically correct. When stablecoins are held for the purpose of conducting international settlements rather than for resale, their qualification as goods contradicts the economic substance of the transactions. In such cases, accounting within intangible assets with the application of the revaluation model (provided an active market exists) ensures a more faithful presentation of information about the enterprise's settlement capabilities.

The proposed algorithm for accounting actions in the event of de-pegging (immediate impairment testing, recognition of loss in the revaluation reserve or profit/loss) addresses the problem identified by Shram *et al.* [8] regarding the absence in Ukrainian practice of clear methodological guidelines for responding to events indicating a decrease in the value of crypto-assets. The recommendations developed in this paper, based on the requirements of IAS 36, fill this gap. At the same time, the issue of recovering previously recognised impairment losses after the restoration of the peg remains debatable. The approach substantiated in this study — permitting revaluation only within the limits of previously recognised losses exclusively for the revaluation model — is more conservative compared to the positions of some foreign researchers who allow for the reversal of impairment losses through profit or loss. This divergence is explained by different interpretations of the nature of stablecoins: if they are considered a specific type of financial instrument, the requirements of IFRS 9 allow for such a reversal; if they are considered non-financial assets, IAS 36 prohibits the reversal of goodwill impairment and significantly restricts the reversal for other assets. Given the absence of an unambiguous qualification of stablecoins in international standards, the conservative approach appears more justified from the perspective of the prudence principle.

The proposed chart of accounts correspondence for recording stablecoin transactions in international trade (Table 2) is a development of the recommendations of Panasiuk *et al.* [12] regarding the need to adapt the Chart of Accounts to new accounting objects. The innovation of the proposed approach lies in the integration of several accounting methodologies: accounting for the receipt of stablecoins from foreign buyers, accounting for settlements with suppliers, accounting for exchange differences, and accounting for impairment. This distinguishes the proposed model from existing developments, which usually address

individual accounting aspects in isolation. At the same time, the proposed correspondence is not indisputable. The use of account 122 “Intangible Assets” to account for stablecoins intended for current settlements may cause methodological objections, since intangible assets are defined as non-current assets. This contradiction is resolved by applying the revaluation model, which allows for the reflection in the balance sheet of an amount corresponding to fair value, as well as by the possibility of rapid turnover of such assets, which brings their functional characteristics closer to current assets. An alternative solution could be the introduction of a separate synthetic account “Virtual Assets” into the Chart of Accounts, but this requires amendments to regulatory documents at the level of the Ministry of Finance of Ukraine.

The results of the statistical analysis of stablecoin market dynamics correlate with the forecasts of Kumar *et al.* [5] regarding the formation of a hybrid model of international trade with the active use of digital means of payment. The doubling of stablecoin transaction volumes over the past year, revealed in this study, confirms the thesis about the growing demand for stable instruments for cross-border settlements, which is driven by both the inefficiency of traditional banking channels and the development of regulatory frameworks in leading jurisdictions. From the perspective of accounting methodology, this trend creates a request for the development of separate standards or clarifications regarding the specifics of stablecoin accounting. The current practice of applying IFRS by analogy does not allow for adequate consideration of the hybrid nature of these instruments.

The limitations of this study include the lack of empirical testing of the proposed methodological recommendations on the basis of specific enterprises. This opens up prospects for further research, which should focus on developing industry-specific accounting methodologies for stablecoins in foreign economic activity, creating internal corporate standards for accounting policies regarding digital assets, and analysing the tax consequences of applying various stablecoin valuation models.

4. Conclusions

The study's findings confirm that stablecoins represent a distinct accounting object that cannot be reduced to traditional categories of assets within the current system of international or national standards. Their hybrid nature combining the functions of a medium of exchange, a store of value, and, in certain cases, an investment instrument necessitates the development of specialised methodological approaches to their recognition, measurement, and disclosure in financial statements.

The economic substance of stablecoins is determined not by their technological form but by the purpose of holding and the nature of the underlying collateral. Fiat-backed stablecoins with transparent reserve structures, regular audits, and active trading on global exchanges demonstrate characteristics

that bring them functionally closer to highly liquid assets, albeit without the status of cash equivalents. Algorithmic stablecoins, due to their inherent instability and the absence of reliable value maintenance mechanisms, require a more conservative accounting treatment based on the cost model with mandatory impairment testing.

The comparative analysis of valuation models confirmed that the cost model, while formally compliant with IAS 38, does not reflect the economic reality of stablecoins with stable value and an active market. The revaluation model provides more relevant information for users of financial statements, provided that fair value can be reliably measured. For enterprises engaged in trading stablecoins as commodities, the application of IAS 2 is justified, but only to the extent that such assets are held exclusively for resale and not for settlement purposes.

The proposed chart of accounts correspondence for recording stablecoin transactions in international trade integrates the accounting of acquisition, valuation, settlement, exchange differences, and impairment within a unified methodological framework. The use of account 122 “Intangible Assets” for stablecoins intended for current settlements is a pragmatic solution under the current Chart of Accounts, but it reveals a conceptual contradiction between the non-current nature of intangible assets and the short-term holding period of stablecoins used as a means of payment. This contradiction can be resolved either by introducing a separate synthetic account for virtual assets or by amending the methodological guidelines to permit the classification of certain types of intangible assets as current.

The statistical analysis of the stablecoin market revealed a qualitative shift in its functional purpose. The correlation coefficient of 0.94 between transaction volumes and capitalisation, combined with the narrowing bid-ask spread to 0.08–0.12%, indicates the transformation of stablecoins from speculative instruments into a full-fledged payment infrastructure. This finding has direct implications for accounting methodology: the existence of an active market for leading stablecoins is

no longer a matter of professional judgement but an objective fact that obliges enterprises to consider the possibility of applying the revaluation model.

The problem of de-pegging requires a clear algorithm of accounting actions. Immediate impairment testing, recognition of losses either through the revaluation reserve or directly in profit or loss, and the prohibition of reversing impairment losses under the cost model constitute a conservative approach that aligns with the prudence principle. The restoration of the peg does not automatically justify the recognition of gains; such recognition is possible only under the revaluation model and only within the limits of previously recognised losses.

The harmonisation of national accounting standards with IFRS in the area of virtual asset accounting should proceed not only through the adoption of framework legislation but also through amendments to by-laws that directly regulate accounting methodology. The proposed amendments to the Regulation on the Inventory of Assets and Liabilities and the Methodological Recommendations for the Accounting of Intangible Assets address the most pressing gaps in the current regulatory framework. The mandatory disclosure of information about stablecoins in the notes to financial statements including accounting policies, fair value measurement, and risk concentration will enhance the transparency and comparability of financial reporting.

This study does not exhaust all aspects of the problem. Further research is required in the following directions: the development of industry-specific accounting methodologies for stablecoins in foreign economic activity, the analysis of tax consequences under different valuation models, the empirical testing of the proposed recommendations on actual enterprises, and the monitoring of changes in international standards regarding the accounting of digital assets. The rapid development of the stablecoin market and its increasing integration into global trade finance suggest that the methodological problems identified in this study will only grow in relevance, necessitating continuous updating of both scientific approaches and regulatory frameworks.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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МЕТОДОЛОГІЯ ОБЛІКУ ОПЕРАЦІЙ ЗІ СТЕЙБЛКОЇНАМИ В МІЖНАРОДНІЙ ТОРГІВЛІ: ПИТАННЯ ВИЗНАННЯ ТА ОЦІНКА

Анотація. Зростання використання стейблкоїнів як платіжного інструменту в транскордонній торгівлі створює розрив між стрімкою еволюцією цифрових фінансових інструментів та чинною системою бухгалтерського обліку, якій бракує уніфікованих методологічних підходів до їх визнання, оцінки та розкриття інформації. Метою цього дослідження є розробка теоретичних засад і практичних рекомендацій з бухгалтерського обліку операцій зі стейблкоїнами в міжнародній торгівлі, зокрема в частині їх ідентифікації, класифікації, оцінки та відображення у фінансовій звітності. У дослідженні застосовано комплекс загальнонаукових та спеціальних методів: діалектичний метод та метод абстрагування — для формулювання понятійного апарату; системно-структурний аналіз — для побудови класифікаційної моделі; порівняльно-правовий метод — для аналізу МСФЗ та національних положень (стандартів) бухгалтерського обліку України; економіко-статистичний метод, включаючи кореляційний аналіз, — для дослідження динаміки ринку; метод моделювання — для розробки облікових процедур та кореспонденції рахунків. Результати дослідження засвідчують, що стейблкоїни не можуть бути однозначно класифіковані в межах чинних МСБО 38 або МСБО 2 через їх гібридну природу як засобу платежу та збереження вартості. Запропоновано алгоритм класифікації залежно від мети утримання та наявності активного ринку, який для провідних стейблкоїнів підтверджується статистичними даними: коефіцієнт кореляції між обсягами транзакцій та капіталізацією становить 0,94, а спред між ціною купівлі та продажу — 0,08–0,12%. Порівняльний аналіз моделей оцінки демонструє, що модель собівартості відтерміновує визнання знецінення та унеможлиблює відображення зростання вартості, тоді як модель переоцінки забезпечує більш релевантну інформацію для користувачів. Розроблено та обґрунтовано комплексну кореспонденцію рахунків для відображення операцій з придбання стейблкоїнів, здійснення розрахунків, визнання курсових різниць та знецінення в міжнародній торгівлі. Зроблено висновок про необхідність внесення змін до чинної нормативно-правової бази України на рівні підзаконних актів, зокрема до Положення про інвентаризацію активів та зобов'язань і Методичних рекомендацій з бухгалтерського обліку нематеріальних активів, щодо запровадження положень з обліку віртуальних активів та обов'язкового розкриття інформації про облікову політику, справедливую вартість і концентрацію ризиків. Запропоновані методологічні підходи забезпечують достовірне відображення операцій зі стейблкоїнами, мінімізують податкові ризики та підвищують інформаційну цінність фінансової звітності для стейкхолдерів в умовах цифрової економіки.

Ключові слова: бухгалтерський облік, цифрові активи, стейблкоїни, оподаткування, міжнародна торгівля.

JEL: O32; O34; M12; M15

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ANALYSIS OF APPROACHES TO THE INTEGRATION OF ARTIFICIAL INTELLIGENCE METHODS INTO INTELLECTUAL CAPITAL MANAGEMENT

Abstract. *The article examines approaches to integrating artificial intelligence methods into intellectual capital management systems of higher education institutions in the context of forced migration and organizational transformation. A comparative analysis of the US market-oriented approach and the EU human-centric approach is conducted, revealing fundamental differences in the philosophical foundations of artificial intelligence implementation in human resources management. The research proposes a hybrid model that combines technological flexibility of American People Analytics with European ethical standards, adapted to the specific challenges faced by Ukrainian higher education institutions. The study analyzes key artificial intelligence technologies: Organizational Network Analysis for diagnosing integration and identifying isolated groups, Natural Language Processing for monitoring psychological well-being and early detection of burnout, and Learning Experience Platforms for personalized professional development. Machine learning models including classification, clustering, regression, and optimization algorithms are proposed for workload redistribution and performance prediction. The developed approach integrates exploratory data analysis, predictive modeling, and optimization techniques (convex optimization and genetic algorithms) with fuzzy logic to ensure transparency and interpretability of managerial decisions. The proposed model enables higher education institutions management to proactively forecast risks, optimize resource allocation, segment staff for targeted support, and fairly evaluate performance considering the forced displacement context.*

Keywords: *artificial intelligence, intellectual capital, human resources management, organizational network analysis, natural language processing, workload optimization, higher education institutions.*

1. Introduction

In the context of the knowledge economy, intellectual capital has become a key strategic asset for any organization, and for higher education institutions (HEIs), it represents the absolute foundation of their competitiveness and existence. However, unprecedented challenges caused by war-related migration processes in Ukraine pose a direct threat to the preservation, development, and effective management of this capital [1]. Traditional approaches to human resources management and productivity assessment prove insufficiently flexible to respond to the physical dispersion of academic staff, destruction of established scientific and communication networks, and extreme psychological stress on collectives.

The full-scale war in Ukraine has caused unprecedented transformations in the higher education system. According to recent data, over 40% of academic staff have been forced to relocate, with approximately 15% leaving the country [2]. This has created a critical situation where traditional human resources management methods based on direct supervision and formal hierarchical structures have lost their effectiveness. The destruction of informal scientific networks, loss of access to laboratory infrastructure, and psychological trauma have



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fundamentally changed the context in which academic work is performed.

In this context, artificial intelligence (AI) methods open new horizons for analytics, monitoring, and support of intellectual activity. AI's ability to process vast arrays of unstructured data (such as communication flows or textual feedback) enables a transition from delayed fact-finding (e.g., the resignation of a valuable specialist) to proactive management aimed at identifying 'pain points', supporting social cohesion, and preserving staff well-being [3]. However, implementing AI in such a delicate and ethically sensitive area as human capital management during a humanitarian crisis requires not simple copying of foreign practices, but their deep critical analysis.

Recent studies demonstrate the effectiveness of AI methods in human resources management across various sectors. Research by Chowdhury et al. [4] shows that machine learning-based predictive analytics can reduce employee turnover by 25–30% through early identification of risk factors. Raghavan et al. [5] found that organizations using AI-driven people analytics achieve 40% higher employee engagement and 30% better retention rates. However, these studies primarily focus on stable organizational environments and do not address the unique challenges posed by crisis situations and forced migration.

The European approach to AI ethics, codified in the AI Act and GDPR, emphasizes transparency, explainability, and human-centricity [6]. This contrasts with the more market-oriented US approach, which prioritizes efficiency and return on investment. Recent work by Floridi et al. [7] on ethical AI frameworks provides valuable guidance for developing human-centric AI systems that respect individual rights while delivering organizational benefits.

An emerging area of research focuses on optimization of faculty workload allocation using mathematical programming and AI techniques. Studies by Ozdemir and Gasimov [14] demonstrate the application of linear programming for workload balancing, while recent work by Badri et al. [15] explores simplex method approaches for optimal course assignment. However, these methods often lack consideration of individual preferences and contextual factors such as displacement status or psychological well-being.

The purpose of this study is to analyze existing approaches and models of AI used in different sectors

(particularly in the USA and EU) for assessing the effectiveness of intellectual activity, and to determine their potential for adaptation to the specific tasks of state management of intellectual capital in Ukrainian HEIs. The research examines fundamental philosophical differences between the market-oriented US approach and the human-centric EU approach, analyzes specific technologies such as Organizational Network Analysis (ONA) and Natural Language Processing (NLP), and proposes a comprehensive framework integrating predictive analytics, optimization algorithms, and decision support systems for practical implementation in crisis-affected educational environments.

2. Materials and Methods

Before comparing specific AI implementation models in human resources management, it is essential to outline the fundamental differences in philosophical approaches characteristic of the United States and the European Union. These distinctions have a direct impact on strategic decisions regarding the development, regulation, and practical use of AI in the human resources context [8].

The American approach to AI implementation in HR is characterized predominantly by a pragmatic, market-oriented paradigm. The primary criteria are process efficiency and return on investment (ROI) maximization. The focus is on increasing productivity, optimizing management procedures, and identifying key performers and employees who may potentially leave the organization [9]. The regulatory field in the US is relatively flexible: although legislative restrictions exist, particularly in the area of non-discrimination (e.g., Equal Employment Opportunity Commission — EEOC provisions), technological innovations often outpace regulatory frameworks.

In contrast, the EU adopts a human-centric approach based on ethical principles, transparency of algorithmic decisions, and prioritization of individual rights protection. Key orientations include ensuring fairness, non-discrimination, AI explainability (XAI), and strict compliance with personal data protection norms codified in the General Data Protection Regulation (GDPR) [10]. The EU's regulatory policy is significantly stricter: the Artificial Intelligence Act establishes clear frameworks for classifying AI systems, specifically designating HR technologies as high-risk, requiring additional safety and transparency

Table 1

Comparison of US and EU Approaches to AI in HR

Criterion	US Approach	EU Approach
Philosophy	Market-oriented, efficiency-focused, ROI maximization	Human-centric, ethics-based, individual rights protection
Regulation	Flexible, innovation-first, EEOC guidelines	Strict, compliance-focused, GDPR and AI Act
Key Metrics	Productivity, performance, attrition prediction	Fairness, transparency, employee well-being
HEI Focus	Research productivity analytics, student success prediction	Ethical AI use, staff well-being, skills development

Source: compiled by authors based on [8, 9, 10]

guarantees. Table 1 summarizes the key differences between these approaches.

In the context of educational environment transformation driven by war and the mass migration of academic staff, analytical tools that not only capture individual indicators but also reveal systemic connections shaping the intellectual capital of institutions acquire particular importance. A prominent example is Organizational Network Analysis (ONA), which conceptualizes knowledge not as isolated units but as a dynamic network of interactions through which information circulates, combines, and generates new value [11].

Rather than focusing on formal hierarchies or staffing structures of an organization, ONA visualizes actual flows of information, ideas, and influence. Earlier implementations of ONA relied primarily on surveys, which constrained both accuracy and scalability. Contemporary approaches, widely adopted in the United States and the European Union, employ passive collection of digital interaction traces analyzed through machine learning algorithms. These traces include email metadata (recipients, frequency, excluding content), calendar data (meeting participation), communication records in corporate platforms (Slack, Teams, Zoom), and collaborative document activity (Google Workspace, SharePoint).

On the basis of such data, AI constructs social connection maps that identify critical roles within organizational networks. These include Central Connectors — individuals with extensive ties who often serve as informal leaders, the loss of whom may fragment the network; Brokers — bridges between otherwise disconnected groups and potential sources of innovation; Bottlenecks — overloaded participants who risk obstructing information flows; and Isolates — individuals with limited engagement who face heightened risk of resignation.

In conditions of staff displacement, ONA supports several essential management tasks: diagnosing network gaps by detecting isolation among relocated staff and the emergence of “information bubbles”; identifying and supporting critical intellectual capital by recognizing “hidden leaders” among internally displaced persons (IDPs) who facilitate integration; enabling preventive turnover management by monitoring declines in communication activity; and evaluating the effectiveness of integration measures by comparing network structures before and after interventions.

The mathematical foundation of ONA relies on graph theory and network centrality measures. Let $G = (V, E)$ represent the organizational network where V is the set of employees and E is the set of communication edges. The degree centrality $CD(v)$ of node v is defined as:

$$CD(v) = \frac{deg(v)}{|V| - 1} \tag{1}$$

where $deg(v)$ is the number of connections of node v . Betweenness centrality $CB(v)$, which identifies brokers, is calculated as:

$$CB(v) = \sum_{s \neq t, s \neq v, t \neq v}^{s, t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{2}$$

where σ_{st} is the total number of shortest paths from node s to node t , and $\sigma_{st}(v)$ is the number of those paths passing through v .

In the context of deep social transformations caused by war and mass migration of academic staff, tools capable of not only recording the structure of communications (as in ONA) but also interpreting their content, emotional coloring, and hidden signals gain special relevance. In this sense, Natural Language Processing (NLP) technologies play the role of a ‘stethoscope’ and ‘translator’ of organizational language — they allow ‘hearing’ the collective, identifying problems that are not openly articulated, and assessing the moral-psychological state of the academic community [12].

NLP is the ability of computer systems to understand, interpret, and analyze human language (text or voice). In the HEI context, AI models based on NLP not only process text but extract meaning, emotions, and key themes from it. The main technological components are: Sentiment Analysis (automatic determination of text’s emotional coloring), Topic Modeling (identification of dominant themes in large text arrays), and Named Entity Recognition (NER, identification of names, locations, organizations in text).

In crisis conditions, when traditional surveys may be ineffective, NLP allows deep diagnostics of the academic community’s state. Main application directions include: (1) early diagnosis of IDP problems through anonymous feedback channels and topic modeling; (2) monitoring of psychological state and burnout through sentiment analysis; (3) analysis of skills and knowledge gaps through identification of requests for new competencies; (4) evaluation of management communication effectiveness through analysis of reactions to official messages.

The mathematical foundation of sentiment analysis often employs transformer-based models. For a given text sequence $X = \{x_1, x_2, \dots, x_n\}$, the sentiment score S is computed as:

$$S = \text{softmax}(W \cdot h + b) \tag{3}$$

where h is the contextualized representation from the final layer of the transformer, W is the weight matrix, and b is the bias vector. The softmax function normalizes the output to produce probability distribution over sentiment classes (positive, negative, neutral).

In the context of educational environment transformation caused by war, digitalization, and migration processes, rethinking approaches to professional development of academic staff gains special relevance. One of the key tools for such transformation is the Learning Experience Platform (LXP) — a learning

experience platform representing the evolution of traditional Learning Management Systems (LMS) [13].

Unlike classical LMS that function on the principle of centralized learning process administration (course assignment, completion control), LXP is oriented toward a personalized, flexible, and dynamic approach. It allows forming individual development trajectories, considering both the employee's current role and the organization's strategic needs. In this sense, LXP performs the function not only of content distribution but also of intelligent skills management, automatically identifying and filling 'skill gaps' arising due to environmental changes, technologies, or functional responsibilities.

If ONA and NLP tools allow diagnosing problems and preserving existing intellectual capital, LXP is a means of its growth, adaptation, and preparation for future challenges. In crisis conditions, this gains special weight, as the need for rapid development of new competencies is critical. The platform uses ML models for: (1) recommendation systems based on collaborative filtering and content-based algorithms; (2) skill gap analysis using classification models; (3) learning path optimization through reinforcement learning; (4) impact assessment using regression models to measure the effect of training interventions.

The recommendation system in LXP typically employs collaborative filtering. Let R be an $m \times n$ matrix where R_{ij} represents the interaction (completion, rating) of user i with learning resource j . The predicted rating \hat{R}_{ij} is computed using matrix factorization:

$$\hat{R}_{ij} = p_i^T \cdot q_j \quad (4)$$

where $p_i \in \mathbb{R}^k$ represents user i 's latent factors and $q_j \in \mathbb{R}^k$ represents resource j 's latent factors, with k being the number of latent dimensions.

The practical implementation of AI methods in intellectual capital management requires a comprehensive analytical framework integrating exploratory data analysis, predictive modeling, and optimization algorithms. This section presents the People Analytics approach adapted to the specific challenges of Ukrainian HEIs, focusing on workload optimization and performance forecasting while maintaining ethical standards and human oversight [14, 15].

The initial stage of faculty workload analysis focuses on identifying fundamental patterns and outliers in the data. This requires application of several complementary methods: descriptive statistics to establish the 'average faculty member' baseline; correlation analysis (Pearson, Spearman, Kendall) between different task categories; statistical analysis across task groups (teaching, research, administrative); clustering by individual tasks and task groups using DBSCAN, Gaussian Mixture Models (GMM), or Spectral Clustering; outlier detection using Isolation Forest or UMAP; temporal trend analysis across years; and other analytical approaches that may prove necessary during the investigation.

This stage enables understanding of data structure, workload distribution across faculty members and

years, and observable trends. At this stage, subsequent analysis and modeling methods are determined. The process requires iterative returns to EDA after discovering new patterns for detailed investigation. For clustering analysis, the optimal number of clusters k can be determined using the elbow method by minimizing within-cluster sum of squares:

$$WCSS(k) = \sum_{i=1}^k \sum_{x \in C_i} |x - \mu_i|^2 \quad (5)$$

where C_i represents cluster i , μ_i is the centroid of cluster i , and x represents individual data points (faculty members).

Before proposing changes in faculty workload redistribution, it is necessary to forecast performance indicator changes in the next year assuming continuation of current trends. Given limited historical data, absence of seasonality, and non-stationarity of performance indicators (all verified during EDA), the most suitable forecasting methods are: Exponential Smoothing (ETS), which decomposes data into error, trend, and seasonality components and propagates them to future periods; Bayesian Linear Regression, which builds linear regression with probabilistic intervals, best suited for predictions under stable workload policies; and Polynomial Regression, which finds optimal polynomial functions matching observed trend changes.

Simultaneous use of all three methods with visualization on a common graph is recommended. For Exponential Smoothing, the forecast value y_{t+h} at time $t + h$ can be expressed as:

$$y_{t+h|t} = \ell_t + h \cdot b_t + s_{t+h-m(k+1)} \quad (6)$$

where ℓ_t is the level component, b_t is the trend component, s_t is the seasonal component, and m is the seasonal period length.

The next stage involves building a model to determine the 'weight' of each task. Since workload from individual tasks has no nonlinear relationships with others, linear regression is the optimal method. This model is key to proper workload redistribution across institutional activity directions. The main challenge is system dimensionality (over 150 parameters), preventing calculations for each faculty member separately due to insufficient data. Therefore, linear regression uses all available data, yielding averaged weights across all faculty. Subsequently, refinement for each faculty member can be performed based on their most recent year.

The linear regression model for workload estimation can be expressed as:

$$W = \sum_{j=1}^n \hat{\alpha}_j \cdot x_j + \varepsilon \quad (7)$$

where W represents total workload (FTE), x_j represents hours spent on task j , β_j represents the weight coefficient for task j , and ε represents the error term.

Three redistribution approaches were analyzed for adaptation to Ukrainian HEI context: Manual

Table 2

Comparison of Workload Redistribution Methods

Method	Advantages	Disadvantages
Manual Distribution	Full faculty control; easy interpretability; minimal risk of abrupt changes; accommodates individual preferences; provides clear correction direction	Requires faculty participation; partial automation only; quality depends on conscious faculty choices; may be far from mathematically optimal
Convex Optimization	Mathematically precise and formally optimal; provides unique solution under given constraints; full automation of redistribution	Complex equation system construction; unrealistic results if details omitted; no individual preference accommodation; solution may contain many small changes; transition from continuous to discrete creates errors
Genetic Algorithms	Handles complex rules and constraints including discreteness; supports full or partial automation with flexibility	No guarantee of best or globally optimal solution; strong result dependence on algorithm parameters; requires significant tuning time; faculty cannot influence decisions, only verify post-facto

Source: compiled by authors based on [14, 15]

Distribution, which provides maximum faculty control over workload changes through influence tables showing each faculty member’s contribution; Convex Optimization, which formulates redistribution as an optimization problem with constraints; and Genetic Algorithms, which apply evolutionary principles with transition rules based on the weight model. Table 2 compares these approaches.

For convex optimization, the problem can be formulated as minimizing deviation from target performance indicators subject to workload constraints. The objective function minimizes the weighted sum of squared deviations from institutional KPIs:

$$\min \sum_{k=1}^m w_k \cdot (P_k - T_k)^2$$

$$\text{subject to } \sum_{j=1}^n x_{ij} \leq H_{\max,i} \quad \forall i, \quad x_{ij} \geq 0 \quad (8)$$

where P_k represents predicted performance for KPI k , T_k represents target value for KPI k , w_k represents weight for KPI k , x_{ij} represents hours for faculty i on task j , and $H_{\max,i}$ represents maximum available hours for faculty i .

As illustrated in Figure 1, the workflow of the predictive analytics and optimization framework integrates multiple layers of analysis and decision-making. The process begins with the data input layer, which aggregates historical workload records, performance ratings, and institutional KPIs. This is followed by exploratory data analysis (EDA), including clustering, correlation analysis, and outlier detection. Predictive modeling is then conducted using ETS, Bayesian regression, and polynomial regression in parallel, while a separate weight model applies linear regression to determine task weights. The optimization stage incorporates three alternative approaches — manual distribution, convex optimization, and genetic algorithms — before results are validated for feasibility. Finally, the framework outputs an interactive dashboard that enables visualization and filtering, with arrows in the diagram indicating data flow and feedback loops.

In modern conditions of educational environment transformation caused by both global technological shifts and local crisis factors, direct borrowing of AI application models developed in the USA or EU is not only inefficient but potentially risky. Ukrainian HEIs require a hybrid model that combines the ethical sensitivity of the European approach with the flexibility and adaptability characteristic of American innovative ecosystems, while integrating the predictive analytics and optimization frameworks described above.

The key principle of such a model should be a shift of focus from assessment to support and preservation of academic potential. The proposed hybrid model integrates four strategic components that must be incorporated into the theoretical framework of AI application in Ukrainian HEIs: (1) data contextualization accounting for IDP status and security situation through the Disruption Factor; (2) priority on ‘soft’ data using NLP and ONA for psychological state monitoring; (3) predictive analytics framework combining EDA, forecasting models, and workload optimization with human oversight; (4) ethical foundation based on European AI Act principles (transparency, human-in-the-loop, non-discrimination).

The model employs a layered architecture integrating multiple AI techniques. At the data collection layer, the system gathers information from ONA (communication patterns), NLP (sentiment and topic analysis), LMS logs, performance ratings, and institutional KPIs. The processing layer applies exploratory data analysis for pattern identification, predictive models for trend forecasting, and the workload weight model for task valuation. The optimization layer offers three approaches: Manual Distribution for maximum faculty autonomy, Convex Optimization for mathematical precision, and Genetic Algorithms for handling complex constraints. All outputs pass through a fuzzy logic interpretation layer that translates numerical results into linguistic terms and management recommendations.

Critical to this model is the introduction of a Disruption Factor (*DF*), which adjusts performance

expectations based on contextual constraints. For an individual i , the adjusted performance P_{adj} is calculated as:

$$P_{adj,i} = \frac{P_{actual,i}}{DF_i} \tag{9}$$

where

$$DF_i = w_1 \cdot IDPstatus + w_2 \cdot InfrastructureAccess + w_3 \cdot PsychologicalLoad,$$

with weights w_1, w_2, w_3 determined through expert elicitation and validated against historical data.

3. Results and Discussion

The proposed hybrid model requires systematic implementation across multiple stages. The technical architecture consists of five key layers: (1) Data Collection Infrastructure utilizing existing systems (email metadata, LMS logs, anonymous feedback channels, performance databases) while ensuring GDPR

compliance through data anonymization and aggregation; (2) AI Processing Layer implementing ONA algorithms, NLP pipelines, and ML models for EDA, prediction, and clustering; (3) Optimization Engine offering three alternative approaches (Manual Distribution, Convex Optimization, Genetic Algorithms) with constraint validation; (4) Fuzzy Logic Interpretation Layer translating numerical outputs into linguistic terms and management recommendations; (5) Dashboard Interface providing interactive visualization with filtering, what-if scenario analysis, and explainable AI outputs.

A critical component of the implementation is the Dashboard Development phase, where effective visualization methods identified during EDA are transformed into a web application. This interface provides HEI administrators with graphical access to data and analysis results, enabling filtering by faculty members, departments, years, and task categories. The dashboard includes: real-time performance metric tracking against institutional KPIs; workload distribution

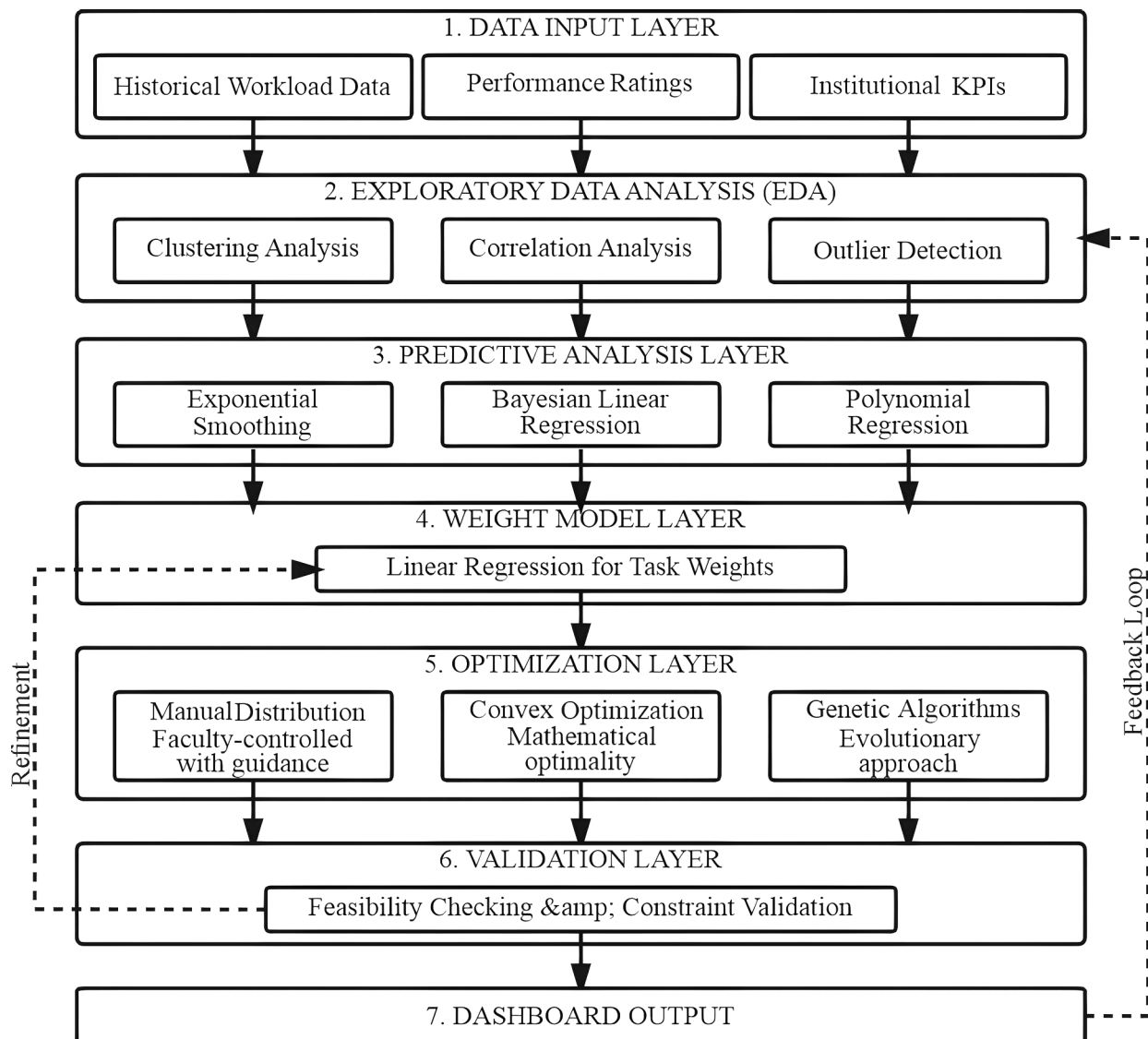


Figure 1. Workflow Diagram of Predictive Analytics and Optimization Framework
 Source: proposed by the authors

visualizations with comparative benchmarks; predictive forecast displays with confidence intervals; optimization scenario comparisons; and alert notifications for faculty at risk of burnout or resignation.

Validation of the model involves multiple approaches: (1) Expert validation through consultations with HEI administrators, HR specialists, and AI ethics experts to ensure practical relevance and ethical soundness; (2) Pilot implementation in select departments to test technical feasibility and gather user feedback, particularly regarding the Manual Distribution approach; (3) Performance metrics evaluation comparing traditional assessment methods with AI-augmented approaches, measuring improvements in early risk detection, staff retention, workload balance, and achievement of institutional KPIs; (4) Ethical auditing ensuring compliance with GDPR and AI Act requirements, with particular attention to transparency, non-discrimination, data protection, and proper application of the Disruption Factor; (5) Iterative refinement based on stakeholder feedback, with regular returns to EDA for validation of model assumptions and identification of emerging patterns.

The conducted analysis demonstrates that the intellectual capital of higher education institutions faces critical threats due to unprecedented challenges caused by war-related migration and psychological stress. Traditional management approaches prove inadequate as they cannot adequately respond to physical dispersion and destruction of informal connections among academic staff. In this context, implementing artificial intelligence methods becomes not a technological whim but a strategic necessity, enabling transition from delayed loss acknowledgment to proactive management and support.

Critically important is the development not of copies of foreign practices but of a Hybrid AI Model. This model should organically combine the technical flexibility of the American approach (using highly developed People Analytics, ONA, and LXP technologies for effective monitoring and forecasting) with the human-centric ethics of the European Union. This requires strict adherence to principles of Transparency, Non-discrimination, and Human-in-the-loop, where HR-AI technologies in the Ukrainian context perform the role of a support tool rather than control or punitive scoring. The key innovation of this model is the inclusion of a Disruption Factor that adapts performance assessment considering the IDP context and security situation, combined with a comprehensive predictive analytics framework integrating exploratory data analysis, multiple forecasting methods, and flexible optimization approaches.

The technological framework of such a model is based on the integration of multiple complementary AI approaches creating a closed management cycle: (1) Organizational Network Analysis (ONA) for integration diagnostics, identifying isolated groups and network gaps, enabling stitching of torn academic community and preventive turnover management; (2)

Natural Language Processing (NLP) as a well-being diagnostics tool, providing anonymous monitoring of psychological state and burnout, enabling early detection of 'pain points'; (3) Learning Experience Platform (LXP) as a strategic development tool, personalizing professional development and filling crisis skill gaps; (4) Predictive Analytics framework combining Exponential Smoothing, Bayesian Linear Regression, and Polynomial Regression for performance forecasting; (5) Workload Optimization engine offering three alternative approaches (Manual Distribution, Convex Optimization, Genetic Algorithms) with different tradeoffs between faculty autonomy and mathematical optimality.

To ensure humanitarian sensitivity and management transparency, the system employs Fuzzy Logic as an interpretation layer, creating transparent and interpretable rules. This allows translating numerical ML model results (Classification, Clustering, Regression, Optimization) into management decision language (e.g., 'IF Mood Very Poor AND Integration Low THEN Intervention Critical'). The fuzzy inference system enables non-technical stakeholders to understand and trust AI recommendations while maintaining the precision of underlying mathematical models.

The practical implementation through a web-based dashboard transforms these analytical capabilities into actionable management tools. By providing interactive visualizations, what-if scenario analysis, and real-time monitoring of key performance indicators, the system enables HEI leadership to make data-driven decisions while preserving human oversight and accommodating faculty preferences. The Manual Distribution approach, in particular, empowers faculty members to participate actively in workload planning, fostering buy-in and reducing resistance to technological change.

Thus, the integration of AI methods into intellectual capital management represents a conceptual transformation enabling HEI management to proactively forecast risks, optimize resource allocation, segment staff for targeted support, and fairly assess activity. The proposed Hybrid AI Model ensures not only technical efficiency but also resilience, competitiveness, and human-centricity of Ukrainian higher education institutions under the most challenging conditions.

4. Conclusions

This study is primarily conceptual, and the proposed model requires empirical validation through pilot implementations in Ukrainian HEIs. Future research should focus on: (1) developing and calibrating specific algorithms for the Disruption Factor calculation based on empirical data from displaced faculty; (2) conducting longitudinal studies to evaluate the model's effectiveness in reducing staff turnover, improving well-being, and achieving institutional KPIs; (3) exploring the integration of additional data sources such as social media analytics (with appropriate ethical safeguards); (4) investigating the scalability of the model to different organizational contexts beyond higher education; (5) refining the fuzzy logic rule base

through systematic expert elicitation and machine learning from historical decisions; (6) developing more sophisticated genetic algorithm configurations for the optimization engine; (7) comparing the three optimization approaches empirically to determine optimal selection criteria for different institutional contexts.

The proposed hybrid model provides HEI administrators with a roadmap for implementing AI-driven intellectual capital management systems. Key recommendations include: (1) starting with low-risk, high-value applications such as EDA and anonymous feedback analysis before implementing optimization algorithms; (2) prioritizing the Manual Distribution

approach for initial deployment to build trust and demonstrate value before introducing more automated methods; (3) establishing ethical oversight committees to ensure compliance with GDPR and AI Act requirements; (4) investing in staff training to build AI literacy and reduce resistance to technological change; (5) adopting an iterative approach with continuous monitoring and refinement based on stakeholder feedback; (6) ensuring proper dashboard design with intuitive interfaces and explainable AI outputs; (7) maintaining transparent communication about data usage, privacy protection, and the role of AI as a support tool rather than replacement for human judgment.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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АНАЛІЗ ПІДХОДІВ ДО ІНТЕГРАЦІЇ МЕТОДІВ ШТУЧНОГО ІНТЕЛЕКТУВ УПРАВЛІННЯ ІНТЕЛЕКТУАЛЬНИМ КАПІТАЛОМ

Анотація. У статті розглянуто підходи до інтеграції методів штучного інтелекту в системи управління інтелектуальним капіталом закладів вищої освіти в умовах вимушеної міграції та організаційної трансформації. Проведено порівняльний аналіз ринково-орієнтованого підходу США та людиноцентричного підходу ЄС, що дозволило виявити фундаментальні відмінності у філософських засадах впровадження штучного інтелекту в управління людськими ресурсами. У дослідженні запропоновано гібридну модель, яка поєднує технологічну гнучкість американської концепції People Analytics з європейськими етичними стандартами, адаптованими до специфічних викликів, що постали перед українськими закладами вищої освіти.

У роботі проаналізовано ключові технології штучного інтелекту: аналіз організаційних мереж для діагностики інтеграції та виявлення ізольованих груп; обробка природної мови для моніторингу психологічного стану та раннього виявлення професійного вигорання; платформи для створення персоналізованого досвіду навчання для персоналізованого професійного розвитку. Запропоновано використання моделей машинного навчання, включаючи класифікацію, кластеризацію, регресію та алгоритми оптимізації, для перерозподілу навантаження та прогнозування результативності.

Розроблений підхід інтегрує методи дослідницького аналізу даних, прогнозного моделювання та оптимізації (зокрема, методи опуклої оптимізації та генетичні алгоритми) з використанням шару нечіткої логіки, що забезпечує прозорість та інтерпретованість управлінських рішень. Запропонована модель дозволяє керівництву закладів вищої освіти проактивно прогнозувати ризики, оптимізувати розподіл ресурсів, сегментувати персонал для цільової підтримки та справедливо оцінювати результативність з урахуванням контексту вимушеного переміщення.

Ключові слова: штучний інтелект, інтелектуальний капітал, управління людськими ресурсами, аналіз організаційних мереж, обробка природної мови, оптимізація навантаження, заклади вищої освіти.

JEL: O33; L86; M15

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ARTIFICIAL INTELLIGENCE IN AUTOMATED FINANCIAL RISK MANAGEMENT SYSTEMS

Abstract. *The article is aimed at studying the use of artificial intelligence in automated financial risk management systems to improve the accuracy, efficiency and efficiency of managerial decision-making in the financial sector. The study consists in a comprehensive study of the theoretical and methodological foundations of the use of artificial intelligence in management systems, analysis of modern approaches to the classification and assessment of financial risks using machine learning algorithms, formation of the architecture of the decision support system based on forecasting models, as well as assessment of the effectiveness of the built models based on the results of simulation modeling. Within the framework of the study, a model for forecasting the credit risk of bank customers has been developed, which allows assessing solvency based on historical data and modern machine learning methods. The research method is modeling using machine learning tools, including neural networks and ensemble learning methods (Random Forest), as well as data analysis using platforms to visualize results and evaluate the effectiveness of models. Particular attention is paid to data preparation, selection of relevant features, evaluation of model accuracy, and construction of interpreted visualizations such as SHAP graphs, ROC curves, etc. The result of the study was the creation of an effective model for predicting credit risk, which demonstrates a sufficiently high level of classification accuracy and the ability to adapt to changes in incoming conditions. The practical significance of the study lies in the possibility of implementing the developed model into the existing automated financial risk management systems of banking institutions, which will reduce the level of credit losses, increase financial stability and provide more accurate risk management. This approach contributes to the development of intelligent financial systems, increasing the level of automation of managerial decisions and strengthening the competitiveness of financial institutions in modern market conditions.*

Keywords: *artificial intelligence, financial risks, machine learning, credit risk, neural networks, automated control system, forecasting, classification.*

1. Introduction

Financial risks are an integral part of the operations of any business or financial institution, and their effective management is key to ensuring stability and profitability. The main classifications of financial risks include: market risks associated with fluctuations in asset prices, interest rates, or exchange rates; credit risks arising in the event of insolvency of counterparties; operational risks due to internal failures, errors or fraud; liquidity risks associated with the inability to quickly sell assets without significant losses; as well as legal and reputational risks arising from non-compliance with regulatory requirements or negative assessment of activities by partners and clients.

Sources of financial risks are divided into external and internal. External ones include economic instability, political changes, natural disasters, and market fluctuations that affect the financial performance of the enterprise. Internal sources are associated with imperfection of management processes, insufficient control, human errors and technological failures. A systematic approach to risk classification allows you to more effectively identify potential



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threats and develop adaptive strategies for their neutralization.

Thus, financial risks are a complex phenomenon that encompasses various types and sources of uncertainty, and their management requires the use of integrated approaches, including the use of modern automated systems and artificial intelligence technologies to improve the quality of analysis and forecasting of risk factors. Financial risk management is a key area in the activities of financial institutions, banks and corporations. The main goal of financial risk management is to timely identify, assess and minimize possible threats, which allows you to make informed decisions on capital preservation and maintaining financial stability.

In modern conditions of dynamic market development and high competition, automated financial risk management systems have become an integral part of collecting, processing and analyzing large amounts of data for timely detection of potential threats and decision-making. These systems integrate a variety of tools and technologies, including statistical analysis and modeling techniques, as well as the latest intelligent approaches. In recent years, much attention has been paid to the use of artificial intelligence algorithms, which can improve the accuracy of predictions and the adaptability of systems to changing conditions. Structurally automated financial risk management systems consist of data collection modules, analytical tools, decision support systems, as well as monitoring and control modules [1].

The current economic situation is characterized by a high degree of uncertainty, complexity of financial processes and increased risks faced by enterprises, banks and other financial institutions. Under such conditions, effective financial risk management becomes a key task that requires the introduction of the latest approaches and tools. One of the most promising areas is the use of artificial intelligence (AI) technologies, which allow automating data analysis, identifying hidden patterns, and making informed management decisions in conditions of uncertainty [5].

Artificial intelligence is becoming one of the key tools for transforming the financial sector, providing automation of complex processes, increasing the accuracy of forecasts, and improving risk management. With the ability to process large amounts of data and find hidden patterns, AI technologies allow financial institutions to respond effectively to rapid market changes and minimize possible losses.

The article is aimed at studying the use of artificial intelligence in automated financial risk management systems to improve the accuracy, efficiency and efficiency of managerial decision-making in the financial sector.

The objectives of the study are:

- 1) description and analysis of modern methods and approaches to financial risk management in banks and insurance companies and assessment of financial risks using machine learning algorithms;

- 2) comprehensive study of the theoretical and methodological foundations of the use of artificial intelligence in financial risk management systems;
- 3) study of the opportunities, advantages and problems of using artificial intelligence in automated financial risk management systems;
- 4) analysis of the features of deep learning models, decision trees, ensemble methods, as well as criteria for evaluating their effectiveness
- 5) formation of the architecture of the decision support system based on forecasting models;
- 6) exploring the possibility of using artificial intelligence to improve the accuracy of financial risk forecasting, fraud detection, and credit and insurance risk management;
- 7) assessment of the main challenges and limitations in the use of AI for financial risk management;
- 8) evaluation of the effectiveness of the built models based on the results of simulation modeling;
- 9) development of a model for forecasting the credit risk of the bank's customers, which allows assessing solvency on the basis of archival data and modern methods of machine learning, which recognizes the novelty of the research.

Thus, the study consists in generalizing theoretical and methodological approaches to the use of artificial intelligence in management systems, analyzing modern methods of classifying and assessing financial risks using machine learning algorithms, creating an architecture of a decision support system based on predictive models, and evaluating the effectiveness of the developed models based on the results of simulation modeling.

As part of the study, it is necessary to develop a model for forecasting the credit risk of bank customers, which would allow assessing solvency using historical data and modern machine learning methods. The research method includes modeling using machine learning tools, including neural networks and ensemble learning techniques such as Random Forest, as well as data analysis using platforms to visualize results and evaluate the performance of models. Particular attention should be paid to data preparation, selection of appropriate features, evaluation of model accuracy, and construction of interpreted visualizations such as SHAP graphs, ROC curves, etc.

Artificial intelligence is not only a tool for processing large amounts of financial information [2], but also a full-fledged participant in the decision-making process in automated management systems. Thanks to the capabilities of machine learning, neural networks, and other data analysis methods, AI is able to predict, classify, and optimize financial decisions, taking into account a wide range of risks: market, credit, operational, currency, etc.

2. Materials and Methods

Financial risk management is a key area in the activities of financial institutions, banks and corporations. In modern conditions of dynamic market

development and high competition, automated financial risk management systems have become an integral part of collecting, processing and analyzing large amounts of data for timely detection of potential threats and decision-making. These systems integrate a variety of tools and technologies, including statistical analysis and modeling techniques, as well as the latest intelligent approaches. In recent years, much attention has been paid to the use of artificial intelligence algorithms, which allow to increase the accuracy of forecasts and the adaptability of systems to changing conditions. Structurally automated control systems of the Russian Federation consist of data collection modules, analytical tools, decision support systems, and monitoring and control modules [11].

The main elements of the classification of financial risks include:

- market risks associated with fluctuations in asset prices, interest rates or exchange rates;
- credit risks arising in the event of insolvency of counterparties;
- operational risks arising from internal failures, errors or fraud;
- liquidity risks associated with the inability to quickly sell assets without significant losses;
- as well as legal and reputational risks arising from non-compliance with regulatory requirements or negative assessment of activities by partners and clients.

Sources of financial risks are divided into external and internal. External factors include economic instability, political changes, natural disasters and market fluctuations that affect the financial performance of the enterprise. Internal sources are related to imperfection of management processes, insufficient control, human error and technological failures.

A systematic approach to risk classification allows you to more effectively identify potential threats and develop adaptive strategies for their neutralization. Thus, financial risks are a complex phenomenon that encompasses various types and sources of uncertainty, and their management requires the use of integrated approaches, including the use of modern automated systems and artificial intelligence technologies to improve the quality of analysis and forecasting of risk factors.

The research method involves modeling using machine learning tools, in particular neural networks and ensemble learning methods such as Random Forest, as well as in data analysis using platforms to visualize results and evaluate the effectiveness of models. Let's consider this issue in more detail.

One of the most common artificial intelligence technologies in the financial sector is machine learning [1]. It allows you to create models that automatically learn from historical data, predict the behavior of financial indicators, identify anomalies and potential risks. In particular, classification and regression techniques are widely used to assess customer creditworthiness, predict exchange rate fluctuations, and detect fraudulent transactions [9]. Another important technology is deep

learning, which is based on multi-layered neural networks. They are able to work with unstructured data, such as text information, images, or sound signals, which expands the capabilities of automatic analysis of financial documents, news feeds, and social networks to assess market trends [10]. Another important technology is deep learning, which is based on multi-layered neural networks. They are capable of working with unstructured data, such as text information, images, or audio signals, which expands the capabilities of automatic analysis of financial documents, news feeds, and social networks to assess market trends [10].

Natural Language Processing (NLP) technologies are used to automatically analyze and analyze textual information, including news, financial reports, and legislative documents. Thanks to NLP, you can quickly draw conclusions about potential changes in the market, identify risks related to reputation or regulatory requirements. Robotic process automation (RPA) combined with artificial intelligence allows you to optimize routine operations such as transaction processing, reporting, compliance monitoring, which significantly reduces time and reduces the human factor in risk management processes. Financial risk management also benefits from the application of AI-powered decision support systems that integrate real-time analytics, simulate different scenarios, and provide guidance for management. So, to better understand the impact of the use of artificial intelligence on financial risk management, it is advisable to summarize the main aspects that determine the role of AI in this context. The use of modern technologies in the financial sector can significantly reduce various risks, optimize processes and increase the efficiency of institutions. Since each of the types of financial risks has specific characteristics depending on the field of activity, it is important to outline the impact of artificial intelligence technologies on the management of these risks. Table 1 shows the main areas of use of artificial intelligence for financial risk management.

Thus, artificial intelligence technologies in the financial sector create new opportunities to improve the efficiency of financial risk management, automate analytical processes, and adaptively respond to external and internal threats, which confirms their important role in modern automated management systems. To adequately assess the impact of artificial intelligence on the financial sector, it is necessary to take into account both its innovation potential and the possible risks it can cause. Only by applying a balanced approach to the use of this technology, it is possible to integrate it into financial processes as efficiently as possible, providing both economic benefits and maintaining the security and stability of the financial system. Despite the significant benefits of using artificial intelligence in the financial sector, the adoption of these technologies comes with certain risks. Process automation, algorithm-based decision-making, and the use of large amounts of data can pose threats to both banks and insurance companies. In particular,

Table 1

The impact of the use of artificial intelligence on financial risk management

Name	The impact of using AI
Credit risk management	AI makes it possible to more accurately assess customer creditworthiness, reducing the risk of non-payments and unpredictable financial losses
Fraud risks	Application of algorithms to detect anomalies and prevent fraudulent transactions, which reduces possible financial losses
Investment risks	Using AI to Predict Market Fluctuations and Analyze Investment Opportunities
Regulatory risks	Improving compliance control with AI to analyze and verify compliance with regulatory requirements
Personalization of services	Analysis of individual customer needs to create personalized financial products
Operational risks	Automate and optimize financial operations to reduce human error and errors
Cyber protection and security	Increase financial data protection and protect against cyberattacks with algorithms to detect anomalous activity
Liquidity risks	Forecasting the need for liquid funds and optimizing financial management

there is a risk of technical glitches, fraud, data privacy breaches, and ethical and social issues.

It is important to be aware of these risks in order to ensure the reliable functioning of financial institutions and their effective management. Table 2 below shows the main risks associated with the use of artificial intelligence, as well as their impact on the financial sector.

Financial risk management traditionally includes risk assessment, monitoring and making appropriate management decisions. Artificial intelligence can significantly improve these processes by automating routine tasks, increasing the accuracy of predictions, and reducing the subjectivity of assessments. For example, based on historical data, machine learning models can detect complex dependencies between variables that affect credit, market, or operational risk. A key benefit of AI in risk management is its ability to adapt to changing market conditions. Traditional models usually have a fixed structure and limited retrofit options. Instead, AI systems are able to learn from new data on their own, making them particularly effective in dynamic environments. In addition, thanks to its integration with digital platforms, artificial intelligence can work in real-time, which greatly improves the speed of response to potential threats. In the field of financial analysis, AI also acts as an analytical tool for building forecasting models, analyzing scenarios, detecting fraudulent transactions, and improving the overall level of security of the financial system. It is especially important to use explanatory models (Explainable AI), which allow you to get not only the result, but also understand the logic of decision-making,

which is critically important for financial institutions operating in a highly regulated environment.

Overall, the role of artificial intelligence in risk management is to streamline the processes of identifying, evaluating, and responding to financial threats. The use of intelligent algorithms allows you to reduce decision-making time, minimize the impact of the human factor and increase the effectiveness of the risk management system. Machine learning (ML), artificial neural networks (AI), and expert systems are key components of the modern approach to financial risk analysis and management. These technologies make it possible to identify hidden patterns in financial data, predict potential threats, and support decision-making based on large amounts of information [6].

Machine learning is a subfield of artificial intelligence that involves building models capable of learning from historical data without explicit programming logic. In the financial sector, machine learning allows you to simulate the behavior of markets, assess lending risks, detect fraud, and conduct portfolio analysis. The main machine learning methods used in the financial field include regression analysis, decision trees, support vector method, ensemble methods (random forest, gradient increase), clustering (k-means, DB-SCAN), and reinforcement algorithms [8]. Artificial neural networks (SHNMs) are mathematical models inspired by the structure of the human brain that effectively recognize complex patterns in data. In financial applications, SNMs are especially useful for tasks that require a high level of forecasting accuracy, such as assessing a customer’s solvency or detecting anomalies in transactions. For the analysis of time series,

Table 2

Risks of Using Artificial Intelligence to Manage Financial Risks

Name	Risk description
Algorithmic errors	Errors in AI models can lead to wrong decisions
Cybersecurity	Threats of cyberattacks and data breaches
Regulatory risks	Lack of clear regulations on the use of AI and the need to adapt algorithms
Operational risks	Failure of automated systems in the process of financial decision-making
Ethical risks	The Impact of Automation on the Labor Market

both classical multilayer perceptrons and deep neural networks (GNM), recurrent networks (RNM, LSTM) are used. Expert systems are software complexes that simulate the process of thinking of an expert in a certain subject area. They are based on a knowledge base (rules, patterns, heuristics) and an inference mechanism that allows you to draw logical conclusions. In financial analysis, expert systems are used to automate decision-making in difficult situations, such as when assessing investment risks or choosing the optimal hedging strategy. The combination of the above technologies provides increased forecasting accuracy, flexibility in adjusting models for specific tasks, and the ability to work with different types of data. Table 3 presents the main characteristics of the comparison of machine learning methods, neural networks and expert systems in the context of financial risk management.

In today’s automated financial risk management systems, AI models are increasingly being used to assess and predict risks. Such models have the ability to detect complex patterns in data that are not amenable to traditional analytical analysis and provide flexibility in decision-making based on a variety of scenarios [11]. Forecasting models are based on historical data containing information about previous financial losses, changes in the market situation, credit ratings of customers, macroeconomic indicators, etc. The main task of these models is to build an algorithm that predicts the probability of a risk event with high accuracy. The main types of models used in this context include:

- classification models (e.g. logistic regression, decision trees, SVM) that allow you to determine whether an object belongs to the risk category or not;
- regression models that predict the size of expected financial losses;
- neural networks are universal models that can work in both classification and regression modes;
- combined ensemble models (for example, Random Forest or Gradient Boosting), which increase accuracy by combining the results of several algorithms.

The process of building a model consists of several successive stages, shown in Fig. 1: Data preparation, model selection, training, quality assessment, testing, implementation. Particular attention should be paid to increasing the interpretation of models — the use of tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), which allow you to understand the influence of individual variables on the outcome of the forecast.

This model covers the full lifecycle of financial risk analysis — from data collection and pre-processing to risk forecasting and monitoring. The key components are the data filtering and normalization stages, training the model based on previous experience, and integrating the results into the management decision-making process.

Thus, the use of artificial intelligence in financial risk forecasting processes can significantly improve the accuracy of assessments, automate control processes, and respond to potential threats in a timely manner, which is critical in a dynamic financial environment.

Let’s consider the basic structure of models for preventing financial risks based on neural networks. Neural network-based financial risk warning models are typical examples of the use of AI technology for risk management. The basis of these models is deep learning architecture, which typically includes layered neural networks such as convolutional neural networks (CNNs), recurrent neural networks (RNMs), or long-term memory networks (LTCs). The principle of model design is to predict future potential financial risks by training patterns and features from a large amount of historical data. The input layer of the model receives multidimensional financial data, including market performance, macroeconomic data, financial statements of companies, etc. Hidden layers are responsible for extracting and transforming features, capable of automatically learning complex nonlinear relationships. The output layer provides risk warning signals or risk probabilities.

The model architecture can be customized to meet specific application scenarios. For example, for time series data, LSTM layers can effectively capture long-term dependencies; For structured data, fully connected layers can learn complex combinations of features. Model design also takes into account attention mechanisms that allow the model to focus on the most relevant information, increasing the accuracy of forecasting. Models typically use a multitasking learning system, predicting multiple risk metrics, which helps improve the model’s ability to generalize. To account for the characteristics of high dimensionality and sparseness of financial data, model design includes dimensionality reduction techniques and regularization techniques, such as principal component analysis (PCA) and L1/L2 regularization, to prevent overtraining and increase model robustness [11]. Strategies for training and optimizing neural network-based

Table 3

Comparison table

Method	Scope	Advantages	Limitations
Machine learning	Risk Forecasting, Fraud Detection	Automatic Data Learning, Adaptability	The Need for Quality Data, Black Box
Neural networks	Time series, complex dependencies	High precision, generalizability	Complexity of interpretation, requirements for computing resources
Expert Systems	Risk assessment, decision-making	Interpretation, knowledge-based	Narrowness of the subject area, difficulty in updating knowledge

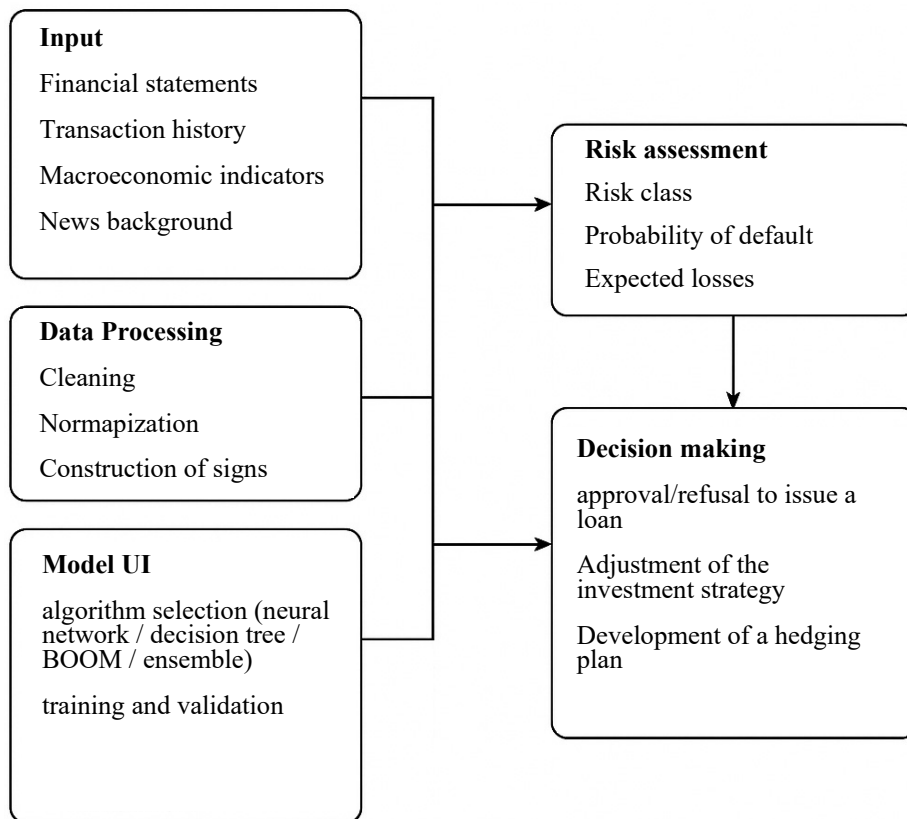


Figura1. Model for forecasting financial risks

financial risk warning models are key steps to ensure model performance. The learning process typically uses supervised learning methods, using labeled historical data as a learning toolkit. The design of the target function of the model should take into account the specifics of financial risk management. For example, asymmetric loss functions can be used to display various costs for missed reports and false alarms. To improve the model's generalization ability, techniques such as cross-validation are commonly used to evaluate model performance, while regularization techniques such as Dropout are used to prevent overtraining. In terms of algorithm selection optimization, adaptive learning speed techniques such as Adam are widely used, which can effectively handle the sparseness and non-stationarity of financial data. Batch normalization methods can accelerate model convergence and improve performance [10].

Model training also faces the problem of sample imbalance, as financial risk events are usually rare in historical data. To solve this problem, methods such as oversampling, undersampling, or generative-adversarial networks (GANs) can be used to balance the sample distribution. Model optimization is an iterative process that involves steps such as feature development, model training, performance evaluation, and parameter adjustments. Expert knowledge can also be incorporated into this process, such as the use of pre-trained word embedding to process text data or the design of specific network structures based on knowledge of the financial field. Therefore, effective

model training requires a combination of high-quality data processing, the right choice of optimization algorithms, and deep expertise in the industry. The iterative nature of this process allows us to achieve high forecasting accuracy and adaptability to difficult conditions of financial markets.

Evaluating the model and analyzing the interpretation is a crucial step in ensuring the reliability and effectiveness of financial risk warning models based on neural networks. Evaluation metrics should be chosen based on specific risk management objectives, with commonly used metrics including accuracy, precision, completeness, etc. For financial risk warnings, the timeliness of model warnings and the level of false alarms are especially important. Therefore, time-weighted valuation indicators can be used, or economic costs can be entered as evaluation criteria. The stability and reliability of the model are also important aspects of the evaluation. Competitive random testing or stress testing can be used to evaluate the performance of the model under extreme conditions.

In addition, it is necessary to focus on the model's ability to generalize, and methods such as Rolling Forecast can be used to evaluate the effectiveness of the model in different periods. However, the black-like nature of neural network models creates difficulties for their application in the financial sector, especially in regulatory requirements and risk management practices, where model interpretation is required. To solve this problem, various methods can be applied to improve the interpretation of models. These methods include trait

importance analysis, interpretation of SHAP values (Shapley additive explanations), locally interpreted model-agnostic explanations (LIME), etc. [10].

These techniques can help to understand the basis for model decision-making, identify key risk drivers, and provide support for risk management decisions. Visualization techniques are also an effective means of improving model interpretation. For example, the use of heat maps to demonstrate the influence of various features on prediction results, or the use of decision trees to approximate the decision-making process of neural networks. These interpretation analyses not only help to increase the validity of the model, but also provide direction for its further optimization.

3. Results and Discussion

At this stage of the study, the task of forecasting the credit risk of bank customers is formulated, as well as the preparation of an appropriate dataset for training artificial intelligence models. The purpose of modeling is to classify customers based on historical financial indicators into two groups: solvent and potentially problematic. To implement the case, an open dataset from the Kaggle platform was used, which includes variables describing the client’s profile: age, income, number of open loans, debt repayment history, the presence of delinquencies, etc. [8]. After uploading the data, pre-processing was carried out: clearing duplicates, excluding missing values, converting categorical variables to numerical ones (one-hot coding), as well as normalizing numerical features. Visual analysis of the data was also carried out to detect anomalies and distribution by class. Correlation analysis made it possible to establish the most influential variables for modeling, such as the history of delinquencies and the debt ratio. As a result of the training, a training sample was formed, suitable for further use in machine learning [9].

Within the framework of the study, a practical case of building a model for forecasting the credit risk of bank customers was implemented. The main goal is to create an intelligent classification system capable of determining whether the client will be able to service the loan in a timely manner in the future. Such a system allows the bank to reduce the likelihood of losses due to non-repayment of loans, increase the efficiency

of risk management and make informed credit decisions. For the simulation, an open dataset from the Kaggle platform — Home Credit Default Risk — was used. This dataset contains more than 300,000 customer records with various characteristics such as age, income level, number of dependents, credit history, type of housing, employment, etc. The first step was to clean and transform the data. A significant number of missing values were identified and removed in categories where the complement is inappropriate. Numerical features were normalized using a mini-max scale. Categorical variables are encoded in one-hot encoding for compatibility with machine learning algorithms. Sample balancing was also carried out using the SMOTE method to eliminate the imbalance between classes (solvent and insolvent clients). Table 3 describes the main variables chosen to build the model.

For comparison, two models were created: Random Forest Classifier as a basic neural network (ANN) and an artificial neural network (ANN) as a more complex variant based on Tensor-Flow/Keras. Random Forest provides interpretation, while the neural network is able to detect nonlinear dependencies in data more deeply. A random forest provides interpretation, while a neural network is able to detect nonlinear dependencies in data more deeply. Both models are trained on 80% of the data, 20% is reserved for test sampling. For the neural network, an architecture with three hidden layers, ReLU activation, and an output layer with the softmax function was used. Adam was used as an optimizer. Dropout is used to prevent overtraining. After training the model, a comparative analysis of the results was carried out according to key metrics: accuracy, completeness, F1 balance. Below is a comparative table of models (Table 5).

As can be seen from Table 5, the random forest model showed the highest accuracy and an F1 score, showing a good balance between completeness and accuracy. The neural network also showed high performance, somewhat inferior to the decision tree. This shows the potential of using AI models to effectively identify financial risks based on historical customer data. To improve the interpretation of the model, SHAP (Shapley Additive Explanations) techniques have been applied, which allow you to determine which variables most influence the model’s decisions. The

Table 4

Main variables for building a model

Variable Name	Description	Variable Type	Variable Name	Description	Variable Type
AMT_INCOME_TOTAL	Total Client Revenue	Numeric			
AMT_CREDIT	Amount of Requested Loan	Numeric			
DAYS_EMPLOYED	Duration of employment (in days)	Numeric			
NAME_HOUSING_TYPE	Housing type				
TARGET	Target variable (0 is good, 1 is risk)	Binary			
CNT_CHILDREN		Number of dependents			
NAME_EDUCATION_TYPE	Client’s level of education				

Table 5

Comparison of models by main metrics

Metrics	Logistic Regression	Random Forest	Logistic Regression
Accuracy	0.76	0.84	0.81
Povnota	0.69	0.80	0.77
F1-Ball	0.72	0.82	0.79

SHAP analysis showed that the key factors were the client’s income, age, and length of service. Fig. 2 shows a graph in the form of a SHAP scatter chart.

After training the neural network model to classify the client’s credit risk, an important step is to interpret its results. Interpretation is a critical characteristic for the banking sector, where it is necessary not only to provide a forecast, but also to explain the reasons for the decision. One of the most effective approaches to interpretation is the use of SHAP (SHapley Additive Explanations), a method based on game theory that allows you to quantify the contribution of each feature to the model solution.

SHAP values demonstrate which customer characteristics (income, age, debt, number of open loans, etc.) had the greatest impact on the final decision — whether to classify the customer as reliable or risky. Figure 1 presented earlier shows a generalized summary graph of SHAP. It depicts the top 10 traits that most affect the model’s results. Red dots indicate high values of the trait, blue dots indicate low values. For example, a high level of indebtedness has a positive SHAP value, indicating an increase in the likelihood of classifying a client as risky. Visualization of the SHAP study allows us to draw several important conclusions:

- the key risk factors were signs related to the level of income, the history of overdue payments and the number of open loans;
- the model demonstrates logical behavior, since a high financial burden or unstable payments really increase credit risk;

– The positive point is that the impact of the signs meets the expectations of financial experts, that is, the model is not only accurate, but also understandable.

For the in-depth analysis, the error matrix (confusion matrix) depicted in Table 5 was also used, which showed that the model has a high sensitivity to identifying risky clients, i.e. most potentially dangerous applications were identified correctly.

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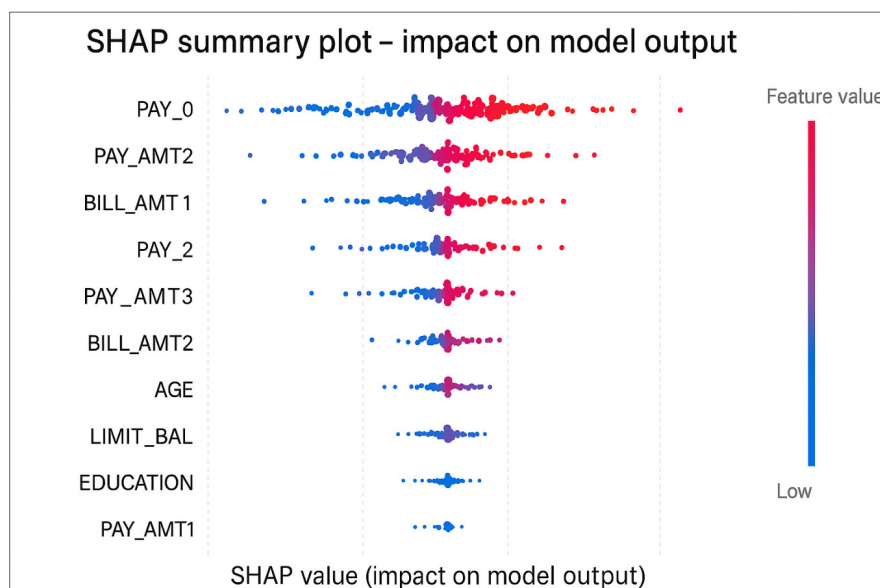


Figure 2. Graph of the influence of signs on the forecast

Table 6

Error matrix for a neural network

	Forecast: Reliable	Forecast: Risky
Fact: Reliable	321	45
Fact: Risky	28	106

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Based on this table, key indicators can be calculated: accuracy 84.8%; completeness 79.1%; F1 indicator: 74.4%. These values indicate a fairly high quality of the model, especially considering that in risk management tasks it is more important to minimize false negative results (i.e. not to miss a risky client).

In addition, the ROC curve shown in Fig. 2, demonstrates the relationship between sensitivity (level of true positive results) and specificity (level of false positives) of the model. The area under the curve (AUC) was 0.89, indicating the model’s high discriminatory capacity.

Therefore, the use of SHAP analysis, error matrix, and ROC curve allows not only to assess the accuracy of the model, but also to make it transparent to financial analysts and regulators. This is important

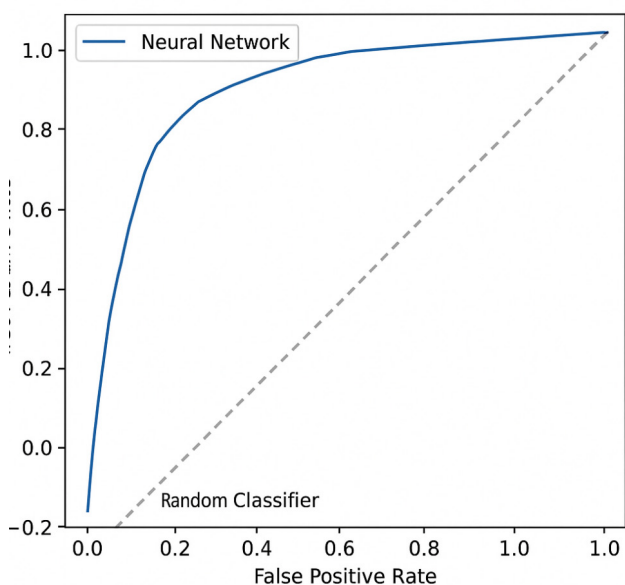


Figure 3. ROC curve of a neural network

for making informed management decisions in the banking sector.

4. Conclusions

In the course of the study, the opportunities, advantages and problems of using artificial intelligence in automated financial risk management systems were analyzed. The main attention was paid to the analysis of theoretical foundations, classification of financial risks, technical features of the implementation of intelligent systems, as well as practical modeling on the example of forecasting credit risks. General approaches to financial risk management are considered, their classification and features in modern economic conditions are determined.

The basic principles of building automated financial risk management systems are analyzed and the feasibility of introducing intelligent methods, in particular machine learning and neural networks, into financial analytics is substantiated.

A study of modern methods of artificial intelligence used for risk analysis and forecasting has been carried out. The features of deep learning models, decision trees, ensemble methods, as well as criteria for evaluating their effectiveness are considered. Particular attention is paid to the interpretation of models, which is an important factor for the implementation of AI in risk management practices in accordance with regulatory requirements.

A practical case was implemented to build a model for forecasting the credit risk of a bank client. Real data was pre-processed, several models were built and tested (random forest, neural network), and accuracy was estimated using metrics such as F1 score and ROC curve. In addition, the analysis of the importance of features using SHAP graphs is carried out and the architecture of the system that can be used to integrate such a model into a practical automated control system is substantiated.

In general, the results of the work confirm the high efficiency of using artificial intelligence methods for automated analysis and forecasting of financial risks. Such models can not only improve the accuracy of risk identification, but also ensure the efficiency of decision-making in financial institutions. At the same time, their implementation requires proper technical and organizational support, including the issues of interpretation, validation and adaptation to changes in the market environment.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ШТУЧНИЙ ІНТЕЛЕКТ В АВТОМАТИЗОВАНИХ СИСТЕМАХ УПРАВЛІННЯ ФІНАНСОВИМИ РИЗИКАМИ

Анотація. Метою представленої статті є дослідження застосування штучного інтелекту в автоматизованих системах управління фінансовими ризиками для підвищення точності, оперативності та ефективності прийняття управлінських рішень у фінансовій сфері. Дослідження полягає у комплексному вивченні теоретичних і методичних основ застосування штучного інтелекту в системах управління, аналізу сучасних підходів до класифікації та оцінки фінансових ризиків із використанням алгоритмів машинного навчання, формуванні архітектури системи підтримки прийняття рішень на основі моделей прогнозування, а також оцінці ефективності побудованих моделей за результатами симуляційного моделювання. У межах проведеного дослідження розроблено модель прогнозування кредитного ризику клієнтів банку, яка дозволяє здійснювати оцінку платоспроможності на основі історичних даних та сучасних методів машинного навчання. Методом дослідження є моделювання за допомогою інструментів машинного навчання, зокрема нейронних мереж і методів ансамблевого навчання (Random Forest), а також аналізування даних із використанням платформ для візуалізації результатів і оцінки ефективності моделей. Особливу увагу приділено підготовці даних, вибору релевантних ознак, оцінці точності моделей та побудові інтерпретованих візуалізацій, таких як SHAP-графіки, ROC-криві тощо. Результатом проведеного дослідження стало створення ефективної моделі прогнозування кредитного ризику, яка демонструє достатньо високий рівень точності класифікації та здатність до адаптації при зміні вхідних умов. Практичне значення дослідження полягає у можливості впровадження розробленої моделі до існуючих автоматизованих систем управління фінансовими ризиками банківських установ, що дозволить зменшити рівень кредитних втрат, підвищити фінансову стабільність і забезпечити більш точне управління ризиками. Такий підхід сприяє розвитку інтелектуальних фінансових систем, підвищенню рівня автоматизації управлінських рішень та зміцненню конкурентоспроможності фінансових установ у сучасних ринкових умовах.

Ключові слова: штучний інтелект, фінансові ризики, машинне навчання, кредитний ризик, нейронні мережі, автоматизована система управління, прогнозування, класифікація.

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THE ESG (ENVIRONMENTAL, SOCIAL, AND GOVERNANCE) CONCEPT IN MODERN ECONOMIC SCIENCE AND ITS ROLE IN SHAPING SUSTAINABLE DEVELOPMENT

Abstract. *The assessment of the role of the ESG (Environmental, Social, and Governance) concept is an important task for ensuring sustainable socio-economic development and strengthening the resilience of modern economic systems. At the same time, within contemporary economic science, there remains a lack of unified methodological approaches that allow for a comprehensive and objective evaluation of the impact of ESG factors on sustainable development outcomes. In this context, it is particularly relevant to consider the interaction of environmental, social, and governance components, as well as the system of external and internal factors that either stimulate or constrain sustainable transformation processes. An important scientific challenge is the improvement of analytical tools, methods, and stages for assessing ESG implementation, taking into account current global economic, environmental, and institutional changes.*

The study employs a set of theoretical and empirical methods that enable the achievement of the research objectives, including bibliometric analysis, statistical analysis, abstraction, synthesis, induction, and deduction. Bibliometric mapping using the VOSviewer tool is applied to identify key research trends and conceptual linkages in the scientific discourse on ESG and sustainable development. The empirical basis of the study relies on official statistical data from Eurostat, which reflect environmental and social dimensions of sustainable development, including greenhouse gas emissions, labour market indicators, and social inclusion metrics.

The results of the study confirm that ESG principles play a significant role in enhancing the sustainability of economic systems, improving corporate resilience, and supporting long-term socio-economic stability. The integration of ESG factors contributes to environmental responsibility, social inclusion, and governance quality, which together form the foundation for sustainable development. Consequently, ESG performance requires systematic monitoring and quantitative assessment at both corporate and macroeconomic levels.

The findings indicate an increasing need to develop and implement a new generation of public and corporate policies based on ESG principles, aimed at ensuring balanced economic growth, environmental protection, and social well-being. The proposed analytical approach may be useful for policymakers, investors, and corporate stakeholders, as it enables timely assessment of ESG impacts and supports the formulation of effective strategies for sustainable development in the future.

Keywords: *ESG, sustainable development, environmental responsibility, social inclusion, corporate governance, socio-economic stability, energy security.*

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1. Introduction

In the contemporary business landscape, which is characterized by rapid change and increasing complexity, Environmental, Social, and Governance (ESG) considerations have emerged as essential elements of corporate strategy. ESG refers to a framework that evaluates

a company's approach to environmental stewardship, social responsibility, and the quality of its governance practices. These dimensions are now widely recognized as critical benchmarks for measuring overall corporate effectiveness and long-term sustainability.

The environmental component of ESG addresses how organizations manage their interactions with the natural environment, including the efficient use of resources, waste reduction, and efforts to mitigate carbon emissions. The social aspect focuses on a company's relationships with employees, communities, and society at large, encompassing labor standards, community involvement, and respect for human rights. Governance, in turn, relates to the systems and processes that guide corporate decision-making, emphasizing transparency, accountability, board composition, executive remuneration, and engagement with stakeholders [1].

The growing importance of ESG in modern business extends beyond its contribution to environmental protection and social equity. It also plays a significant role in shaping long-term financial outcomes and strengthening corporate reputation. Empirical research indicates that companies with strong ESG performance often demonstrate greater market resilience and lower exposure to operational and reputational risks. Furthermore, as investors and consumers increasingly prioritize ethical conduct and environmental responsibility, ESG performance has become a decisive factor in attracting investment, customers, and skilled professionals.

The purpose of this paper is to comprehensively examine the role and relevance of ESG in today's business environment and to assess how the integration of ESG principles can enhance corporate sustainability and overall performance. The study begins by outlining the core concepts and structural elements of ESG, followed by an analysis of their relationship with long-term corporate sustainability objectives. Through selected case studies, the paper illustrates the practical implementation of ESG strategies and evaluates their effectiveness in real-world business contexts.

An important driver of the widespread adoption of the ESG approach is the strengthening of regulatory requirements and standards for non-financial reporting at both international and national levels. In many countries, companies are increasingly required to disclose information related to their environmental impact, social policies, and corporate governance practices. Such transparency enhances trust among investors, regulators, and society, while also enabling comparative analysis of corporate performance in the context of sustainable development.

Moreover, the integration of ESG principles into corporate governance frameworks fosters the development of a more responsible managerial culture and long-term strategic thinking. Companies that actively implement ESG practices tend to focus not only on short-term financial outcomes but also on creating long-term value for all stakeholders. This approach

improves business resilience and adaptability to global challenges, including climate change, social inequality, and ongoing transformations in labor markets.

In summary, ESG can be regarded as a comprehensive management tool that integrates economic, environmental, and social dimensions of corporate development. Its application contributes to enhanced competitiveness, risk mitigation, and sustainable growth in an increasingly globalized and regulated business environment. As a result, the ESG concept is becoming an integral element of strategic planning and decision-making in modern companies.

2. Materials and Methods

Within contemporary economic science, the ESG (Environmental, Social, Governance) concept is increasingly established as an integrated analytical paradigm that shapes the directions of sustainable development at the macro-, meso-, and micro-levels. Within this paradigm, the interconnection between ESG principles and energy security assumes particular significance, as energy security is no longer viewed solely as a techno-economic category but rather as a component of long-term socio-economic stability and environmental balance. Under current conditions, ESG-based approaches are being progressively incorporated into public energy policy, regulatory frameworks, and investment strategies, thereby forming a new logic for the development of the energy sector.

The implementation of ESG principles stimulates profound structural transformations of energy systems, notably through the expansion of renewable energy sources, modernization of network infrastructure, improvements in energy efficiency, and strengthening of institutional governance capacity. At the same time, energy market participants, adapting to these evolving requirements, are developing innovative operational models that integrate economic performance with climate neutrality, social responsibility, and transparency of managerial decision-making. This evolution of business models indicates a shift from traditional interpretations of energy security toward an ESG-oriented framework.

At the intersection of these processes, a comprehensive set of mechanisms for sustainable energy development is emerging. These mechanisms include ESG-based criteria for investment project selection, systems for assessing environmental and social risks, integrated indicators of energy security, as well as instruments of non-financial and public reporting. Collectively, these mechanisms ensure the alignment of energy policy objectives with broader sustainable development goals and enable the evaluation of transformation outcomes not only from an economic perspective but also from environmental and social viewpoints.

In order to identify key scientific categories, dominant conceptual approaches, and current research trends in the integration of ESG principles into energy security policy, a bibliometric analysis was conducted using the VOSviewer tool. Figure 1 presents an overlay

visualization of the scientific discourse, illustrating the interrelationships among core concepts, their evolution over time, and the priority directions of contemporary research in the context of sustainable development, ESG transformation, and energy security.

To clarify the essence of the ESG (Environmental, Social, and Governance) concept, it is fundamentally important to clearly define each of its components, as well as to disclose their content, significance, and role within the modern system of corporate governance and sustainable development. It is precisely the detailed examination of the environmental, social, and governance dimensions that enables a comprehensive assessment of the impact of business activities on the environment, society, and the quality of managerial processes.

Defining each ESG component makes it possible to avoid a formalistic approach to the implementation of sustainable development principles and ensures a transition from declarative commitments to systematic analysis and practical application of relevant instruments. In this context, the environmental component reflects the level of corporate responsibility for the use of natural resources and the minimization of negative environmental impacts; the social component characterizes a company’s relationships with employees, consumers, and society as a whole; and the governance component determines the quality of corporate governance, transparency of decision-making, and the effectiveness of control mechanisms.

Environmental Factors (E)

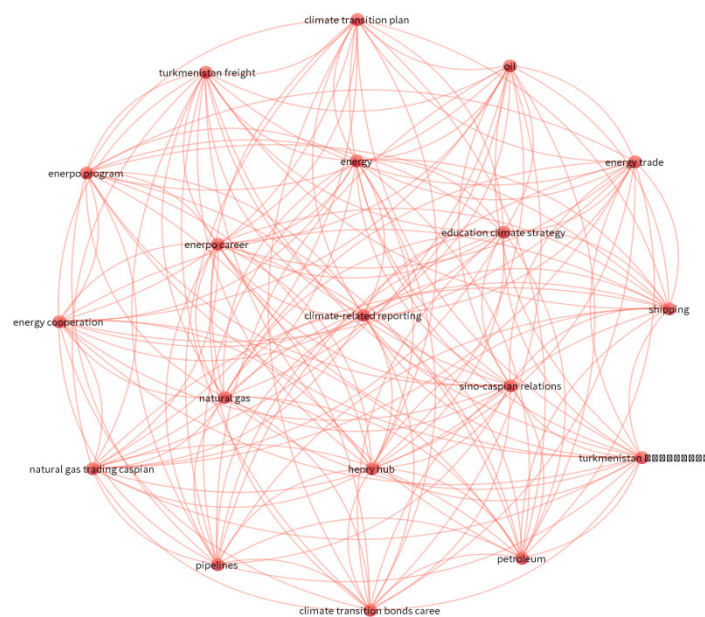
Environmental factors constitute a central component of the ESG framework and primarily address the influence of corporate operations on the natural environment. In the face of escalating global challenges

such as climate change, biodiversity degradation, depletion of natural resources, and environmental pollution, the effective management of environmental impacts has become a critical criterion for evaluating corporate sustainability. Among these challenges, climate change stands out as one of the most pressing global issues, largely driven by greenhouse gas emissions generated by business activities.

To mitigate their environmental impact, companies are increasingly required to implement measures aimed at reducing their carbon footprint. These measures include the transition to renewable energy sources, improvements in energy efficiency, and investments in initiatives designed to compensate for unavoidable emissions. In parallel, responsible resource management plays a vital role and involves the efficient use of water, energy, and raw materials. This requires the adoption of sustainable sourcing policies, optimization of production processes, minimization of material losses, and, where feasible, the application of circular economy principles that promote reuse and recycling [2].

Waste generation is another significant consequence of corporate activity with substantial environmental implications. By introducing systematic waste management practices—such as waste reduction, recycling programs, and environmentally sound disposal methods—companies can substantially limit their negative ecological effects. Furthermore, the reduction of carbon emissions not only contributes to addressing global climate concerns but also strengthens a firm’s competitive position, as environmentally conscious consumers and investors increasingly favor businesses with low-carbon strategies.

As illustrated in Table 1, organizations can meaningfully decrease their ecological footprint by



Picture 1. Overlay Visualization of the Scientific Discourse on the Implementation of ESG Principles in the Context of Energy Security and Sustainable Development

Source: Developed by the author based on data from The Lens database using VOSviewer

implementing a wide range of environmentally responsible practices. These practices extend beyond basic reductions in energy consumption and waste generation to encompass broader strategies for managing environmental impacts. The adoption of clean energy solutions, including solar and wind power, enables a significant decrease in greenhouse gas emissions. Improvements in energy efficiency can be achieved through the use of advanced energy-saving technologies in both production facilities and office environments, such as LED lighting systems, energy-efficient equipment, and optimized heating, ventilation, and air-conditioning systems.

In addition, smart energy management systems allow companies to monitor and regulate energy consumption more effectively by employing digital tools, sensors, and data analytics to reduce unnecessary energy losses. Environmentally responsible procurement policies further support sustainability objectives by prioritizing eco-friendly materials and selecting suppliers that adhere to sustainable production standards.

Enhancing supply chain performance plays a crucial role in reducing the environmental footprint of business operations. This can be achieved by upgrading logistics and transportation systems to minimize carbon emissions, including the selection of energy-efficient transport modes and the reduction of unnecessary long-distance deliveries. Close collaboration and transparent communication with suppliers are equally important, as they help ensure compliance with environmental standards and motivate partners to introduce sustainable practices throughout the supply chain.

The implementation of circular economy principles encourages the extension of product life cycles through reuse, repair, and remanufacturing, thereby decreasing the demand for raw materials and limiting waste generation. Effective waste management within organizations requires the introduction of structured waste segregation and recycling systems, including separate collection streams and composting of organic waste. In addition, reducing the use of excessive packaging and single-use products—particularly those made from non-recyclable materials—supports the transition toward sustainable packaging alternatives.

Responsible water resource management is another essential component of environmental sustainability. Companies can reduce water consumption by applying water-efficient technologies in production processes

and facility operations, such as low-flow sanitary equipment and optimized irrigation systems. The collection and reuse of rainwater for technical purposes, including cleaning and landscape maintenance, further contributes to water conservation. Protecting water quality also remains a priority, requiring the adoption of advanced wastewater treatment technologies to prevent contamination of natural water bodies [3].

Sustainable development efforts extend to the design and operation of office and production facilities. The construction or modernization of buildings in accordance with green building standards involves the use of environmentally friendly materials, improved thermal insulation, and the effective use of natural lighting. At the product development stage, ecological design principles emphasize the selection of sustainable materials and the creation of products that can be easily disassembled and recycled at the end of their life cycle. Finally, biodiversity protection must be considered in corporate decision-making, as business activities can significantly affect natural ecosystems. Measures aimed at preserving and restoring biodiversity help mitigate these impacts and support long-term ecological balance [4].

Thus, the environmental dimension of ESG encompasses a wide range of managerial decisions and practices aimed at reducing the negative impact of business activities on the natural environment. At the same time, a qualitative description of corporate environmental initiatives needs to be complemented by quantitative indicators that allow for an objective assessment of the scale of environmental challenges and the effectiveness of implemented measures. It is precisely statistical data that make it possible to move from a declarative level of environmental responsibility to measurable outcomes.

For this purpose, the use of official statistics of the European Union, particularly data provided by Eurostat, is highly appropriate, as they reflect key trends in the impact of economic activity on the natural environment. Indicators related to greenhouse gas emissions, the structure of energy consumption, waste generation and recycling, water use, and the deployment of renewable energy sources enable a quantitative characterization of the environmental footprint of business activities in European countries.

The analysis of these indicators makes it possible not only to trace the dynamics of environmental

Table 1

Environmental Effects of Corporate Activities and Mitigation Approaches

Environmental Dimension	Company Case	Degree of Impact	Key Sustainability Actions
Atmospheric emissions (GHG)	Longi Green Energy	High	Transition to renewable energy sources and reduction of carbon intensity
Efficiency of natural resource use	Kweichow Moutai	Moderate	Supply chain optimization and improved resource allocation
Waste generation and recycling	Shui Jing Fang	Moderate	Adoption of circular economy practices and waste reuse programs

Source: Combination of indicators proposed by the author

changes within the EU, but also to align corporate environmental practices with broader European sustainable development trends. Such an approach provides a deeper understanding of the role of business in achieving the environmental objectives of the European Union and creates an empirical basis for assessing the effectiveness of ESG principle implementation in the modern economy.

Against this background, the assessment of environmental responsibility within the ESG framework requires a shift from qualitative descriptions of corporate practices to their empirical verification. Among the wide range of environmental indicators, greenhouse gas emissions represent one of the most informative and internationally comparable measures of the environmental impact of economic activity. This indicator directly reflects the contribution of business operations to climate change and serves as a core benchmark for evaluating progress toward decarbonization and climate neutrality.

Therefore, to substantiate the environmental dimension of ESG with empirical evidence, the following section focuses on the analysis of greenhouse gas emissions in the European Union based on official Eurostat statistics. This approach enables the alignment of corporate-level environmental responsibility with macroeconomic sustainability trends and contributes to a more objective evaluation of the role of ESG principles in fostering sustainable development.

According to Eurostat, total greenhouse gas emissions in the European Union amounted to approximately 3.66 billion tonnes of CO₂ equivalent in 2022, while in 2023 they declined to about 3.4 billion tonnes of CO₂ equivalent. These absolute values confirm a sustained downward trend in emission levels and demonstrate tangible progress in the decarbonization of the EU economy. Such dynamics constitute a key indicator of the effective implementation of the environmental component of the ESG framework as an integral element of the sustainable development strategy, as illustrated in Table 2.

Social Factors (S)

Social factors within the ESG framework focus on the ways in which a company influences social well-being and contributes to societal development through its business activities. This dimension encompasses

respect for human rights, employment conditions, employee relations, community engagement, and broader social accountability. In the context of sustainable development, social factors extend beyond ethical considerations and represent a strategic foundation for long-term corporate stability and value creation.

Respect for human rights constitutes a core element of the social dimension. Companies are expected to safeguard fundamental employee rights, prevent exploitative labor practices, and ensure that similar standards are upheld throughout their supply chains. This includes rejecting child labor, forced labor, and unsafe working conditions, while actively promoting fair labor standards and improved living conditions. A responsible approach to human rights requires not only compliance with legal norms but also proactive initiatives aimed at enhancing social conditions at both local and global levels [5].

Equally important are labor practices that promote employee well-being and organizational sustainability. These practices include providing safe and healthy workplaces, ensuring equitable remuneration, respecting freedom of association and collective bargaining rights, and preventing discrimination in all its forms. By fostering inclusive and diverse work environments, companies can support employee development, enhance job satisfaction, and improve overall productivity. Such practices contribute to workforce stability and reinforce the company's social legitimacy [1].

Corporate engagement with local communities represents another key aspect of social responsibility. Beyond traditional philanthropic activities, meaningful community involvement entails collaboration with local stakeholders to support education, vocational training, employment creation, and socially oriented development initiatives. As illustrated in Table 3, companies can actively contribute to community development by investing in human capital and supporting projects that generate long-term social value. These efforts strengthen relationships with local communities and enhance corporate reputation.

Social performance also plays a decisive role in shaping brand perception and maintaining durable relationships with customers and other stakeholders. Fair compensation systems, secure working conditions, opportunities for professional growth, and respect for employee rights create a positive organizational

Table 2

Dynamics of Greenhouse Gas Emissions in the European Union as an Environmental ESG Indicator

Indicator / Year	2021	2022	2023	2024
Total GHG emissions, EU (million tonnes of CO ₂ equivalent)	3 780	3 660	3 400	3 320
Annual change (million tonnes of CO ₂ eq.)	–	–120	–260	–80
Trend interpretation	Post-pandemic recovery	Moderate decline	Accelerated reduction	Stabilisation of decline

Source: Author compilation based on data from Eurostat (Statistical Office of the European Union), available at: <https://ec.europa.eu/eurostat>

Table 3

Social Dimension of ESG: Key Areas of Corporate Social Impact and Response Measures

Social ESG Dimension	Illustrative Corporate Case	Degree of Social Impact	Strategic Social Response Measures
Employment conditions and labor protection	Midea Group	High	Implementation of occupational health and safety systems; enforcement of fair labor standards
Community engagement and social investment	Alibaba Group	Medium	Support for local education initiatives and community-based development programs
Human rights compliance in business operations	Tencent Holdings	High	Strengthening human rights due diligence and monitoring across supply chains

Source: Combination of indicators proposed by the authors

climate that directly influences employee engagement and performance [6]. Furthermore, policies promoting diversity and inclusion enhance creativity and innovation while fostering a sense of belonging and organizational commitment among employees.

Finally, responsible supply chain management is essential to ensuring social sustainability beyond a company’s direct operations. By enforcing compliance with labor and human rights standards across suppliers and business partners, companies mitigate reputational risks and reinforce ethical business conduct. Complementary initiatives—such as employee wellness programs, flexible working arrangements, and continuous training—further strengthen employee engagement and social resilience, reinforcing the social pillar of ESG as a key driver of sustainable corporate development.

Within the system of Sustainable Development Goal (SDG) indicators developed by Eurostat, a number of statistical measures directly capture the social dimension of sustainable development. In particular, these indicators include the risk-of-poverty rate after social transfers, which reflects the effectiveness of social protection mechanisms; labour market participation and employment rates, which characterize access to decent work and economic inclusion; as well as indicators related to educational attainment and social inclusion, measuring access to quality education and opportunities for human capital development.

The availability of these indicators provides a robust empirical basis for assessing the role of social factors within the ESG framework. By quantifying outcomes related to income distribution, employment, and education, Eurostat data enable an objective evaluation of how business activities and public policies influence

social welfare and living standards. Consequently, SDG-related social indicators serve as essential tools for linking the Social pillar of ESG with measurable progress toward sustainable development, allowing researchers to move beyond normative assessments toward evidence-based analysis of social impacts.

The analysis of socio-economic indicators within the SDG-monitoring framework demonstrates that the social dimension constitutes a fundamental pillar of sustainable development. Empirical evidence based on Eurostat data confirms that social sustainability can be quantitatively assessed through indicators reflecting poverty risk, labour market inclusion, access to education, and material well-being. The persistence of a relatively high share of the population at risk of poverty or social exclusion—despite improvements in employment and educational attainment—highlights the structural nature of social challenges in the European Union.

At the same time, positive dynamics in labour market participation and rising levels of tertiary education attainment indicate progress in human capital development and economic inclusion, which are essential prerequisites for long-term economic resilience. These trends suggest that sustainable development cannot be achieved solely through economic growth or environmental improvements, but requires balanced advancement in social outcomes, including decent work, income security, and equal access to opportunities.

Therefore, the Social component of ESG plays a critical role in translating economic activity into broader societal benefits. By linking measurable social indicators with policy and corporate practices, the ESG framework enables an integrated approach to sustainable development, in which social inclusion, workforce quality, and human well-being are treated

Table 4

Trends in Key Social SDG Indicators in the European Union

Indicator	2018	2019	2020	2021	2022	2023	2024
Population at risk of poverty or social exclusion	21.7%	21.1%	21.6%	21.7%	21.6%	21.4%	21.0%
Employment rate (20–64, EU)	71.9%	72.7%	71.7%	73.0%	74.6%	75.3%	75.8%
Tertiary education attainment (25–34)	38.7%	39.6%	40.7%	41.5%	42.0%	43.1%	45.1%

Source: Author compilation based on data from Eurostat (Statistical Office of the European Union), available at: <https://ec.europa.eu/eurostat>

as strategic drivers of long-term sustainability rather than secondary outcomes. This confirms the necessity of incorporating social indicators into sustainability assessments to ensure comprehensive and evidence-based evaluation of development progress.

Governance Factors (G)

The governance dimension of the ESG framework refers to the system of internal rules, procedures, and institutional arrangements that shape how a company is directed and controlled. It focuses on the quality of decision-making processes, the distribution of responsibilities, and the mechanisms that ensure transparency, accountability, and ethical conduct within an organization. Effective corporate governance is a fundamental prerequisite for operational stability and plays a decisive role in fostering confidence among investors, customers, regulators, and society at large.

Transparency represents a cornerstone of sound governance, as it requires companies to provide clear and reliable information regarding their financial performance, strategic objectives, ownership structure, and risk management practices. Open disclosure reduces information asymmetry between management and stakeholders, thereby enhancing trust and enabling more informed investment and consumption decisions. In this context, transparency is not limited to financial reporting but also extends to non-financial disclosures related to sustainability risks and corporate conduct.

Accountability is another essential element of governance, ensuring that corporate leaders are held responsible for their decisions and actions. Clearly defined roles, internal control systems, and oversight mechanisms contribute to aligning managerial behavior with legal requirements and ethical standards. When accountability structures are effectively implemented, companies are better positioned to prevent misconduct, address operational failures, and manage risks in a timely and responsible manner.

The composition and functioning of the board of directors significantly influence the effectiveness of governance arrangements. Board independence and diversity—encompassing professional experience, gender, cultural background, and expertise—enhance the board’s capacity to critically evaluate management decisions and identify strategic and operational risks.

A diverse and independent board is more likely to provide balanced oversight and to integrate long-term considerations into corporate strategy, including social and environmental responsibilities [7].

As summarized in Table 3, a well-designed governance framework ensures that corporate decisions reflect the interests of a broad range of stakeholders rather than focusing solely on short-term financial outcomes. Transparent and accountable governance structures improve risk identification and mitigation, thereby reducing the likelihood of adverse financial, legal, and reputational consequences [8]. Moreover, investors increasingly recognize strong governance practices as an indicator of long-term value creation, which can enhance a company’s attractiveness to responsible and sustainability-oriented capital.

Corporate governance also has a direct impact on brand perception and organizational legitimacy. Companies that demonstrate responsible leadership and regulatory compliance are more likely to gain public trust and maintain durable relationships with stakeholders. By ensuring adherence to applicable laws and ethical norms, robust governance mechanisms help prevent compliance failures that could result in significant economic losses or damage to corporate reputation [9].

Overall, effective governance serves as an integrative element within the ESG framework, supporting the alignment of economic performance with social and environmental objectives. By embedding transparency, accountability, and inclusive decision-making into corporate structures, governance practices contribute to long-term resilience and play a crucial role in advancing sustainable development [10].

As presented in Table 4, corporate governance effectiveness is shaped by multiple institutional drivers, including decision-making transparency, board composition, and remuneration structures. These factors collectively influence managerial accountability and the long-term sustainability of corporate performance.

As shown in Table 6, a comparative analysis of ESG disclosures from six internationally recognized companies—based on their most recent sustainability or ESG reports—demonstrates a high degree of convergence in ESG priorities, while also revealing sector-specific and governance-related differences. Across all analyzed companies, environmental responsibility is positioned

Table 4

Key Corporate Governance Drivers and Their Influence on ESG Performance

Governance Dimension	Illustrative Corporate Case	Degree of Influence	Governance Enhancement Mechanisms
Transparency of managerial decision-making	COFCO Sugar	High	Expansion of non-financial and strategic disclosures; improved reporting clarity
Diversity and independence of the board	Alibaba Group	Medium	Strengthening board composition through gender, professional, and experiential diversity
Executive remuneration and incentive alignment	Tencent Holdings	Medium	Development of balanced compensation frameworks linked to performance and sustainability goals

Source: Combination of indicators proposed by the author

as a central strategic objective, primarily reflected through commitments to energy efficiency, greenhouse gas emission reduction, and the gradual transition toward renewable energy sources. These measures are framed not only as environmental imperatives but also as instruments for enhancing long-term operational resilience.

In the environmental dimension, the companies consistently report initiatives aimed at minimizing their ecological footprint, including investments in clean energy technologies, optimization of production processes, and implementation of internal carbon management systems. However, the depth of environmental integration varies depending on industry characteristics and capital intensity. Energy-intensive and manufacturing-oriented firms tend to report higher upfront investment requirements, whereas digital and service-based companies emphasize indirect emission reductions through energy-efficient data centers and supply chain management.

The social component of ESG disclosures highlights a strong focus on human capital development, employee well-being, occupational health and safety, and diversity and inclusion policies. In addition, several companies place growing emphasis on broader societal engagement, including digital inclusion, consumer data protection, and public welfare initiatives. These efforts reflect an expanding understanding of corporate social responsibility, extending beyond internal workforce considerations to encompass user rights, community development, and social resilience.

With regard to governance, all six companies underscore the importance of transparency, ethical conduct, and internal control mechanisms. Key governance

practices include enhanced disclosure of non-financial information, independent board oversight, risk management frameworks, and compliance systems designed to address increasingly complex regulatory environments. Governance is presented as a critical enabling factor that ensures the credibility and effectiveness of environmental and social initiatives.

Despite the demonstrated commitment to ESG integration, the analysis also identifies several common implementation challenges. These include rising operational and compliance costs, particularly related to maintaining high environmental standards, adapting to heterogeneous regulatory regimes across jurisdictions, and ensuring the accuracy and consistency of ESG data collection. In many cases, environmentally sustainable operations require substantial initial capital investments, while comprehensive ESG reporting demands advanced data management systems and cross-departmental coordination.

At the same time, the examined ESG reports point to significant long-term opportunities arising from ESG adoption. These opportunities include enhanced corporate reputation and brand value, improved risk mitigation through proactive environmental and social governance, and strengthened market positioning by responding to increasing demand for sustainable products and services from investors and consumers. Collectively, the findings suggest that ESG practices, when effectively implemented, function not as a cost burden but as a strategic asset contributing to sustainable development and long-term value creation.

As summarized in Table 6, the comparative analysis of ESG practices across six global companies indicates that environmental responsibility, social

Table 6

Performance Comparative Analysis of ESG Practices in Selected Global Companies

Company	Environmental Focus	Social Focus	Governance Focus	Key ESG Challenges	Long-Term ESG Opportunities
Apple Inc.	Renewable energy use; carbon neutrality targets	Employee well-being; supply chain labor standards	Transparency; board oversight	Supply chain emissions; compliance complexity	Brand trust; innovation leadership
Microsoft	Carbon-negative strategy; energy efficiency	Digital inclusion; employee development	Data governance; risk management	High investment costs; data tracking	Market leadership; risk reduction
Amazon	Emission reduction initiatives; sustainable logistics	Workforce safety; community programs	Compliance systems; disclosure	Operational scale; regulatory scrutiny	Efficiency gains; investor confidence
Google (Alphabet)	Renewable energy procurement; AI for sustainability	User data protection; diversity initiatives	Ethical AI governance; transparency	Data center energy demand	Competitive differentiation
Siemens	Energy-efficient technologies; decarbonization solutions	Workforce training; occupational safety	Institutional governance frameworks	Capital-intensive transformation	Industrial sustainability leadership
Shell	Energy transition investments; emission reduction pathways	Community engagement; workforce transition	Regulatory compliance; reporting standards	Transition risks; stranded assets	Strategic repositioning; resilience

Source: compiled by the author based on publicly available ESG and sustainability reports of the selected companies

engagement, and governance quality are increasingly treated as interdependent components of corporate strategy, reinforcing the role of ESG as a key driver of sustainable development.

4. Conclusions

Thus, the analysis demonstrates that the ESG (Environmental, Social, and Governance) framework plays a crucial role in shaping sustainable development across economic sectors by enhancing environmental responsibility, social inclusion, and governance

quality. A comprehensive evaluation of sustainability outcomes requires a multidimensional system of ESG indicators that reflects the sensitivity of development trajectories to economic shocks, regulatory changes, and structural transformations. The observed dynamics of ESG performance underline the growing need for a renewed public policy approach focused on the systematic integration of ESG principles into economic and energy strategies, enabling long-term resilience, balanced growth, and the transition toward sustainable development models in modern economies.

ADDITIONAL INFORMATION

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CONFLICT OF INTEREST

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КОНЦЕПЦІЯ ESG (ENVIRONMENTAL, SOCIAL, GOVERNANCE) У СУЧАСНІЙ ЕКОНОМІЧНІЙ НАУЦІ ТА ЇЇ РОЛЬ У ФОРМУВАННІ СТАЛОГО РОЗВИТКУ

Анотація. Оцінювання ролі концепції ESG (Environmental, Social, Governance) є важливим завданням для забезпечення сталого соціально-економічного розвитку та зміцнення стійкості сучасних економічних систем. Водночас у межах сучасної економічної науки досі відсутні уніфіковані методологічні підходи, які б дозволяли здійснювати комплексну та об'єктивну оцінку впливу ESG-факторів на результати сталого розвитку. У цьому контексті особливо актуальним є врахування взаємодії екологічної, соціальної та управлінської складових, а також системи зовнішніх і внутрішніх чинників, які або стимулюють, або, навпаки, стримують процеси сталих трансформацій. Важливим науковим завданням є вдосконалення аналітичних інструментів, методів і етапів оцінювання імплементації ESG з урахуванням сучасних глобальних економічних, екологічних та інституційних змін.

У дослідженні використано сукупність теоретичних і емпіричних методів, що дали змогу досягти поставлених цілей, зокрема бібліометричний аналіз, статистичний аналіз, абстрагування, синтез, індукцію та дедуцію. Для ідентифікації ключових наукових трендів і концептуальних взаємозв'язків у науковому дискурсі щодо ESG та сталого розвитку застосовано бібліометричне картування з використанням інструменту VOSviewer. Емпіричну основу дослідження становлять офіційні статистичні дані Eurostat, які відображають екологічний і соціальний виміри сталого розвитку, зокрема показники викидів парникових газів, ринку праці та соціального включення.

Результати дослідження підтверджують, що принципи ESG відіграють суттєву роль у підвищенні стійкості економічних систем, зміцненні корпоративної адаптивності та забезпеченні довгострокової соціально-економічної стабільності. Інтеграція ESG-факторів сприяє формуванню екологічної відповідальності, соціальної інклюзії та високої якості корпоративного управління, які в сукупності становлять основу сталого розвитку. У зв'язку з цим показники ESG потребують системного моніторингу та кількісної оцінки як на корпоративному, так і на макроекономічному рівнях.

Отримані висновки свідчать про зростаючу потребу у формуванні та реалізації нового покоління державних і корпоративних політик, заснованих на принципах ESG, що спрямовані на забезпечення збалансованого економічного зростання, охорони довкілля та соціального добробуту. Запропонований аналітичний підхід може бути корисним для органів державної влади, інвесторів і корпоративних стейкхолдерів, оскільки він дає змогу своєчасно оцінювати вплив ESG та підтримує розроблення ефективних стратегій сталого розвитку в майбутньому.

Ключові слова: ESG, сталий розвиток, екологічна відповідальність, соціальна інклюзія, корпоративне управління, соціально-економічна стабільність, енергетична безпека.

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DEVELOPING A DRONE ECONOMY: A METHODOLOGICAL FRAMEWORK

Abstract. *The emergence of the drone economy represents a transformative element of modern digitalized national economies, integrating unmanned aerial vehicles (UAVs) into strategic industries such as energy, agriculture, logistics, infrastructure, and defense. This study proposes a comprehensive methodological framework for assessing the development of the drone economy, addressing its technological, economic, regulatory, industrial, and sustainable development dimensions. The research employs a systems approach, combining literature review, system-structural analysis, comparative assessment, statistical normalization, and expert judgment to construct an integral index of drone economy development (DEI). In addition, a sector-specific efficiency indicator is introduced to evaluate the impact of UAV implementation on productivity, cost reduction, safety, and environmental, social, and governance (ESG) outcomes. The proposed indicators enable a holistic assessment of UAV integration, capturing both direct and indirect effects, as well as structural and institutional constraints. The framework also facilitates cross-country and cross-sectoral comparisons and provides guidance for policymakers, industry stakeholders, and investors in identifying priority areas for fostering the drone economy. The findings highlight the importance of combining technological adoption with ESG principles to achieve sustainable, efficient, and socially responsible industrial transformation. By integrating drone technologies into strategic sectors, countries can enhance competitiveness, optimize resource utilization, and promote digital and green growth. The study contributes to the literature by offering a systematic tool for evaluating the multi-dimensional impact of UAV adoption and establishing a foundation for further research on the role of drones in economic development and sustainable industrial ecosystems.*

Keywords: *drone economy, UAV integration, strategic industries, sustainable development, ESG framework, digital transformation, technological innovation*

1. Introduction

The formation of the drone economy is one of the key components of the digital transformation of modern national economies, which is especially relevant in the context of global challenges related to ensuring sustainable development, increasing resource efficiency and strengthening economic security. The use of UAVs in strategic industries contributes to the optimization of production processes, reducing costs, increasing safety and minimizing negative environmental impacts.

In modern conditions, the drone economy is considered not only as a technological phenomenon, but as a complex socio-economic ecosystem that integrates digital technologies, institutional mechanisms, innovative business models and principles of sustainable development [1].

It should be noted that global processes of technological transformation are significantly changing approaches to the development of strategic industries in leading countries of the world. Under the influence of digitalization, automation and the introduction of intelligent systems, the role of traditional production factors is being rethought and new models of industrial policy are being formed. In these conditions, strategic industries, in particular the defense-industrial complex, energy, transport and logistics infrastructure, agro-industrial and mining and



metallurgical sectors, are increasingly considered as platforms for the implementation of high-tech solutions capable of ensuring the long-term competitiveness of national economies.

One of the key elements of modern technological transformation is unmanned aircraft systems, which in foreign practice go beyond military use and are actively integrated into civil and industrial processes. In countries with a developed innovation infrastructure, UAVs are used as a tool for increasing the efficiency of production facility management, monitoring critical infrastructure, ensuring security and optimizing resource use [2]. Thus, unmanned technologies are becoming a component of broader industrial ecosystems that combine physical assets with digital platforms for data collection and analysis [3].

In recent years, the scientific literature has seen a significant increase in the number of studies devoted to the use of unmanned aerial vehicle (UAV) in various industries, in particular in the context of technological transformation of strategic sectors. An important source of generalization of current trends are thematic special issues of the international journal “Drones”, which focus on critical industrial applications of UAVs, including inspection, maintenance, safety monitoring and assessment of the environmental condition of facilities with increased risk to people and equipment (for example, nuclear or oil facilities) — this direction emphasizes the importance of unmanned technologies in ensuring the safety and efficiency of industrial systems in foreign practice.

Separate review works focus on the technical aspects of the introduction of UAVs into industrial operations. Thus, works analyzing the architecture of systems for real-time surface inspection using drone swarms demonstrate that the coordination of several UAVs using the Internet of Things (IoT) and optimization algorithms allows you to automate complex processes of monitoring the state of infrastructure, which is important for large-scale industrial facilities — from energy networks to buildings [4]. This approach corresponds to the global trends of digital transformation of production and Industry 4.0, where automated systems and drone platforms act as a source of operational data for management decisions. Another area of research is devoted to the inspection and monitoring of large infrastructure facilities in industrial conditions. Comprehensive literature reviews show that unmanned systems can significantly reduce time and financial costs of inspection, increase occupational safety, and improve the quality of technical diagnostics compared to traditional methods — such conclusions are contained in reviews of works investigating unmanned inspections and non-destructive testing of large industrial facilities and structures [5].

Considerable attention is paid to the integration of UAVs with data processing systems, in particular in combination with electronic sensor systems and artificial intelligence. An analysis of recent research with an emphasis on automatic data processing and

autonomous control demonstrates that the use of predictive navigation algorithms, deep learning and complex controllers can significantly improve the efficiency and accuracy of industrial missions performed by drones — this is important for complex sectors such as energy and manufacturing [6; 7; 8]. It should be noted that a number of scientific works consider the monitoring of energy infrastructure — from photovoltaic and wind power plants to thermal networks and power lines. Aviation platforms with multi-sensor sets allow for regular inspections of the technical condition of energy system elements, which meets the priorities of the digital transformation of the energy sector in the EU and the USA and contributes to increasing its reliability and resilience to man-made threats [9]. However, a review of foreign research also indicates the existence of significant technological and regulatory barriers. Thus, the issues of flight autonomy in complex industrial conditions, localization within facilities, processing of large data sets in real time, and integration with existing control systems stand out as the main technical challenges that require standards for the widespread implementation of UAVs in industrial sectors.

Foreign experience in the development of strategic industries shows that unmanned aerial vehicle are considered an important element of technological transformation aimed at increasing the efficiency, safety and sustainability of production systems [10]. In leading countries of the world, UAVs are integrated into long-term industrial development strategies as a component of digital infrastructures that combine physical assets with analytical and management platforms.

In general, it should be noted that the formation of the drone economy is a complex and multi-level process that encompasses not only the introduction of unmanned aerial vehicles (UAVs) into production and service processes, but also the creation of an appropriate institutional, technological and regulatory ecosystem. In leading countries of the world, drones are already transforming the functioning of strategic industries, in particular energy, the agricultural sector, transport and logistics, the defense industry, infrastructure and environmental monitoring.

The analysis of contemporary research indicates that comprehensive approaches to the formation of the drone economy are still in the early stages of development. Existing studies are predominantly focused on assessing the efficiency of unmanned aerial vehicles (UAVs) within specific sectors. In particular, the literature demonstrates significant economic effects from the application of UAVs in agriculture, logistics, and infrastructure, as evidenced by analytical reports of international organizations and consulting companies. At the same time, there is a clear lack of integrated methodological tools for assessing the overall level of development of the drone economy. Most current studies tend to concentrate on isolated dimensions of UAV implementation — technological, economic, or regulatory — which limits the ability to form a holistic understanding of the drone economy as a systemic

phenomenon. In contrast, the drone economy should be considered as a multidimensional ecosystem characterized by the interaction of technological solutions, market mechanisms, institutional frameworks, and sustainable development factors. This perspective is consistent with the modern paradigm of digital transformation, where value creation is driven by the integration of heterogeneous components into a unified system.

Given the above, this study employs a methodological approach aimed at developing a composite indicator for assessing the level of development of the drone economy. The proposed approach is based on the integration of multiple dimensions and is designed to:

- provide a comprehensive assessment of the drone economy development level;
- enable cross-country and cross-sectoral comparisons;
- identify structural weaknesses and priority areas for development;
- account for the contribution of drone technologies to the achievement of sustainable development goals.

2. Materials and Methods

This study develops a methodological framework for assessing the formation and development of a drone economy as an emerging component of modern economic systems. The research is based on a combination of theoretical, empirical, and quantitative methods aimed at identifying key structural elements of the drone economy and constructing an integrated assessment tool.

The research adopts a systems approach, which allows the drone economy to be considered as a complex, multi-level ecosystem integrating technological, economic, social, environmental, and infrastructural components. This approach is complemented by the principles of sustainable development, ensuring that the proposed framework captures the interdependence between economic efficiency, social responsibility, and environmental sustainability. In addition, a comparative analysis of existing economic concepts (including digital economy, Industry 4.0, and green economy) is applied to justify the positioning of the drone economy as a distinct and integrative development paradigm.

To achieve the research objectives, the following methods are employed:

- *literature review and content analysis* — to identify existing approaches to defining and measuring technology-driven economic systems and to conceptualize the notion of a drone economy;
- *system-structural analysis* — to determine the key components and internal relationships within the drone economy ecosystem;
- *comparative analysis* — to assess similarities and differences between the drone economy and related economic paradigms;
- *statistical normalization methods* — to ensure comparability of heterogeneous indicators;

- *index method* — to construct an integrated indicator reflecting the overall level of drone economy development;
- *expert judgment* — to determine weighting coefficients for individual indicators.

The proposed methodology is subject to certain limitations, including data availability constraints, potential subjectivity in assigning weights, and differences in national statistical systems. However, these limitations do not undermine the applicability of the framework but indicate directions for further refinement.

3. Results and Discussion

In contemporary academic discourse, the concept of the “drone economy” does not yet have a universally accepted definition, but it is actively emerging through research on the unmanned aerial vehicle (UAV) market and its impact on economic processes. Most international studies focus not on the term itself, but on the economic effects of drone adoption across various industries. Market reports emphasize that UAVs are transforming traditional business models, creating new economic segments and generating significant economic benefits [11]. The commercial drone sector, including logistics, agriculture, and infrastructure monitoring, is rapidly expanding, forming new service markets and digital solutions [12].

Several researchers [13] regard UAVs as a disruptive technology capable of radically changing operational processes in multiple economic sectors. In particular, their role in enhancing efficiency, automating processes, and creating competitive advantages for enterprises is highlighted. At the same time, a practical dimension of the so-called “drone ecosystem” [14; 15; 16] is emerging, encompassing not only drone manufacturing but also software, data analytics, service provision, and flight management infrastructure. Analytical reports also note that drones significantly increase business process efficiency, reduce costs, and improve data quality for managerial decision-making [17]. For example, in agriculture, drones optimize resource usage and increase crop yields, while in infrastructure sectors, they reduce maintenance and inspection costs. Moreover, research highlights the creation of new labor markets and professions associated with drone development, maintenance, and data analytics [18].

From the authors’ perspective, the “drone economy” can be defined as the set of economic relations, institutions, and activities arising from the development, production, implementation, and utilization of UAVs, as well as the processing and commercialization of the data they generate, aimed at enhancing efficiency, competitiveness, and sustainable development of economic systems.

As a new direction in economic development, the drone economy is characterized by a complex, multi-level structure that integrates technological, production, service, and institutional components into a single system. Its formation occurs within the context of

digitalization, Industry 4.0, and the increasing role of data as a key economic resource. Unlike traditional sectoral models, the drone economy exhibits a pronounced ecosystemic nature, encompassing a wide range of interconnected actors and processes. We propose an ecosystemic approach to the structure of the drone economy, whose main components are:

- UAV manufacturing;
- Service sector (Drone-as-a-Service, DaaS);
- Data analytics and processing;
- Infrastructure;
- R&D sector.

The first fundamental element is UAV manufacturing, which includes enterprises engaged in the development and production of hardware: drones, sensors, cameras, navigation systems, and flight control software-hardware complexes. This segment defines the technological level of the drone economy, as it is the source of key innovations ensuring global market competitiveness. Drone manufacturing is increasingly integrated with other high-tech sectors, such as microelectronics, artificial intelligence, and telecommunications.

The second critical component is the service sector, encompassing UAV-based services. Currently, this segment demonstrates the fastest growth, developing new business models such as Drone-as-a-Service (DaaS). Services include infrastructure inspection, agricultural monitoring, aerial imaging, logistics operations, search and rescue missions, among others. Its development enhances the operational efficiency of enterprises in strategic sectors, reducing costs and minimizing risks.

The third structural element is the data analytics and processing sector, which gains importance in the context of the digital transformation of the economy. Drones serve not only as operational tools but also as sources of large datasets requiring processing, analysis, and interpretation. Artificial intelligence, machine learning, and geographic information systems are extensively applied in this segment, transforming collected data into valuable managerial decisions that improve enterprise and sector performance.

Another essential component is infrastructure, ensuring the functioning of the drone economy. It includes airspace management systems, charging and service stations, telecommunications networks, and regulatory frameworks governing UAV usage. Infrastructure plays a key role in scaling drone technologies, as wide adoption is limited without adequate regulatory and technical support.

A separate and significant component is the research and development (R&D) sector, which ensures the continuous advancement of technology, development of new solutions, and adaptation of UAV systems to the specific needs of different industries. Universities, research institutes, startups, and large tech companies interact in this segment. The role of R&D increases under global market competition, where innovation becomes the key to leadership.

Thus, the structure of the drone economy is a complex integrated system that combines manufacturing, services, analytics, infrastructure, and research, enabling the formation of new economic relations and the transformation of traditional industrial sectors. It is worth noting that the development of the drone economy generates a wide spectrum of effects across economic, social, and environmental dimensions. Their integrated nature underlines the importance of drone technologies as a tool for promoting sustainable development.

The results of the study are aimed at substantiating a comprehensive approach to assessing the development of the drone economy as a multi-dimensional and dynamically evolving system. Thus, traditional evaluation methods do not fully capture the complexity and cross-sectoral nature of drone technologies. In particular, the fragmented use of individual indicators limits the ability to assess the systemic impact of unmanned aerial vehicles on economic transformation processes. In this context, there is a need to develop an integrated analytical tool that would allow for a holistic assessment of the drone economy, taking into account its economic, technological, social, environmental, and infrastructural dimensions. Such an approach ensures the consideration of both direct and indirect effects of drone technologies, as well as their role in shaping new value chains and innovation ecosystems.

Given this, it is proposed to use an integral index of drone economy development, which aggregates the key components of its functioning and reflects the level of UAV integration into strategic sectors of the economy, taking into account the ecosystem approach.

It is proposed to calculate the integral indicator of drone economy development based on the following formula:

$$DEI = w_1T + w_2E + w_3R + w_4S + w_5ESG \quad (1)$$

where all components are normalized in the interval [0;1], which ensures their comparability:

DEI — integral index of drone economy development;

T — technological component (level of UAV implementation, digitalization);

E — economic component (productivity, cost reduction);

R — regulatory component (normative and legal support);

S — industry component (level of integration into strategic industries);

ESG — indicator of sustainable development (environmental, social and management effects);

w_i — weighting factors.

In order to ensure correct aggregation of indicators, a normalization procedure is used. For development-stimulating indicators, the following formula is used:

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (2)$$

In turn, for development disincentive indicators, it is advisable to use the following calculation formula:

$$X_{norm} = \frac{X_{max} - X_i}{X_{max} - X_{min}} \quad (3)$$

This allows all indicators to be brought to a single scale.

In turn, the technological component (T) characterizes the level of implementation of unmanned technologies and digitalization of production processes. Its formation is based on an assessment of the intensity of UAV use, the level of automation and integration of modern digital technologies. The technological component should be calculated using the formula:

$$T = \frac{1}{n} \sum_{j=1}^n T_j \quad (4)$$

where:

- T — integral technological indicator;
- T_j — normalized partial indicators;
- n — number of technological indicators.

The main technological indicators can be:

- number of UAVs per unit of manufacturing enterprises;
- level of process automation;
- share of AI/IoT use;
- investment in drone technologies.

The economic component (E) reflects the effectiveness of the implementation of drone technologies in terms of productivity, costs and financial results.

$$E = \frac{1}{n} \sum_{j=1}^n E_j \quad (5)$$

where:

- E — economic indicator;
- E_j — normalized economic indicators.
- n — number of economic indicators.

The main technological indicators are:

- productivity growth;
- cost reduction;
- return on investment (ROI);
- revenue growth.

The regulatory component (R) reflects the level of institutional support for the development of the drone economy.

$$R = \frac{1}{n} \sum_{j=1}^n R_j \quad (6)$$

where:

- R — regulatory indicator;
- R_j — normalized indicators of the regulatory component;
- n — number of indicators of the regulatory component.

The main regulatory indicators are:

- availability of a regulatory framework;
- development of UTM systems (a comprehensive network security solution that combines the functions of a firewall, antivirus, intrusion prevention system (IPS), VPN, and web content filtering in a single device or software);

- availability of certification;
- government support.

The industry component (S) characterizes the degree of integration of UAVs into strategic industries.

$$S = \frac{1}{m} \sum_{i=1}^m S_i \quad (7)$$

where:

- S — the industry indicator;
- S_i — the level of UAV uses in the i -th industry;
- m — the number of strategic industries.

In turn, the sustainable development component (ESG) reflects environmental, social and governance effects.

$$ESG = \frac{E_{env} + E_{soc} + E_{gov}}{3} \quad (8)$$

where:

ESG — an indicator of the sustainable development component;

E_{env} — an integral indicator of the environmental effect of UAV use, reflecting the level of reduction in negative environmental impact. Such indicators include:

- reduction in emissions CO₂ (through process optimization);
- reduction in resource use (fuel, water, fertilizers);
- efficiency of environmental monitoring;
- reduction in environmental risks (e.g. accidents).

E_{soc} — an integral indicator of social impact, characterizing the impact of UAV use on safety, employment and quality of life. Social impact indicators include:

- increased occupational safety;
- reduced injuries;
- creation of new jobs;
- improved quality of life (through effective services).

E_{gov} — an integral indicator of the quality of governance of UAV implementation processes, reflecting the level of institutional capacity and transparency.

Among the indicators:

- transparency of technology use;
- digital governance;
- level of regulatory coherence;
- availability of standards and controls.

Let us give a detailed description of the calculation of integral indicators.

1. Environmental component:

$$E_{env} = \frac{1}{k} \sum_{j=1}^k E_{env_j} \quad (9)$$

where:

- k — number of environmental indicators;
- E_{env_j} — normalized indicators.

2. Social component:

$$E_{soc} = \frac{1}{p} \sum_{j=1}^p E_{soc_j} \quad (10)$$

where:

- p — number of social indicators;
- E_{soc_j} — normalized indicators.

Table 1

Indicators of the environmental component E_{env}^*

Designation	Indicators	Decoding
E_{env_1}	Emission reduction CO ₂	Percentage of emission reductions due to the use of UAVs
E_{env_2}	Resource saving	Reduction in fuel, water, fertilizer use (%)
E_{env_3}	Environmental monitoring	Share of territories/objects monitored by UAVs (%)
E_{env_4}	Reduction of accident rate	Reducing environmental incidents (%)

*data sources: ESG reports, industry assessments

Source: compiled by the authors

Table 2

Indicators of the social component E_{soc}^*

Designation	Indicators	Decoding
E_{soc_1}	Occupational safety	Injury reduction (%)
E_{soc_2}	Workplaces	Drone employment growth (%)
E_{soc_3}	Access to technology	Share of businesses using UAVs (%)
E_{soc_4}	Quality of service	Quality improvement (logistics, inspections) (%)

*data sources: statistical data and expert assessments

Source: compiled by the authors

3. Governance component:

$$E_{gov} = \frac{1}{q} \sum_{j=1}^q E_{gov_j} \tag{11}$$

where:

q — the number of management indicators;

E_{gov_j} — normalized indicators.

The identification of three key components — environmental, social, and governance — is grounded in the widely recognized international ESG concept, which serves as a standard framework for assessing the sustainability of economic systems. This approach is extensively applied by international organizations, investors, and researchers to evaluate the impact of business activities and technological innovations on the environment, society, and governance structures. The use of these three components allows for:

- ensuring a comprehensive coverage of the key dimensions of sustainable development;

- avoiding duplication of indicators;
- maintaining a balance between methodological detail and practical applicability;
- ensuring comparability of results with international studies and benchmarks.

Moreover, the integration of the ESG approach into the methodology for assessing the drone economy makes it possible to account not only for the economic outcomes of UAV implementation, but also for their long-term environmental and social implications. This is fully consistent with contemporary principles of sustainable development and responsible investment. Alongside the assessment of the overall level of drone economy development, particular importance is attached to the analysis of the effectiveness of UAV utilization at the level of individual strategic sectors. This is due to the fact that the impact of drone technologies is inherently heterogeneous and depends on sector-specific characteristics, including the level of technological maturity, investment capacity, and the

Table 3

Indicators of the governance component $E_{gov_i}^*$

Designation	Indicators	Decoding
E_{gov_1}	Transparency	Availability of open data/reporting (0–1)
E_{gov_2}	Digital governance	Level of use of data-driven solutions (%)
E_{gov_3}	Regulatory coherence	Coherence of policies and standards
E_{gov_4}	Institutional capacity	Level of governance development

*data sources: international indices and expert assessment

Source: compiled by the authors

institutional environment. An analysis of international experience demonstrates that the deployment of UAVs in sectors such as energy, agriculture, logistics, and infrastructure is associated with significant economic and operational benefits. In particular, there is evidence of increased productivity, reduced maintenance costs, improved safety levels, and a decrease in environmental impact. However, in most existing studies, these effects are evaluated in isolation, without considering their cumulative and systemic impact.

In this regard, there is a clear need to develop a generalized indicator that would enable the integration of the key outcomes of UAV implementation within a specific sector and facilitate the assessment of investment efficiency in drone technologies. Such an indicator makes it possible to combine economic, operational, and sustainability-related effects of UAV usage and to evaluate them in relation to investment costs, thereby providing a comprehensive assessment of the effectiveness of drone technology implementation in strategic sectors.

$$E_i = (\Delta P_i + \Delta C_i + \Delta S_i + \Delta ESG_i) / I_i \quad (12)$$

where:

E_i — the effectiveness of UAV uses in industry i ;
 ΔP_i — productivity gain;
 ΔC_i — cost savings;
 ΔS_i — increasing security level;
 ΔESG_i — improving sustainable development indicators;

I_i — investments in the implementation of UAVs.

Productivity growth is defined as the relative change in production volumes or work performed:

$$\Delta P = \frac{P_a - P_b}{P_b} \quad (13)$$

where

P_a, P_b — productivity before and after the implementation of UAVs.

In turn, the cost reduction is calculated using the formula:

$$\Delta C = \frac{C_a - C_b}{C_b} \quad (14)$$

where

C_a, C_b — costs before and after the implementation of innovations.

The safety improvement indicator is defined as a reduction in the number of incidents or injuries:

$$\Delta S = \frac{S_a - S_b}{S_b} \quad (15)$$

where

S_a, S_b — the level of hazardous incidents before and after the implementation of innovations.

The change in the sustainable development effect is determined as the difference in the integral ESG indicator before and after the implementation of UAVs.

$$\Delta ESG_i = ESG_a - ESG_b \quad (16)$$

In turn, investments in the implementation of UAVs include capital and operating costs:

$$I_i = CapEx_i + OpEx_i \quad (17)$$

In order to ensure comparability of the components of the efficiency indicator, a normalization procedure is used. Since all components $\Delta P_i, \Delta C_i, \Delta S_i, \Delta ESG_i$ are stimulants (the larger the value, the higher the effect), their normalization is carried out according to the formula:

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (18)$$

where:

X_i — actual value of the indicator;
 X_{min}, X_{max} — minimum and maximum values in the sample.

After normalization, all indicators acquire values in the range [0;1], which provides the possibility of their aggregation.

The proposed indicator of the effectiveness of UAV use is based on a combination of economic, technological and sustainable development effects and allows:

- to assess the feasibility of introducing UAVs in a specific industry;
- to compare the effectiveness of their use between different sectors;
- to identify areas for increasing investment efficiency;
- to take into account not only economic, but also environmental and social effects.

In order to integrate the assessment of the level of development of the drone economy and the effectiveness of the use of unmanned technologies in strategic industries, we propose a general indicator of the effectiveness of the development of the drone economy, which is defined as the product of the integral index of the development of the drone economy and the indicator of the effectiveness of the use of UAVs in the relevant industry:

$$DDE_i = DEI \cdot E_i \quad (19)$$

where:

DDE_i — efficiency of drone economy development in the i industry;

DEI — integral index of drone economy development;

E_i — the effectiveness of UAV uses in the industry.

The proposed indicator allows us to take into account both the general level of development of the drone economy and the effectiveness of the use of unmanned technologies in specific industries. Such integration provides a deeper understanding of the mechanisms of the functioning of the drone economy and allows us to identify imbalances between the potential and its implementation. In particular, the situation in which a high level of development of the drone economy is accompanied by low efficiency of the use of UAVs in industries indicates the presence of structural or institutional constraints. At the same time, high values of the indicator DDE_i characterize an effective combination of a favorable environment and effective use of technologies.

Thus, the proposed approach provides a more comprehensive understanding of the impact of drone technologies on the development of strategic industries and meets the modern requirements of sustainable and inclusive economic development. In general, we note that the proposed approach provides a comprehensive assessment of the development of the drone economy, covering technological, economic, regulatory and environmental aspects of its functioning. Its use allows us to form a holistic picture of the level of integration of unmanned technologies into strategic industries. In addition, the proposed toolkit creates an analytical basis for making informed management decisions at the state and industry levels. It also helps identify key factors that constrain the development of the drone economy and determine priority areas for its stimulation. An important advantage of the approach is the possibility of adapting it to the specifics of individual countries and industries, taking into account their economic and institutional characteristics. In the context of sustainable development, it allows assessing not only economic results, but also environmental and social effects of the introduction of UAVs. Thus, the proposed approach forms a methodological basis for strategic management of the development of the drone economy in the context of digital transformation.

3.1. Strategic and Policy Implications of Drone Economy Development

The analysis of the integral indicators of the drone economy (DEI) and the effectiveness of UAV use (DDE) demonstrates that unmanned aerial technologies are not only a tool for operational optimization but also a strategic lever for national economic development. The deployment of drones in strategic sectors — energy, agriculture, logistics, infrastructure, and defense — creates systemic opportunities for enhancing productivity, reducing costs, increasing safety, and promoting sustainability. From a policy perspective, these outcomes carry several important implications.

First, the drone economy has the potential to strengthen economic resilience and competitiveness. High DEI and DDE values indicate sectors where UAV integration maximizes operational efficiency and return on investment, suggesting priority areas for targeted governmental support and incentives. Policymakers can use these indicators to identify structural bottlenecks, prioritize investment, and develop sector-specific roadmaps for drone adoption. In strategic industries such as energy and defense, timely adoption of UAV technologies can improve national security, ensure continuity of critical services, and reduce reliance on outdated, labor-intensive processes.

Second, the development of a drone economy has regulatory and institutional implications. Effective UAV integration requires coherent legal frameworks, safety standards, air traffic management, and certification systems. The DEI framework highlights the importance of regulatory maturity as a core component of drone ecosystem development. Countries that

proactively align drone policies with technological innovation are better positioned to attract foreign investment, foster public-private partnerships, and accelerate industrial modernization. Moreover, the integration of ESG metrics into UAV evaluation ensures that policy decisions consider long-term environmental and social outcomes, promoting responsible technological deployment.

Third, the drone economy supports sustainable development and environmental policy objectives. UAV deployment allows for precise monitoring of natural resources, early detection of environmental hazards, and optimization of resource use. This contributes to reducing emissions, minimizing industrial accidents, and improving ecological monitoring. Policymakers can leverage these capabilities to meet climate goals, enhance energy efficiency, and implement evidence-based environmental regulations. At the same time, the inclusion of social indicators, such as occupational safety and job creation, ensures that drone policies align with broader societal objectives, including workforce development and social inclusion.

Finally, the drone economy has strategic geopolitical and security dimensions. Countries that establish advanced UAV ecosystems gain technological sovereignty, enhance the competitiveness of domestic industries, and reduce dependency on foreign technologies. Strategic sectors, particularly defense and critical infrastructure, benefit from improved situational awareness, rapid data acquisition, and autonomous operational capabilities. In this context, the DEI and DDE indicators provide policymakers with a quantitative foundation for evaluating the national readiness for drone integration, allowing for informed decisions on technology acquisition, international collaboration, and defense modernization.

In summary, the development of the drone economy extends beyond technological and economic gains to encompass policy, regulatory, social, environmental, and strategic dimensions. The proposed integrated indicators provide a robust analytical tool for governments, industry leaders, and investors to assess sectoral readiness, prioritize strategic interventions, and align UAV deployment with long-term national objectives. By bridging operational effectiveness with policy and strategic planning, the drone economy becomes a critical instrument for fostering sustainable, resilient, and competitive industrial systems.

4. Conclusions

This study develops a comprehensive methodological framework for assessing the formation and development of the drone economy as a multidimensional, ecosystem-based phenomenon. The research demonstrates that UAV technologies are not merely technological tools, but integral components of modern economic systems, capable of transforming strategic industries such as energy, agriculture, logistics, infrastructure, and defense.

Key contributions of this study are as follows:

Holistic Conceptualization: The drone economy is conceptualized as a multi-level ecosystem integrating technological, economic, social, environmental, and regulatory components. This approach emphasizes the interdependence between efficiency, sustainability, and governance, highlighting that UAV adoption must be evaluated not only in terms of immediate economic gains but also through its broader systemic impact.

Integrated Assessment Tool: A novel integral index of drone economy development (*DEI*) is proposed, aggregating technological, economic, regulatory, industrial, and ESG-based sustainability indicators. This composite indicator enables cross-sectoral and cross-country comparisons, providing a unified framework for assessing UAV integration and the overall development of drone ecosystems.

Sectoral Efficiency Evaluation: Beyond the general development index, an effectiveness indicator for UAV deployment in individual strategic sectors is developed. This measure integrates economic, operational, and sustainability effects relative to investment costs, allowing stakeholders to identify the most productive and impactful applications of drone technologies.

Integration of ESG Principles: Incorporating environmental, social, and governance factors into

the evaluation ensures that drone economy development aligns with the principles of sustainable development and responsible investment. This enables long-term evaluation of UAV impacts, such as emission reductions, resource efficiency, improved occupational safety, job creation, and enhanced governance transparency.

Strategic Governance Insights: The combined use of DEI and sector-specific effectiveness indicators provides actionable insights for policymakers, industry leaders, and investors. The framework identifies structural or institutional constraints, guides investment priorities, and supports the development of regulations and digital infrastructures to facilitate UAV adoption.

Overall, the proposed framework bridges the current methodological gap in the assessment of drone economies, offering a rigorous, multi-dimensional, and practical tool for monitoring, benchmarking, and guiding UAV-driven technological transformations. Future research should focus on empirical validation of the index across multiple countries, the incorporation of real-time data analytics, and the exploration of dynamic feedback loops between UAV deployment, industrial performance, and ecosystem sustainability.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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РОЗВИТОК ДРОНОВОЇ ЕКОНОМІКИ: МЕТОДОЛОГІЧНА ОСНОВА

Анотація. Виникнення дрової економіки є трансформаційним елементом сучасних цифровізованих національних економік, інтегруючи безпілотні літальні апарати (БПЛА) у стратегічні галузі, такі як енергетика, агропромисловий сектор, логістика, інфраструктура та оборона. У дослідженні запропоновано комплексну методологічну рамку для оцінки розвитку дрової економіки, що охоплює технологічні, економічні, регуляторні, галузеві та аспекти сталого розвитку. Використано системний підхід, поєднуючи огляд літератури, системно-структурний аналіз, порівняльну оцінку, статистичну нормалізацію та експертну оцінку для побудови інтегрального індексу розвитку дрової економіки (DEI). Крім того, запропоновано секторний показник ефективності, що дозволяє оцінити вплив впровадження БПЛА на продуктивність, скорочення витрат, безпеку та результати у сфері екології, соціальної відповідальності та управління (ESG). Запропоновані індикатори забезпечують комплексну оцінку інтеграції БПЛА, враховуючи як прямі, так і непрямі ефекти, а також структурні та інституційні обмеження. Рамка методології сприяє порівнянню між країнами та галузями та надає рекомендації для політиків, представників промисловості та інвесторів щодо пріоритетних напрямів розвитку дрової економіки. Результати підкреслюють важливість поєднання технологічного впровадження з принципами ESG для досягнення сталого, ефективного та соціально відповідального розвитку промисловості. Дослідження робить внесок у літературу, пропонуючи системний інструмент для оцінки багатовимірного впливу впровадження БПЛА та створює основу для подальших досліджень ролі дронів у економічному розвитку та формуванні сталих промислових екосистем.

Ключові слова: дрова економіка, інтеграція БПЛА, стратегічні галузі промисловості, сталий розвиток, ESG-підхід, цифрова трансформація, технологічні інновації.

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