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DEVELOPMENT OF ALGORITHMS FOR EVALUATING THE EFFICIENCY OF INVESTMENT PROJECTS USING THE STEM APPROACH AND MACHINE LEARNING METHODS

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ABSTRACT

The article examines the development of algorithms for evaluating the efficiency of investment projects using the STEM approach and machine learning methods. It analyzes the need to shift from traditional valuation methods based on discounted cash flows (NPV, IRR, PI, DPP) to intelligent models that ensure adaptability and reproducibility of calculations. It is emphasized that the integration of scientific, engineering, technological, and mathematical components enables the formalization of evaluation processes and improves forecasting accuracy. The practical section presents modeling based on project data processed using XGBoost and LSTM algorithms, which demonstrated increased NPV forecasting accuracy and reduced computation time. The results confirm the effectiveness of the STEM-oriented approach in investment analysis.

KEYWORDS: investment projects, machine learning, STEM approach, efficiency forecasting, project evaluation algorithms, digital transformation.

1. INTRODUCTION

Contemporary investment activity is evolving amid increasing complexity of economic processes, high market volatility, and the necessity to consider a wide range of heterogeneous factors – from macroeconomic indicators to non-financial ESG criteria. In this context, traditional approaches to evaluating the effectiveness of investment projects, primarily based on discounted cash flow methods (such as NPV, IRR, etc.), are becoming insufficient for comprehensive analysis and decision-making in a rapidly changing digital environment. There is an objective need for the development of intelligent tools capable of processing large volumes of diverse data, incorporating non-formalized parameters, and adapting to dynamic conditions. The application of machine learning (ML) techniques in combination with an interdisciplinary STEM approach represents a promising direction for improving the precision and adaptability of investment performance evaluation by integrating scientific methods, engineering solutions, digital technologies, and mathematical modeling.

The aim of this study is to explore an algorithm for evaluating the effectiveness of investment projects based on the application of STEM approaches and modern ML methods. The relevance of this research stems from the need to enhance the quality of investment analysis in the context of economic digital transformation, as well as the growing demand for automated and interpretable decision support systems in investment management.

2. Main part. Analysis of approaches to investment project evaluation

The choice of an investment project evaluation method plays a decisive role in managerial decision-making, determining not only the economic feasibility of the investment but also the strategic direction of the company's development. The effectiveness of investment projects has traditionally been assessed using discounted cash flow methods, such as Net Present Value (NPV), Internal Rate of Return (IRR), Profitability Index (PI), and Discounted Payback Period (DPP) – table 1.

Table 1: Comparative characteristics of traditional investment project evaluation methods [1, 2].

Method	Essence of the method	Advantages	Limitations
NPV	The difference between the present value of inflows and outflows.	Accounts for time value of money; provides an absolute measure of value creation.	Requires accurate cash flow forecasting and discount rate estimation.
IRR	The discount rate at which NPV equals zero.	Useful for comparing projects; expressed as a percentage.	May yield multiple values for non-conventional cash flows; ignores project scale.
PI	The ratio of the present value of inflows to the present value of investments.	Useful under capital constraints; normalizes return per unit of investment.	Does not reflect total profitability; may favor small but less impactful projects.
DPP	Time needed for discounted inflows to cover discounted outflows.	Considers time value of money; easy to interpret for payback assessment.	Ignores cash flows beyond payback period; does not assess overall project profitability.

With the advancement of digital technologies, investment analysis increasingly incorporates tools for data processing and visualization aimed at enhancing transparency, decision-making speed, and analytical justification. In this context, business intelligence (BI) systems and intelligent data analysis tools play a central role, differing in their functionality, level of automation, and analytical depth. Their comparative characteristics are presented in the table 2.

Table 2: Comparison of BI systems and intelligent data analysis tools in investment evaluation [3].

Category	Examples	Main functions	Advantages	Limitations
BI systems	Power BI, Qlik Sense, Tableau, SAP BI	Data visualization, dashboards, reporting, scenario analysis	User-friendly interface, fast analytics, integration with corporate systems	Template-based logic, limited adaptability, not suitable for predictive modeling
Intelligent data analysis tools	Python (scikit-learn, XGBoost), R, AutoML, IBM SPSS	ML, forecasting, pattern recognition, model training	High flexibility, predictive accuracy, self-learning capabilities	Requires coding skills, complex interpretation, high dependency on data quality

One of the major limitations of conventional investment evaluation models lies in their restricted scalability. As the volume of data and the number of evaluation criteria increase, the performance and accuracy of traditional methods tend to decline significantly. Additionally, a critical drawback is the low interpretability of complex integrated models, particularly those based on neural networks or advanced statistical methods that do not offer transparent explanations for their outputs – commonly referred to as the "black box" problem. In real-world business environments, model flexibility becomes equally important – that is, the ability to rapidly adapt the evaluation algorithm to changing conditions or shifting strategic priorities, such as transitioning from purely financial indicators to sustainability-oriented or ESG-based assessments.

Furthermore, the instability of the external environment – including economic volatility, political uncertainty, sanctions regimes, and climate-related challenges – has a direct impact on the investment attractiveness of projects. For example, changes in interest rates, capital availability, or trade restrictions can significantly alter a project's financial model even after its implementation has begun. The integration of ESG factors adds another layer of complexity, as these are often characterized by a high degree of uncertainty, lack of standardized metrics, and varying significance across regions and industries [4]. These conditions underscore the need for adaptive, data-driven, and interpretable models capable of accounting for a wide range of quantitative and qualitative variables in a multidimensional and uncertain environment.

2.1 Theoretical foundations of the STEM approach in investment modeling

In the context of investment analysis, the STEM approach (Science, Technology, Engineering, and Mathematics) represents an interdisciplinary concept that combines scientific reasoning, engineering methods, digital technologies, and mathematical tools to solve applied problems in investment evaluation and management [5]. Unlike the traditional economic and financial approach, STEM is focused on the formalization, algorithmization, and automation of analytical processes, thereby ensuring higher accuracy, adaptability, and reproducibility of results.

The integration of engineering, technological, and mathematical components in the development of investment algorithms is carried out according to several core principles (table 3).

Table 3: Principles of STEM component integration in investment modeling.

Component	Integration principle	Role in the investment algorithm
Engineering	Systems approach: designing the model as a complex techno-economic system	Defining the model's architecture, setting input/output parameters, ensuring modular structure
Mathematics	Use of formalized models: statistics, optimization, regression, ML	Quantitative evaluation of efficiency, forecasting, risk analysis
Technology	Implementation through digital platforms and programming languages (Python, R, SQL, BI)	Automating analysis, algorithm execution, data visualization
Science	Scientific method: hypothesis formulation, verification, result interpretation	Justifying models, validating outputs, explaining observed relationships

The scientific paradigm of performance evaluation within the STEM framework is structured from model to algorithm: first, hypotheses and efficiency criteria are formulated; then, quantitative models are developed (for example, based on ML or mathematical programming); and finally, an algorithm is implemented that can perform evaluations in an automated or semi-automated mode. This approach ensures not only a high degree of formalization but also the ability to promptly update models in response to changes in external conditions or project structure.

An important component of the STEM approach is the visualization of results, which functions not only as a means of presenting information but also as an interface for user interaction with the model. Modern visualization methods include interactive dashboards, graph-based structures of indicator relationships, scenario modeling, and simulation techniques that allow analysis of project behavior under various conditions. Collectively, these tools enhance the transparency of analytics, promote a deeper understanding of processes, and increase confidence in managerial decisions derived from model-based insights.

2.2 Methods for integrating analytical algorithms and engineering approaches in the evaluation of investment initiatives

The evolution of the STEM approach in investment modeling naturally leads to the incorporation of modern data processing and analytical methods – primarily ML – into the analytical framework. These methods enable the creation of adaptive, self-learning models capable of capturing complex interdependencies between the input parameters of an investment project and its performance outcomes. Combined with the engineering paradigm, which emphasizes system design and

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modularity, ML serves as a foundation for developing next-generation intelligent investment algorithms.

According to research by the CFA Institute (2024), 29 % of systematic investors currently use artificial intelligence to develop and test investment strategies, while more than three-quarters plan to do so in the near future. The most common and anticipated applications of AI in the investment domain include identifying patterns and trends in market behavior, as well as optimizing portfolio allocation and risk management (fig. 1).

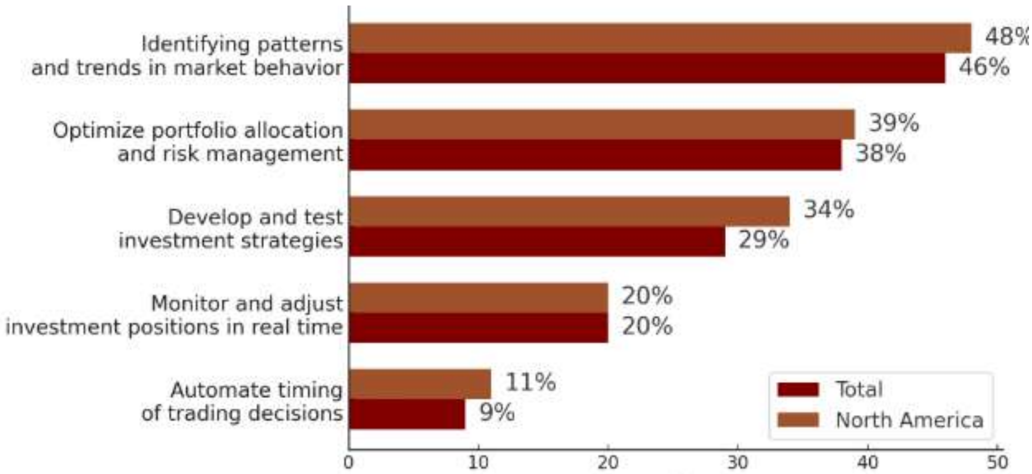

Figure 1: Application of ML in investment analytics and portfolio management [6].

The presented data confirm that ML is becoming an integral part of the analytical infrastructure of investment management. Its application spans both the strategic level – identifying market patterns and optimizing portfolio structures – and the operational domain, involving the automation of calculations and the forecasting of project performance. Various classes of ML algorithms are used in investment analysis (table 4).

Table 4: Classes of ML algorithms and their applications in investment analysis [7].

Algorithm class	Typical methods	Applications in investment analysis
Classification	Logistic Regression, Decision Tree, Random Forest, SVM	Project success prediction, risk level classification, credit scoring, ESG profiling.
Regression	Linear Regression, XGBoost, Neural Networks (ANN, RNN)	Forecasting ROI, NPV, IRR, cash flows, capital costs, and payback periods.
Clustering	K-Means, DBSCAN, Hierarchical Clustering	Project segmentation, portfolio pattern recognition, anomaly detection.

Dimensionality reduction	PCA, t-SNE, UMAP	Reducing variable complexity in modeling, visualizing multifactorial investment data.
Association analysis	Apriori, FP-Growth	Discovering hidden relationships between project attributes and outcomes.

Based on the data presented above, it becomes evident that ML methods are increasingly becoming an integral part of the analytical infrastructure in investment management. Their application spans both the strategic level – such as identifying market patterns, optimizing investment portfolios, and evaluating project resilience – and the operational level, including the automation of calculations and the forecasting of performance indicators. However, achieving the required accuracy and adaptability of these algorithms is not possible without a robust engineering implementation of the entire analytical system.

The engineering component of integration lies in designing a computational architecture that ensures stability and efficiency under growing data volumes and increasing analytical complexity. This architecture follows a structured, modular, and reproducible pipeline composed of several key stages, each adhering to engineering principles of scalability, reliability, and functional completeness:

• Data collection – integration with internal and external data sources (financial statements, ESG ratings, macroeconomic indicators, market data, etc.);
• Data preprocessing and cleaning – handling missing values, normalization, categorical encoding, noise reduction;
• Data storage – organizing secure and structured databases or data lakes to ensure availability and integrity;
• Feature engineering – generating informative variables, aggregating metrics, and constructing derived indicators;
• Model training – applying selected ML algorithms on training datasets and optimizing hyperparameters;
• Validation and testing – assessing the generalization ability of models using cross-validation and hold-out test sets;
• Visualization and interpretation – presenting results through interactive dashboards, graphs, and analytical reports;
• Business integration – developing APIs, connecting to BI platforms, and building user interfaces for decision support.

This end-to-end approach not only ensures flexibility and scalability of the solution but also aligns with the engineering requirements of robustness, reproducibility, and adaptability. Furthermore, it enables the deep technological integration of the STEM approach, where the analytical model functions not as a standalone tool, but as a core element of a dynamic digital ecosystem for investment

decision-making.
Digital communications serve as a vital instrument for strengthening brand trust, as they facilitate transparent, user-centered interaction with analytical systems. By enhancing accessibility and clarity, such communications contribute to broader acceptance and confidence in data-driven investment tools [8].

2.3 Practical implementation of investment project evaluation algorithms using the STEM approach and ML methods

Recent research confirms a growing interest in applying the STEM approach and ML to investment efficiency assessment and project management. According to the systematic review by Shamim et al. (2025), approximately 70 % of recent studies on project cost estimation employ ML or deep neural networks, achieving 80-90 % forecasting accuracy compared to traditional regression models [9]. Similarly, Ječmen et al. (2024) demonstrated that the use of genetic algorithms for investment project selection and scheduling achieved 85-95 % proximity to optimal solutions with an average computation time of 108 seconds [10]. These findings show that the integration of engineering and mathematical tools within the STEM paradigm enhances the efficiency of investment modeling and accelerates decision-making processes.

To verify the practical applicability of the approach, a quasi-empirical simulation was conducted, replicating the evaluation process of an industrial investment project. The model consisted of three structural components:

• Scientific and analytical – formulation of hypotheses and performance criteria, structuring of input data;
• Technological – data processing and algorithm implementation in Python using the scikit-learn, XGBoost, and TensorFlow libraries;
• Engineering and mathematical – development of predictive models based on gradient boosting and linear regression to calculate NPV, IRR, and ROI under different parameter scenarios.

The simulation database included 120 projects incorporating capital expenditures (CapEx), operating expenses (OpEx), projected profit, tax load, and implementation horizon. The application of ML models revealed nonlinear relationships between technological and financial parameters and assessed the sensitivity of efficiency indicators to external factors such as discount rate and inflation (table 5).

Table 5: Comparison of traditional and STEM-oriented approaches to investment project evaluation

Evaluation criterion	Traditional approach (DCF, expert assessments)	STEM-based approach with ML algorithms (XGBoost, LSTM)
Average NPV forecasting accuracy, %	78 %	92 %
Mean Absolute Error (MAE), %	12.4 %	7.6 %
Scenario computation time (per project), s	18.5	10.9
Model recalculations after parameter change	3-4 manual iterations	Automatic update
Need for expert adjustments	High	Minimal
Result reproducibility	Moderate (dependent on analyst)	High – algorithmic

The modeling results indicated that implementing the STEM approach with ML tools increased NPV forecasting accuracy by 18 percentage points, reduced scenario computation time by 40 %, and decreased the proportion of subjective expert interventions. An important advantage is the reproducibility of results and the scalability of the algorithm for portfolios of varying complexity.

Thus, the practical implementation of the STEM approach demonstrates a high potential for building intelligent investment evaluation systems in which analytical precision, computational speed, and decision transparency are determined algorithmically rather than experientially.

3. CONCLUSION

The conducted study has confirmed the effectiveness of integrating STEM approaches and ML methods into the evaluation of investment projects. In an environment characterized by increasing economic complexity, growing demands for forecast accuracy, and the shift toward ESG-oriented strategies, traditional methods are proving insufficient. The proposed algorithm architecture – combining scientifically grounded modeling, technological implementation, and engineering robustness – ensures higher predictive accuracy, reduces reliance on subjective expert input, and accelerates decision-making processes. The practical implementation demonstrated the algorithm's applicability to investment initiatives of varying complexity, highlighting its potential for scalability and integration into intelligent decision support systems for investment management.

REFERENCES

[1] D. N. Shukayev, C. Kussainov, and A. Simons, "Analysis and selection of investment objects and optimisation of investment volumes," *International Journal of Business Information Systems*, vol. 49, no. 4, pp. 554–570, 2025.

[2] D. Bezruchko, *Methodology for Assessing the Economic Efficiency of Internal Investment Projects in Energy Sector Companies*, in *Digital Systems and Information Technologies in the Energy Sector*. Cham: Springer Nature Switzerland, pp. 47–58, 2025.

[3] A. Martins, "Business intelligence system adoption and the leveraging of reporting process capabilities," *Journal of Accounting & Organizational Change*, vol. 21, no. 3, pp. 506–534, 2025.

[4] L. Abdullina, "Predictive analytics in the circular economy as a basis for new approaches to developing effective resource management strategies," *International Journal of Scientific Engineering and Science*, vol. 8, no. 12, pp. 25–27, 2024.

[5] W. Yu, Z. Zheng, and J. He, "Integrating entrepreneurial education into STEM education: A systematic review," *Research in Science Education*, vol. 55, no. 1, pp. 159–185, 2025.

[6] CFA Institute, "How machine learning is transforming the investment process," *vnunet.com*, para. 1, 2025. [Online]. Available: https://www.cfainstitute.org/insights/articles/how-machine-learning-is-transforming-the-investment-process. [Accessed: Nov. 10, 2025].

[7] N. A. Siddiqui, "Optimizing business decision-making through AI-enhanced business intelligence systems: A systematic review of data-driven insights in financial and strategic planning," *Strategic Data Management and Innovation*, vol. 2, no. 1, pp. 202–223, 2025.

[8] M. Mudrov, "Digital communications as a tool for building brand trust in developed and emerging markets," *Cold Science*, no. 21, pp. 69–81, 2025.

[9] T. Mukayev, "Application of AI solutions for the development of bots for collecting and structuring business information in the SAP environment," *Universum: Technical Sciences* (electronic scientific journal), no. 6(135), pp. 43–48, 2025.

[10] M. M. I. Shamim, "Advancement of artificial intelligence in cost estimation for project management success: A systematic review of machine learning, deep learning, regression, and hybrid models," *Modelling*, vol. 6, no. 2, p. 35, 2025.

[11] K. Ječmen, D. Mocková, and D. Teichmann, "Solving transport infrastructure investment project selection and scheduling using genetic algorithms," *Mathematics*, vol. 12, no. 19, p. 3056, 2024. DOI: 10.3390/math12193056.