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AUTOMATED RISK MANAGEMENT SYSTEMS IN INTERNATIONAL ECONOMY AND GLOBAL INVESTMENTS

The article explores the growing significance of automated risk management systems (ARMS) in the context of the global investment ecosystem, especially amid rising financial volatility, geopolitical tensions, and the increasing complexity of capital flows. The relevance of this study is determined by the growing dependence of institutional investors and global financial markets on the speed, adaptability, and analytical precision of automated systems. The work identifies key structural elements of ARMS, including data aggregation, predictive analytics, decision-making algorithms, and real-time dashboards, which collectively allow for dynamic and informed risk mitigation in rapidly changing environments. Particular attention is paid to the integration of machine learning and artificial intelligence, which provide ARMS with self-learning capabilities and the ability to detect non-linear market patterns and black swan events.

The study analyzes practical implementations in leading financial institutions, such as BlackRock's Aladdin and JPMorgan's AI models, showing how automation reshapes risk forecasting and capital allocation. It is emphasized that the transition from traditional models, such as Value at Risk and scenario analysis, to algorithmic frameworks not only increases operational efficiency but also introduces a new set of regulatory, ethical, and systemic challenges. These include algorithmic opacity, technological inequality between developed and emerging markets, and the need for international standards in data governance and model accountability.

Through the comparative analysis of traditional and automated models, the article highlights the advantages of ARMS in terms of speed, accuracy, and scalability, while also recognizing the importance of human oversight in ensuring responsible decision-making. It is concluded that the effective development and implementation of automated risk management strategies require a multidisciplinary approach, combining technological innovation with financial regulation, ethical guidelines, and cross-border cooperation. The findings support the notion that ARMS are not only tools of efficiency but essential components of financial sustainability and resilience in an increasingly algorithm-driven world.

Keywords: automated risk management systems (ARMS); artificial intelligence (AI); risk management; international economy; global investments; financial technologies; data analytics; international financial system; digital infrastructure; financial stability

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АВТОМАТИЗОВАНІ СИСТЕМИ РИЗИК-МЕНЕДЖМЕНТУ В МІЖНАРОДНІЙ ЕКОНОМІЦІ ТА ГЛОБАЛЬНИХ ІНВЕСТИЦІЯХ

У статті досліджується зростаюче значення автоматизованих систем управління ризиками (ARMS) у контексті глобальної інвестиційної екосистеми, особливо на тлі зростання фінансової волатильності, геополітичної напруженості та ускладнення потоків капіталу. Актуальність цього дослідження зумовлена зростаючою залежністю інституційних інвесторів і світових фінансових ринків від швидкості, адаптивності та аналітичної точності автоматизованих систем. У роботі виокремлено ключові структурні елементи ARMS, зокрема агрегування даних, прогнозну аналітику, алгоритми прийняття рішень і інформаційні панелі в реальному часі, які в сукупності забезпечують динамічне й обґрунтоване управління ризиками в умовах швидких змін. Особлива увага приділяється інтеграції машинного навчання та штучного інтелекту, які надають ARMS здатності до самонавчання та виявлення нелінійних ринкових закономірностей і подій типу "чорний лебідь".

У дослідженні проаналізовано практичне впровадження ARMS у провідних фінансових установах, зокрема аналітичної платформи Aladdin від BlackRock та моделей ШІ в JPMorgan, що демонструють трансформацію прогнозування ризиків і розподілу капіталу під впливом автоматизації. Підкреслюється, що перехід від традиційних моделей, таких як Value at Risk та сценарний аналіз, до алгоритмічних структур не лише підвищує ефективність операцій, а й породжує нові виклики регуляторного, етичного та системного характеру. До них належать непрозорість алгоритмів, технологічна нерівність між розвиненими та країнами, що розвиваються, а також потреба в міжнародних стандартах управління даними й відповідальності моделей. Порівняльний аналіз традиційних і автоматизованих підходів дозволяє виділити переваги ARMS у швидкості, точності та масштабованості, одночасно визнаючи важливість людського контролю для забезпечення відповідального прийняття рішень. Зроблено висновок, що ефективна розробка та впровадження стратегій автоматизованого управління ризиками потребує міждисциплінарного підходу, що поєднує технологічні інновації з фінансовим регулюванням, етичними нормами та міжнародною співпрацею. Отримані результати підтверджують, що ARMS — це не лише інструменти ефективності, а й ключові компоненти фінансової стійкості та адаптивності в дедалі більш алгоритмізованому світі.

Ключові слова: втоматизовані системи управління ризиками (ARMS); штучний інтелект (AI); управління ризиками; міжнародна економіка; глобальні інвестиції; фінансові технології (FinTech); аналітика даних; міжнародна фінансова система; цифрова інфраструктура; фінансова стійкість

Introduction. Today, the global economy is facing growing instability: increasingly frequent financial crises, escalating geopolitical conflicts, persistently high inflation and sharp fluctuations in exchange rates create difficult conditions for the cross-border movement of capital. According to the International Monetary Fund (IMF), the total volume of global foreign direct investment reached a record $41 trillion in 2023, increasing by $1.75 trillion or 4.4% compared to the previous year [1]. According to OECD statistics, investment flows into developing economies continue to show positive dynamics, which increases the importance of reliable systems for risk assessment and management [2].

The financial environment is becoming increasingly complex, particularly amid rapid digitalization and destabilization of global supply chains. New forms of economic threats—such as cyberattacks, sanction regimes, and platform shutdowns—intensify pressure on participants in international markets. Under such conditions, risk management goes beyond a corporate function and becomes a critical element of strategic planning at the level of governments, corporations, and institutional investors.

Traditional approaches to investment risk management have historically relied on manual expert evaluation, historical data analysis, and financial models such as Value at Risk (VaR), scenario analysis, and stress testing. These methods assumed market stability and linear asset behavior, which no longer reflect the modern dynamics of global finance.

Classical models often fail to account for sudden "black swan” events—rare but devastating disruptions. The 2008 financial crisis revealed the inability of VaR models to predict collapses caused by systemic interconnected risks. In 2008, investor David Einhorn compared VaR to “an airbag that works all the time, except when you have a car accident,” emphasizing that a 99% VaR “does not evaluate what happens in the last one percent,” where the real catastrophe lies[3]. He also noted that such models may create a false sense of security among executives and regulators, encouraging excessive but formally acceptable risk-taking.

Likewise, the collapse of Archegos Capital in 2021 and the catastrophic FX losses of Credit Suisse in 2022 exposed fatal flaws in leverage management and systemic failures in counterparty banks' risk controls, as well as how outdated risk management models fail in high-frequency turbulent markets.

These cases exposed a systemic problem: financial institutions still rely on routine checks and historical data, while today we need real-time machine learning and stress tests with non-linear scenarios. Archegos showed how hidden leverage turns into a "time bomb", and the failure of Credit Suisse - the dangers of delaying hedging in sharp market fluctuations.

The shortcomings of these approaches include subjectivity, delayed responses, and poor adaptability to rapidly changing market conditions.

As a result, traditional investment risk management models no longer meet modern challenges, which is pushing financial institutions to transition to next-generation automated risk 6management systems.

Actuality. In the rapidly complex global financial environment, investment risk management is becoming critical to ensuring sustainable economic growth. Financial crises, sharp fluctuations in exchange rates, aggravation of geopolitical tensions and sanctions conflicts make global investments more vulnerable. At the same time, there is an increase in the volume of cross-border capital, including in developing economies, which requires a new risk management architecture capable of taking into account both local and global threats.

In these conditions, approaches that ensure efficiency, flexibility and accuracy in forecasting and neutralizing risks are especially important. Automated risk management systems (ARMS), based on the use of big data, machine learning algorithms and artificial intelligence, are becoming an integral part of modern investment infrastructure. They allow processing huge amounts of information in real time and making informed decisions even in conditions of high market turbulence.

The topic is especially relevant for developing countries, which are actively integrating into the global financial system, but often do not have the resources and technological base for adequate risk management using traditional methods.

Problem statement. Despite the active implementation of automated risk management systems in global investment processes, there are a number of fundamental problems that hinder their widespread and effective use. One of the key problems remains the lack of universal international standards regulating the architecture, algorithmic transparency and responsibility in the use of such systems. This complicates cross-border cooperation and leads to fragmentation of approaches in different countries and institutions.

Technological inequality between developed and developing countries is also a serious challenge. The lack of access to modern digital infrastructures, high-quality data and AI competencies deprives many markets of the opportunity to fully utilize the benefits of automation. This creates an asymmetry in global risk management and forms dangerous "blind spots" in the international investment system.

In addition, the issue of trust is acute: closed algorithms, possible errors in decision-making, inexplicable actions of systems based on opaque models - all this gives rise to risks of both a reputational and legal nature. These issues highlight the need for further research, ethical regulation and intergovernmental cooperation in the field of digital risk management.

Literature analysis. A review of the academic literature on automated risk management systems in the context of international economic activity reveals a growing interest in interdisciplinary research. Scholars increasingly focus on the integration of artificial intelligence, machine learning, and big data analytics into financial risk forecasting processes, especially in the context of cross-border investments. The literature highlights the limitations of traditional models including VaR, stress testing, and historical backtesting, especially when applied to high-frequency and volatile markets. For example, Barucci and Renaud (2002) show that models using high-frequency data outperform traditional models such as GARCH(1,1) and RiskMetrics in estimating volatility and calculating VaR[4].

In addition, a report by the Bank for International Settlements highlights that stress tests often do not take into account the interaction of market and credit risks and are dependent on the subjective decisions of risk managers[5].

A number of studies point to the effectiveness of AI-based models in identifying systemic risks and improving the accuracy of market forecasts. Kou et al. discuss the application of neural networks in risk modeling and highlight their ability to adapt to nonlinear conditions[6]. In addition, Chen and colleagues discuss the importance of operational decision-making tools in managing global investment portfolios in the face of economic uncertainty.

These studies highlight the need to reconsider traditional risk management methods and implement more adaptive models that take into account the peculiarities of modern financial markets.

Main part. Against the backdrop of the challenges outlined, automated risk management systems based on big data analysis, machine learning, and artificial intelligence algorithms are becoming increasingly important[7]. Below, we will consider their features, advantages, real-life application cases, as well as the challenges they face in the global investment context.

Risk management is a systematic approach to identifying, assessing, managing and monitoring risks that may affect the achievement of the objectives of a business entity.

In modern conditions, risk management is an important tool for ensuring the efficiency and safety of the activities of business entities. This is due to the following factors: the complexity and uncertainty of the external environment, competition, normative regulation.

The modern economic environment is characterized by high dynamics, uncertainty and risks. Risk management allows business entities to be more prepared for changes in the external environment and minimize the negative impact of risks on their activities.

In the modern world, competition between business entities is very high. Risk management allows business entities to be more competitive, as it allows them to avoid losses associated with risks and increase the efficiency of their activities.

In many countries of the world, there is regulatory regulation of risk management. This is due to the fact that risks can have a negative impact on the economic system of the country and its citizens.

The role of risk management in the activities of business entities can be presented as follows:

1. Ensuring the efficiency and safety of the business entity's activities.
2. Increasing the competitiveness of the business entity.
3. Ensuring transparency and accountability of the business entity's activities.

Risk management helps the business entity avoid losses associated with risks and increase the efficiency of its activities.

Risk management allows the business entity to be more prepared for changes in the external environment and increase its competitiveness.

Risk management helps an entity to provide informative and unbiased information about its risks to authorities and other interested parties.

The role of risk management in the activities of entities can be presented as ensuring the efficiency and safety of the entity's activities, increasing the competitiveness of the entity, and ensuring transparency and accountability of the entity's activities.

Risk management helps an entity to avoid losses associated with risks and increase the efficiency of its activities.

Risk management allows an entity to be better prepared for changes in the external environment and increase its competitiveness.

Risk management helps an entity to provide informative and unbiased information about its risks to authorities and other interested parties.

Risk management measures implemented within the framework of risk management can have a positive impact on the activities of business entities in the following aspects: financial, operational, marketing, investment, legal, etc.

Risk management can help a business entity avoid financial losses associated with risks. For example, with the help of risk management measures, a business entity

can reduce the likelihood of force majeure circumstances

that can lead to a stoppage of production or loss of goods.

A typical automated risk management system can be divided into several key components. These include, first of all, a data collection and filtering module, an analysis and forecasting module, and a decision-making module integrated with execution systems. All signals of increased risks, such as volatility spikes or changes in asset correlations or market anomalies, are generated automatically by the system. Such systems are often accompanied by visual dashboards that display key risk indicators in real time[8].

With the advancement of technology in the 21st century, risk management is gradually moving away from manual methods, moving towards automated platforms that analyze big data in real time. These systems use Big Data, machine learning, AI and neural networks, which helps to create more flexible and accurate approaches to investment risk management[9][10].

These systems use the capabilities of Big Data, AI and machine learning, including neural network algorithms, which allows them to build adaptive and accurate risk minimization strategies. One of the most famous examples is Aladdin, an analytical platform from BlackRock, widely used in investment management. It analyzes millions of parameters in real time and provides portfolio management recommendations based on global market changes. At JPMorgan, AI models are actively implemented to forecast default probabilities and market volatility by analyzing news flows and behavioral patterns. Crypto platforms use automation to control liquidity, predict risks, and flexibly customize trading approaches. Such solutions are especially in demand at the global level, where the speed of decisions and the reliability of analytics are critical. Automation not only enhances the efficiency of risk management but also enables better consideration of country-specific and market-specific factors amid global economic uncertainty.

Despite the high level of automation, humans remain an important element of control. Risk specialists check the logic of algorithms, verify atypical signals, and make final decisions in case of conflicts between the automated model and the macroeconomic context. Some banks use a hybrid approach: AI algorithms provide recommendations, but final actions are taken manually after approval. According to McKinsey & Company, the use of AI in risk management can reduce forecasting errors by 20–50% and administrative costs by 25–40% [11]. In addition, companies that have implemented such systems note a reduction in decision-making time from several hours to minutes, which is critical in conditions of high volatility.

However, relying on automation without proper restraints is risky. For example, during the May 2010 Flash Crash, automated trading algorithms caused the S&P 500 to plummet by more than 9% in a matter of minutes, after which the market recovered just as quickly. Analysis showed that the chain of automated orders was triggered without human intervention, resulting in multibillion-dollar losses. Incidents like these highlight the need for built-in safeguards and dual controls.

Unlike classical models such as Value at Risk or stress testing, ASRMs are able to take into account nonlinear relationships between assets, external factors (news flows, geopolitical events) and even investor behavior patterns while AI systems adapt to a changing environment (see Table).

Traditional methods are focused on stable distributions and do not take into account real-time market dynamics, while AI systems adapt to a changing environment.

Table – Comparison of Traditional and Automated Risk Management Systems

Criterion	Traditional Models	ARMS
Response time	Hours – Days	Seconds – Minutes
Consideration of external factors	Limited	Yes (news, geopolitics, behavior)
Model flexibility	Low	High
Self-learning capability	Absent	Yes (machine learning)
Human factor	High	Minimized (with oversight)

At the same time, the approaches to using automated risk management systems (ARMS) themselves continue to actively develop. One of the key areas has become the implementation of the concepts of explainable AI (XAI) and responsible AI, which make the work of algorithms more transparent and interpretable for risk specialists and regulators. This is especially important in conditions where automated decisions are made in highly stressful situations and can have a significant impact on the investment management strategy.

ARMS include modules for taking into account ESG risks. ESG (Environmental, Social, Governance) are environmental, social and management factors that reflect the company's non-financial risks. Sustainability metrics are integrated into risk assessment models and asset returns. This allows taking into account the influence of non-financial factors when forming investment portfolios and reducing long-term risks.

Automated stress testing modules perform scenario analysis in real time. The calculation includes non-linear dependencies between assets, macroeconomic indicators and external shocks. This approach increases the accuracy of assessing potential risks in conditions of market instability.

The development of ARMS directly depends on the requirements of international regulation in the field of artificial intelligence. The European AI Act adopted in 2024 establishes a classification of AI systems by risk level and introduces strict requirements for transparency, data management and verifiability of algorithms for high-risk systems, which include financial ARMS[12]. This obliges financial institutions in the EU to review the architecture of their automated decisions and implement additional interpretability and control mechanisms.

In the United States, the NIST AI Risk Management Framework (AI RMF 1.0) has become a benchmark for the implementation of ethically and technically sustainable AI systems. This framework offers standardized approaches to assessing AI risks, including reliability, sustainability, security and discrimination risks.

These international initiatives are already influencing the practice of developing ARMS, stimulating the unification of standards and increasing the level of trust in automated systems in international investment activities.

The effectiveness of ARMS models depends on the quality of the input data; in order for the models to produce accurate results, they need to be fed with quality data. If the data is incomplete, erroneous, or outdated, the model will begin to produce distorted or incorrect results. A particular problem is the systematic data error that occurs when training models on historical data, which may contain structural distortions or fail to take into account rare but significant events.

In international investment practice, additional challenges arise from the heterogeneity of data sources across countries, format incompatibility, and differences in market transparency. As a result, "blind spots" may appear where ARMS are unable to adequately assess risks.

Modern ARMS development approaches include mandatory data quality checks (data validation) and tools for monitoring bias in models. However, this issue remains a significant challenge and requires international standardization.

The conducted research demonstrates that automated risk management systems have become a key component of the global investment ecosystem. Unlike classical approaches, these solutions are characterized by increased responsiveness, improved forecast accuracy and minimization of human errors. This is especially relevant in the context of global instability, when a delay in decision-making can lead to significant financial losses.

At the same time, the widespread introduction of automation raises a number of new issues. One of the key challenges is the need for international standardization of approaches to algorithmic risk management. Different countries have different standards in the field of data regulation, financial monitoring, and cybersecurity. In addition, ethical questions remain: how to ensure the transparency of algorithms, who is responsible for erroneous decisions of AI systems, and how to avoid discrimination in models trained on historically distorted data.

This technological imbalance makes emerging markets weak links in the global financial system. When automated algorithms in one country fail to take into account the risks of others due to differences in data and infrastructure, it creates dangerous blind spots. A local crisis can instantly escalate into a chain reaction, as happened during the Asian financial crisis of 1997 – only now with algorithmic acceleration[13][14].

In the context of increasing instability of the global economy and the growth of cross-border investment flows, automated risk management systems are no longer an optional tool and are becoming a critical element of sustainable financial management. The analysis showed that these systems outperform classical methods in terms of data processing speed, forecast accuracy and minimization of human factor influence. They provide a quick response to changes in global markets and the ability to take into account local risk characteristics.

However, automation cannot be considered a universal tool. Its effectiveness depends on the quality of the source data, the transparency of algorithms, and the level of trust from financial system participants. In addition, there is an obvious need for international coordination, the creation of uniform standards and ethical norms for the use of AI in risk management[15].

Future research should be aimed at studying algorithmic resilience in the context of systemic crises, integrating ESG factors into automated models, and developing solutions adapted to emerging markets. This is the only way to achieve a fair and technologically balanced development of the global investment environment[16].

Thus, automated systems do not simply complement classical risk management, but gradually form a new paradigm for working with investment risks. Their implementation requires an interdisciplinary approach, a combination of technical, legal and ethical solutions. Only if these conditions are met can we ensure not only technical but also institutional stability of the investment process in the context of global turbulence.

Conclusion. This article raised the issue of the obsolescence of traditional risk accounting systems and how to fix it. The obvious solution is automation and the use of modern technologies such as big data, machine learning and artificial intelligence. Thanks to them, the risk system increases the speed of work, accuracy and adaptability to rapidly changing realities. ARMS systems provide real-time monitoring, early detection of anomalies and dynamic adjustment of changing market conditions, significantly increasing the sustainability of investment strategies.

We also considered the possible risks that such a system carries, such as: ethical, regulatory and systemic risks. The lack of global standards, uneven technological development and opaque algorithmic decision-making remain critical problems. These problems are especially acute in emerging markets, where underdeveloped infrastructure can lead to increased systemic vulnerability.

The most logical and expected future of ARMS lies in the so-called hybrid models. These models combine technological efficiency with human oversight, international cooperation and ethical governance. Further interdisciplinary research is essential to address issues of transparency, algorithmic accountability and the integration of ESG principles. Only by ensuring such an integrated approach can ARMS contribute to the creation of sustainable, inclusive and safe global investment systems

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