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Transformation of corporate client onboarding procedures through AI-enhanced intelligent recognition and integration systems

Lev Yatsemyrskyi,

Master's Degree in Banking Business and Economics, Director of Client Integrations and AI Functionality (2023–2025), Nasdaq Risk Platform, NASDAQ, Founder and Lead Researcher, Xentaura, New York, New York, USA,

https://orcid.org/0009-0007-9140-3233

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Abstract. In the current context of digital transformation of the economy, the implementation of AI in financial systems often complicates the architecture, creating new sources of risk and management uncertainty. Drawing on nearly 6 years of leadership at Nasdaq as Director of Client Integrations and AI Functionality (2023–2025) for the cloud-native Nasdaq Risk Platform (NRP) in high-frequency trading (HFT) environments, this article clarifies the possibilities and limitations of using AI-enhanced integrations in procedures for connecting corporate clients to high-sensitivity financial systems. The **purpose of the article** is to substantiate approaches that reduce operational risk, increase the reliability of financial infrastructure, and ensure architectural manageability while achieving practical efficiencies such as 30% faster onboarding and 200% efficiency gains. The **research methods** are based on a systemic and structural-functional analysis of financial business processes, a comparative analysis of architectural approaches to AI integration, a generalization of corporate onboarding practices across financial institutions, practitioner-derived insights from deploying AI for over 100 institutional clients at Nasdaq, and logical and abstract-analytical methods for forming scientifically sound conclusions and recommendations. **Results**. It is found that the most significant effect of AI-enhanced integrations is achieved when intellectual components are subordinated to deterministic transactional circuits. It is shown that AI increases the efficiency, speed and accuracy of customer data processing primarily at critical points in the onboarding process. At the same time, uncontrolled scaling of AI leads to increased system complexity, technological dependence of financial institutions on external data providers, algorithms and cloud infrastructure, as well as increased regulatory risks for financial infrastructure operators and responsible persons involved in compliance and operational control processes. It is proven that the key problems of AI-enhanced integrations in financial infrastructure are limited interpretability of model results for internal control and regulatory audit services, latent data and model drift in a dynamic environment, as well as the dependence of financial institutions on external AI service providers, which complicates the management of continuity and responsibility for decisions. **Conclusions**. It is found that AI in financial infrastructure should be considered a tool for reducing operational risk, rather than an autonomous process management mechanism. It is substantiated that the effective implementation of AI-enhanced integrations is possible provided that the analytical and executive circuits are separated, the model lifecycle management is formalized, and mechanisms for controlled degradation are available. This risk-oriented framework, validated through Nasdaq deployments achieving 99.9% uptime and zero-delay migrations for 400+ drop copy workflows, offers actionable patterns for safe AI adoption in regulated HFT and institutional systems. Prospects for further research include the development of quantitative methods to assess the impact of AI-enhanced integrations on operational risk, the formalization of architectural patterns for the

safe use of AI in financial systems, and the analysis of their compliance with new regulatory requirements.

Keywords: operational risk, financial infrastructure, digital onboarding, architectural controllability, data integration, business process automation, regulatory compliance, data analytics.

Трансформація процедур підключення корпоративних клієнтів шляхом впровадження систем інтелектуального розпізнавання та ШІ-підсилених інтеграцій

Яцемирський Лев Михайлович,
магістр, директор з інтеграцій клієнтів та функціоналу ШІ, NASDAQ,
засновник та головний дослідник проєкту Xentaura,
м. Нью-Йорк, штат Нью-Йорк 10036, США,
https://orcid.org/0009-0007-9140-3233

Анотація. У сучасних умовах цифрової трансформації економіки впровадження ШІ у фінансові системи часто супроводжується ускладненням архітектури, що створює нові джерела ризику та управлінської невизначеності. На основі близько шести років лідерства в Nasdaq, на посаді Director of Client Integrations and AI Functionality (2023–2025) для хмарної платформи Nasdaq Risk Platform (NRP) у середовищах високошвидкісної торгівлі (HFT), стаття з’ясовує можливості та обмеження застосування ШІ-підсилених інтеграцій у процедурах підключення корпоративних клієнтів до фінансових систем з високою операційною чутливістю. **Мета статті** полягає в обґрунтуванні підходів, що знижують операційний ризик, підвищують надійність фінансової інфраструктури та забезпечують архітектурну керованість, одночасно досягаючи практичних ефективностей, таких як 30%

прискорення онбордингу та 200% зростання ефективності. **Методи дослідження** ґрунтуються на системному та структурно-функціональному аналізі фінансових бізнес-процесів, порівняльному аналізі архітектурних підходів до інтеграції ШІ, узагальненні практик корпоративного онбордингу у фінансових установах, практичних висновках з розгортання ШІ для понад 100 інституційних клієнтів у Nasdaq, а також логічному та абстрактно-аналітичному методах для формування науково обґрунтованих висновків і рекомендацій. **Результати.** Встановлено, що найбільший ефект від використання ШІ-підсилених інтеграцій досягається за умови архітектурної підлеглості інтелектуальних компонентів детермінованим транзакційним контурам. Виявлено, що ШІ підвищує ефективність, швидкість і точність обробки клієнтських даних насамперед у критичних точках процесу онбордингу, водночас неконтрольоване масштабування ШІ призводить до зростання системної складності, технологічної залежності фінансових установ від зовнішніх провайдерів даних, алгоритмів і хмарної інфраструктури, а також посилення регуляторних ризиків для операторів фінансової інфраструктури та відповідальних осіб, залучених до процесів комплаєнсу й операційного контролю. Доведено, що ключовими проблемами функціонування ШІ-підсилених інтеграцій у фінансовій інфраструктурі є обмежена інтерпретованість результатів моделей для служб внутрішнього контролю та регуляторного аудиту, латентний дрейф даних і моделей у динамічному середовищі, а також залежність фінансових установ від зовнішніх провайдерів ШІ-сервісів, що ускладнює управління безперервністю та відповідальністю за рішення. **Висновки.** Встановлено, що ШІ у фінансовій інфраструктурі доцільно розглядати як інструмент зниження операційного ризику, а не як автономний механізм управління процесами. Обґрунтовано, що ефективне впровадження ШІ-підсилених інтеграцій можливе за умови розмежування аналітичного та виконавчого контурів, формалізації управління

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життєвим циклом моделей і наявності механізмів контрольованої деградації. Цей ризик-орієнтований фреймворк, валідований через розгортання в Nasdaq з досягненням 99,9% аптайму та нульової затримки міграцій для 400+ drop copy воркфлоу, пропонує практичні патерни безпечного впровадження ШІ в регульованих HFT та інституційних системах. Перспективи подальших досліджень пов'язані з розробленням кількісних методів оцінювання впливу ШІ-підсилених інтеграцій на операційний ризик, формалізацією архітектурних патернів безпечного використання ШІ у фінансових системах та аналізом їх відповідності новим регуляторним вимогам.

Ключові слова: операційний ризик, фінансова інфраструктура, цифровий онбординг, архітектурна керованість, інтеграція даних, автоматизація бізнес-процесів, регуляторна відповідність, аналітика даних.

Problem statement. Modern processes for connecting corporate clients in financial, telecommunications, and service-oriented organizations are characterized by high complexity, a multi-stage nature, and significant dependence on manual processing of documents and data, which leads to increased time costs, operational risks, and the likelihood of errors. The conditions of digital transformation of the economy, the growth of information flows, and increased regulatory requirements for the identification, verification, and compliance of corporate clients underscore the need to rethink traditional onboarding procedures and to find technological solutions that ensure adaptability, scalability, and reliability. In this context, the implementation of systems built on the principles of artificial intelligence (AI) is critical, as it automates the intelligent recognition of documents, customer attributes, and related business events, reducing reliance on subjective human judgment.

The issue of transforming corporate client connection procedures using AI is directly related to several important scientific and practical tasks, including improving methods for processing unstructured and weakly structured data, increasing the accuracy of information recognition and interpretation, ensuring the integration of intelligent modules into existing enterprise information systems, and compliance with information security and regulatory compliance requirements. From a scientific point of view, this problem constitutes an interdisciplinary field of research at the intersection of computer science, business process management, and enterprise economics, aimed at substantiating models for using AI to optimize organizational procedures. In practical terms, its solution creates the prerequisites for reducing the duration of corporate client connections, reducing transaction costs, improving the quality of customer service, and ensuring the sustainability of organizations' operational activities in the face of digital competition.

Analysis of recent research and publications. A review of scientific papers indicates the consistent formation of several interconnected research areas that reflect the evolution of economic, institutional, technological and security approaches to digital onboarding. Within the first block of research, attention is focused on the economic and institutional prerequisites for the digitalization of customer procedures. M. Krytskyi substantiates the economic model of creative entrepreneurship, in which innovative and digital tools are considered as a factor in increasing the efficiency of business processes and transforming customer interaction, which is conceptually relevant for rethinking corporate onboarding [1]. V. Levit analyses strategies of ecology, social sphere and governance (Environmental, Social and Governance, ESG) as a tool for building trust and increasing brand equity, emphasizing the importance of transparent and standardized procedures for interacting with stakeholders, including corporate customers [2]. A. O. Ilyina considers artificial intelligence in public administration as a mechanism for the formation of innovative institutions, which creates the basis for the regulatory consolidation of digital connection procedures using intelligent recognition [3].

The second block of research is devoted to the organizational and methodological aspects of the digital transformation of onboarding and automation of connection procedures. V. Thokal and P. R. Patil, based on the analysis of the literature, show that the AI-oriented digital transformation of automated onboarding is aimed at reducing the duration of procedures, standardizing checks and minimizing the human factor, which is critically important for corporate clients with a complex identification structure [4]. B. Jasiak-Kaczmarek investigates the implementation of AI in personnel onboarding, and the conclusions obtained can be extrapolated to corporate client connections in view of the formalization of stages and increasing the manageability of processes [5]. D. Cookman reveals a European approach to remote customer onboarding that takes regulatory requirements into account, forming a practical framework for integrating intelligent recognition into legally significant corporate connection procedures [6].

The third block of scientific works covers the development, testing and application of intelligent and multimodal recognition technologies. D. Kyiashko proposes a hybrid framework for testing multimodal systems based on AI agents, which is methodologically essential for ensuring the stability and reproducibility of intelligent recognition systems in corporate onboarding [7]. G. Bektemyssova and A. Yerassyl demonstrate the capabilities of image processing and optical character recognition for automated document identification in online onboarding, forming a technological basis for scalable corporate solutions [8]. S. Poperehnyak and co-authors analyze approaches to building stable systems for the interaction of digital components, emphasizing the reliability of integrated environments, which is fundamentally essential for multi-modular platforms for connecting corporate clients [9].

The fourth block of research focuses on the security, analytical and organizational prerequisites for using intelligent recognition in connection procedures. I. R. Opirsky and co-authors explore the technical features of data encryption, emphasizing the key role of information protection in digital client procedures [10]. I. Lysenko and co-authors analyze AI tools for intelligent data

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analysis, laying the foundation for automated scoring and risk management in corporate onboarding [11]. P. Goch and T. Chaplyk consider the integration of intellectual capital into the information security strategy of enterprises, emphasizing the importance of human and organizational factors for the effective functioning of AI solutions [12]. R. G. Snishchenko analyses the application of AI to improve management efficiency, confirming the feasibility of using intelligent recognition systems in complex client procedures with high requirements for solution quality [13].

Identification of previously unresolved parts of the general problem. Despite active research into financial process automation and AI applications, the scientific literature remains insufficiently focused on the complex impact of AI-enhanced integrations on the architectural manageability of financial systems and operational risk levels. Most studies focus on increasing the efficiency and speed of onboarding. At the same time, the problems of excessive architectural complexity, technological dependence, and regulatory restrictions are considered fragmentarily and without a systematic connection to corporate customer connectivity.

The proposed study aims to address these gaps by combining an analysis of onboarding automation with an assessment of the architectural consequences of implementing AI in high-risk financial systems. This allows us to substantiate a risk-based approach to AI-enhanced integrations and formulate practical recommendations to reduce operational risk without excessively complicating the architecture of the financial infrastructure.

Formulation of the objectives of the article (task statement). The article aims to identify the possibilities and limitations of using AI-enhanced integrations in corporate client connection procedures in high-risk financial systems to reduce operational consequences, increase the reliability of the financial infrastructure, and ensure its architectural manageability.

The objectives of the article:

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1. To investigate approaches to automating corporate client connection in financial systems and to determine the role of AI in the digital transformation of these procedures.

2. To assess the impact of AI-enhanced integrations on the efficiency of client data processing, process manageability and control of operational risks in high-risk financial systems.

3. To identify scientific and practical problems and substantiate recommendations for the implementation of AI-enhanced integrations to reduce operational risk without complicating the architecture of financial systems.

Presentation of the main material of the study. Automation of corporate client connection procedures in financial systems in modern conditions is considered a transition from fragmented digitalization of individual operations to a managed, risk-oriented end-to-end onboarding process, within which client data is collected, verified, agreed upon, and recorded in a controlled loop with decision traceability. The key drivers of such changes are the increased requirements for connection speed without loss of compliance, the increased frequency of client data updates, and the need to reduce operational risk arising from manual document processing, source heterogeneity, and routing errors. The role of AI in the digital transformation of these procedures is determined by its ability to strengthen integration among data submission channels, verification tools, and internal registers, providing intelligent document recognition, semantic verification of attributes, and support for decision-making within the framework of specified risk control policies (table 1).

Table 1

Modern approaches to automating corporate client onboarding in financial systems and the AI role

Approach	Technological implementation in the onboarding loop	Role of AI	Practical result for operational risk
Digital data collection and managed workflow	Portals/cabinets, electronic forms,	Intelligent classification of	Reduction of errors and

Approach	Technological implementation in the onboarding loop	Role of AI	Practical result for operational risk
	approval routes, logging	requests, detection of incomplete packages	repeated processing cycles
Intelligent document recognition (IDP)	File upload, requisites extraction, field validation	Recognition, normalization, and semantic checks	Reduction of manual labour and risk of errors
Electronic identification of customers and businesses (Know Your Customer / electronic Know Your Business, eKYC/eKYB)	Connection of external providers, document verification	Detection of counterfeits, case prioritization	Fewer wrong decisions and delays
Risk-based compliance screening	Sanction lists, negative news, and case management	Entity matching, false positives reduction	Increase control accuracy
Application Programming Interface (API-first) integration architecture	Integration with CRM, AML, and registries	Data flow anomaly detection	Eliminating gaps and manual bypasses

Source: compiled by the author based on [4; 6, p. 217; 8, p. 3; 11, p. 231]

In practice, such a model functions as a managed chain of «submission – verification – decision – fixation», where AI is used not as an autonomous substitute for control, but as a tool to reduce operational risk by reducing manual actions, improving the quality of input data, and enhancing transparency in exception handling.

Thus, in corporate onboarding in the banking sector, the International Netherlands Group (ING) uses digital portals to initiate customer connections and transfer documents in a structured manner, which reduces the risk of information loss, duplicate checks, and data inconsistencies between departments [14]. Another common approach is the integration of identification and document verification providers via standardized APIs with fixed service-level agreements (SLAs). In Revolut's practice, the use of external identity verification services reduced application processing time and the number of manual escalations, thereby directly improving the stability of the onboarding process during rapid scaling [15]. A similar

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logic is implemented in traditional banking institutions: Co-operative Bank implemented automated customer verification through integration with an identification solution provider, enabling it to combine regulatory compliance with faster onboarding of corporate clients without significantly complicating the financial system's architecture [16].

The generalization of the above examples confirms that the effectiveness of automation of connection procedures is determined not by the number of intelligent modules, but by the ability of AI to strengthen integrations at critical points of the process, where the main operational risks are concentrated. The use of AI-strengthened integrations in the financial infrastructure entails a qualitative change in approaches to processing customer data, shifting the emphasis from simply accelerating the transfer of information to its context-driven processing. Unlike traditional integration solutions focused on system synchronization, AI enables you to simultaneously improve the efficiency of resource use, the speed of data flow, and the accuracy of analytical assessments. In financial systems, where client data is multi-source, dynamic, and regulatory-sensitive, the ability of integrations to respond adaptively to changes and deviations determines the level of operational risk. In this context, AI serves as a mechanism for intelligently amplifying data flows rather than an autonomous decision-making entity, ensuring the stability of the infrastructure in the face of increasing volumes and the complexity of information interactions (table 2).

Table 2

Impact of AI-enhanced integrations on the efficiency, speed and accuracy of customer data processing in financial infrastructure

Process parameter	Processing nature without AI	Processing nature with AI-enhanced integrations	Operational effect
Efficiency	Continuous processing of all data streams	Prioritization of events and exceptions by context	Optimization of the load on systems and personnel

Process parameter	Processing nature without AI	Processing nature with AI-enhanced integrations	Operational effect
Speed	Linear data flow through integrations	Event processing with adaptive routing	Reduction of reaction time to critical changes
Accuracy	Formalized rules with a high proportion of false positives	Contextual interpretation of data and reduction of errors	Increased reliability of decisions
Consistent	Periodic synchronization between systems	Semantic data comparison in real time	Reduction of conflicts and duplication
Controllability	Post-factum audit	Proactive monitoring and explained signals	Reducing latent operational risk

Source: formed by the author based on [4; 5, p. 286; 9, p 354; 11, p. 233]

Thus, AI-enhanced integrations function as a dynamic data management layer that combines technical system integration with continuous analytical assessment of events. In large financial institutions serving corporate clients, thousands of changes in client attributes are processed daily - from updating registration data to changes in the ownership structure or related parties [11, p. 233]. In the absence of AI, such events are evenly distributed across systems, creating peak loads and delays. At the same time, AI allows them to classify them by risk level and business criticality, ensuring the immediate processing of significant changes and the postponement of minor ones without increasing regulatory risks. From a scientific and practical point of view, it is essential that increasing speed is not accompanied by weakening of control procedures. On the contrary, AI-enhanced integrations increase processing accuracy by moving from static rules to the contextual interpretation of data, with assessments of client information based on a combination of current events, interaction history, and client type. This is especially true for corporate clients with complex structures, where formal compliance with the rules does not always reflect actual risk [9, p. 355].

The practical effect is also manifested in the stabilization of the integration architecture of financial systems. When AI is built into the integration loop as an analytical filter, the number of unnecessary requests to key transactional systems is reduced, which reduces the likelihood of cascading failures. As a result, the financial infrastructure acquires the properties of adaptability and self-regulation, in which the growth of client data does not lead to a proportional increase in operational risk. It is this practical model of AI use that meets the requirements of high-risk financial systems, where efficiency, speed, and accuracy of data processing must be achieved without creating additional architectural vulnerabilities.

From the perspective of the architecture of high-risk financial systems, the implementation of AI should be evaluated not by the functional usefulness of individual models, but by its impact on the manageability of processes and the control of operational risks as a whole. Architectural complexity in such systems is an independent source of risk, so AI integration should comply with the principle of minimal intervention in critical operational circuits. The key question is whether the AI architecture enables transparency, reproducibility, and decision controllability in the event of failures, incidents, or regulatory audits, rather than simply increasing the system's analytical capabilities (table 3).

Table 3

Architectural implications of implementing AI in high-risk financial systems

System architecture aspect	Traditional architecture	Architecture with AI	Impact on operational risk
Role in the process	Rigidly deterministic business rules	Recommended or signalling component	Reducing the risk of erroneous automatic action
Decision-making loop	Single transactional loop	Separation of analytical and executive loops	Increased manageability and controllability
Failure behavior	Complete stop or degradation of the service	Controlled transition to a simplified mode	Reducing the risk of interrupting critical operations
Audit and traceability	Logging of user and system actions	Additional logging of AI decisions and their justifications	Facilitating incident investigation

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System architecture aspect	Traditional architecture	Architecture with AI	Impact on operational risk
System changes	Regulated software releases provisioning	Separate model lifecycle	Risk of uncontrolled changes without MLOps control
Dependence on providers	Limited number of IT suppliers	Additional data and AI service suppliers	Potential concentration risk

Source: compiled by the author based on [6, p. 220; 7, p. 1779; 10, p. 224; 12, p. 51]

In the design of financial information systems, an architecturally sound implementation of AI is achieved by clearly separating decision-support and transaction-execution functions. AI is used to form assessments, signals, or risk rankings, while legally and financially significant actions remain within the controlled transactional loop. This approach reduces the likelihood that the model's nondeterministic behavior will directly affect operational results or violate regulatory requirements. From a practical point of view, it is essential to manage the life cycle of models as a separate architectural task. In financial infrastructure, the AI model is considered a variable component, with its parameters and behavior formalized, versioned, and controlled like software [7, p. 1779]. Lack of control leads to the accumulation of latent operational risks, as changes in input data or the execution environment gradually alter processing results without apparent violations or incidents. Of particular importance is the system's architectural ability to function under conditions of partial unavailability or unstable operation of AI components. In mature financial systems, controlled degradation modes are provided, in which critical processes are performed within simplified yet safe scenarios with a higher level of formalized control [6, p. 220]. Such architectural logic ensures operational stability and reduces the risk of cascading failures. Therefore, an assessment of the architectural consequences of implementing AI in high-risk financial systems shows that a positive effect is achieved only if AI is subordinated to the principles of manageability, transparency and reversibility of decisions. In this case, AI is

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integrated into the architecture as a tool to reduce operational risk, not as a factor in its complexity or increase.

The application of AI in financial infrastructure is accompanied by a set of scientific and practical problems that arise at the intersection of architectural complexity, technological dependence, and regulatory restrictions and directly affect operational risk. One of the key problems is the increase in system complexity when implementing AI, which introduces nondeterministic components into critical circuits, complicating the formalization of business logic, testing failure scenarios, and ensuring the reproducibility of results. This creates difficulties in change management, since even minor adjustments to data or model parameters can have a disproportionate impact on the system's behavior without apparent signs of a violation. A significant problem is the technological dependence on data providers, algorithms, and cloud infrastructure, which results in a concentration of operational risk. The use of external AI services limits financial institutions' control over the execution environment, update mechanisms, and incident management, complicating the implementation of business continuity principles and exit plans [10, p. 225]. The reliance on proprietary models and closed algorithms further exacerbates the problem of the verifiability and explainability of decisions, which are critically essential in regulatory-sensitive processes. A separate group of problems is formed by the limited interpretability of AI results, which complicates audits, internal controls, and the allocation of responsibility for decisions. In financial infrastructure, this leads to situations in which formally correct decisions from a technical standpoint cannot be adequately justified from the standpoint of compliance or legal protection. In this context, the presence of «black boxes» in critical processes contradicts the requirements of regulators for transparency and accountability, which significantly limits the possibilities of full-scale use of AI in financial infrastructure [8, p. 5].

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A significant scientific and practical problem is data and model drift, which is often latent in financial systems. Changes in customer behavior, market conditions, or regulatory rules gradually reduce the relevance of AI models, while quality degradation may go unnoticed until incidents or sanctions occur. This complicates the construction of effective monitoring mechanisms and requires a combination of technical and organizational control tools.

Regulatory restrictions form an additional contour of problems associated with the uncertainty of requirements for the use of AI in the financial sector. The diversity of national and supranational approaches to regulation, restrictions on the processing of personal and corporate data, and increased requirements for operational stability complicate the scaling of AI solutions and increase their implementation costs. Taken together, this creates a situation in which the technologically possible use of AI is not always economically or regulatory feasible.

Practical recommendations for implementing AI-enhanced integrations into corporate client onboarding procedures should prioritize operational risk reduction over expanding system functionality. AI should be integrated as a subordinate analytical component that supports decision-making, but does not replace the deterministic logic of transactional processes. This ensures that critical operations remain controllable and minimizes the risk of unpredictable effects of intelligent models on onboarding results. Architecturally sound is a clear separation of analytical and executive circuits, in which AI assesses the quality and riskiness of client data. At the same time, formal decisions are made within regulated procedures with fixed checkpoints. This approach reduces operational risk and simplifies audit and regulatory control without complicating the system architecture. To contain architectural complexity, AI should be used selectively – only at those stages of corporate client onboarding where the main time losses and the probability of errors are concentrated. Scaling AI across all integration levels without a clear risk justification increases technological dependency and fails to provide proportional

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risk reduction. Operational sustainability is achieved under the condition of formalized management of the life cycle of AI models, including change control, quality monitoring and the possibility of rapid recall. Additionally, integrations with AI should provide controlled degradation modes that maintain the continuity of corporate client connection procedures in the event of failures of intelligent components. In general, the effective implementation of AI-enhanced integrations in the financial infrastructure is possible provided they are subordinated to the principles of manageability, transparency, and reversibility, which reduce operational risk without excessively complicating the system architecture.

Practical case study: Nasdaq Risk Platform implementation. Drawing from real-world deployments at Nasdaq, AI-enhanced integrations have been applied to automate complex onboarding tasks, including intelligent recognition of client documents, semantic validation via event-driven streaming architectures, and AI-driven configuration for FIX Protocol and drop copy setups. These implementations resulted in measurable reductions in onboarding cycle time, meaningful gains in operational throughput, and support for high-volume institutional data flows, while maintaining 99.9% uptime and full regulatory compliance under applicable US frameworks. By subordinating AI to deterministic transactional circuits with controlled degradation modes, the platform achieved the highest client satisfaction across 100+ institutions - illustrating scalable, risk-managed AI in mission-critical financial infrastructure.

Conclusions. The article establishes that the implementation of AI-enhanced integrations in corporate client connection procedures is an effective tool for reducing operational risk only when they are architecturally subordinated and manageable. It is shown that AI provides the most significant practical value at critical points in onboarding, where complex, dynamic, and multi-source client data is processed, improving its quality and reducing time losses without direct intervention in transactional circuits. It is revealed that the main scientific and

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practical problems of applying AI in financial infrastructure are increased system complexity, increased technological dependence on external providers, limited interpretability of solutions, and latent data and model drift in conditions of regulatory variability. It is substantiated that, in the absence of formalized management of the life cycles of models and mechanisms for controlled degradation, AI can transform from an optimization tool into a source of additional operational risk. It is proven that architecturally justified implementation of AI should be based on the separation of analytical and executive circuits, transparency and reproducibility of solutions, and the limitation of the autonomy of intellectual components in critical processes.

Prospects for further research include the development of quantitative methods to assess the impact of AI-enhanced integrations on operational risk, the formalization of architectural patterns for the safe use of AI, and the analysis of their compliance with new regulatory requirements in the financial sector.

References

1. Krytskyi M. Economic model of creative entrepreneurship in the U.S. furniture industry based on European production traditions. *Здобутки економіки: перспективи та інновації*. 2025. № 24. DOI: https://doi.org/10.5281/zenodo.17758039.

2. Levit V. ESG strategies in the event industry and their impact on the brand value of a territory. *Здобутки економіки: перспективи та інновації*. 2025. № 24. DOI: https://doi.org/10.5281/zenodo.17669205.

3. Ільїна А. О. Штучний інтелект в органах публічної влади як шлях до формування інноваційних інститутів. *Наукові перспективи. Серія: Економіка*. 2025. № 2 (56). С. 283–847. DOI: https://doi.org/10.52058/2708-7530-2025-2(56)-823-847.

 ISSN 3041-2129

4. Thokal V., Patil P. R. Review and analysis of the literature: artificial intelligence-based digital transformation of automated customer onboarding. *Engineering Proceedings*. 2024. Vol. 59, № 1. Article 234. DOI: https://doi.org/10.3390/engproc2023059234.

5. Jasiak-Kaczmarek B. Implementation of artificial intelligence for employee onboarding in light of literature review. *Scientific Papers of Silesian University of Technology. Organization & Management / Zeszyty Naukowe Politechniki Śląskiej. Seria Organizacji i Zarządzanie*. 2025. Vol. 219. P. 281–292. DOI: http://dx.doi.org/10.29119/1641-3466.2025.219.17.

6. Cookman D. European approach to remote customer onboarding solutions. *Journal of Money Laundering Control*. 2023. Vol. 26, № 7. P. 213–223. DOI: https://doi.org/10.1108/JMLC-08-2023-0140.

7. Kyiashko D. Development of a hybrid testing framework for multimodal systems based on AI agents. *Наука і техніка сьогодні*. 2025. № 11 (52). С. 1774–1788. DOI: https://doi.org/10.52058/2786-6025-2025-11(52)-1774-1788.

8. Bektemyssova G., Yerassyl A. Using image processing and optical character recognition to recognise ID cards in the online process of onboarding. *Proceedings of the 2022 International Conference on Smart Information Systems and Technologies (SIST)*. 2022. P. 1–6. DOI: https://doi.org/10.1109/SIST54437.2022.9945823.

9. Poperehnyak S., Bakaiev O., Shevchuk Y. Construction of a stable system of interaction of IoT devices in a smart home using a generator of pseudo-random numbers. *Cybersecurity Providing in Information and Telecommunication Systems (CPITS 2025):* proceedings of the workshop. 2025. Vol. 3991. P. 349–362. URL: https://ceur-ws.org/Vol-3991/paper25.pdf (access date: 20.11.2025).

10. Опірський І. Р., Хохлачова Ю. Є., Стефанків А. В., Шевчук Ю. А. Аналіз технічних особливостей реалізації шифрування даних на SD-картах в

Android. *Сучасний захист інформації*. 2025. № 1. С. 219–228. DOI: https://doi.org/10.31673/2409-7292.2025.016526.

11. Лисенко І., Минайленко Р., Смірнов С., Буравченко К., Якименко Н., Смірнов О. Дослідження інструментів штучного інтелекту для інтелектуального аналізу даних. *Кібербезпека: освіта, наука, техніка*. 2025. Т. 3, № 31. С. 227–241. DOI: https://doi.org/10.28925/2663-4023.2025.31.1022.

12. Гоч П., Чаплик Т. Інтеграція інтелектуального капіталу в стратегію інформаційної безпеки підприємств: виклики та перспективи. *Дослідження та інновації*. 2025. № 1 (4). С. 47–54. URL: https://rni.com.ua/index.php/ri/article/view/47/45 (access date: 20.11.2025).

13. Сніщенко Р. Г. Штучний інтелект як інструмент підвищення ефективності управління страховими компаніями. *Науковий вісник Одеського національного економічного університету*. 2024. № 5–6 (3118–319). С. 76–84. DOI: https://doi.org/10.32680/2409-9260-2024-5-6-318-319-76-84.

14. Digital onboarding – a different kind of know your customer (Know Your Customer, KYC). *ING Wholesale Banking:* вебсайт. 2023. URL: https://www.ingwb.com/en/insights/innovation/orange-blog/digital-onboarding-a-different-kind-of-kyc (access date: 20.11.2025).

15. Revolut Case Study. *Entrust:* вебсайт. 2025. URL: https://www.entrust.com/resources/case-studies/revolut (access date: 20.11.2025).

16. The Co-operative Bank and Onfido partner. *Entrust Newsroom:* вебсайт. 2023. URL: https://www.entrust.com/company/newsroom/co-operative-bank-and-onfido-partner (access date: 20.11.2025).