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Innovation Project Selection and Evaluation Using Artificial Intelligence Models and Methods

Mersaid Aripov
DSc, Professor, National University of Uzbekistan named after Mirzo Ulugbek, Uzbekistan

Maftuna Ismoilova Qaxramon qizi
Independent Researcher, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Uzbekistan

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Abstract

This article examines the application of artificial intelligence (AI) models and methods in the selection and evaluation of innovative projects. With the increasing complexity of decision-making processes in innovation management, traditional evaluation techniques often fail to ensure objectivity, scalability, and predictive accuracy. The study analyzes machine learning algorithms, decision-support systems, and multi-criteria evaluation models used in project selection. The methodological framework is based on a systematic review of academic literature and empirical findings from recent studies. The results demonstrate that AI-based approaches significantly improve decision quality, reduce uncertainty, and enhance predictive capabilities. The article also discusses the limitations and challenges associated with AI implementation in innovation evaluation processes.

Keywords: Artificial intelligence, innovation projects, project evaluation, machine learning, decision-making systems, predictive analytics, multi-criteria decision analysis.

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1. Introduction

Innovation plays a crucial role in economic growth, competitiveness, and technological advancement. The process of selecting and evaluating innovation projects is complex due to uncertainty, risk, and the multidimensional nature of innovation outcomes. Traditional evaluation methods, such as expert judgment and financial analysis, often lack objectivity and fail to capture dynamic interactions between variables [1].

Recent advancements in artificial intelligence have introduced new opportunities for improving decision-making processes in innovation management. AI models, including machine learning, neural networks, and data-driven decision-support systems, provide enhanced analytical capabilities and allow organizations to process large volumes of data efficiently [2].

The need for accurate and reliable evaluation mechanisms has led to the integration of AI technologies

into innovation project management. This article aims to explore how AI models and methods contribute to the effective selection and evaluation of innovative projects, based on empirical research and scientific literatur.

2. Methodology

The research methodology is based on a systematic literature review and comparative analysis of existing studies related to AI applications in innovation project evaluation. Scientific articles indexed in databases such as Scopus, Web of Science, and IEEE Xplore were analyzed.

The following methods were applied:

- Comparative analysis of traditional and AI-based evaluation approaches
- Review of machine learning algorithms used in project selection
- Analysis of multi-criteria decision-making (MCDM) models integrated with AI
- Evaluation of case studies demonstrating AI implementation in innovation management

Key AI methods identified in the literature include:

- Artificial Neural Networks (ANN) for predictive modeling [3]
- Decision Trees and Random Forest for classification tasks [4]
- Support Vector Machines (SVM) for risk assessment [5]
- Fuzzy logic systems for handling uncertainty in decision-making [6]

The methodological framework also considers hybrid models combining AI techniques with traditional decision-making tools.

3.Results

The analysis of scientific studies shows that AI-based methods significantly enhance the effectiveness of innovation project evaluation.

Firstly, machine learning models improve predictive accuracy in assessing project success. For example, artificial neural networks can identify complex nonlinear relationships between variables such as market demand, technological feasibility, and financial performance [3].

Secondly, decision-support systems powered by AI enable automated evaluation processes. These systems reduce human bias and provide consistent decision criteria, which is particularly important in large-scale project portfolios [7].

Thirdly, multi-criteria decision-making models integrated with AI allow for comprehensive evaluation of innovation projects. These models consider economic, technological, environmental, and social factors simultaneously, improving the overall quality of decisions [8].

Empirical studies indicate that organizations using AI-based evaluation tools achieve higher success rates in innovation projects compared to those relying solely on traditional methods [9]

4. Discussion

The integration of artificial intelligence (AI) into the selection and evaluation of innovation projects represents a fundamental transformation in how organizations approach strategic decision-making. Unlike traditional evaluation methods, which rely heavily on expert judgment, financial indicators, and static analytical tools, AI-based approaches enable dynamic, data-driven, and scalable decision processes. This section provides a comprehensive analysis of the advantages, limitations, and practical implications of applying AI models in innovation project evaluation, based strictly on findings from established scientific literature.

One of the most significant advantages of AI in innovation project evaluation is its ability to process and analyze large volumes of data. Traditional evaluation frameworks are often constrained by limited data processing capacity and rely on simplified assumptions. In contrast, AI systems—particularly machine learning

models—can handle both structured and unstructured data, including market trends, customer feedback, technological indicators, and financial metrics. According to Russell and Norvig [2], AI systems are specifically designed to identify patterns and relationships within large datasets that are beyond human cognitive capabilities. This capability is particularly relevant in innovation management, where decision-making involves multiple interdependent variables.

The application of machine learning algorithms, such as artificial neural networks (ANN), has demonstrated strong predictive performance in evaluating the success probability of innovation projects. Neural networks can model nonlinear relationships between input variables and outcomes, which is essential in complex innovation environments where cause-effect relationships are not straightforward [3]. For example, variables such as technological novelty, market readiness, team expertise, and investment level interact in highly complex ways. ANN models are capable of capturing these interactions and providing accurate predictions regarding project viability.

Another critical advantage of AI-based evaluation is the reduction of subjectivity and bias in decision-making. Traditional methods often depend on expert panels, where decisions may be influenced by cognitive biases such as overconfidence, anchoring, or groupthink. Kahneman [10] highlights that human decision-making is inherently prone to systematic errors, especially under uncertainty. AI systems, by contrast, rely on data-driven algorithms that apply consistent evaluation criteria across all projects. This enhances objectivity and ensures that decisions are based on empirical evidence rather than personal judgment.

Furthermore, AI models enable continuous learning and adaptation. Machine learning systems improve their performance over time as they are exposed to new data. This characteristic is particularly valuable in innovation management, where market conditions, technologies, and competitive environments are constantly evolving. As new project outcomes become available, AI systems can update their models, refine their predictions, and improve future decision-making processes. This adaptive capability represents a significant improvement over static evaluation methods, which often fail to incorporate new information effectively.

The integration of AI with multi-criteria decision-making (MCDM) models also enhances the comprehensiveness of project evaluation. Innovation projects are inherently multidimensional, involving economic, technological, environmental, and social factors. Traditional evaluation approaches often struggle to balance these diverse criteria. However, AI-enhanced MCDM models, such as those based on the Analytic Hierarchy Process (AHP), allow decision-makers to systematically evaluate multiple criteria simultaneously [8]. By combining AI with MCDM, organizations can achieve a more holistic assessment of innovation projects, leading to better-informed decisions.

In addition to improving evaluation accuracy, AI-based decision-support systems significantly increase efficiency. Automated evaluation processes reduce the time and resources required for project assessment. Turban et al. [7] emphasize that AI-driven decision-support systems can process large numbers of project proposals quickly and consistently, enabling organizations to manage extensive innovation portfolios. This is particularly important in industries characterized by rapid technological change, where timely decision-making is critical for maintaining competitiveness.

Despite these advantages, the implementation of AI in innovation project evaluation presents several challenges that must be carefully addressed. One of the most critical issues is data quality. AI models rely heavily on the availability of accurate, complete, and representative datasets. Provost and Fawcett [11] note that poor data quality can significantly reduce the reliability of machine learning models, leading to inaccurate predictions and suboptimal decisions. In the context of innovation projects, data may be incomplete, uncertain, or biased, particularly for early-stage projects where limited historical information is available. This creates a significant challenge for AI-based evaluation systems.

Another important limitation is the interpretability of AI models. Many advanced AI techniques, particularly deep learning models, operate as “black boxes,” meaning that their internal decision-making processes are not easily understandable to humans. This lack of transparency can reduce trust in AI-based decisions, especially in high-stakes environments such as investment evaluation. Decision-makers may be reluctant to rely on models whose reasoning they cannot fully explain. This issue has led to increasing interest in explainable AI (XAI), which

aims to make AI models more transparent and interpretable.

The complexity of AI implementation also poses significant challenges. Developing and deploying AI systems requires specialized expertise in data science, machine learning, and software engineering. Additionally, organizations must invest in infrastructure, including data storage, processing capabilities, and integration with existing information systems. These requirements can create barriers to adoption, particularly for small and medium-sized enterprises (SMEs) and organizations in developing economies.

Ethical considerations also play an important role in the use of AI for innovation project evaluation. AI systems may inadvertently reinforce existing biases if they are trained on biased data. For example, if historical data reflects unequal access to funding or resources, AI models may perpetuate these inequalities in future decision-making. Ensuring fairness, transparency, and accountability in AI systems is therefore essential for responsible innovation management.

To address these challenges, many researchers advocate for hybrid approaches that combine AI models with traditional evaluation methods. Hybrid systems leverage the strengths of both approaches: the analytical power and scalability of AI, and the contextual understanding and expertise of human decision-makers. For instance, fuzzy logic systems can be integrated with machine learning algorithms to better handle uncertainty and qualitative factors in innovation evaluation [6]. Such hybrid models provide more robust and flexible evaluation frameworks, capable of addressing the limitations of purely AI-based or purely traditional methods.

Another promising direction is the use of ensemble learning techniques, such as Random Forest, which combine multiple models to improve predictive accuracy and robustness [4]. Ensemble methods reduce the risk of overfitting and enhance the stability of predictions, making them particularly suitable for complex decision-making environments. In innovation project evaluation, ensemble models can integrate different types of data and provide more reliable assessments of project success.

The role of predictive analytics in innovation management is also expanding. Bertsimas and Kallus [12] emphasize the transition from predictive to prescriptive analytics, where AI systems not only forecast outcomes but also recommend optimal decisions. In the context of innovation project selection, prescriptive analytics can suggest which projects to prioritize, how to allocate resources, and how to manage risks effectively. This represents a significant advancement over traditional evaluation methods, which typically focus only on assessment rather than decision optimization.

Moreover, AI enables scenario analysis and simulation, allowing organizations to evaluate the potential outcomes of different strategic decisions. By simulating various scenarios, decision-makers can better understand the risks and uncertainties associated with innovation projects. This capability enhances strategic planning and supports more informed decision-making.

The adoption of AI in innovation project evaluation is also influenced by organizational factors, including culture, leadership, and readiness for digital transformation. Organizations that embrace data-driven decision-making and invest in digital capabilities are more likely to successfully implement AI-based evaluation systems. Conversely, resistance to change and lack of technical expertise can hinder adoption.

5. Conclusion

The study confirms that artificial intelligence models and methods play a significant role in improving the selection and evaluation of innovation projects. AI-based approaches provide higher accuracy, objectivity, and efficiency compared to traditional evaluation methods.

Machine learning algorithms, decision-support systems, and multi-criteria evaluation models enable organizations to make informed decisions in complex and uncertain environments. While challenges such as data quality and model interpretability remain, ongoing research and technological advancements are expected to address these issues.

The integration of AI into innovation management processes is not only a technological necessity but also a strategic advantage in the modern knowledge-based economy.

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