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EXPLAINABLE ARTIFICIAL INTELLIGENCE

PROACTIVE PERSONNEL RISK ASSESSMENT

TASK ALLOCATION AMONG PERFORMERS

DIGITAL TWINNING IN SMART AGRIBUSINESS

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CONTENTS

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Explainable AI for Industry 5.0: Shedding light on the black box

Sergey Mikhailovich Avdoshin
E-mail: savdoshin@hse.ru

Elena Yuryevna Pesotskaya
E-mail: epesotskaya@hse.ru

HSE University, Moscow, Russia

Abstract

The rapid development of artificial intelligence (AI) is accompanied by increasing computational complexity and decreasing model transparency, which significantly limits its adoption in critical domains that require a high level of trust, interpretability, and justification of decisions. Under these conditions, the field of Explainable Artificial Intelligence (XAI) has gained particular importance as it focuses on approaches and technologies that enable understanding of AI system logic and interpretation of their outputs. This article examines the timely topic of implementing XAI in the context of Industry 5.0. Special attention is given to practical application scenarios: the authors present concrete industrial cases from IBM, Siemens, and other companies demonstrating how XAI contributes to enhancing the reliability, safety, efficiency, and trustworthiness of AI systems. The study includes a systematic search and analysis of the literature in this domain and proposes well-grounded key criteria for comparing existing XAI approaches. The article also outlines the advantages, current limitations, and promising directions for the development of XAI, highlighting the opportunities it opens for improving effectiveness, transparency, and trust in business.

Keywords: XAI, explainable artificial intelligence, Industry 5.0, machine learning, industry

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Introduction

The emergence of explainable artificial intelligence (XAI) is directly associated with the rapid progress of modern machine learning methods, particularly deep neural networks. These models have demonstrated outstanding performance across a wide range of tasks; however, they have also come to be perceived as so-called "black boxes", that is, highly complex systems whose internal mechanisms are largely opaque to users [1]. In contrast to earlier AI systems, such as expert systems or rule-based models that were relatively transparent, contemporary deep learning algorithms contain millions of parameters. As their complexity has increased, interpreting the decisions they produce has become nearly impossible in practice. This has given rise to what is often described as an "explainability barrier", which limits the adoption of AI due to insufficient trust in opaque models [2].

Modern society expects artificial intelligence to be not only effective, but also reliable, transparent, and fair [3–5]. A lack of clear explanations for algorithmic decisions leads to concerns among users as well as regulatory authorities.

Explainable artificial intelligence has emerged as a response to this challenge. Its primary aim is to improve the interpretability and transparency of AI black-box models. XAI seeks to bridge the gap between the growing complexity of modern algorithms and the human need to understand the results they generate. Within the XAI paradigm, methods, techniques, and algorithms are developed to provide interpretable and intuitively meaningful explanations of AI-driven decisions. In this way, XAI offers developers, users, and regulators clear and well-reasoned explanations.

Within the human-centric vision of Industry 5.0, XAI is regarded as a key enabler of successful AI deployment. It allows users to understand and trust algorithmic outcomes, which is essential for effective human-machine interaction. Explainable AI also helps ensure that digital systems remain ethical, accountable, and aligned with human values and objectives [6, 7].

For business leaders, XAI is no longer merely a technical add-on, but a necessary condition for effective decision-making and governance. As algorithmic complexity increases, black-box models deprive managers of the ability to assess the rationale behind decisions that underpin strategic and operational actions. The adoption of XAI helps address this challenge by providing transparent explanations of algorithmic behavior. This supports more informed and responsible decision-making, reduces organizational risks, and creates new opportunities for innovation and development. For companies seeking to remain competitive in the context of Industry 5.0, the implementation of XAI becomes a strategic necessity [8–10].

In this study, the authors analyze contemporary approaches and requirements related to explainability that aim to enhance the transparency and reliability of intelligent systems and to strengthen trust in their decisions. A systematic literature review on XAI was conducted based on defined inclusion and exclusion criteria, analysis of citation databases, and structured synthesis of the selected publications. Section 1 examines the nature of XAI in the context of Industry 5.0, discusses its role and the black-box problem in business applications, and compares existing approaches. Section 2 focuses on opportunities for applying XAI in business and key directions for its adoption. Section 3 presents practical cases and industry examples demonstrating the effectiveness of XAI in corporate settings. Section 4 analyzes barriers and limitations that hinder the widespread adoption of XAI and assesses associated risks. Finally, Section 5 discusses promising directions for future development and potential trajectories for the use of XAI in business decision-making.

1. The Concept of explainable AI in the context of Industry 5.0

1.1. Industry 5.0 and explainable AI

The widespread adoption of artificial intelligence (AI) in critical domains has revealed a number of challenges related to explainability, particularly in the context of Industry 5.0. The European Commission defines Industry 5.0 as a model of industry that complements the existing Industry 4.0 paradigm with a human-centric approach and resilience to external disruptions [11]. While Industry 4.0 primarily focused on technologies such as autonomy, digital connectivity, and data-driven processes, Industry 5.0 places humans at the center, emphasizes close integration with AI, and incorporates social responsibility as a core principle. Industry 5.0 positions human involvement as a key element of production and management processes [11, 12] and promotes closer collaboration between humans and AI or robotic systems in the workplace. In this paradigm, humans are not removed from decision-making processes; instead, technologies are designed to augment human capabilities, enhance comfort and safety, and enable personalized production tailored to individual needs.

Under these conditions, XAI becomes a crucial factor for both trust and effectiveness, serving as a bridge between the growing complexity of modern black-box models and the demand for reliable and transparent AI systems. XAI is commonly defined as the ability of a system to provide human-understandable explanations of how decisions are made [13]. Its goal is to make AI models transparent, interpretable, and trustworthy by explaining both the internal processes and the outputs of algorithms [14].

The motivation for developing XAI in business is largely driven by ethical and legal considerations. First, regulators increasingly impose requirements for algorithmic transparency. In the European Union, the concept of a “right to explanation” for decisions made by automated systems is actively discussed. For example, in the banking sector, if a loan application is rejected by an automated decision-making system, the client has the right to be informed about the reasons behind that decision [15]. Such regulations, including the requirements of the General Data Protection Regulation (GDPR), compel organizations to implement explainability mechanisms; otherwise, the use of black-box models may entail legal risks and consequences [16].

Second, socio-organizational factors also play a significant role. As noted by Zavodna et al. [17], insufficient transparency of AI systems leads to resistance among users and managers during implementation. In business practice, there is growing evidence that opaque AI systems are often rejected by organizations, ultimately reducing the effectiveness of digital transformation initiatives.

Ensuring explainability is therefore a necessary condition for building trust in AI among employees, customers, and service users. According to recent studies [18, 19], XAI helps identify and mitigate model biases, ensure compliance with ethical standards, and improve the justification of algorithmic decisions. As a result, explainability increases users’ willingness to accept and effectively utilize AI-based systems. It can be concluded that within the human-oriented paradigm of Industry 5.0, where machines are intended to complement rather than replace humans, transparency of AI decisions becomes a prerequisite for safe and productive human-AI collaboration.

As part of this study, a systematic literature search and analysis on XAI was conducted based on defined inclusion and exclusion criteria, citation database analysis, and structured organization of the selected materials (*Fig. 1*). The research is grounded in a comprehensive review and analysis of scientific literature on explainable artificial intelligence and its applications in business and Industry 5.0.

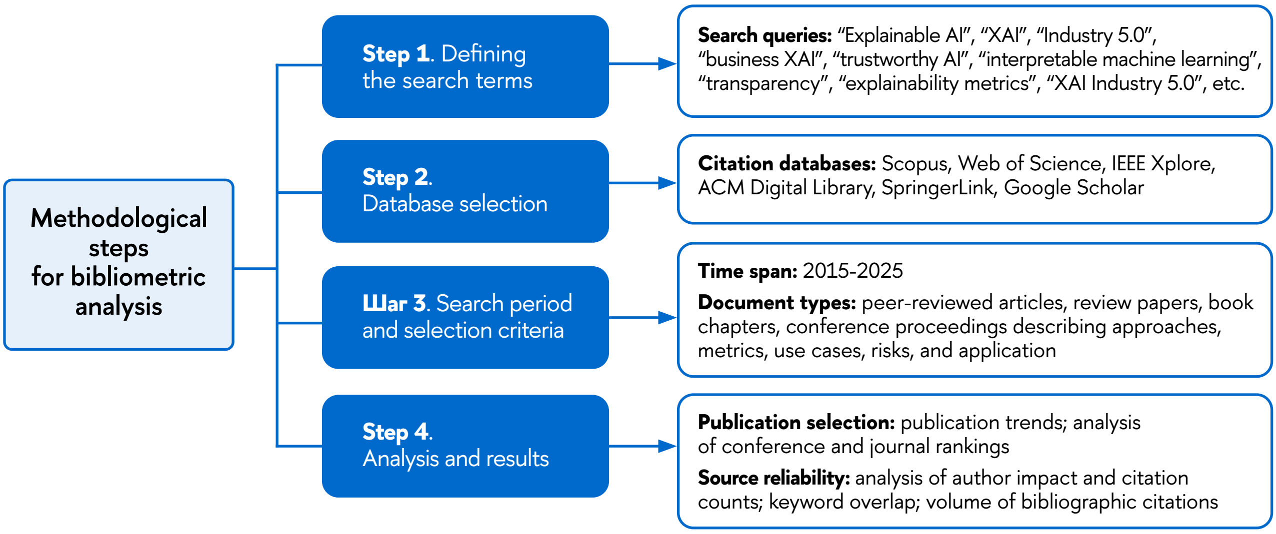

Fig. 1. Bibliometric analysis methodology.

The most significant growth in publications is observed in the period from 2021 to 2024, which can be attributed to the increasing business interest in algorithmic transparency and evolving regulatory requirements.

The thematic structuring was carried out along the following directions, which form the basis of the structure of this study:

- conceptual foundations of XAI;
- methods and metrics;
- applications in business;
- barriers and risks;
- regulatory aspects.

It is important to note that explainability is not a single or static attribute. In academic research on XAI, it is treated as a complex, multidimensional criterion that encompasses a range of aspects, from model transparency (the extent to which its internal mechanisms are accessible for understanding) and interpretability (the extent to which one can understand why a specific decision was made), to accuracy, fairness, the faithfulness of explanations (i.e., avoiding misleading rationales), and accountability. For example, a simple and transparent model may be easy to understand, but not necessarily accurate. For this reason, each XAI project must strike a balance between these dimensions.

Joyce et al. [20] propose to view explainability as a function of comprehensibility that reflects both transparency and interpretability. Arrieta et al. [14], along with Murdoch [21], place these concepts within a broader framework of responsible AI, extending them with notions such as trust, reliability, and related considerations. In this article, the authors propose an original map of the most commonly discussed explainability properties (*Fig. 2*).

At present, there is no single, widely accepted standard that defines what should be considered explainability in artificial intelligence. This multidimensionality reflects the inherent complexity of the concept itself and highlights the need for systematization and alignment of terminology and evaluation approaches for XAI, depending on the application context, including the industry, model type, and target audience.

There is also no universal set of quantitative or qualitative metrics for measuring the level of explainability. Different approaches rely on different criteria, ranging from subjective user understanding of explana-

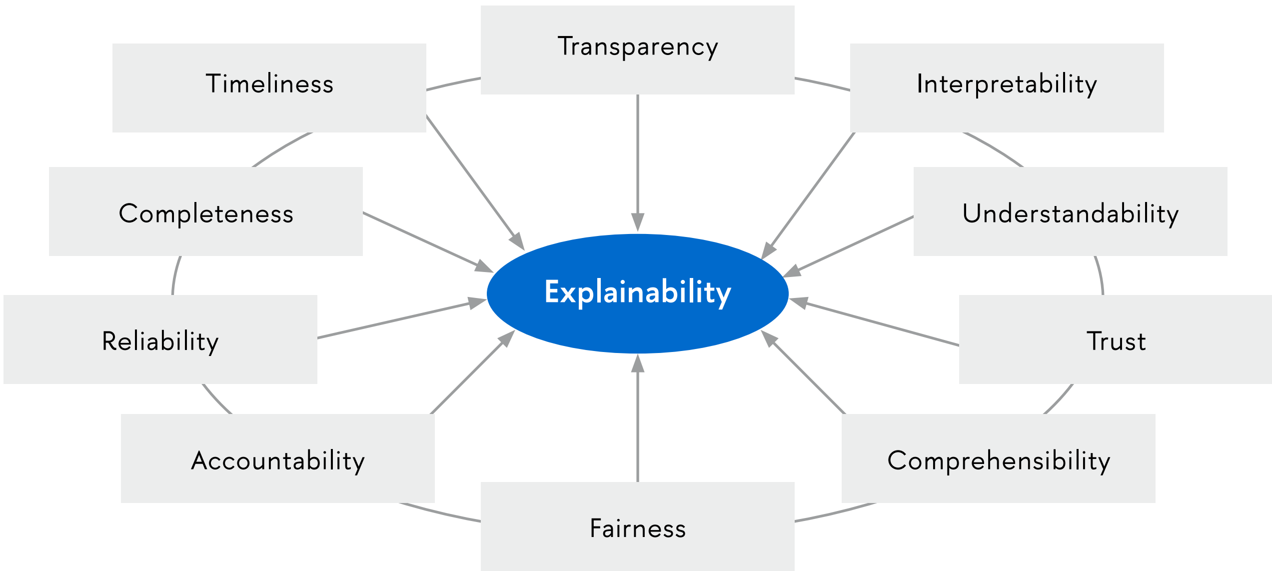

Fig. 2. Overview of key explainability characteristics.

tions to formal measures of stability and local fidelity of interpretations [22, 23]. As a result, the adoption of explainable AI requires not only technical implementation, but also methodological effort to determine what constitutes "sufficient" explainability in a given context.

Despite the diversity of existing approaches, it can be argued that the comparison of explainability methods is based on a number of recurring criteria [13, 14, 20, 21]. The following characteristics are most frequently discussed in the literature:

- Type of explanation (local vs. global, post-hoc vs. built-in / intrinsic).
- Transparency and interpretability (the extent to which a human can understand the model's reasoning).
- Stability of explanations (the degree to which explanations change in response to small variations in input data).
- Accuracy and informativeness of explanations (whether the explanation correctly reflects the model's underlying logic).
- Robustness to noise and adversarial attacks (high or low robustness).
- Temporal and computational complexity, which is particularly important for industrial applications and real-time processing (high, medium, or low).

These criteria are widely discussed in international studies and are commonly used as a basis for the systematic comparison of XAI approaches.

1.2. The "black box" problem and AI trust in business

The demand for responsible, transparent, and human-centric artificial intelligence in business is steadily growing, in line with current technological and managerial trends. Best practices are gradually emerging, industry-specific guidelines are being developed, primarily in the financial sector and healthcare, and many companies begin to define explainability requirements independently, based on the specifics of their business processes.

In managerial and business domains, the use of artificial intelligence is already becoming routine, ranging from recommendation systems in e-commerce to algorithms for business process optimization and data-driven decision-making. However, the willingness of companies and organizations to entrust critical processes to black-box models remains limited.

A black-box model refers to a system whose internal structure is hidden or too complex to be understood by humans. Many high-performing machine learning algorithms, including deep neural networks and ensemble methods, are characterized by a high degree of opacity. While such models were previously applied to narrowly scoped tasks, this lack of transparency was not considered critical. However, as AI systems have increasingly been deployed in domains that directly affect human decision-making and activities, opacity has become a fundamental issue, as emphasized in a number of XAI studies [24–26]. As AI systems began to influence decisions with real-world consequences, the lack of transparency turned into a serious concern. For businesses, a key question arises: if the internal workings of an algorithm are not understood, can its decisions be trusted?

The absence of explanations makes it difficult to detect errors and biases. Hidden biases in training data may lead to unfair or discriminatory outcomes. For example, algorithms used for recruitment or customer selection may unintentionally discriminate against certain groups of applicants.

When it comes to trust in artificial intelligence, especially in high-risk domains such as transportation, finance, and industry, people tend to reject even highly accurate model outputs if no rational explanation is provided. In the banking sector, for instance, both clients and managers expect to understand the reasons behind a loan rejection. In industrial settings, the absence of explanations may result not only in distrust, but also in critical safety risks if a model fails. Any decision of significant importance must therefore be accompanied by explanations that are understandable to humans. Without this, the use of black-box models in such domains is generally considered unacceptable.

A trade-off between model accuracy and interpretability is widely discussed in the literature. Indeed, the most transparent models, such as shallow decision trees, often demonstrate lower accuracy on complex tasks compared to deep neural networks. Conversely, efforts to maximize performance metrics frequently result in highly complex models at the expense of interpretability. In practice, this leads either to a simpler, so-called ‘gray-box’ models with limited performance, or to powerful black-box models whose high accuracy is achieved through a loss of transparency [27, 28]. The objective of XAI is to reduce this gap by offering methods that preserve predictive performance while providing meaningful explanations. However, this trade-off has not yet been fully resolved, and the question of how much performance can be sacrificed for the sake of transparency remains open.

In summary, the black-box problem is not merely a technical metaphor, but a serious barrier to the widespread adoption of artificial intelligence across business domains.

2. Business needs for explainable artificial intelligence

Based on the results of the bibliometric analysis, the authors found that the most densely represented application domains of explainable artificial intelligence today are finance and industry. In these areas, XAI is used both to build trust in algorithmic systems and to support operational and strategic decision-making. The energy sector, public administration, and healthcare appear predominantly in studies of a regulatory and normative nature, reflecting the growing attention to transparency, auditability, and non-discrimination of algorithms in high-risk domains.

Logistics is emerging as a new and rapidly developing area of XAI application. Although the number of publications in this field remains relatively limited, the domain demonstrates strong growth and increasing interest from both researchers and companies in explainability for supply chain systems and intelligent optimization (*Table 1*).

Table 1.

Bibliometric analysis of XAI application areas in various industries

Source	Finance	Industry	Energy	Business	Economics	Management	Logistics	Public sector	Healthcare	Research focus and key ideas
1. Martins et al. (2024) [10]	X			X	X	X				Overview of XAI in finance; SHAP/LIME; transparency of credit scoring
2. Gramegna & Scardapane (2021) [31]	X					X				Discrimination assessment; explainability in credit risk
3. Hjelkrem & de Lange (2023) [32]	X					X				Explaining deep learning models in open banking
4. Poyiadzi et al. (FACE, 2020) [30]	X	X		X	X		X			Counterfactual explanations; applicability across domains
5. Weitz et al. (2022) [18]				X		X				AI acceptability; reduction of organizational resistance
6. Chehbi-Gamoura (2023) [6]				X		X				Explainability in decision-making
7. Tabassi (NIST AI RMF, 2023) [16]	X	X	X	X	X	X		X	X	Regulatory requirements for XAI
8. EU AI Act (2024) [41]	X	X	X	X	X	X		X	X	Legal requirements for explainability
9. Ahmed et al. (2022) [12]		X		X	X		X			XAI in Industry 4.0 / Industry 5.0
10. Adadi & Berrada (2018) [13]	X	X		X	X	X			X	XAI taxonomy; post-hoc methods
11. Arrieta et al. (2020) [14]	X	X	X	X	X	X		X	X	Responsible AI; properties of explainability
12. Černevičienė & Kabasinskas (2024) [42]	X			X	X	X				Systematic review of XAI in finance; tasks: scoring; SHAP/ANN/XGBoost methods
13. Brasse et al. (2023) [43]				X	X	X				XAI in information systems; classification of research directions
14. Samek W., Montavon G., et al. (2019) [1]	X			X	X	X				Survey of XAI methods; taxonomy of rule-based, model-agnostic and intrinsic models; widely cited
15. Carvalho et al. (2019) [44]		X		X	X		X			Systematic review of XAI challenges; industry-focused limitations and opportunities
16. Molnar (2025) [45]	X	X		X		X				Comprehensive interpretability; model-agnostic techniques; stability of explanations
17. Angelov et al. (2021) [46]	X	X		X						Explainable-by-design methods; self-explainable models; interpretable fuzzy-rule
18. Rai (2020) [47]	X			X	X	X				Explainable AI in management and decision support; accountability frameworks
19. Samek & Müller (2017) [22]		X	X	X						Visualization techniques; explainability evaluation; relevance propagation
20. Liao & Varshney (2021) [48]	X	X		X		X				Human-centered XAI; user modeling; adaptive explanations for stakeholders
21. Chamola V et al. (2023) [49]		X	X	X	X	X	X			Explainability in cyber-physical systems; domain-aware explanations; OT/IT integration
22. Belle & Papantonis (2021) [50]				X	X	X				Logic-based XAI; symbolic reasoning; foundations for transparent decision-making

The integration of explainable algorithms into real-world practice helps mitigate the black-box problem and makes AI systems more understandable and acceptable for business use. Requirements for explainable AI in business, economics, and management can be classified into several key dimensions that reflect both the practical needs of organizations for explainable algorithms and the demands imposed by the external environment.

A. Trust and transparency of decisions. Trust is regarded as a fundamental prerequisite for the functioning of artificial intelligence systems in the digital economy [29]. Explainable AI can provide explanations in a human-understandable form, thereby reducing the risks of mistrust and discrimination, and justifying AI-based recommendations to clients, shareholders, auditors, and employees. For example, XAI-based credit scoring systems can detail the contribution of individual factors such as income level or credit history, thus meeting regulatory requirements and strengthening customer trust. In human resource management, explainability helps prevent unjustified decisions. If an algorithm filters out job candidates, a company must ensure that this occurs for relevant reasons rather than due to hidden discrimination. By providing HR specialists with interpretable criteria and information about which skills or competencies were decisive, XAI makes the selection process more transparent and fair. This reduces the risk of bias and increases employee trust in such systems.

B. Integration of AI into operational workflows. Explainability facilitates the integration of algorithms into everyday work processes, reduces staff resistance, and helps establish a shared "language" between humans and AI systems. At the organizational level, researchers introduce the concept of AI acceptability, which reflects the willingness of employees and managers to adopt and use AI tools. Empirical studies show that the main barriers are socio-organizational factors, largely related to trust and understanding [16, 43]. Employees may resist algorithmic decision-making due to fears of losing control or skepticism toward "machine-generated" outcomes. However, when systems provide clear explanations and involve users in the decision-making process, the likelihood of mutual and trust-based collaboration increases. For instance, engineers are more likely to rely on a predictive system if it indicates which specific sensor readings led to a given forecast and provides relevant contextual information.

C. Strategic management and business analytics. XAI supports top management and business owners in strategic decision-making. Businesses increasingly rely on analytical models for strategic planning, risk assessment, and analysis of consumer behavior. However, executives are often unwilling to base decisions on model outputs if the underlying assumptions and reasoning are unclear. As a result, explainable models, such as econometric models with interpretable coefficients or advanced machine learning models enriched with XAI explanations, are preferred in corporate analytics.

Recent surveys, including the work by Tchuente, Lonlac, and Kamsu-Foguem [9], propose a structured evaluation approach based on theoretical foundations, application context, data and task characteristics, and solution methodology (TCCM: Theory, Context, Characteristics, Methodology). In real-world settings, it is important to explain the entire managerial decision-making process: why a particular question is posed, why specific data are used, how the model arrives at its conclusions, and whether domain experts validate these explanations in practice. Without human validation of explanations, the application of XAI in business remains incomplete. This is why experts recommend establishing an iterative cycle consisting of model development, explanation generation, expert evaluation of explanations, and subsequent adjustment of the model or its application.

D. Control of complex industrial systems. Modern industrial environments generate vast amounts of data, ranging from equipment sensor readings to financial and logistics information. AI models are capable of identifying hidden patterns in these data and optimizing operations. Nevertheless, engineers and operators must understand these patterns, especially when systems propose non-standard actions, such as shutting down a machine due to a detected anomaly. XAI enables the integration of explanatory modules into industrial analytics systems, clarifying which sensors or indicators exceeded normal thresholds, why a failure is predicted, or which factor was decisive in identifying a product defect.

For these purposes, the FACE (Feasible and Actionable Counterfactual Explanations) approach has proven effective and is well documented in the literature [30]. FACE identifies realistic and achievable pathways from the current state to a desired outcome while accounting for feasibility constraints such as technological tolerances, safety requirements, and operational regulations. As a result, personnel receive explanations from AI systems in an understandable form, whether as charts, textual descriptions, or visual highlights of problematic components within system diagrams. These explanations indicate which factors were critical to the system's conclusions and what changes are required. If a robot or automated production line behaves unpredictably, this poses risks to both personnel and production safety. The availability of explanations, for example, "the robot reduced speed because a sensor detected a deviation in raw material quality," allows engineers to analyze the data and rules underlying the decision and to adjust the algorithm to prevent similar errors in the future.

E. Compliance with regulatory requirements. Many sectors of the economy are subject to strict regulation, including finance, industry, and energy. To avoid reputational and legal risks, businesses require ethical oversight mechanisms and algorithmic audit procedures. XAI tools provide technical support for these initiatives. In effect, explainability becomes a competitive advantage: companies that can demonstrate the transparency and fairness of their algorithms gain greater trust from both consumers and regulators [10], including in the context of regulations such as the GDPR [15] and the AI Act [41].

In summary, in business, economics, and management, explainable AI enhances the transparency of business analytics, improves human-algorithm interaction within organizations, and supports compliance with ethical and regulatory standards. Explainability is gradually becoming part of corporate data culture. Managerial decisions are now expected to be not only data-driven, but also explanation-driven, that is, accompanied by clear and understandable justifications. Only when algorithmic decisions are supported by meaningful explanations are all stakeholders willing to accept and endorse them.

3. Practical applications of XAI: Use cases and industries

Explainable artificial intelligence is most in demand in domains where automated decisions have a direct impact on people, their health, well-being, rights, and safety. In such contexts, improving predictive accuracy alone is insufficient. It becomes essential to ensure that decisions are understandable and well justified, which makes XAI a critical component of AI deployment.

Below, we outline key business domains in which XAI is already being applied or actively introduced, along with representative use cases and tasks where explainability plays a decisive role.

3.1. Financial sector

Finance can be regarded as one of the core sectors and among the most heavily regulated areas of AI application. Here, explainability directly affects not only customer trust but also compliance with mandatory legal and ethical requirements. At the same time, a well-known tension exists between accuracy and interpretability: deep learning models often demonstrate high predictive performance but remain difficult to explain. To improve transparency, banks tend to rely either on more interpretable models, such as gradient boosting methods where feature importance can be assessed, or on the application of XAI techniques. These include interpretable scoring cards and monotonic Gradient Boosting Machines (GBMs), which preserve logical relationships between input factors and the final score.

Methods such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive Explanations) are gaining increasing popularity, particularly in credit scoring, investment analysis, and risk assessment, as reported in recent studies [31–33].

Credit scoring and loan approval. When credit decisions are made automatically, banks are often required to provide borrowers with reasons for rejection. Customers have the right to understand why their application was denied, while banks must ensure that model decisions are not based on discriminatory attributes such as gender, age, or ethnicity. SHAP, for instance, provides numerical estimates of feature contributions. These values can be simplified and communicated as human-readable justifications, for example: insufficient income (–20 points), short credit history (–15), high current debt (–10). The model can then analyze what changes in the input data would lead to a different outcome and suggest ways for the customer to improve creditworthiness. This approach satisfies regulatory requirements while also improving transparency and customer understanding.

Investments and trading. In investment analysis, explainability acts as a trust-building factor between the system and its users. Algorithms that generate investment recommendations must justify them in order to persuade investors to follow such advice. Investors relying on AI-based recommendations need to understand which macroeconomic or market signals underlie a forecast. Explanations may take the form of narrative reasoning, for example: "We recommend reducing equity exposure due to emerging risk signals, such as rising inflation and declining corporate earnings." Such explanations help justify decisions and reduce both regulatory and reputational risks.

Risk analysis and fraud detection. The growing complexity of financial transactions and the constant evolution of fraud schemes require explainable solutions. In this area, XAI serves as a tool for expert validation of model behavior. Explainability helps clarify why a transaction was flagged as suspicious, for example due to an unusual geographic location or an exceeded transaction limit. This makes it possible to distinguish genuine threats from false positives and reduces operational costs. The use of XAI in insurance analytics and risk management further improves the interaction between algorithmic outputs and expert judgment, enabling model correction, retraining, and the creation of additional competitive advantages [34].

3.2. Industry

Another key domain for XAI adoption is industry and so-called smart manufacturing, where AI is used to predict equipment failures, optimize product quality, and manage supply chains. In the context of Industry 5.0, it becomes critical not only to predict events but also to explain the reasoning behind algorithmic recommendations. This allows engineers and operators to trust system outputs and act upon them.

Predictive maintenance. Traditional maintenance approaches face multiple challenges. Algorithms often generate numerous false alarms without explaining their origin, leading to unnecessary inspections and downtime. Moreover, sensor-based data are highly dynamic: after repairs or upgrades, equipment behavior changes, reducing predictive accuracy and causing data drift. Operators may also receive opaque alerts without understanding which parameters triggered them or what actions should be taken.

Research by Watanabe et al. shows that constrained generalized additive models (GA2M+) combine strong predictive performance with a structure that is more interpretable for engineers and aligned with the physical logic of processes [35]. Risk attribution techniques for time series analysis enable the assessment of individual factor contributions within specific observation windows. Surrogate rule-based decision trees built on top of black-box models translate complex predictions into simple, operator-friendly explanations, while counterfactual explanations indicate which parameter changes would reduce failure probability to an acceptable level.

A practical example is IBM Maximo Predict [36], which uses AI together with sensor data, maintenance reports, and failure histories to forecast equipment breakdowns and provide interpretable explanations to specialists. As shown by Hermans et al. [37], incorporating SHAP analysis and interpretable models into predictive maintenance systems can reduce false-positive alerts by more than 90 percent, significantly increasing engineer trust and operational efficiency.

Quality control. XAI is also becoming increasingly important in product quality inspection. Computer vision algorithms are widely used to detect defects on production lines, but traditional models often limit output to binary classifications without explaining the reasons behind them. This undermines operator trust and complicates root cause analysis. Interpretation techniques such as LIME and SHAP allow visualization of image regions that were decisive for classification. As a result, engineers can better understand system decisions, identify defect sources more quickly, and more confidently adopt automated quality control.

Logistics. Logistics and supply chain management benefit from AI in route optimization, resource allocation, and warehouse management. However, inventory and delivery optimization algorithms are often perceived by managers as black boxes, which reduces their willingness to adopt recommended strategies. Explainability helps overcome this barrier. Systems that clearly demonstrate which factors, such as demand growth, supplier delays, or transportation cost changes, influenced a decision inspire greater trust and improve alignment between human judgment and algorithmic recommendations. Experimental studies show that the use of SHAP and LIME increases transparency and trust in AI-driven logistics and inventory management decisions [38].

The concept of industrial XAI for manufacturing processes is actively promoted by Siemens. In its technical report [39], the company emphasizes explainability as a core requirement for industrial AI, stating that it must be ensured throughout the entire lifecycle of AI systems, from problem formulation to monitoring and operational support. This example highlights the growing role of XAI as a mandatory element for transparency and governance in Industry 5.0 systems.

The range of domains in which AI can be applied is much broader. Beyond business, transparency and explainable AI are increasingly relevant in social domains such as healthcare, politics, law, and public administration, where the cost of decisions is particularly high and public trust is critical. At the same time, many areas remain less explored from an XAI perspective, especially where AI adoption is still limited. These include agriculture, such as crop yield forecasting and machinery management, energy systems optimization, the entertainment industry, where understanding audience preferences is essential, as well as culture and the arts.

4. Barriers to XAI adoption: Economic, technical, and organizational factors

Despite the clear benefits of XAI in terms of trust enhancement and risk reduction, its widespread adoption in business still faces significant barriers. A central question in the business environment is return on investment. If the benefits are not immediately visible or do not directly translate into profit growth, XAI may be perceived as an optional feature. To convince management or investors, tangible effects must be demonstrated: increased customer loyalty, reduced error rates, or lower compliance costs. Such conclusions require empirical evidence, yet compared to traditional AI deployments, there are still relatively few published cases that quantify the impact of XAI.

To further clarify and empirically validate the key barriers to XAI adoption in business and industrial contexts, a targeted bibliographic analysis of scientific publications was conducted (*Table 2*). The analysis included only studies in which XAI is examined not as an abstract technical concept, but in the context of real-world applications in organizations, industry, digital manufacturing, corporate governance, the financial sector, or the regulation of high-risk AI systems.

Table 2.

Taxonomy of XAI adoption barriers

Type of barrier based on bibliographic analysis	Source
1. Technical limitations (integration complexity, lack of standards, low performance of XAI methods)	[7], [8], [9], [10], [12], [25], [27], [28], [36], [39], [40], [43], [49], [58]
2. Organizational challenges (lack of competencies, need for staff training, process changes)	[6], [7], [8], [9], [11], [12], [17], [18], [19], [29], [36], [39], [47], [48], [43], [54], [55]
3. Economic barriers (implementation costs, return on investment (ROI), resource constraints)	[7], [8], [9], [12], [17], [18], [19], [29], [34], [36], [39], [42]
4. Regulatory and compliance barriers	[3], [4], [10], [11], [12], [15], [16], [29], [34], [36], [39], [41], [42]
5. User-related / human factors (trust, cognitive load, non-intuitive explanations)	[6], [8], [9], [11], [17], [18], [19], [29], [36], [39], [47], [48], [49], [54], [55]

The most frequently cited barrier in the literature relates to organizational challenges. The human factor, rooted in long-standing reliance on personal expertise and intuition, often leads to organizational resistance to the adoption of XAI. Not all organizations are ready to accept "advice from a machine." Concerns arise as to whether employees will trust insights generated by AI without an adequate level of explainability. In addition, effective use of XAI requires new roles, ranging from explanation designers to interpretation specialists. Investments in staff training are therefore necessary so that employees perceive XAI as a supportive tool rather than a threat to their professional position.

Resistance may also result in slower decision-making processes. Explainable models require time for review and interpretation, which contrasts with the business drive for speed and efficiency. If not properly integrated into workflows, XAI can reduce operational agility. This creates a need for time-saving solutions, for example, reducing the number of meetings because all participants immediately understand the algorithm's logic and spend less time debating the validity or transparency of its outcomes.

Another important barrier is the lack of personalization of explanations. Most current XAI systems provide standardized explanations without accounting for the user's level of expertise, task, or situational context. As a result, explanations may be overly complex for some users and overly simplistic for others. Research has begun to explore adaptive explanation approaches, in which the system assesses whether the user has understood previous explanations and adjusts the level of detail accordingly. However, such methods have not yet been widely adopted in practice.

Technical limitations and resource constraints represent another major obstacle. Many XAI methods remain at the level of research prototypes, often implemented as scripts or notebooks that are difficult to integrate into production environments. These methods can be computationally intensive, slow, and dependent on access to the internal structure of models. For example, generating a single explanation using LIME may require hundreds or even thousands of model evaluations, resulting in substantial computational overhead [40]. In real-world settings, engineering teams are forced to seek compromises, such as caching, approximation techniques, or optimization of XAI components, to ensure that explanations can be delivered in real time or within acceptable latency. Users are unlikely to tolerate long delays while a system "thinks" about an explanation.

In addition, there is a lack of widely accepted industry standards for explanation formats and no unified platform that supports all models out of the box. As a result, companies often develop XAI solutions tailored to their specific needs. This leads to duplicated efforts, increased costs, and limited scalability, as each organization invests its own time and resources into bespoke implementations.

Finally, high implementation costs and complexity pose a significant constraint. Explainability is often treated as an additional module that requires interface redesign, business process adaptation, and substantial team preparation. In financial institutions, for example, it is not sufficient to generate explanations for scoring models; employees must be trained, client-facing interfaces updated, and explanations presented in a clear and compliant manner. These associated costs can hinder adoption, particularly when XAI is not explicitly mandated by regulators or industry standards. Consequently, even where the importance of explainability is acknowledged, XAI may still be perceived as a secondary feature rather than a necessary strategic investment.

The identified barriers can be represented in the form of a risk map, allowing for the assessment of their likelihood and potential negative impact. In *Fig. 3*, the authors highlight key risks with medium to high probability of occurrence and the most significant economic, technical, and organizational consequences associated with the implementation and use of XAI in business contexts. *Table 3* presents the mitigating measures.

To overcome the identified risks and barriers, it is necessary not only to advance technologies and system architectures, but also to establish new standards, develop relevant competencies, and adapt business processes. In addition, specialized artifacts need to be designed, which are discussed in the following sections.

5. The future of XAI adoption in business AI solutions

Industry 5.0 effectively positions explainable AI as a standard rather than an optional feature. This requirement creates the foundation for genuine human-AI partnership, which is frequently highlighted as a core principle of Industry 5.0. In the factories and organizations of the future, highly skilled operators and managers will make decisions jointly with AI systems: the AI will identify risks or optimization opportunities, explain the logic behind its recommendations, while the human expert, having understood this logic, will approve or reject the proposed action, introducing human judgment, creativity, intuition, and responsi-

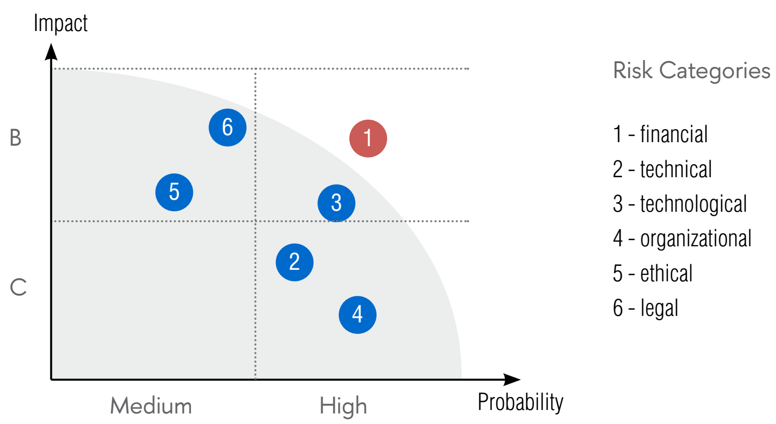

Fig. 3. Mapping of key risks for XAI adoption.

Table 3.

Mitigations

Key Risks	Mitigations
1. Unclear return on investment, budget constraints, additional costs for XAI integration	XAI dashboards and monitoring panels; explainability KPIs; phased pilots; stop-criteria
2. Infrastructure upgrades and high computational cost of XAI methods	Approximations and caching; precomputation; hybrid models: fast rule-based components with asynchronous explanations
3. Complex integration of XAI outputs into system architecture; lack of unified standards	XAI explanation interfaces with REST APIs and JSON outputs; modular architecture solutions
4. Resistance to change, lack of XAI expertise, complex user interfaces	Training materials (XAI guidelines, workshops); two-level explanations; UX/UI protocols
5. Risks of discrimination, bias, manipulative or incomplete explanations, erosion of trust	Multi-level bias audits; removal or restriction of sensitive attributes; counterfactual testing; regular drift monitoring
6. Leakage of confidential information through explanations; lack of accountability	Control of explanation granularity and access; built-in output filtering policies; logging and audit trails

bility. Such synergy is only possible when supported by a robust XAI infrastructure combined with appropriate organizational changes.

5.1 Development of regulatory requirements

Regulatory pressure remains one of the most powerful drivers of XAI adoption in business. In Europe, the proposed AI Act places a strong emphasis on explainability, transparency, and auditability, defining them as fundamental requirements for high-risk AI systems, ranging from financial decision models to industrial applications. Legislators are gradually formalizing expectations regarding algorithmic explainability, particularly in critical domains.

In the financial sector, for example, regulations may require that all decision-making models provide clients with clear information about the key factors influencing outcomes. Future scoring and trading systems will be expected to demonstrate transparency, avoid discriminatory behavior, and explicitly disclose associated risks. A promising direction is the emergence of self-diagnostic algorithms that not only explain their outputs but also automatically check for prohibited dependencies and integrate explanation generation directly into reporting and compliance workflows.

5.2. Human-machine symbiosis

Modern XAI systems must be context-aware and capable of adapting explanations to domain-specific logic. This requires close collaboration with subject-matter experts and the incorporation of domain knowledge, including ontologies and formal rules.

Seminal works by d'Avila Garcez et al. and Besold et al. propose approaches for embedding logical reasoning into neural networks through neuro-symbolic AI methods, which combine deductive reasoning with deep learning. These approaches enable models to rely on explicit rules, ontologies, and domain knowledge, thereby improving interpretability, traceability, and documentation of reasoning processes.

In the future, business decision support systems are likely to evolve toward delivering not only predictions (for example, the risk of a deal failure) but also structured and readable justifications. Such systems may reference similar historical cases, statistical evidence, and explicitly indicate which facts and assumptions underpin their conclusions.

Research on explanation interfaces by Kim et al. and Rong et al. highlights the importance of tailoring explanations to the user. In practice, this may result in interactive dashboards for executives and managers, where market forecasts and strategic recommendations are accompanied by visualizations illustrating the underlying assumptions and key drivers. Particular attention will be paid to aligning these interfaces with managerial reasoning styles and providing appropriate abstractions, diagrams, and visual summaries.

5.3. Embedding XAI into business processes and organizational knowledge sharing

When aggregated, explanations generated by XAI systems can reveal broader organizational patterns and serve as a basis for high-level managerial insights. In this sense, XAI may accelerate bottom-up feedback: instead of lengthy reports prepared by middle management, consolidated explanations produced by AI systems can provide executives with a rapid understanding of what is happening and why.

It is conceivable that future systems will adapt to organizational culture and business specifics, learning which types of explanations decision-makers find most understandable and presenting insights in a familiar style. Complex managerial situations may require not a single recommendation, but multiple alternative scenarios, each accompanied by its own explanation. AI systems may propose several options, justify each of them, or suggest decomposing a complex problem into sub-tasks, explaining why such decomposition improves decision quality.

This leads to the concept of end-to-end explanations that cover the entire decision-making process, from problem formulation to the final choice. At the same time, it is crucial to maintain a balance, ensuring that explanations clarify rather than distort reality. A multi-level explanation approach appears particularly promising: a concise, high-level explanation for initial understanding, complemented by a more detailed version for verification and deeper analysis.

The XAI artifacts proposed in this study (*Table 4*) are derived from an analysis of existing documentation practices, monitoring approaches, and UX methodologies, while extending them with new elements that address business needs and identified risks. As such, they represent an original contribution by the authors to the development of XAI in an organizational and business context.

Research highlights the importance of model documentation as a key mechanism for transparency and knowledge transfer across teams. Mitchell et al. [56], for example, emphasize the role of model interpretation documents such as Model Cards, while Gebru et al. [57] argue for the value of Datasheets for Datasets, which describe intended use cases, data sources, identified limitations, and mechanisms for generating explanations. The relevance of such documentation becomes particularly pronounced in large organizations, where knowledge transfer cannot rely solely on informal communication or code repositories. Well-structured documentation enables faster onboarding of new models, especially in contexts of staff turnover or solution scaling.

Equally important is the design of interaction interfaces. Whereas explanations of model outputs were previously accessible mainly through specialized analytical tools, explanations are now increasingly embedded directly into operational applications. As a result, analysts or managers can receive contextual comments alongside predictions, clarifying which factors influenced the outcome and how strongly it deviates from typical behavior. Moreover, explanation formats can be adapted to the user's role, ranging from concise business summaries to detailed technical breakdowns. Such interfaces significantly enhance AI acceptance in corporate environments, particularly when decision-making time is limited.

Table 4.

Key XAI artifacts in business contexts

Artifact	Purpose / Function	User
XAI documentation and protocols (Model Cards, Datasheets)	Formalized description of the model, data, and limitations to ensure transparency and auditability	Model developers, auditors, regulators
Explanation interfaces (Explainability UI/UX)	Interactive access to explanations within the user interface	End users, analysts, operators
XAI monitoring dashboards and panels	Visualization of factors influencing predictions to support managerial decision-making	Middle and senior management
Automated XAI validation frameworks	Automated verification of explanation quality and detection of deviations from expected behavior	Quality engineers, risk management teams, internal audit
Training and supporting materials (XAI guides, workshops)	Supporting staff in adopting and understanding XAI through training courses and guidelines	Managers, business analysts, learning and development specialists

At the strategic level of model operation, visual monitoring panels and reporting views can be used to regularly track the distributions of key features and predictions, detect data and target drift, and automatically generate alerts when thresholds are exceeded. Such monitoring supports timely identification of quality degradation and enables corrective actions (e.g., resolving data quality issues or triggering model retraining) [58].

Special attention is also given to the automated validation of explanations. In regulated domains such as banking or healthcare, manual review of every explanation is infeasible. As a result, frameworks are being developed to automatically assess explanations for compliance with internal policies, absence of discriminatory patterns, and overlooked risks. This shifts XAI from a visualization layer to an integral component of organizational quality assurance systems.

Finally, sustainable XAI adoption is impossible without educational and supporting materials accessible not only to developers, but also to a broader range of employees. These materials include guidelines, training programs, and step-by-step instructions for interacting with XAI systems. Their purpose is to lower entry barriers and enable responsible use, particularly for professionals involved in data interpretation who may lack technical backgrounds. According to Donoso-Guzmán et al. [59], human-centered approaches to XAI evaluation that account for the goals and contexts of different user roles are especially promising. Such evaluation frameworks can also be applied to tailor explanations to corporate practices and managerial expectations, helping to anticipate which explanations will be perceived as convincing, excessive, or insufficient, and how arguments should be structured for different stakeholders.

Overall, XAI artifacts do more than merely explain individual outcomes; they facilitate the integration of AI into organizational reasoning, turning it into a transparent, accessible, and governable tool.

The outlined perspectives form a roadmap for XAI development in the coming years. The dominant trend is a deeper integration of AI and human judgment, shifting from narrowly focused explanations of individual predictions toward human-centered intelligence embedded in collective decision-making processes. In this sense, XAI is evolving from a standalone interpretability module into a design paradigm for AI systems that are inherently conceived for collaboration with humans.

Conclusion

Explainability has become a critical requirement for AI applications in business, industry, and management, where real financial resources, safety, and responsibility toward people are at stake. It is increasingly a factor of both competitiveness and regulatory compliance: organizations that are able to explain the behavior of their algorithms are better positioned to withstand regulatory scrutiny and to gain the trust of customers and stakeholders. Even today, XAI facilitates the integration of AI into smart manufacturing and the financial sector, positively influencing the development prospects of Industry 5.0, where human-centricity, safety, and sustainability play a central role.

Explainable AI enables companies to meet these demands by providing tools for algorithm monitoring, decision rationale reporting, and control of discriminatory behavior. In the foreseeable future, XAI may become an integral part of enterprise quality management systems. Just as ISO standards currently exist for business processes, similar standards may emerge for the explainability and ethical compliance of AI components embedded in organizational workflows.

Decision-makers equipped with algorithms that can justify their outputs gain a powerful instrument that combines the strength of data-driven models with the clarity and logical structure of traditional analysis. This enables more informed yet innovative decision-making: while AI can uncover non-obvious patterns, explainability makes these insights acceptable and actionable in practice. New forms of organizational learning based on interaction with XAI systems may further accelerate the dissemination of best practices and institutional knowledge.

At the same time, it must be acknowledged that large-scale adoption of XAI is still constrained by economic, technical, and organizational barriers. The greatest potential for XAI development lies in domains where regulatory pressure, high cost of error, and strong data and process discipline converge, such as finance, insurance, manufacturing, and industrial operations. Where organizations deliberately invest in explainability and embed it into system architectures, quality processes, and user experience design, explainable AI can become a source of sustainable competitive advantage. ■

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About the authors

Sergey Mikhailovich Avdoshin

Candidate of Sciences (Technology);

Professor, School of Computer Engineering, HSE Tikhonov Moscow Institute of Electronics and Mathematics, HSE University, 34 Tallinskaya St., Moscow 123458, Russia;

E-mail: savdoshin@hse.ru

ORCID: 0000-0001-8473-8077

Elena Yuryevna Pesotskaya

Candidate of Sciences (Economics);

Associate Professor, School of Software Engineering, Faculty of Computer Science, HSE University, 11 Pokrovsky Blvd., Moscow 109028, Russia;

E-mail: epesotskaya@hse.ru

ORCID: 0000-0003-2129-4645

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A comprehensive approach to building an intelligent system for proactive personnel risk assessment in critical infrastructure*

Denis Nikolaevich Biryukov
E-mail: vka@mil.ru

Andrey Sergeevich Dudkin
E-mail: vka@mil.ru

Alexander Viktorovich Frolov
Email: vka@mil.ru

A. F. Mozhaysky Military-Space Academy, St. Petersburg, Russia

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Abstract

Modern challenges in organizational security, particularly within critical infrastructure sectors (energy, transportation, finance, IT), necessitate innovative solutions to mitigate risks associated with hiring unreliable personnel. This requires a shift from conducting fragmented checks to the creation and implementation of comprehensive systems for proactive risk assessment. The urgency of developing such systems is driven by the high frequency and catastrophic consequences of insider incidents, coupled with the inability of traditional methods to detect complex, multi-stage threats originating from employees. However, building intelligent systems that semantically integrate heterogeneous data (biographical, behavioral, financial, digital) presents new systemic challenges. The aim of this article is to analyze the key methodological, ethical-legal, and architectural requirements for designing such systems. The work sequentially examines: 1) ethical and legal dilemmas (fairness, privacy, the right to explanation) and the constraints imposed by personal data legislation; 2) specific cyber threats targeting the compromise of the knowledge base and system logic, along with architectural countermeasures based on Security by Design principles; 3) a comparative analysis of the technological components of a multi-level assessment system (documentary verification, psychometric testing, AI analysis), justifying the necessity for their integration. The scientific novelty lies in a synthetic approach that forms a holistic methodology, considering not only technological efficiency but also fundamental legal constraints and information security requirements. The practical significance of the work consists in formulating systemic requirements for the design of secure, lawful, and socially responsible intelligent decision support systems for personnel security.

Keywords: proactive assessment of personnel risks, intelligent decision support systems, ontological modeling, semantic integration, psychometric testing in personnel security, AI analysis of behavioral and biographical data, ethical and legal restrictions on personal data processing, cyber resilience of personnel assessment systems

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Introduction

The problem of insider threats in critical infrastructure organizations (energy, transportation, finance, IT) is not new [1] and remains one of the most acute problems in the field of modern security. Research data indicates that a significant portion of incidents, including data leaks, sabotage, and corruption, is caused by the actions of insiders [2]. The scale and complexity of these threats have multiplied with the development of digital technologies. According to IBM Security, most data leaks in the energy sector are related to the human factor, including employee errors and malicious actions [3]. In Russia, according to a study by "Rostelecom-Solar," 45% of companies face incidents caused by unreliable personnel, with 22% of these incidents leading to catastrophic consequences [4].

In response to growing threats, states are tightening regulatory requirements. In the EU, Directive NIS2 obliges companies to implement employee vetting systems, including social media analysis and polygraph tests. In Russia, Federal Law No. 152-FZ "On Personal Data" and Government Decree No. 1119 regulate the collection and processing of candidate information but leave gaps regarding the use of AI algorithms. In the USA, for example, the Cybersecurity Act requires companies in the energy sector to conduct annual personnel audits for connections with extremist groups. In Russia, as noted by "HeadHunter," every second organization conducts preliminary candidate checks, yet only 27% have an in-house security service [5].

Traditional candidate assessment methods, such as resume analysis, interviews, or reference checks, prove ineffective in identifying complex, multi-stage, and intentionally concealed threats. Their key limitation is the fragmentation of data and the lack of semantic integration of heterogeneous information sources: biographical, behavioral, financial, and digital traces of a candidate. This leads to a reactive, rather than predictive, approach to personnel security, which, given the high cost of insider incidents (including both direct and reputational losses), becomes an unacceptable risk to the sustainable functioning of organizations.

In response to this challenge, technological solutions using artificial intelligence (AI), psychometric testing, and automated data verification are emerging in scientific literature and on the market [6–10]. However, their application often remains isolated, failing to solve the problem of comprehensive candidate assessment. Moreover, the creation of centralized intelligent systems aggregating confidential personal data generates new, systemic risks. These include both ethical-legal dilemmas – questions of fairness, discrimination, privacy, and the right to explanation of automated decisions [11, 12] – and unique cyber threats aimed at compromising the semantic knowledge base and assessment algorithms themselves.

Thus, the relevant scientific and practical task is the development not just of another vetting tool, but of a holistic methodology for designing systems for proactive personnel risk assessment. Such a methodology should ensure the semantic integration of heterogeneous data to identify complex threat scenarios, while being embedded within strict ethical-legal frameworks and considering cybersecurity requirements for the designed system itself.

The aim of this article is to analyze the key methodological, ethical, legal, and architectural requirements for building an intelligent risk assessment system for personnel recruitment in critical infrastructure facilities. The focus is not on a detailed description of the internal ontological model (which is the subject of a separate study), but on the systemic constraints and conditions under which its implementation would be correct, safe, and lawful.

The scientific novelty of the work lies in the synthesis of three aspects usually considered in isolation:

1) a comparative analysis of the technological components of a multi-level assessment system (AI, psychometrics, data verification);
2) a comprehensive analysis of ethical-legal dilemmas and regulatory requirements;
3) proactive modeling of cybersecurity threats inherent to the ontological system itself and the formulation of architectural countermeasures based on Security by Design and Privacy by Design principles.

The structure of the article reflects the logic of the sequential formation of system requirements. The first section examines the ethical and legal aspects that define the fundamental design boundaries. The second section is dedicated to analyzing new vectors of cyber threats and the resulting architectural requirements for system security. The third section contains a comparative analysis of existing technological assessment methods (documentary verification, psychometric testing, AI analysis), justifying the need for their integration within a unified methodology. The conclusion formulates the main findings and defines directions for further research.

1. Ethical and legal aspects of applying an ontological approach in candidate assessment

The shift to comprehensive candidate assessment systems based on semantic integration of heterogeneous data and artificial intelligence methods gives rise to a number of ethical and legal dilemmas [13]. Balancing organizational security with the protection of individual rights requires careful analysis prior to the design and implementation of such systems.

Key moral and ethical dilemmas.

The principle of fairness and non-discrimination. Automated systems based on historical data can reproduce and amplify existing societal biases. For example, identifying "potentially unreliable" candidates based on analysis of social activity can lead to discrimination based on indirect attributes (political views, religious affiliation, social status). This contradicts both ethical norms and labor legislation.

The right to privacy and digital autonomy. Integrating data from open sources (social networks, forums, etc.) with data from corporate and state databases contributes to creating an exhaustive digital profile of an individual without their explicit consent for creating such a profile and without informing the potential candidate about it. The question arises about the boundaries of permissible surveillance: where does the employer's legitimate interest in a candidate's reputation end, and where does unacceptable intrusion into private life begin?

The right to explanation. A hiring decision based on the output of an ontological model and AI algorithms may, not without reason, be perceived by a candidate as unfair and unexplainable, as most machine learning models operate as "black boxes." In accordance with evolving legal doctrine (e.g., the "right to explanation" in GDPR), a candidate should have the opportunity to challenge an automated decision and receive a meaningful explanation of its reasons.

System requirements and constraints imposed by legislation.

Transparency and controllability of ontological tools. In the context of Russian legislation (Federal Law No. 152-FZ "On Personal Data"), data processing must be specified, limited to stated purposes, and understandable to the data subject. This generates a systemic requirement for the ontology: its structure and key logical rules must be available for review by both the candidates themselves (in the part concerning them) and regulatory bodies. An organization may be required to disclose not the specific settings of generative AI (as a trade secret), but at least the principles, categories, and attributes upon which the assessment is built.

Limitations on the content and structure of ontologies. Legislation does not directly regulate the structure of ontologies, but the basic principles of personal data processing (lawfulness, purpose limitation, and data minimization) impose serious constraints on it:

- the ontology should not include redundant classes and properties that do not have a direct and provable relation to professional qualities and risks for a specific position (e.g., sexual orientation, philosophical beliefs, etc.);
- ogical rules and the risk scenarios themselves must be justified and documented by research or statistics to exclude arbitrary and discriminatory interpretation.

The requirement of human control. The final hiring decision, especially one based on an assessment of "unreliability," cannot be fully automated. The system should provide results as a recommendation, and the final decision must be made by a human (HR specialist or manager), who bears responsibility for it.

The established ethical-legal frameworks define conceptual constraints for the ontological model. However, their practical implementation and ensuring compliance with the requirements that an intelligent decision support system for personnel recruitment must satisfy are impossible without considering a new class of applied tasks – namely, the tasks of ensuring the cybersecurity of the designed intelligent system itself. A centralized knowledge base accumulating confidential personal profiles becomes, in itself, an object of critical importance and generates unique attack vectors. A comprehensive analysis of these threats and the architectural countermeasures necessary to protect the integrity, confidentiality, and availability of the ontology constitutes the subject of separate consideration in the next section.

2. Current threats and additional requirements for ensuring information security in the implementation of ontological modeling

Creating a unified ontological knowledge base, accumulating confidential biographical, financial, and behavioral data about candidates, transforms the threat landscape for an organization. The integrated ontology, being the core of the decision support system, itself becomes a holistic object of high value and, consequently, a priority target for cyberattacks. This imposes specific constraints on its architecture, content, and management processes.

Classification of new vectors of cyber threats.

Compromise of the ontology. Unlike fragmented data, a compromised ontology allows a malicious actor to:

- make unauthorized changes to ontological relationships between specific concepts to systematically and purposefully reduce the system's sensitivity to certain threats;
- add false facts or entire scenarios to the ontology aimed at discrediting specific candidates (targeted "black PR") or, conversely, concealing their real risks.

Leakage of the confidential semantic network – the foundation of the ontology. The theft of the knowledge base is equivalent to obtaining a structured dossier on all candidates who have undergone vetting. In this case, not only candidate attributes (experience, education) are disclosed, but also logical connections between them (e.g., "Candidate A is connected to Company B, which participated in a dubious tender"), which also represents a leakage of contextual information.

Insider misuse of access to the ontology. A security service employee or knowledge engineer with rights to modify the ontology can manipulate it for corrupt or other unlawful purposes, remaining "in the shadows" due to the complexity of verifying semantic changes.

Architectural constraints and countermeasures. To counter the indicated threats, the system architecture must be based on the "Security by Design" principle (an approach to software development where security is built into the product at the concept stage, not added post facto [14]):

- all operations modifying the ontology (adding classes, properties, individuals, rules) must be recorded in a structure resistant to tampering. The use of blockchain technologies or similar distributed ledgers to create a verifiable and irrefutable change log can be recommended, which directly contributes to proving insider actions within the organization's infrastructure [15]. This imposes an architectural constraint: the ontology management system must be integrated with a secure logging module;
- the ontology itself should be used to model security policies. It is necessary to introduce, for example, classes such as AuditEvent, SystemUser, AccessRole and relationships like hasPermission, performedAction. This should allow, using the same ontology, to describe, control, and audit data access within

the system, implementing the RBAC (Role-Based Access Control) concept;

- personal data, being particularly sensitive, should be stored in encrypted form, and the ontology should operate only with their cryptographic hashes or tokens to establish semantic links, without the need for constant decryption and access to the semantics of facts.

Cybersecurity requirements directly affect the implementation of ontological modeling as well. The ontology should not contain redundant data. For example, to establish a fact of “financial unreliability,” in some cases, the presence of the attribute “hasCreditDelinquencyStatus = true” may be sufficient, without the need to store detailed delinquency history in the ontology itself. This reduces the damage in case of its compromise.

It is also recommended to design the ontology as several linked but physically or logically separated modules. Public data (from social networks and other publicly available resources) can reside in one module, while sensitive data (polygraph results, connections with law enforcement) – in another, with stricter access control. This limits potential risks and damage in case of compromise.

The ontology population process should include a stage of mandatory verification of scenarios and features entered by expert analysts. A cross-validation system is proposed, where a new inference rule, scenario, or class is activated only after confirmation by several independent experts. This should counteract the risk of “semantic sabotage.”

Thus, the design of an ontological system for risk assessment in personnel recruitment must take into account that the designed tool for risk management itself becomes a source of new, systemic vulnerabilities, creating the possibility of new cyber threats. The response to this challenge is the implementation of a multi-layered security architecture based on the principles of continuous and comprehensive auditing, strict access segregation, end-to-end encryption, and minimal sufficiency of ontological models. Only such comprehensive protection should make it possible to mitigate the risks inherent in centralized repositories of confidential data and intelligent decision support systems based on them.

The proposed ontological approach should be implemented not as a closed system in terms of the methodology for making decisions to reject a candidate, but as a transparent decision support tool embedded within ethical-legal frameworks. This requires designing the ontology considering “Privacy by Design” principles (an approach where privacy and data protection considerations are integrated into the design phase of any system, service, product, or process), implementing explainability mechanisms (Explainable AI, XAI), and ensuring the ability to audit all its modifications. Only under these conditions can a balance be achieved between the operational security of an organization and fundamental human rights.

3. A multi-level system for personnel risk assessment in critical infrastructure: an ontological approach, psychometric testing, and AI analysis

Without claiming universality, the focus should be on the following key risks associated with hiring new employees:

1. *Professional incompetence*. According to Checkster, 78% of candidates provide false information about skills and experience, increasing the risk of errors in critical projects.
2. *Connections with criminal structures*. Undetected employee connections can lead to data leaks or sabotage.
3. *Drug and other addictions*. Employees with addic-

tions more frequently violate security protocols, as confirmed by Russian Ministry of Internal Affairs statistics.

4. *Financial problems*. Indebtedness makes candidates vulnerable to corruption, as noted in studies by credit bureaus.

Review of existing approaches: documentary verification and psychometric testing. Modern personnel vetting methods can be divided into two main categories: documentary verification and psychometric testing. Various technological solutions can be applied in this context.

Documentary verification.

Verification of work history and education. Using state databases (Pension Fund, Ministry of Internal Affairs) and university APIs. For example, the "SearchInform" platform automates requests to 98% of Russian educational institutions, reducing verification time from 7 to 2 days. In Russia, 67% of companies use the Unified Register of Diplomas from the Ministry of Education and Science, which allows detecting 18% of forged documents. However, the system has limitations: universities often process requests for up to 14 days; 32% of educational institutions do not update information about graduates. In 2023, 12% of resumes contained false data about education, as noted in the 2023 report on resume falsifications by the Russian Union of Industrialists and Entrepreneurs.

Direct contact with previous employers helps clarify actual achievements. According to MIT, 30% of references contain hidden negative assessments.

Social Media Monitoring. Various tools can be applied for social media monitoring (depending on countries, social networks, etc.). For example, platforms like SocialIntelligence Corp analyze publications for radical views. In 2023, 7% of candidates in the energy sector were screened out due to posts on Telegram supporting extremist groups.

Psychometric testing.

MMPI and BigFive questionnaires. The MMPI-2 has been used for quite some time [16] and identifies tendencies toward manipulation (Scale L) and aggression (Scale Pd). In an MIT study, the test identified 80% of candidates with criminal inclinations. For instance, 9.7% of those convicted for terrorism showed clinical scales above the norm. Big Five: the assessment of Conscientiousness correlates with employee reliability ($r = 0.62$, $p < 0.01$) [17].

Stress resistance assessment. Application of case techniques simulating emergency situations. For example, a case method from "Media Netology" facilitates predicting behavior in crisis situations, and the "Crisis Management" test from PwC reduced staff turnover by 25% in the energy sector.

Various technological solutions with certain advantages and disadvantages can be applied during documentary verification and psychological testing. Some of them are considered below.

Ontological models.

These models [11, 18] can be used for semantic analysis of resumes and cross-referencing their data with incident databases. The Palantir system is used in the USA to identify candidates connections with terrorist organizations, demonstrating 85% accuracy, and can also correlate candidates' employment periods, for example, with cyber incidents in the CISA database.

AI-algorithms.

NLP analysis of resumes [12] allows, for example, identifying contradictions in dates and facts (IBM Watson algorithms reduce errors by 40% and detect date contradictions with 93% accuracy).

Computer vision: analysis of video interviews [19] for micro-expressions (e.g., the HireVue platform analyzes micro-expressions (frequent blinking (>20 times/min) correlates with secretiveness ($r = 0.71$)) predicts candidate reliability with 78% accuracy).

Polygraph.

Used for candidates with “red flags” [20, 21].

In some cases, conducting additional in-depth checks may be required:

- verification of professional competence (e.g., the CISSP exam for cybersecurity specialists confirms knowledge of security standards);
- analysis of credit (financial) history (Equifax and NBKI services identify financial vulnerability of candidates. A Deloitte study shows that 33% of employees with a credit burden >50% of income are involved in fraud and/or corruption. In 40% of cases, debts exceeding income are identified);
- blockchain for transaction verification (the Chainalysis service tracks candidates cryptocurrency transfers. In 2023, 5 cases of money laundering among top managers, 12 candidates with connections to sanctioned wallets were identified), as well as for logging and proving insider actions within the organization’s infrastructure [22].

At the same time, it should be noted that, at present, there is a lack of integration between the considered methods. For example, AI does not consider polygraph results, leading to fragmented assessment; ontological models are rarely used and even more rarely integrated with psychological tests. Polygraph examinations are quite expensive per candidate and are inaccessible for small businesses.

Comparative analysis of approaches. A comparative analysis of the effectiveness of candidate assessment methods was conducted during the research (*Table 1*). The data presented in *Table 1* were obtained as a result of a comprehensive analysis of open scientific publications, reports from consulting companies, and the HR technology market, and the approximate implementation cost was estimated based on an analysis of the average service cost on the market in 2025 [23–28]. Naturally, within the analysis that was conducted, the complexity of the methods (e.g., MMPI, Big Five questionnaires) and the need to involve qualified specialists to interpret the results were not assessed. It is well known that the quality of polygraph examinations heavily depends on the expert conducting them, which certainly affects the final implementation cost. When conducting AI analysis, it is difficult for a non-specialist to correlate the quality of the applied models and candidate testing results, so the average market service cost must be considered. However, it was revealed that ontological models are not popular, and their implementation cost cannot be estimated as there are no similar offerings on the service mar-

Table 1.

Comparative analysis of approaches

Method	Accuracy, %	False positives, %	Implementation cost, USD/cand.
Documentary verification	60–68	22–28	8–15
Psychometric testing	75–80	15–20	18–50
AI analysis	85–90	8–12	50–100
Polygraph	81–91	12–18	70–110

ket, which limits the understanding of their contribution to identifying unreliable employees.

Various combinations of the approaches we considered are successfully applied by organizations in different countries. For example, the CLEAR system for civil servants (USA) combines credit history and social media checks and reduced hiring risks in the public sector by 40% (CLEAR Program Annual Report. U.S. Department of Homeland Security). In China, social credit scores are analyzed alongside transaction analysis on Alipay; however, this approach is criticized for privacy violations (in 2019, over 10,000 officials voluntarily confessed to corruption under pressure from the system). In Germany, the Xayn platform uses Federated Learning to analyze data without centralization, complying with GDPR.

Conclusion

This research was dedicated to solving the relevant task of forming systemic foundations for designing intelligent systems for proactive personnel risk assessment in critical infrastructure organizations. The work justifies the necessity of shifting from fragmented checks to a comprehensive approach capable of identifying complex insider threats.

The main results obtained within this article are as follows:

1. Key ethical-legal frameworks have been defined, serving as mandatory context for any technological development in this field. Dilemmas of fairness, privacy, and explainability, as well as specific legislative requirements imposing constraints on the collection, processing, and interpretation of candidate data, have been analyzed.
2. Specific cybersecurity requirements arising from the creation of a centralized ontological knowledge base have been formulated. A set of architectural countermeasures based on Security by Design and Privacy by Design principles is proposed to protect the integrity, confidentiality, and availability of the assessment system itself.
3. A comparative analysis of technological components (documentary verification, psychometric testing, AI analysis) has been conducted, and the methodological necessity of their deep semantic integration for transitioning from reactive to predictive risk assessment models has been proven.

Thus, the practical significance of the work lies in creating a comprehensive set of requirements and constraints for architects and developers of intelligent systems for proactive personnel risk assessment in organizations. The proposed approach allows us to design systems where technological efficiency does not contradict legal norms, ethical principles, and fundamental information security requirements.

Directions for future research. Further work involves transitioning from the formulated systemic requirements to concrete implementation, focusing on developing and verifying a formal ontological model intended for semantic data integration and identifying risky candidate behavior scenarios. For this, it is necessary:

- to classify suspicious actions of candidates for vacant positions and types of threats originating from them;
- to develop a methodology for constructing scenarios based on justified ontological relations;
- to consider issues of integrating the model with the upper-level UFO ontology to ensure methodological rigor.

As envisioned, this will allow us to move from the conceptual foundations outlined in the article to creating practical tools for intelligent decision support systems for proactive personnel risk assessment in critical infrastructure organizations. ■

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About the authors

Denis Nikolaevich Biryukov

Doctor of Sciences (Technology), Professor;

Head of Department, Department of Information Collection and Processing Systems, A. F. Mozhaysky Military-Space Academy, 13 Zhdanovskaya St., St. Petersburg 197198, Russia;

E-mail: vka@mil.ru

ORCID: 0000-0003-1300-2470

Andrey Sergeevich Dudkin

Candidate of Sciences (Technology), Associate Professor;

Deputy Head of Department, Department of Information Collection and Processing Systems, A. F. Mozhaysky Military-Space Academy, 13 Zhdanovskaya St., St. Petersburg 197198, Russia;

E-mail: vka@mil.ru

ORCID: 0000-0003-0283-9048

Alexander Viktorovich Frolov

Applicant for Department, Department of Information Collection and Processing Systems, A. F. Mozhaysky Military-Space Academy, 13 Zhdanovskaya St., St. Petersburg 197198, Russia;

E-mail: vka@mil.ru

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Enterprise performance management based on digital twin technology in the fifth-generation industry

Yury Filippovich Telnov [a]
E-mail: Telnov.YUF@rea.ru

Tatyana Konstantinovna Kravchenko [b]
E-mail: tkravchenko@hse.ru

[a] Plekhanov Russian University of Economics, Moscow, Russia

[b] Graduate School of Business, HSE University, Moscow, Russia

Abstract

In the context of the increasing need to improve the management efficiency of enterprises that support the implementation of the principles of digital transformation based on the concept of the fifth-generation industry, the relevance of research on the development of appropriate systems in terms of ensuring continuous targeted and sustainable development, customer-centricity and social orientation of production is increasing. Digital twin technology and its multi-agent implementation act as effective means of building enterprise performance management systems. At the same time, the lack of scientific research in this area determines the purpose of the article, which is to develop a product-resource approach to enterprise performance management based on digital twins in the fifth-generation industry. A distinctive feature of the proposed approach developed by the authors is the use of dynamic enterprise performance management technology based on digital twins, which ensures the integration of business processes and resources used at the level of not only one enterprise, but also at the level of network value chains based on a common digital platform of the business ecosystem. The paper analyzes approaches to the intellectualization of enterprise management, on the basis of which the requirements for an enterprise performance management system are formulated, ensuring the solution of interrelated tasks of targeted enterprise development, the formation of flexible value chains, and the rational and sustainable use of enterprise resources. The possibilities and disadvantages of the efficiency management process in EPC class systems are analyzed. The paper substantiates the use of digital twin technology and its multi-agent implementation to build an enterprise performance management system in the context of mass customization and the network nature of value chains in the fifth-generation industry. A process for managing the efficiency of enterprises at all stages of the life cycle based on the technology of digital twins of products and resources has been developed, dynamically ensuring the targeting, adaptability and sustainability of the functioning and development of the enterprise.

Keywords: fifth-generation industry, targeting, adaptability, sustainability, enterprise performance management, product digital twin, resource digital twin

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Introduction

The main goals of the digital transformation of enterprises include increasing labor productivity, improving the quality of products and services provided, mass customization of production, flexibility and adaptability of production and business processes due to the widespread use of technologies using digital platforms and digital twins [1–3]. Full automation of production very often leads to negative social consequences: an increase in unemployment, a decrease in creativity in work, violations of the protection of production systems from unintended and malicious actions, overproduction of products with environmental violations, excessive consumption of expensive resources: material, energy, financial, which generally leads to unstable economic development.

In the process of digital transformation, based on the principles of the 4th generation industry, new forms of organizing corporate relations of enterprises are being developed within the framework of creating business ecosystems, forming digital and network enterprises based on integrated software and hardware platforms

[4–6]. The basis for the creation of such enterprises are new digital technologies such as Industrial Internet, cloud technologies, processing of big data, machine learning, multi-agent systems, generative artificial intelligence, etc. The fourth-generation industry concept allows for flexible digital and networked enterprises that dynamically learn how to build value chains based on big data to meet specific consumer needs.

In terms of works reflecting the possibilities of building multi-agent systems that optimize the use of resources in dynamic business processes based on simulation, one should note [7–9], which presents effective methods of dynamic support for operational management decision-making. In [10], an approach is proposed to form various scenarios for the strategic development of socio-economic systems using an evolutionary optimization algorithm based on simulation modeling. At the same time, the operational and strategic management contours are considered separately in these works.

In modern conditions of digital enterprise development, a more rapid strategy update is required based on the need for continuous business process changes and the reverse dynamic effect of strategy changes on operational business processes. At the same time, the main focus in such production systems is on the operational management horizon, and issues of strategic planning for sustainable development on a long-term time scale are practically not considered. In addition, the requirements of mass customization, when the consumer interactively participates in the development and customization of products for their own needs [11], complicate the solution of the tasks of coordinating goals between participants in joint economic activities. The emerging problems of digital transformation of enterprises based on the principles of the 4th generation industry necessitate further intellectualization of enterprise management processes, ensuring their targeted, adaptive and sustainable development.

The above-mentioned principles of enterprise development in recent years are reflected in the concept of the 5th generation industry [12, 13], in which production becomes human-centered not only from the point of view of consumers of products and services, but also from the point of view of manufacturers themselves, that is, employees of enterprises, for whom their role in decision-making increases, with different levels of control, even in robotic production. At the same time, production requires greater safety and sustainability in terms of the consumption of necessary resources. Enterprises of the 5th generation industry acquire a self-organizing form of functioning in accordance with dynamically updated goals, which are determined not only by the needs of changes in the market situation, but also are set taking into account the social needs of society in the broadest context.

In parallel with the concept of the fourth and fifth generation industry, the concept of creating smart enterprises (intelligent enterprises) is developing in the world [14–16]. In the concept of smart enterprises, the main principles are to achieve sustainable development, increasing trust between enterprise participants, conducting investment research by modeling market behavior, rethinking strategy and business models, flexible budget planning, continuous monitoring of business processes, receiving feedback at all levels of management by measuring business results, in-depth understanding of processes and interdependence. between them. This concept fully implements the approach to creating self-learning intelligent enterprises on a new technological basis.

In [17], the principles of intelligent, self-configurable production are developed, which reflect the idea of a continuous cycle of goal setting, configuration and reconfiguration of value chains, monitoring and controlling the execution of business processes in order to ensure sustainable development based on the use of neural network modeling technologies, processing big data, and multi-agent systems. This formulation of the problem is very close to the established approach to continuous engineering and digital transformation of enterprises, outlined in [18]. At the same time, the sustainability of an enterprise will be understood as an enterprise capable of "... finding the optimal ratio between all its elements, establishing connections between them that make it possible to maintain vital parameters at a given level for as long as possible, effectively countering the disturbing effects of the external environment" [19]. From the point of view of sustainability, it is important to ensure that all resources are balanced in order to achieve the targets of efficiency and effectiveness, as well as their compliance with the necessary standards of use in terms of meeting the needs of the external environment.

To implement the principles of intellectualization of production and business processes in the fifth-generation industry, the article proposes the construction of an enterprise performance management system that would ensure the solution of the following interrelated tasks:

- Targeted development of enterprises aimed at flexible and dynamic formation of goals and plans in accordance with the rapidly changing environment and social needs.
- The formation of flexible value chains that ensure the dynamic realization of market needs in accordance with the strategic and operational objectives of the enterprise.
- Sustainable and balanced use of enterprise resources in production and business processes, aimed at safe, environmentally friendly and socially justified use.

The article proposes to build such an enterprise performance management system based on the development of a product-resource approach to the organization of digital twins using multi-agent technology that allows dynamic monitoring of strategic goals by measuring process efficiency indicators, accumulating big data and timely updating of the strategy. The implementation of the proposed approach will require the creation of a new generation of digital platforms based on the principles of the 5th generation industry.

1. Analysis of the traditional approach to enterprise performance management in an EPM system

In modern conditions, the main goals of enterprise development are continuous innovation, ensuring sustainable development, environmentally friendly production, flexibility, cost-effectiveness, quality improvement, speed and adaptability of production and business processes, which determine the vector of development of targeted companies. At the same time, the companies' focus is realized at the strategic and operational levels.

- At the strategic level, business objectives are considered in all areas of activity and promising, possibly new types of activities are highlighted, taking into account the ongoing changes in the external environment and the current state of the company's competencies and potential.
- At the operational (product) level for certain types of activities which determines the possibilities of organizing production and business processes, taking into account the interests of all stakeholders: consumers, investors, management, staff, external organizations.

At the strategic level, business goals are usually organized in the form of various types of balanced scorecard (BSC) or strategic maps [20]. Classically, the goals of the main activities are reflected at the third level (the level of internal business processes). Types of activities in modern conditions of client-centricity and dynamic implementation are interpreted as organizational services provided to various categories of consumers [21]. On the other hand, the declaration of the possibilities of implementing services is reflected in the concepts of competencies and abilities of organizations [22].

A set of key performance indicators (KPIs) is used to measure the achievability of goals. Libraries (repositories) containing descriptions and templates for calculating indicators are usually used to select a set of goals and KPIs in accordance with the chosen strategy [23]. Subsequently, these indicators are reflected in specialized information and analytical systems equipped with tools for analyzing the effectiveness of business processes (Enterprise Performance Management, EPM) [24–26] and extracting knowledge from the collected data in process monitoring (Process Mining) [27].

For the targeting development of enterprises, it is very important to ensure the interaction of the organization's goals at the strategic level and key performance indicators at the operational level. The process of correlating goals with operations that ensure their fulfillment is called goal operationalization [21]. To move from strategic goals to operational goals, goal environment diagrams are usually used [28]. Such interaction is carried out as a result of consistent detailing of strategic goals in the form of sets of measures to achieve them. For events, in turn, the business processes that execute them and key performance indicators that measure the results of the processes are determined. An example of a diagram of the goal's environment is shown in *Fig. 1*. In enterprise performance management systems [25], key performance indicators are monitored; they are used to analyze the achievement of goals and possible subsequent changes in both the regulatory KPIs and the goals themselves at the BSC level.

The business performance management process in the EPM system is shown in *Fig. 2*.

Let's look at the business performance management process in the EPM system in more detail. Based on the company's strategy and external sources of information about the competitive environment, a balanced scorecard and goal environment diagrams are built.

The development of business processes based on BSC and goal environment diagrams is usually carried out in BPMN notation and implemented using Low-Code tools. The EPM system binds software modules that collect data on the performance of key performance indicators to software components that implement business process operations, and sets planned process performance indicators (KPIs).

As a result of the information collection, a special EPM module that implements methods for extracting knowledge from processes (Process Mining) is quickly

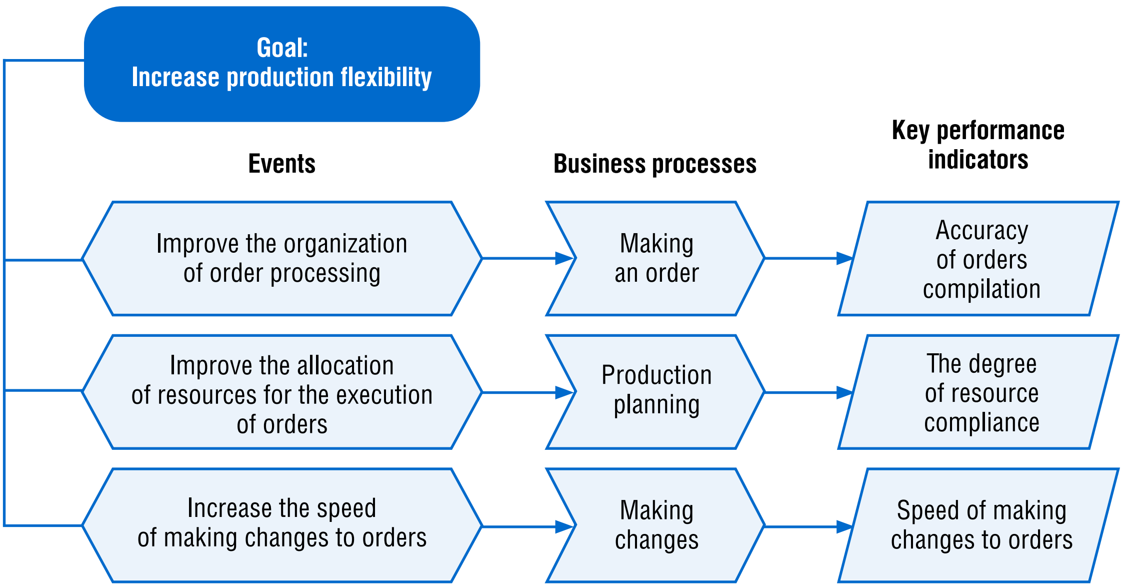

Fig. 1. Diagram of the goal's environment.

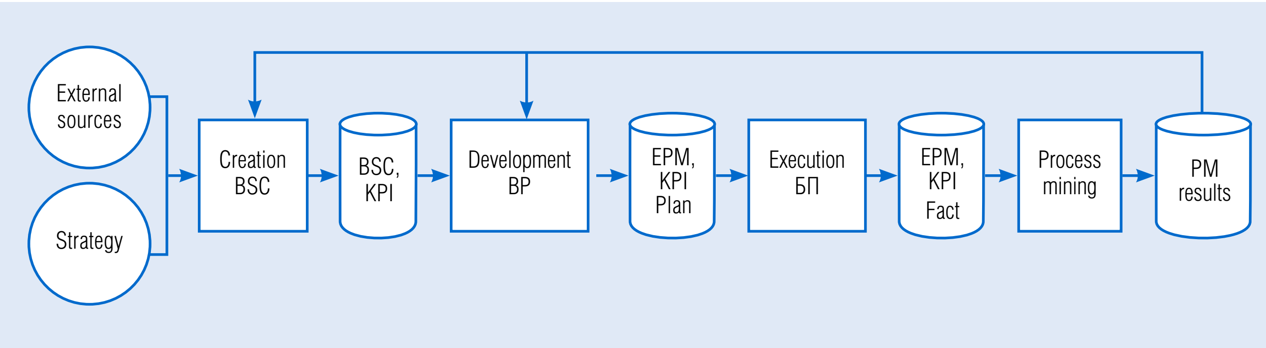

Fig. 2. The process of enterprise performance management in the EPM system.

analyzed for the performance of operations. At the same time, the analysis of both individual indicators and their integration by convolution and subsequent evaluation is carried out.

Based on the data obtained, both the current situation is analyzed and a forecast is made using machine learning methods for necessary changes in tactical goals at the business process level and strategic goals at the enterprise level.

The described process of enterprise performance management in the EPM system is successfully applied in traditional business, which are characterized by a relative regularity of operational processes, and the main thing is to monitor key performance indicators that regulate the achievement of goals, and strategic goals are formed rather for new business processes that are subsequently implemented on a regular basis. The structure of the business processes themselves and their participants is relatively stable.

The fourth-generation industry and its development in the fifth generation are characterized by the high variability of business and production processes within the framework of mass customization of products and services provided, which are carried out in business ecosystems based on digital platforms. In [18, 32], principles and models for creating network enterprises for changeable business goals were developed, providing a dynamic configuration of business and production processes based on digital twin technology and asset administrative shells implementing them. For such enterprises, it is necessary to improve the methods of managing the effectiveness of enterprises, taking into account the implementation of the requirements for dynamically ensuring the targeting, adaptability and sustainability of the enterprise.

2. Enterprise performance management based on digital twin technology

In the modern mass-customized production, an original process configuration can be built for each product or product-related project, in which different performers are involved at each moment, selected on a digital platform. Making decisions about the development of product lines, the transition to the production of new products and the modernization of existing ones, and the customization of products to meet the needs of specific customers necessitate the management of not only processes but also products at the operational level. Dynamic product management also involves the dynamic configuration of business processes for changing business goals, requiring the selection of the best resources under certain constraints on their use and compliance with sustainability requirements, and in a network environment on a single digital platform of the business ecosystem.

The specifics of the fifth-generation industry make it necessary to accelerate product innovations (updating of nomenclature, technologies, mass customization), on the one hand, and ensuring the sustainability of the use of all resources in processes, on the other hand. From this point of view, the goals of the process level should reflect the goals of customer orientation, flexibility and adaptability of business and production processes, and the last level of the strategic map related to the use of resources and technologies should reflect the goals of sustainability. In this regard, the importance of developing a product-resource approach to improving the efficiency of enterprise management in the digital economy is increasing.

In the product resource approach, the innovative stage of product quality development is very important, where a set of functional and non-functional product requirements is formed, which is the basis for product and service design and specification of subsequent SLA – Service Level Agreements with future business partners. These requirements specify the key indicators of process efficiency in relation to the specific parameters of the products produced and the resources used. The formation of requirements is based on the analysis of the external market of products and technologies and is implemented using the QFD quality deployment method and the FMEA method of analyzing the types, consequences and causes of potential nonconformities [29–31].

The analysis of the implementation of requirements for the production of products and the use of resources from the perspective of achieving operational goals in the industry of the fourth and fifth generations directly in the traditional EPM class system is almost impossible to implement due to the large number of qualitative and quantitative characteristics and their dynamic changes from one type of product to another. In this regard, it is advisable to develop a dynamic technology for enterprise performance management based on digital twins.

Digital twins, in accordance with the RAMI architectural framework [2], are information models that reflect at each moment the state of both manufactured products and used resources (equipment, production lines, entire enterprises). Moreover, the formation and use of product information by stages of its life cycle is carried out in the process of interaction of the digital twin of the product with the digital twin of resources

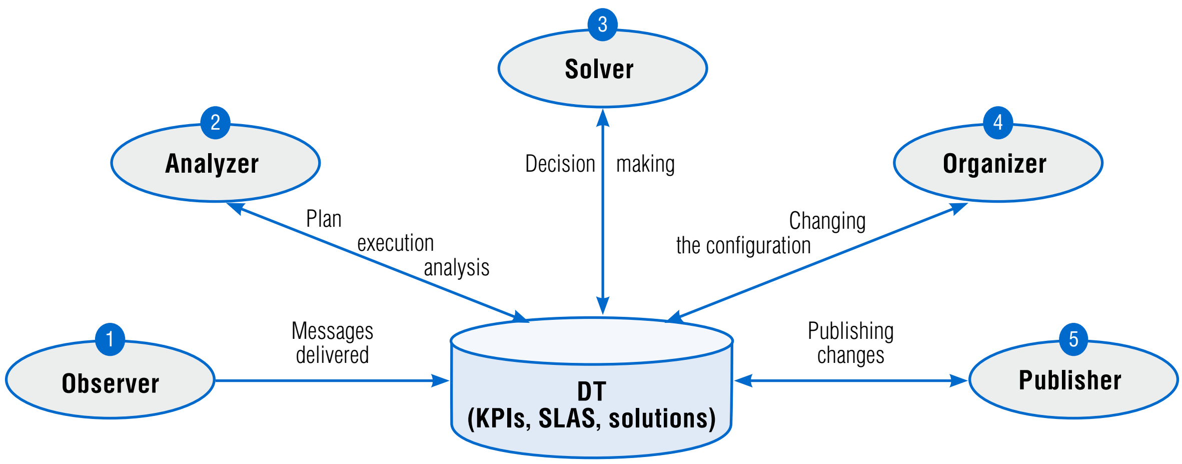

Fig. 3. Architecture of the intelligent agent (built on the basis of [17]).

based on multi-agent technology [14]. For a digital twin in the form of an intelligent agent, a typical set of components is proposed that allows automating the processing of various situations in the decision-making process about responding to events both in the outside world and when coordinating interaction with other agents (*Fig. 3*).

Consider the main components of an intelligent agent that implement the functions of situation processing:

- Observer collects data on the behavior of real objects displayed in the digital twin, interprets the received data and enters it into various submodels of the digital twin.
- The analyzer identifies possible deviations from the regulatory values of key KPIs and Service Level Agreements (SLAs).
- The solver makes decisions about the need to change the states of real objects and initiates interaction (negotiations) with other intelligent agents, makes decisions based on the results of negotiations.
- The organizer carries out information exchange with other intelligent agents by sending requests and receiving responses.
- The publisher records the decisions made and updates key performance indicators and SLA indicators.

In accordance with the presented architecture of an intelligent agent implementing the functions of a digital twin, the schematic diagram of the enterprise performance management process (product manufacturing) is implemented in the form of a technological scheme shown in *Fig. 4*.

Let's consider this scheme in more detail. The process of developing a new product concept should correspond to the goals that are laid down in the company's strategy in the form of a set of requirements, reflected in a balanced scorecard. At the same time, a product digital twin (PDT) is created, into which key performance indicators are transferred from the diagrams of the environment of the BSC goals, for example, the accuracy of the order's compliance with the originally formulated requirements, the degree of compliance of resources with the order, the speed of order execution, etc. Using the domain ontology, services for analyzing

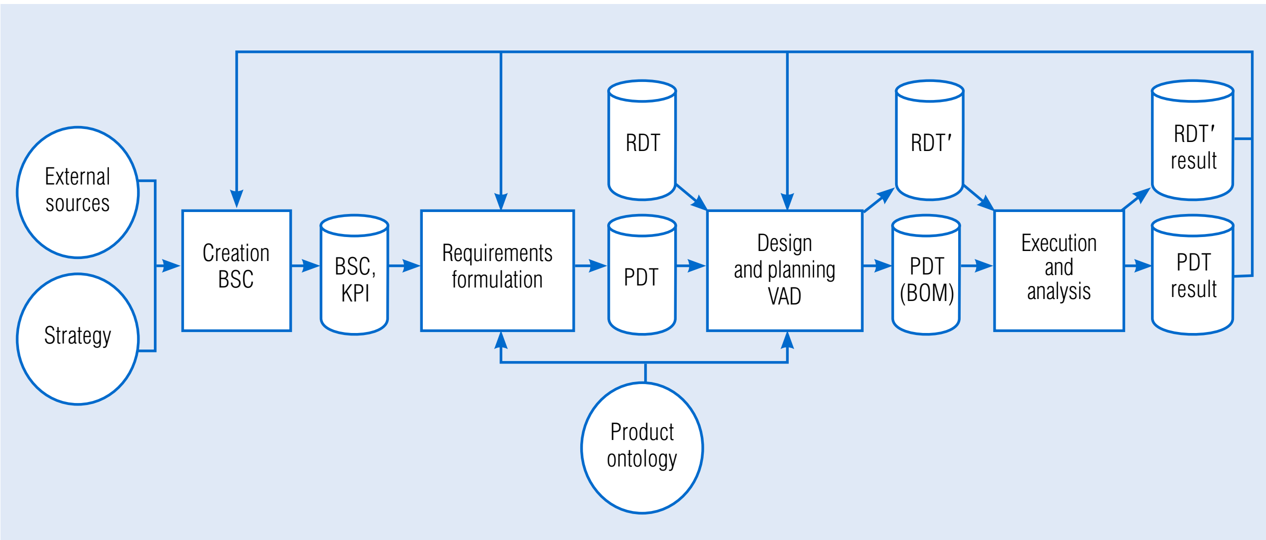

Fig. 4. The process of managing the performance of product manufacturing based on digital twin technology.

the market of similar products, materials, technologies, competitors and suppliers and selecting promising consumer characteristics of a future product are launched from the digital twin. As a result, functional and non-functional requirements are formed, which are entered into the corresponding submodel of the PDT.

In the process of designing a product from the digital twin of the product, a service is launched to form the design of the product and the value-added chain (VAD) with the selection of specific business partners for its implementation. As a result of the design in the digital twin of the product, a description of its structure (Bill of Materials, BOM) and the structure of the technological process are displayed in the subsystem of the product design.

Resource digital tweens (RDT) are involved in the design process, which reflect the profiles of the ability to perform various operations. Resource digital tweens are created both at the level of enterprises that are part of a common business ecosystem on a single digital platform, and at the level of specific equipment that implements operations. As a result of the selection and coordination of resources during the design process, RDTs capture participation in a specific value chain for the subsequent implementation of an innovative project. Then at the planning stage, quantitative and qualitative characteristics of the product production plan are formed, which is specified in the form of service level agreements with subcontractors and recorded in both the digital twin of the product and the digital twin of resources.

The production process starts from the product digital twin according to the plan contained in this twin, and unfolds according to the designed value chain in a sequence of operations. In the process of production (execution of value chains), statistics are accumulated in digital counterparts of products and resources on the progress of work, which, as noted in the previous section, is used both to quickly respond to changes and to analyze goals in the short and long term.

Thus, the analysis of the efficiency of the use of individual resources is carried out by launching analytical and predictive services in the digital counterparts of resources, and analyzing the effectiveness of end-to-end processes by launching the corresponding services from the digital counterparts of products. As a result of the analysis, there may be a revision of the parameters of requirements and key performance indicators related to the production and provision of services, as well as a possible change in the strategic goals of the enterprise.

During the execution of the main processes, monitoring operations can be launched to analyze not only their operational efficiency, but also the analysis of related supporting processes: electricity consumption, materials, environmental protection measures, information protection, etc. For this, a sub-model of regulatory attributes for resource use in terms of compliance with the conditions of sustainable operation must be set in the resource digital tweens. The analysis of the operational efficiency of resource use provides a basis for forecasting the sustainability of both the main and supporting business and production processes.

Compared to the approach to managing the efficiency of business processes in the EPM system, this approach based on digital twins has a number of advantages.:

1. Providing enterprise performance analysis using digital counterparts for both the system as a whole and for individual products and resources.
2. Increasing the efficiency and adaptability of value chains to meet changing market goals.
3. Ensuring the integration of business processes and resources used at the level of not only one enterprise, but also at the level of network value chains formed on the basis of a common digital platform of the business ecosystem.
4. Providing analysis and management of the sustainability of resource use in various production and business processes.

Conclusion

The digital transformation of enterprises based on the concept of the fifth-generation industry involves massive customization of production, increasing the creative role of employees, the social orientation of economic activity of enterprises and necessitates the use of artificial intelligence technologies in optimizing business processes and the use of resources in them. As a result of the research we conducted, it can be concluded that in order to solve the problem of increasing the performance of enterprise management, it is necessary to create a system based on digital twin technology, which should ensure continuous targeting and sustainable development, customer-centricity and social orientation of production.

The analysis of traditional enterprise performance management systems has shown the limitations of their application for the dynamic operating conditions of enterprises, which necessitate timely changes in the strategic and operational goals of enterprises in accordance with changing product needs, taking into account the requirements of sustainable resource use.

The enterprise performance management process developed in the work based on the use of digital twin technology for products and resources at all stages of the life cycle allows you to quickly reflect the state of all related processes, monitor compliance with requirements and key performance indicators, predict the development of situations using machine learning methods and tools, and formulate proposals for correcting goals at the operational and strategic levels.

The application of the dynamic technology we developed for enterprise performance management will make it possible to fully implement the principles of the fifth-generation industry in the digital transformation of enterprises and increase the efficiency of enterprise management at all stages of the life cycle. ■

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About the authors

Yury Filippovich Telnov

Doctor of Sciences (Economics), Professor;

Head of the Department, Department of Applied Informatics and Information Security, Plekhanov Russian University of Economics, 36 Stremyanny Lane, Moscow 117997, Russia;

E-mail: Telnov.YUF@rea.ru

ORCID: 0000-0002-2983-8232

Tatyana Konstantinovna Kravchenko

Doctor of Sciences (Economics), Professor;

Professor, Department of Business Informatics, Graduate School of Business, HSE University, 26–28 Shabolovka St., Moscow 119049, Russia;

E-mail: tkravchenko@hse.ru

ORCID: 0000-0002-6479-6250

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Learning-to-Rank in B2B e-commerce catalogs: A digital experiment and conversion analysis

Fedor Vladimirovich Krasnov
E-mail: fedor.krasnov@vseinstrumenti.ru

Research Center, Vi.Tech LLC, Moscow, Russia

Abstract

Amid intensifying competition in the B2B e-commerce sector, particularly within the Do-It-Yourself (DIY) segment, traditional static search architectures increasingly suffer from limited adaptability and declining retrieval relevance. This study examines the limitations of rule-based ranking approaches and proposes a dynamic product ranking framework based on the Learning-to-Rank paradigm implemented with LightGBM. The primary objective of the research is to quantitatively evaluate the economic return on investment (ROI) associated with the deployment of personalized ranking algorithms. A simulation-based digital experiment was conducted using a synthetic user clickstream model to approximate real-world interaction behavior. The results indicate that the proposed dynamic ranking model yields significant improvements in search effectiveness, as measured by the metric, while simultaneously generating quantifiable gains in key business performance indicators. Specifically, the implementation resulted in a 2.1 percentage point increase in the conversion rate and a 14.5% uplift in incremental revenue. These observed effects achieved statistical significance. These findings provide empirical evidence supporting the economic viability of transitioning from static search systems to intelligent ranking architectures, highlighting their strategic importance for scalable and competitive B2B e-commerce platforms.

Keywords: Learning-to-Rank, B2B e-commerce, LightGBM, economic efficiency, return on investment (ROI), total cost of ownership (TCO), simulation-based analysis, conversion optimization, DIY retail segment, information retrieval

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Introduction

Search functionality constitutes one of the core components of user experience (UX) and a critical determinant of competitiveness in e-commerce platforms. In the B2B Do-It-Yourself (DIY) segment, in particular characterized by high catalog complexity, pronounced demand seasonality, and heterogeneous user intent, the quality of search results directly influences conversion rates and customer retention metrics.

The evolution of search systems in e-commerce has progressed from static inverted indexes and manually tuned relevance rules toward hybrid architectures based on machine learning techniques and semantic analysis. Nevertheless, a substantial proportion of market participants continue to rely on simplified solutions grounded in binary term matching, caching of frequent queries, and static product catalogs. While such approaches were initially effective during the early stages of online sales channel development, their relevance and scalability have declined as product assortments (SKU matrices) expand and user queries become increasingly complex.

The growth of data volumes, the need to support multilingual interfaces, and the diversification of product portfolios have collectively rendered static search systems insufficient in terms of both retrieval quality and economic efficiency.

At the same time, the B2B DIY market exhibits ongoing supplier consolidation and intensifying competitive pressure, prompting leading platforms to adopt next-generation intelligent search mechanisms. For small and medium-sized enterprises (SMBs) operating under constrained computational and financial resources, this situation creates a structural tension. On the one hand, achieving search accuracy, personalization, and response speed comparable to market leaders has become a strategic necessity. On the other hand, companies must maintain an acceptable total cost of ownership (TCO) and ensure rational utilization of infrastructure resources.

Currently, there is no methodologically grounded and economically optimized framework that supports a staged transition from static search architectures to intelligent systems capable of balancing relevance quality, computational performance, and operational cost.

The objective of this study is to develop and provide a quantitative economic justification for the implementation of a dynamic Learning-to-Rank model within a B2B e-commerce catalog. The proposed methodology is designed to isolate and empirically evaluate the impact of personalized ranking on key economic performance indicators, including conversion rate (ΔCR) and revenue (ΔRev), using synthetic modeling of user behavior.

1. Background and related work

Recent research on search systems for e-commerce indicates that the market is undergoing a phase of qualitative transformation driven by assortment expansion, shifts in user behavior, and intensifying competition across online sales channels. Traditional static search mechanisms based on binary term matching and caching of frequent queries have proven increasingly insufficient under conditions of high data variability and increasingly complex user intent.

In recent Russian academic and applied literature (e.g. [1]), a clear transition is observed from static inverted indexes toward hybrid architectures that combine full-text, semantic, and personalized search capabilities. Within this transformation, the focus extends beyond improving retrieval relevance to encompass the economic sustainability of technological solutions, including the reduction of total cost of ownership (TCO) and the enhancement of return on investment (ROI).

The relationship between economic efficiency and user experience in the DIY segment has been extensively examined in studies of major international market players [2, 3]. These works emphasize that improvements in search relevance and personalization directly translate into measurable gains in business performance indicators.

Practical cases of search system transformation in the B2B DIY sector have been demonstrated by companies such as STD "Petrovich" and JSC "TD Elektrotekhmontazh" (ETM), which presented their projects on the RUWARD platform. The Petrovich case [4] illustrates how the development of an integrated supplier account system enhanced the completeness and structural consistency of catalog data, thereby establishing a foundation for the subsequent implementation of intelligent search and recommendation mechanisms.

Similarly, the ETM project [5] documents the introduction of dynamic product data management and user segmentation strategies, resulting in increased conversion rates and reduced catalog maintenance costs.

Over the past decades, the Learning-to-Rank paradigm based on training models using labeled relevance data has emerged as a central methodology for improving search result quality [6, 7]. Survey studies and foundational works confirm the universality and theoretical significance of LtR approaches across a broad range of Information Retrieval tasks [8].

Comparative analysis of adjacent markets, including DIY, electronics, furniture, and jewelry, reveals converging trends in search system development: increasing emphasis on personalization, semantic enrichment, and the integration of multimodal features such as images, textual descriptions, and brand attributes [9]. At the same time, each industry retains domain-specific characteristics that shape architectural choices and investment priorities.

This body of literature establishes the technological and economic context for the present study and motivates the need for a quantitatively grounded assessment of dynamic ranking implementation in B2B e-commerce environments.

As illustrated in *Table 1*, search architectures across e-commerce segments differ substantially in terms of data structure, dominant ranking signals, personalization depth, and economic objectives. Despite this heterogeneity, a common structural pattern emerges: as catalog complexity and user intent variability increase, static retrieval mechanisms become insufficient, necessitating hybrid architectures and adaptive ranking strategies. In this context, dynamic ranking mechanisms increasingly serve as the integrative layer that aligns technical relevance with business performance objectives.

Both Russian and international studies ([1, 10–12]) indicate that the successful implementation of intelligent search systems is determined by three interrelated groups of factors:

1) the quality of catalog data (structural consistency, completeness, multimodality);

2) the maturity of the search architecture (presence of a hybrid retrieval layer and adaptive ranking mechanisms);

3) the economic efficiency of the solution (balanced ROI and TCO).

An analysis of the Petrovich and ETM cases further confirms that even moderate investments in catalog automation and data structuring may yield measurable economic benefits. Reported outcomes include a reduction of manual search maintenance costs by up to 30–40% and an increase in search-session conversion rates by 10–15%.

Table 1.

Comparative characteristics of search approaches across different e-commerce segments

Parameter	DIY (B2B/B2C)	Electronics	Furniture	Jewelry
Data Type	Technical specifications, brands, categories	Standard SKUs, device parameters	Multimodal data (images, materials, dimensions)	Visual and stylistic attributes, brand information
Primary Challenge	Long-tail queries, complex SKU structure, B2B pricing models	Frequent SKU updates, high competition, narrow filtering constraints	Semantic ambiguity (style, interior context, materials)	Strong dependence on visual perception and emotional factors
Search Architecture	Hybrid (Redis + Elasticsearch + ANN)	High-performance full-text search with attribute-based filtering	Multimodal (text + image)	Semantic search with visual retrieval
Personalization Level	Moderate (by categories, brands, purchase history)	High (by devices, accessories, behavioral patterns)	High (by style, room context, design history)	Maximum (by aesthetic preferences and gift context)
Economic Objective	TCO reduction, SLA optimization, operational stability under load	Increase in CTR and conversion rate, reduction in CPL	Increased engagement, reduced bounce rate	Growth of average order value (AOV) and customer loyalty
Improvement Methods	Hybrid retrieval, Learning-to-Rank, incremental index updates	Rapid reindexing, ANN over product attributes	Image2Vec, style embeddings, semantic search	Visual similarity ranking, embedding-based re-ranking

Evidence from adjacent e-commerce segments suggests that Learning-to-Rank (LtR) has evolved from an emerging methodological trend into an industry standard for personalization and conversion optimization.

- Electronics (Amazon, JD.com). In this segment, LtR is employed to balance price, margin contribution, and product return probability. This optimization strategy increases not only gross revenue but also net GMV through reduced operational costs and improved inventory efficiency.
- Furniture (Wayfair). Here, LtR extends into multimodal ranking. Models incorporate visual embeddings (e.g., Image2Vec) to evaluate stylistic compatibility, enabling products that do not strictly match textual queries but align with a user's visual preferences to achieve high ranking positions.
- Jewelry (Etsy). In markets dominated by subjective attributes such as aesthetics and emotional resonance, LtR effectively utilizes categorical embeddings to encode latent stylistic preferences, optimizing results for emotional and gift-oriented intent.

Collectively, these examples demonstrate the methodological universality of LtR from ranking based on precise technical attributes (Electronics) to handling complex visual and aesthetic signals (Furniture and Jewelry).

In recent years, hybrid approaches combining traditional lexical retrieval with transformer-based dense retrieval models have gained prominence for enhancing ranking quality and establishing universal benchmarking standards [13–15]. However, one of the primary challenges in deploying such models within production e-commerce systems lies in ensuring computational efficiency and latency control. This issue is actively addressed in research on transformer-based re-ranking and lightweight inference architectures [16].

In summary, although the evolution toward hybrid search systems represents a dominant technological trajectory, dynamic ranking based on Learning-to-Rank is widely recognized as the principal driver of economic effectiveness. Nevertheless, the quantitative economic justification of LtR implementation, particularly under constraints of limited computational resources and the need for infrastructure optimization, remains insufficiently developed.

To address this practice-oriented gap, the following section presents a methodology designed to isolate and empirically evaluate the economic impact of deploying a dynamic ranking model in a B2B e-commerce environment.

2. Methodology

The methodological framework of this study is based on a simplified economic model of an e-commerce platform, in which the product catalog and its ranking logic are treated as the primary determinants of conversion funnel efficiency and generated revenue. Within this framework, search ranking is conceptualized not merely as a technical component of information retrieval, but as a revenue-influencing mechanism embedded in the platform's value generation process.

To enable an isolated assessment of the impact of ranking quality, infrastructure-related engineering costs and traffic acquisition channels (including Cost per Lead (CPL) and SEO expenditures) are excluded from the analysis and treated as constants. This assumption allows the evaluation to focus exclusively on the marginal economic contribution of ranking improvements.

The objective of the proposed methodology is to provide a quantitative estimation of the economic effect (ΔRev) achieved through the transition from a static product ranking model to a dynamic model that depends on user type, geographic region, product category, and machine-learning-based relevance score.

2.1. Catalog interaction model

Within the Customer Journey framework, the primary object of analysis is the navigation scenario through the product catalog, where a user interacts with a hierarchy of categories, nested selection pages, and product listing pages. At this level, user interaction is reduced to the selection of a category followed by the examination of the corresponding product list.

The traffic flow T is modeled as the aggregate number of category visits and is assumed to remain constant across the ranking architectures being compared. This assumption enables an isolated evaluation of ranking effects without confounding variations in traffic volume.

Each session is characterized by:

$$S = \{T_{C_j}, X_i\}_{j=1}^{M},$$

where T_{C_j} denotes the number of visits to category C_j; X_i represents contextual user attributes (e.g., user type, geographic region).

The effectiveness of transitions within funnel stages constrained by category pages is fully determined by the ordering of products, as defined by the ranking function R.

2.2. Ranking-dependent conversion function

A central objective of the methodology is the formalization of a conversion function CR that establishes a direct dependency between economic performance indicators and the order of product presentation on a category page.

Let I_k denote the product located at the k-th position within the list $L(C_j)$, which is generated by the ranking function R. The probability of a purchase I_k occurring during a category page visit is defined as $P_{purchase}\left(I_k, k \mid C_j, X_i\right)$. This probability is contingent upon two primary factors:

1. Relevance (Quality): The degree to which a product I_k aligns with the general expectations associated with category C_j and the contextual preferences of the user X_i. This metric is maximized under dynamic ranking. In e-commerce, relevance estimation traditionally relies on implicit feedback mechanisms [17, 18].

2. Positional Effect (Position): The decay in the probability of a view, click, and subsequent purchase as the product position k in the results list increases. Accounting for position bias is a fundamental requirement for the development of effective ranking systems [19].

The total expected revenue $\Re v_R$ for a selected ranking function R (either static R_{stat} or dynamic R_{dyn}) is calculated as the sum across all categories and products:

$$\Re v_R = \sum_{j=1}^{M} T_{C_j} \cdot \sum_{k \in L(C_j)} \left(P_{purchase}\left(I_k, k \mid C_j, X_i\right) \cdot P\left(I_k\right) \right),$$

where $P(I_k)$ represents the price of product I_k;

M denotes the total number of categories included in the experiment.

2.3. Target metrics and research hypothesis

To assess the economic effect, a system of metrics is utilized that focuses exclusively on the performance of the conversion funnel.

1. Incremental Revenue (ΔRev): The difference between the expected revenue generated by dynamic ranking (R_{dyn}) and static ranking (R_{stat}). This serves as the primary indicator of the economic effect.

2. Conversion Rate (CR): The ratio of the total number of purchases to the total number of category visits.

3. Average Check (AC): The average value of a single transaction, which may fluctuate if dynamic ranking shifts user preferences toward more expensive or more relevant products.

The research is predicated on the hypothesis that the transition to dynamic ranking (R_{dyn}), which employs a machine-learning-based score to adapt product ordering to context X_i, results in a statistically significant increase in total expected revenue compared to static ranking (R_{stat}), ceteris paribus. This approach to linking relevance and financial performance aligns with the classical methodology for the economic evaluation of Information Retrieval systems [20].

The methodology thus focuses on the development of a model capable of isolating and quantifying the effect of ranking quality improvements within a product catalog. To verify this hypothesis and evaluate the economic effect ΔRev under conditions approximating real-world operations, the subsequent section of the study is devoted to the design and implementation of a Digital Experiment. The experimental portion aims to provide empirical confirmation that the increase in retrieval relevance achieved through dynamic ranking leads to sustained growth in key business metrics.

3. Digital experiment

To quantitatively evaluate the economic effect ΔRev from the implementation of the dynamic ranking model R_{dyn}, a controlled digital experiment was designed and conducted. This approach allows for the isolation of the ranking function's influence from other external factors such as marketing campaigns or interface changes thereby ensuring high reliability of the results.

The experiment comprises three key stages:

1. Development of a unified data collection methodology (Implicit Feedback) to create the training sample.

2. Synthetic generation of a controlled clickstream simulating user behavior to verify the model under ceteris paribus conditions.

3. Training of the Learning-to-Rank (LightGBM) model followed by simulation to compare key economic metrics (Rstat vs Rdyn).

Consequently, the objective of this section is to empirically confirm the hypothesis that improvements in relevance quality, as measured by the NDCG@10 metric, translate into sustained growth in expected revenue.

3.1. Data collection

The training of the dynamic ranking model R_{dyn} and subsequent validation of the economic effect ΔRev require a representative array of log data reflecting user behavioral scenarios within the catalog and search results. Data collection focuses on forming session sequences to extract implicit feedback and construct the feature space for the machine learning model.

It is important to note that within the scope of this study, due to the necessity of creating a fully controlled and isolated environment for the digital experiment, a synthetic clickstream was utilized for model training and testing. This clickstream was generated in strict accordance with the structural requirements for real-world logs described below.

Data source, volume, and filtering requirements.

In a production environment, the data source should be a corporate Data Warehouse (DWH). When forming the training sample, several requirements for volume and filtering must be observed to ensure statistical reliability and experimental purity:

- Time horizon: A rolling window of the last 12 months is recommended to account for demand seasonality in the DIY segment and provide sufficient depth for training.
- Product filter: Mandatory exclusion of products with *inactive* or *deleted* statuses.
- User filter: Exclusion of test sessions and administrative users.
- To optimize the machine learning pipeline, data extraction in Parquet format is recommended.

Interaction log formation (implicit feedback).

A pivotal element of data collection is the categorization of action types to form implicit feedback, which serves as the target variable for training the ranking model. Logs are reduced to a uniform structure containing mandatory attributes: *user_id*, *SKU*, a*ction_type*, t*imestamp*, *session_id*, and *price*. User actions are unified across four implicit feedback levels, ordered by increasing significance and reflecting the stages of the conversion funnel:

- Impression (Level 0): The appearance of a product in the results list or category page.
- Click (Level 1): Navigation to the product detail page.
- Add-to-cart (Level 2): Addition of the product to the shopping cart.
- Purchase (Level 3): A completed transaction (linked to *order_id*).

Each *session_id*, a strict chronological sequence of events is reconstructed via *timestamp* to accurately model the customer journey and evaluate the positional effect.

Contextual and economic attributes.

To construct the feature space for the model and evaluate the economic effect, the following attributes are included in the dataset:

- Contextual attributes: *user_type, region, category_id* used for ranking personalization and accounting for external factors.
- Economic attributes: *order_id, quantity, price* required for precise calculation of target business metrics (ΔRev and AC) at the transaction level.

Quality control of the collected dataset includes verifying the consistency of action sequences (*impression* → *click* → *add-to-cart* → *purchase*) and ensuring that the proportion of sessions with active interaction (at least one click) is no less than 15%, which guarantees the representativeness of the training sample.

3.2. Learning-to-Rank model training (LightGBM)

Gradient boosted decision trees, specifically the LightGBM (Light Gradient Boosting Machine) library [21], were selected to implement the dynamic ranking function R_{dyn}. This choice is motivated by several factors critical for a production e-commerce environment:

- High Training and Prediction Speed: LightGBM utilizes Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), which significantly accelerate model construction and reduce inference latency compared to other gradient boosting implementations (e.g., XGBoost), a necessity for online ranking.
- Efficiency with Large-scale Data: Due to memory optimization through histogram-based algorithms, LightGBM effectively processes training samples with high feature dimensionality and large row counts, typical for user click logs.
- Support for LtR-optimized Loss Functions: LightGBM natively supports objective functions optimized for ranking tasks, such as LambdaRank, which utilizes NDCG as the primary metric. This ensures a direct link between model optimization and search quality indicators.

The model constructs an ensemble of weak predictive models (decision trees) sequentially, correcting errors from previous iterations. In the LtR context, the model is trained to predict the relative order of products within a single query or category (Pairwise/Listwise approach) rather than absolute relevance scores (Pointwise approach). The training utilizes the feature space defined in the data collection section, with the target variable represented by implicit feedback levels ($L \in \{0, 1, 2, 3\}$).

3.3. Synthetic clickstream generation algorithm

To provide the controlled environment necessary for training and testing the dynamic ranking model, an algorithm for synthetic interaction log generation was developed. This approach allows for the modeling of key behavioral characteristics of a real-world e-commerce platform, which is critical for evaluating the economic effect under ceteris paribus conditions.

Modeling parameters and assumptions.

The generation of the synthetic dataset is based on a set of fixed parameters that define the distribution of key attributes:

- Product Assortment (P): A fixed set of products distributed across categories (e.g., DIY segments N_c such as Construction Materials, Tools, etc.).
- Client Segmentation (A): Users N_t are distributed across types (A, B, C, D) based on behavioral characteristics that model baseline conversion probability (CR_{base}) and price sensitivity. Segment A exhibits the highest CR_{base}, while segment exhibits the lowest.
- Geographical Segmentation (G): Division into N_g regions used to introduce variability in the average check (AC) via regional coefficients.
- Positional Effect (λ): The probability of interaction (click or purchase) is inversely proportional to the product's rank (position) in the list. The positional effect is modeled using an exponential decay function reflecting the decline in user attention:

$$P\left(action \mid rank\right) \propto \frac{1}{\log_2\left(1+rank\right)} \cdot e^{-\lambda \cdot \left(rank-\mu_P\right)},$$

where μ_P represents the mean target position from which an action is performed;

λ denotes the decay coefficient reflecting rate of CR decline.

Session generation procedure.

The generation of logs is conducted at the session level (*session_id*) in a strict chronological sequence.

1. Session initialization: A unique *user_id* and *session_id* are are assigned. Contextual attributes, including *client_type* $\in A$ and *geo* $\in G$, are selected randomly. The *category* for the current session is then determined.
2. Impression formation: A list of M unique *product_id* is generated, simulating a listing or category page. For each of the M products, a log entry is created with *action_type* = 0 (*impression*), recording the *rank* = 1...M.
3. Interaction modeling: For each product in the results list, the conditional probability P(*action*|*rank*, *client_type*) is calculated sequentially. Based on these probabilities, entries with *action_type* = 1 (*click*) and *action_type* = 2 (*add-to-cart*) are generated. Upon the generation of *action_type* = 3 (*purchase*), a *unique order_id* is assigned, and *price* and *quantity* are calculated based on the average check, adjusted by the client type and region.
4. Chronological binding: Each log entry is assigned a *timestamp*, shifted by a random time interval relative to the preceding event, which ensures the authenticity of the chronological sequence within the *session_sequence*.

The final synthetic clickstream dataset conforms to the structure defined in the Data Collection section and is utilized for both the training and verification of the machine learning model.

3.4. Dynamic ranking model (R_{dyn})

The LightGBM gradient boosting algorithm was selected to implement the dynamic ranking function R_{dyn}. This choice is motivated by its high performance and efficiency when handling large sparse data, which is a critical requirement for e-commerce systems.

Objective function and training.

The product ranking task was formulated as a Learning-to-Rank (LtR) problem within the pointwise paradigm. The target variable serves as the normalized level of implicit feedback, where, $y_i \in \{0, 1, 2, 3\}$ representing the progression from Impression to Purchase. The model was trained using the NDCG@10 metric to optimize the positioning of the most valuable items at the top of the search results.

Feature space.

To construct the *Model_Score*, three groups of features were extracted from the collected clickstream and catalog attributes:

- User features (Personalization): *user_id*, *user_type*, *region*, and aggregated behavioral metrics, such as the user's average check and purchase frequency within a specific category.
- Product features (Relevance): product *price*, *category*, availability status, and attributes modeling quality, such as rating and review count.
- Interaction features (Context): category frequency (*category_freq*), the position of the product in static ranking (R_{stat}), and the keyword match between the category and product title.

The model R_{dyn} calculates the probability of a positive interaction for each (*user_id, user_type, region*) triplet and ranks the products in descending order based on this probability.

4. Experimental results

The quantitative evaluation of the economic effect resulting from the implementation of R_{dyn} was performed by simulating user behavior on the generated clickstream, which provided controlled conditions for comparison. The primary objective of this stage is the empirical comparison of key search quality metrics (NDCG@10) and economic indicators (ΔRev, ΔCR)

for the two ranking functions: static (R_{stat}) and dynamic (R_{dyn}). The gathered data verify the central research hypothesis and demonstrate that improvements in relevance translate into a sustained increase in expected revenue.

4.1. Comparison by category

To verify model quality at the results list level, *Table 2* presents a comparison between dynamic (R_{dyn}) and static (R_{stat}) ranking for three randomly selected categories.

4.2. Ranking results conclusions

The analysis of inference results confirmed the high efficiency of dynamic ranking in prioritizing products with high predicted interaction scores (*Model_Score*) relative to static ranking (R_{stat}). The model consistently reordered products associated with positive user actions (Action: YES) into the top-10 positions across all three test categories, significantly increasing their visibility. The most pronounced effect was observed in the Garden and Outdoor category, where product PROD_001, which received a maximum score of 0.7399, was moved from the 20th position to the 1st. Instances where the model assigned high scores to positions without a recorded action such as in the Plumbing category with a score of 0.6932 are interpreted as latent relevance that remained unrealized under the conditions of a specific test session. The results suggest that the application of the LightGBM algorithm supports improved listing ordering, which is potentially associated with positive gains in ranking quality metrics, specifically NDCG.

Economic effect assessment.

Based on the clickstream simulation, key economic metrics defined in Section "Target Metrics and Research Hypothesis" were calculated. The results derived from the synthetic dataset are presented as follows:

- Calculated revenue increase (ΔRev): 14.5%

Table2.

Comparison of product positioning: dynamic vs static ranking

Category	*Product_ID*	R_{dyn}	R_{stat}	*Model_Score*	*Action*
Construction Materials	PROD_3180	1	17	0.6912	NO
	PROD_0567	2	24	0.5493	NO
	PROD_1657	3	26	0.5208	YES
	PROD_1033	4	12	0.4834	YES
	PROD_1008	5	16	0.4770	YES
	PROD_4964	6	4	0.4592	NO
	PROD_2220	7	23	0.4545	NO
	PROD_3951	8	13	0.4522	NO
	PROD_2462	9	12	0.4471	YES
	PROD_2485	10	17	0.4383	NO
Garden and Outdoor	PROD_3640	1	20	0.7399	YES
	PROD_3667	2	28	0.5948	NO
	PROD_3180	3	12	0.5624	YES
	PROD_1358	4	24	0.5192	NO
	PROD_4143	5	4	0.5103	NO
	PROD_1439	6	12	0.5099	YES
	PROD_2331	7	21	0.4666	NO
	PROD_2551	8	29	0.4615	NO
	PROD_4483	9	23	0.4554	YES
	PROD_3701	10	17	0.4497	YES
Plumbing	PROD_2003	1	25	0.6932	NO
	PROD_0828	2	19	0.5751	NO
	PROD_3790	3	3	0.5748	NO
	PROD_0142	4	3	0.5720	NO
	PROD_1192	5	27	0.5438	NO
	PROD_4513	6	4	0.5359	NO
	PROD_1060	7	16	0.5355	YES
	PROD_4990	8	20	0.5285	NO
	PROD_4287	9	26	0.4780	NO
	PROD_3290	10	11	0.4758	NO

- Change in conversion rate (ΔCR): 2.1 percentage points
- Change in average check (ΔAC): 1.8%

The findings indicate that the enhancement of retrieval relevance through dynamic ranking ensures a sustained and statistically significant increase in expected revenue ($\Delta Rev > 0$), thereby confirming the primary research hypothesis.

5. Discussion and limitations

The digital experiment we conducted confirmed the technological efficiency of the dynamic ranking model we developed and provided a calculated economic effect in the form of a 14.5% revenue increase. However, the results necessitate a critical discussion of methodological aspects and observed anomalies. The elevation of products with confirmed conversions (Action: YES) indicates that features related to implicit feedback and context are successfully captured by the LightGBM model.

An analysis of cases involving high scores in the absence of an action (e.g., PROD_2003 in the Plumbing category) suggests that while the model correctly evaluates product relevance within its category, predictions may not materialize due to external factors excluded from the model, such as stock availability, delivery speed, marketing campaigns, or behavioral noise. This highlights the limitations of the pointwise approach and suggests the potential for transitioning toward listwise or pairwise optimization strategies that account for the context of the entire results list.

A primary limitation of this study is the reliance on a synthetic clickstream which, despite modeling the positional effect, cannot fully replicate the stochasticity and variability of real-world user behavior. Final verification of the economic effect requires full-scale A/B testing in a production environment to account for user adaptation and cross-funnel impacts.

Conclusion

This study analyzed the economic efficiency of transitioning from static to dynamic product ranking within the highly competitive B2B DIY segment. To this end, a Learning-to-Rank (LtR) model based on the LightGBM algorithm was developed, utilizing an expanded feature space and implicit feedback. The digital experiment confirmed the primary hypothesis: the implementation of dynamic ranking provides a statistically significant increase in key business metrics. Simulations on a synthetic clickstream demonstrated a sustained increase in total expected revenue (ΔRev) by 14.5% and an improvement in the conversion rate (ΔCR) by 2.1 percentage points.

These findings provide evidence of the direct economic benefits of improving retrieval relevance through personalized product ordering. Log analysis revealed that the model successfully identifies products with high interaction potential, moving them from the long tail of the listing into the top-10 positions, thereby maximizing the positional effect. However, instances were identified where high predicted scores were not accompanied by actual actions, underscoring the necessity of integrating additional factors, such as inventory levels and logistical constraints, into the final ranking score.

The use of a synthetic clickstream remains a key methodological limitation as it cannot fully replicate the stochastic noise of a real-world operating environment. Consequently, the next critical phase for result verification should involve controlled A/B testing on live production traffic. Furthermore, to further enhance ranking quality, it is advisable to consider a transition from the pointwise paradigm to listwise approaches that account for dependencies between all items in a list. Overall, the LtR approach we developed demonstrates that the consistent transformation of search architecture in the e-commerce segment is not only a technological advancement but also a critical economic decision. Optimization through dynamic ranking, personalization, and system observability facilitates sustainable growth in platform conversion and overall profitability. ■

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About the author

Fedor Vladimirovich Krasnov

Candidate of Sciences (Technology);

Specialist in information retrieval and recommendation systems in e-commerce, Researcher, Research Center, Vi.Tech LLC, 4 Chaginskaya St.(Bldg. 13, Floor 4, Room 15), Moscow 109380, Russia;

E-mail: fedor.krasnov@vseinstrumenti.ru

ORCID: 0000-0002-9881-7371

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A review and comparison of newer methods for task allocation among performers

Timofey Yakovlevich Shevgunov [a,b]
E-mail: shevgunov@gmail.com

Anna Alexandrovna Kroshilina [b]
E-mail: ankrosh@vk.com

[a] Moscow Aviation Institute (National Research University), Moscow, Russia

[b] Graduate School of Business, HSE University, Moscow, Russia

Abstract

This paper presents a description of the current state and the results of an analysis of recent advances in the problem domain of automated task distribution among employees. The purpose of the study is to identify the main trends and patterns in the development of existing task allocation methods, to determine their strengths and limitations, and to justify the need for new approaches and algorithms that can improve the efficiency of task delegation to employees. Using a unified system of notations for the key concepts of the subject area, the article provides a concise descriptive review of ten universal task distribution algorithms published over the past twenty years. The comparative analysis was carried out according to a set of criteria reflecting both the technical and the organizational-behavioral aspects of how these algorithms function. The key evaluation criteria included: the degree to which performer competencies are taken into account; adaptability to changing external conditions and team composition; requirements for completeness and structure of the input data; robustness to incomplete or noisy data; transparency and explainability of decision-making; computational complexity; scalability with an increasing number of tasks and employees; implementation and maintenance costs; and orientation toward personnel development and competence enhancement. The comparative analysis we carried out made it possible to identify the advantages and shortcomings of each method and to formulate recommendations for their most effective practical application. The results showed that none of the examined algorithms can be considered a universal tool for delegation. Furthermore, it was found that comprehensive information about a performer's suitability for solving tasks requiring diverse competencies is either ignored or insufficiently utilized by many algorithms. This observation leaves open the problem of developing new approaches to task allocation and designing new algorithms based on them.

Keywords: task distribution, task allocation, performer assignment, assignment matrix, task delegation algorithms, round-robin algorithm, front based algorithm, genetic algorithm management, product digital twin, resource digital twin

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Introduction

One of the factors determining the achievement of high productivity in the internal workflows of any organization, regardless of its organizational and legal form, is the effectiveness of planning and distributing tasks during the direct implementation of business processes. An increase in overall project complexity or operation under changing environmental conditions inevitably requires management, at the level of the organization or its structural units, to plan more accurately and allocate the available resources more rationally, which is one of the important conditions ensuring rapid adaptation of a company's business processes. At the same time, the limited labor resources available to a company in the short term make it necessary to ensure their optimal utilization over as long working intervals as possible. In addition, there is a growing risk of erroneous decision-making [1] when tasks are distributed manually under workflow conditions close in intensity to the production capacity limits of the company. This risk further increases when tasks differ significantly in their characteristics, are rare or new, and are encountered by performers for the first time.

In organizing the task allocation process within organizations, three key problems are typically identified. The first problem consists in the uneven workload of employees, leading either to actual idle time or to overload of individual employees or their groups. The second problem lies in the absence of a systematic mechanism for taking employee competencies into account and verifying their compliance with the minimum requirements necessary for the effective execution of assigned tasks. The third problem manifests itself in managerial subjectivity during task allocation, which may reduce employee motivation and serve as a potential source of violations of business ethics or established corporate culture norms. One of the characteristic indicators that task allocation within an organization or its subdivision is ineffective is the systematic violation of task deadlines by performers, manifested in the fact that no less than one quarter of all assigned tasks are not completed on time for various reasons, regardless of which performers they were assigned to them. Another characteristic indicator is the systematic duplication of assignments, which may manifest itself either in assigning the same task to two independent performers or in incomplete delegation, when the execution of a task requires continuous personal involvement of a manager to monitor its timing or quality.

The analysis conducted on papers published from 2005 to 2025 aimed at identifying new and original methods of task allocation among performers has shown that, although this research area does not belong to the most prioritized ones, the development of new methods, algorithms, and delegation techniques continues to remain the subject of scientific and practical investigations carried out by individual research groups. The relevance of ongoing research in task allocation methods, the key direction of which is the development of universal algorithms and techniques, is driven by the need to form stable mechanisms for the operational redistribution of tasks capable of ensuring a balance between control and performer autonomy.

A detailed analysis of the sources made it possible to identify a number of new, noteworthy, but rather narrowly specialized solutions, for example those designed for cloud data centers [2], distributed computing systems [3], software developer support systems [4], or control systems for multi-purpose aeromobile systems [5]. Algorithms structurally similar to task allocation algorithms are also used in solving problems such as the distribution of research among academic schools [6], the selection of scientific and methodological information [7,8], and the allocation of credit application flows for commercial banks [9]. Particular attention should be paid to the analysis of changes introduced into established delegation procedures under conditions of mandatory use of remote management technologies [10]. It should also be noted that in foreign practice, certain solutions aimed at improving the efficiency of task allocation [11] may be regarded as results of intellectual property and receive legal protection in the form of patents.

However, the main attention of the authors in analyzing the publications was focused on identifying new universal methods that can be directly applied or quickly adapted for task allocation among performers in organizations of various industries and forms of ownership. This paper presents a review and comparative analysis of ten identified universal methods designed to automate task allocation among performers in companies or their subdivisions. The compiled list includes methods implementing substantially different ideas underlying delegation, while variants of the same algorithms that differ only slightly from their main versions were not included. In order to systematize the descriptions of various methods, a basic formalization of the notation for general factors was carried out in Section 1. Section 2 provides brief substantive descriptions sufficient for forming a general understanding of each of the ten algorithms under review. The formal notation used in the descriptions of some of them may slightly differ from that used in the original publications. Section 3 presents a comparative analysis of the selected algorithms according to a number of criteria, allowing their intrinsic characteristics to be compared and potential areas of application to be identified. The conclusion presents the findings of the current review and recommendations for further development of the analyzed domain.

1. Formalization of the task allocation problem

The subject area of task allocation among performers can be formalized using the following mathematical entities. Let

$$T = \{t_n, n = \overline{1,N}\}$$

denote a non-empty finite set of tasks that must be completed;

$$E = \{e_i, i = \overline{1,I}\}$$

denote a non-empty finite set of performers, or employees;

$$C = \{c_m, m = \overline{1,M}\}$$

denote a non-empty finite set of competencies required by performers from E to complete tasks from the set T.

Each task $t \in T$ is characterized by the following attributes: $C(t)$ is the set of competencies required for its execution; $p(t)$ is the priority of task t, expressed using an ordinal scale, for example, “low,” “medium,” “high,” or “critical”; $s(t)$ is the complexity of task t, expressed quantitatively in terms of labor intensity or the time required for its completion, for example, in hours.

Each performer $e \in E$ is characterized by the following attributes: $C(e)$ is the set of competencies possessed by the performer and applicable to tasks from the set T; $a(e)$ is the available time for task execution, expressed in time units, for example, in hours; $w(e)$ is the current workload of performer e, expressed in time units.

Thus, the problem under consideration can be formulated as follows: it is required to distribute tasks from the set T among performers from the set E in such a way that both task characteristics (required competencies, priority, complexity) and performer characteristics (possessed competencies, available time, current workload) are taken into account. This allows the problem to be classified as an optimization problem in which it is necessary to minimize or maximize a certain objective function subject to a system of constraints. To formalize the assignment, it is convenient to introduce a binary function $x(t, e)$, which takes the value 1 if task t is assigned to performer e, and 0 otherwise.

Depending on managerial objectives, an organization may define different principles for distributing tasks among performers. Examples of key objectives include reducing the risk of personnel overload, ensuring a balanced distribution of workload among team members, or maximizing the utilization of available resources. In addition, in the strategic perspective, the development of employee competencies becomes important, enabling the formation of a more flexible and resilient organizational structure. Therefore, the choice of the optimality criterion is determined not only by current operational needs but also by long-term business priorities, such as operational efficiency, cost reduction, increased resilience to external risks, and the development of human capital. Below, four objective functions are considered, which most fully reflect these organizational goals.

1.1. Minimization of workload for employees with high current utilization

This criterion takes into account the available time for task execution for each employee $a(e)$, as well as task complexity $s(t)$ and task priority $p(t)$. Then the objective function F_1 has the following form:

$$F_1 = \sum_{e \in E} \sum_{t \in T} x(t,e)\big(a(e) - s(t)\big) \to \max. \qquad (1)$$

The optimization process consists in searching for such values of the binary function $x(t, e)$ that ensure the assignment of tasks to those employees who will retain the largest amount of free time after the assignment of the distributed task. Thus, the task is assigned to the less loaded employee, which leads to minimization of the workload of already highly utilized performers. Such an approach allows work to be redistributed in favor of employees with lower current utilization, thereby reducing the risk of burnout and overload. This approach is widely applied in organizations where it is important to maintain stable team performance, for example in call centers or IT support services, where balanced distribution of incoming requests reduces the probability of service failures.

1.2. Workload balancing among performers

The task consists in minimizing disproportions in the distribution of task labor intensity among employees. The average value across performers is calculated as

$$\bar{a} = \frac{1}{\#(E)} \sum_{e \in E} a(e), \qquad (2)$$

which is then sequentially compared with each value $a(e)$. The difference between these values should tend toward a minimum:

$$F_2 = \sum_{e \in E} \left| a(e) - \bar{a} \right| \to \min. \qquad (3)$$

Such a criterion ensures a more uniform distribution of tasks, which is particularly important in teams

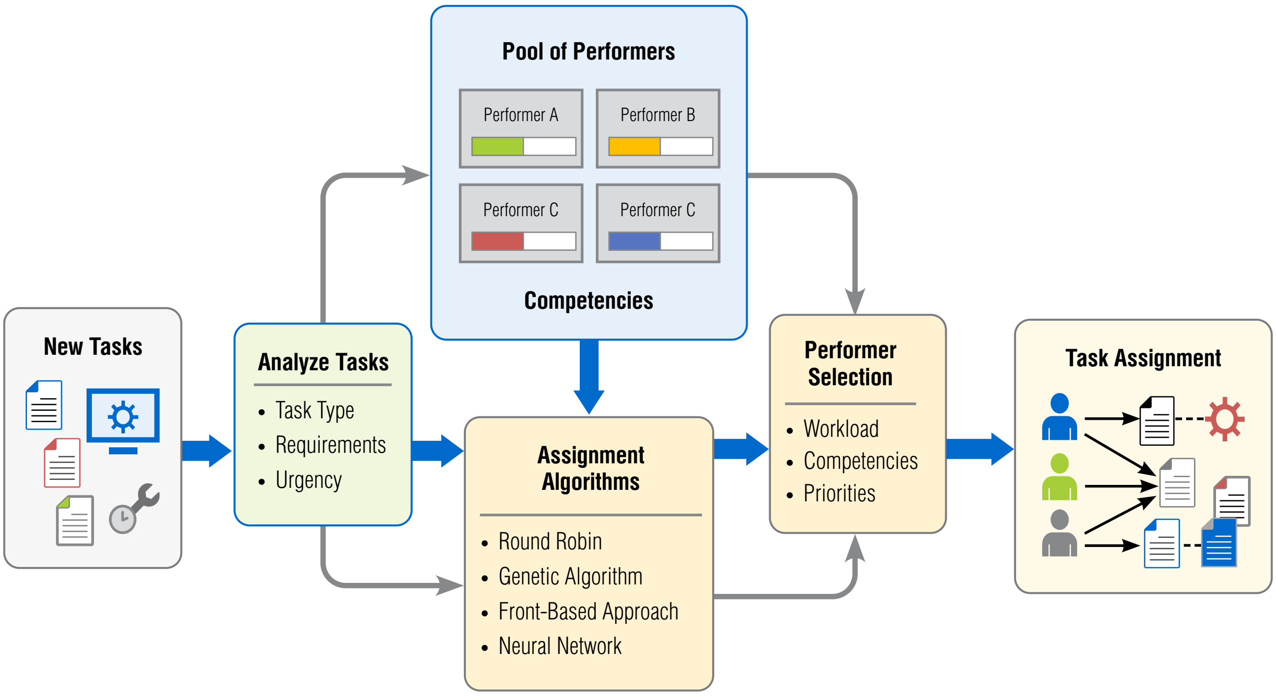

Fig. 2. Block diagram of the task allocation process among performers

where interchangeability of performers is assumed. An example is the distribution of work assignments within a software development team or among consultants of a project group, where excessive concentration of tasks on individual employees may create risks of deadline violations.

Figure 1 presents a generalized block diagram of a typical process of task allocation among performers in an organizational system operating under conditions of a non-stationary task flow and a heterogeneous pool of performers. The process begins with the arrival of new tasks forming a dynamic input flow T. For each task, a preliminary analysis stage is performed, including the determination of the task type, the required competencies $C(t)$, the priority level $p(t)$, and the urgency of execution. At this stage, a set of formalized characteristics is formed, which are subsequently used in the algorithmic task allocation procedure.

In parallel with the task pool, the performer pool E is considered, characterized by individual sets of competencies $C(e)$, current workload $w(e)$, available resource $a(e)$, and possible constraints. An important feature of the model being considered is the presence of uneven workload among performers, which is reflected in the "Performer Pool" block and constitutes one of the key factors in making assignment decisions.

At the next stage, a method or algorithm for task allocation is selected. Depending on organizational objectives and the structure of the input data, various approaches may be applied: cyclic distribution, combinatorial optimization methods, evolutionary algorithms, front based methods, neural network based correctors, and others. Thus, the "Allocation Algorithm" block reflects the variability of possible task flow processing scenarios. Subsequently, a performer is selected for a specific task. The decision is made taking into account a combination of factors: current workload, correspondence between competencies and task requirements, task priority, and strategic objectives, such as workload balancing or employee competency development.

After the task is assigned, the system state parameters are updated, reflecting changes in the workload of each performer. This ensures the relevance of data under conditions of a non-stationary task flow, when new tasks arrive before previously assigned tasks have been completed. Thus, the process presented in the *Fig. 1* has an iterative nature and implements a closed-loop task allocation management mechanism, ensuring adaptation to changes in the composition of tasks, the state of performers, and the selected allocation strategy.

The typical task allocation scheme presented in *Fig. 1* has an inter-industry character and finds application in a wide range of organizational systems. Below are examples from various areas of activity demonstrating the characteristics of the set of tasks T, the set of performers E, the relevant constraints, and the target performance indicators.

In the banking sector, one of the typical allocation tasks is the processing of credit applications from legal entities and individuals. In this case, the set T includes applications of varying levels of complexity and risk, while the set E consists of employees of underwriting, risk analysis, and compliance departments. The constraints include regulatory requirements, internal bank regulations, permissible application processing times, and workload limits for specialists. The target business indicators include the average processing time of an application, the proportion of approved applications with an acceptable risk level, and the throughput of the unit. Similar problems are discussed in studies devoted to the optimization of banking business processes and operational risk management [12].

In medical institutions, task allocation is associated with assigning patients to physicians of appropriate specialization, planning diagnostic procedures, and managing medical staff schedules [13]. In this case, the set T includes consultations, surgeries, and diagnostic examinations, while the set E consists of medical personnel with various competencies $C(e)$. The constraints include waiting time standards, urgency of medical cases, equipment availability, and shift based work schedules. The target business indicators include the total flow of treated patients, average waiting time, and balanced workload distribution among physicians.

In the construction industry, task allocation arises in the planning and coordination of work at construction sites [14]. The set of tasks T may include preparatory work, installation of structures, engineering works, and quality control activities, while the set E consists of specialized teams and subcontracting organizations. The constraints include technological sequencing of work, material delivery deadlines, safety requirements, and fixed project completion dates. Target indicators include adherence to the project schedule, minimization of downtime, and reduction of project costs.

In the judicial system, the distribution of cases among judges represents an assignment problem taking into account specialization, case complexity, and the current workload of the judicial staff [15]. In this case, the set T consists of cases of various categories, while the elements of E are judges with different qualifications and specializations. The constraints include procedural deadlines, requirements for balanced workload distribution, and principles of random case assignment established by regulations. The key target indicators include the average case processing time, compliance with procedural deadlines, and workload balancing among judges.

In service organizations, task allocation is associated with queue management, distribution of service requests, and planning of equipment usage [16]. The set T is formed from incoming requests or applications, while the set E consists of specialists of various profiles. The constraints include service level agreements (SLA), task priority level, geographical distance, and personnel availability. The target indicators include average service time, the percentage of requests completed within the prescribed time, and the personnel workload coefficient.

The examples above demonstrate that the formal model of task allocation based on the sets T and E, the competency functions $C(t)$, $C(e)$, and the binary assignment function $x(t, e)$, is sufficiently universal and can be applied across a wide range of industries. At the same time, specific constraints and objective functions may vary significantly, which justifies further specialization of task allocation algorithms aimed at meeting industry-specific requirements and accounting for the characteristics of incoming task flows.

2. Task allocation algorithms

Currently, there exists a wide variety of approaches to task allocation among performers, including both strict mathematical optimization methods and heuristic algorithms, as well as combined schemes. The choice of a particular approach is determined by the nature of the problem, the dimensionality of the input data, and the requirements for the speed of obtaining a solution. Such methods are widely applied in project management, logistics, service companies, and other domains where rational use of resources and efficient execution of work are required. This section provides a brief review of ten universal task allocation algorithms published over the past twenty years.

2.1. Round-robin algorithm for uniform task distribution among performers

The Round-robin algorithm [17] is one of the typical examples of uniform task distribution, which can be described as the sequential assignment of tasks to performers in a cyclic order. It is assumed that all performers are equal to one another, that is, there are no preferences in favor of any performer based on priority, qualification, or strict rules assigning specific types of tasks to particular individuals, and that all tasks have identical complexity and do not contain formally distinguished subtasks. The objective of this algorithm is to distribute tasks in such a way that no performer experiences overload.

Formally, the algorithm can be described as follows. Let, at a given moment, a set of tasks T be subject to allocation, and let the priority $p(t)$ of each task $t \in T$ be known. For each performer e from the set of performers eligible and available to execute such tasks, E, the current workload $w(e)$ is known.

The tasks from the set T are ranked according to their priority, forming a list T_P, which determines the order of allocation: tasks with a higher value of $p(t)$ are given priority in assignment. For each task t from T_P, a set of candidate performers $E_C(t)$ is formed. In order for a performer e to be included $E_C(t)$, the performer must have sufficient free time to complete task t, taking into account their current workload $w(e)$ and available time $a(e)$:

$$w(e) + s(t) \leq a(e). \tag{4}$$

The selection of a specific performer e for task t may be carried out based on additional criteria, such as minimal workload $w(e)$ at the moment of assignment or achieving a distribution of workload that is close to uniform upon completion of the allocation of all tasks from T. After assigning task t to performer e, their workload is updated as follows:

$$w(e) \leftarrow w(e) + s(t). \tag{5}$$

The cycle is repeated until all tasks from the list T_P have been allocated.

2.2. Algorithm based on the assignment matrix

The mathematical model for optimizing the process of task and labor resource distribution within an enterprise, proposed in [18] using combinatorial optimization methods, formed the basis of an algorithm for task allocation among employees based on constraint analysis and the branch-and-bound method.

The algorithm is based on constructing an assignment matrix, the processing of which results in the selection of a performer e from the set of candidate performers E for each task t from the set of tasks to be allocated T. For each task, along with the priority $P(t)$, expressed using a three-level ordinal scale (low, medium, high), a time constraint is introduced, described by the start date $D_{start}(t)$ and the end date $D_{end}(t)$. Each performer e is characterized by an integral indicator $Q(e)$, as well as the dates $V_{start}(e)$ and $V_{end}(e)$ of the period during which the performer is unavailable. The integral indicator is calculated as a linear combination:

$$Q(e) = w_c Q_c(e) + w_q Q_q(e) + w_t Q_t(e), \tag{6}$$

where $Q_c(e)$ and $Q_q(e)$ represent, respectively, assessments of the volume and quality of completed work;

$Q_t(e)$ represents an assessment of deadline compliance;

w_c, w_q, and w_t are weight coefficients, which in [18] are proposed to be equal to 0.35, 0.4, and 0.25, respectively.

When calculating all performance indicators of performers, the algorithm initially introduces three levels: a baseline level from which performance is measured, a normal level that must be achieved, and a target level toward which the performer should strive.

To construct the assignment matrix and determine the optimal solution, an integer programming algorithm such as the branch-and-bound method [18] is used. The matrix is initialized with cost values corresponding to tasks. In each row of the assignment matrix, the minimum element is identified and subtracted from each element of that row, resulting in at least one zero element appearing in the row. Then, in each column of the matrix, the minimum element is identified and, provided that there is no zero in that column, it is subtracted from the column elements.

A pair (t, e), representing a branching candidate, is selected among those for which the matrix element value equals zero. A coefficient is calculated by summing the minimum value of the corresponding task row and the minimum value of the corresponding performer column. Among all such coefficients, the maximum one is selected, which determines the optimal decision: the task corresponding to the current row is assigned to the performer corresponding to the current column. Since each performer may be assigned only one task, the column of the assigned performer and the row of the assigned task are removed from the assignment matrix.

The algorithm sequentially analyzes subsets of performers, determines the optimal solution for each subset, and excludes it from further consideration. As a result, the best allocation of tasks among all possible combinations of performers is determined.

2.3. Algorithm for optimal workload distribution considering specialization and available time based on an adapted genetic algorithm

In [19], a composite genetic algorithm (GA) was proposed for solving the problem of academic workload distribution. The input data included a set of teachers, which is the set of performers E, and a set of disciplines and types of classes, which is the set of tasks T. In addition, the following characteristics were introduced: $K(e)$ is the qualification of performer e, i.e., the set of disciplines that the teacher is able to teach; and $R(t, e)$ is the relevance of task t to performer e, expressed as a value in the numerical interval [0, 1], representing the degree of correspondence between the performer's qualification and the task content.

The GA includes the following operations: generation of an initial population as a random distribution of workload hours; selection as choosing performers based on specialization and workload criteria; generation of new allocation variants through crossover and mutation; and identification of the current optimal workload distribution subject to constraints.

The algorithm begins by generating an initial population of solutions, which is allocation variants $P_0=\left\{p_q^{(0)}, q=\overline{1,Q}\right\}$, where each variant $p_q^{(0)}$ represents a mapping of the set of tasks T onto the set of performers E, described by binary variables $x(t, e)$, indicating which performer e is assigned to task t. Assignments are generated randomly but in such a way that the constraints are satisfied. The first constraint requires that task t may be assigned to performer e only if $t \in K(e)$. The second constraint requires that, for each performer $e \in E$, the total volume of assigned tasks remains within an admissible workload interval.

For each allocation variant p_q, a fitness function $F(p_q)$ is calculated. It consists of several components. The component $F_1(p_q)$ evaluates the degree of correspondence $R(t,e)$ for all pairs (t, e). The component $F_2(p_q)$ evaluates the uniformity of workload distribution among performers. The component $F_3(p_k)$ evaluates, for all performers, the integral proximity of workload $W(e)$ to the admissible interval $[A_{min}(e), A_{max}(e)]$. Based on the values of $F(p_k)$, a set of the most fit allocation variants P_{sel} is formed.

After evaluation, evolutionary steps are performed. A new generation is formed from the best variants by applying crossover and mutation operators. From the set P_{sel}, pairs of individuals p_a and p_b are randomly selected, to which the GA crossover operator is applied, implementing a random exchange of parts of the task allocation or subsets of pairs (t, e) between the two individuals. The resulting offspring are included in an intermediate generation P_{next}. For some individuals $p \in P_{next}$, a mutation operator is applied, consisting of randomly reassigning certain tasks $t \in T$ to other admissible performers $e \in E$ such that $t \in K(e)$.

The new generation is formed by combining the best individuals from the current generation with the new individuals of the intermediate generation: $P_{new} = P_{sel} \cup P_{nex}$. The algorithm iterations continue until a stopping criterion is reached, defined as the condition that 90% of the individuals in the current population have the same maximum fitness value. As a result of multiple iterations, an assignment matrix $X = \{x(t, e)\}$ is obtained that satisfies all constraints and optimizes the selected criteria. In cases where the number of optimized parameters exceeds fifty, multi-agent genetic algorithms (MAGAMO) [20] may be used to reduce solution time, enabling efficient large-scale multi-objective optimization.

2.4. Heuristic algorithm for optimal allocation

The heuristic algorithm for optimal distribution of objects among storage units proposed in [21] has polynomial computational complexity and can be applied to solving problems in various domains, such as distribution of parallel big data processing flows, warehouse logistics, and automated scheduling. It may also be adapted to the problem of task allocation among performers. This is a heuristic greedy algorithm in which the allocation decision at each step is made without consideration of long-term consequences. The algorithm aims at uniform filling of storage units and minimization of the difference between the most and least loaded units. In [21], objective functions, formalization of the problem, and results of experimental studies evaluating the algorithm's effectiveness are also presented.

Tasks $t \in T$ are sorted, forming a list ordered in descending order of their labor intensity $s(t)$. Task allocation is performed iteratively until the list is exhausted. At each iteration, two tasks are assigned to performers: the most labor-intensive and the least labor-intensive tasks from T. The index of the candidate performer is determined as the remainder of the division of the task's position in the list by the number of performers. When adding task t to performer e, the following condition must be satisfied:

$$w(e) + s(t) > a(e), \tag{7}$$

otherwise, the task is not assigned to the given performer and is instead considered for the next candidate performer. After assigning a task to a performer, their workload is updated according to formula (5), and the assigned tasks are removed from the list. Since the algorithm is a polynomial-time heuristic greedy algorithm, it ensures high computational speed and satisfactory allocation quality even for large data volumes under strict time constraints.

2.5. Algorithm based on random sample partitioning

To address the problem of uneven task distribution among employees, which leads to overload of some and underutilization of others, [22] describes software that enables, with the participation of a human manager, the effective allocation of new tasks based on the analysis of current employee workload $w(e)$ and task complexity $s(t)$. The software is based on the Random Sample Partition Algorithm (RSP) [23], which processes large volumes of data by dividing them into smaller data blocks available for direct human analysis. The analysis results are presented in a convenient form for the manager, who subsequently makes the final decision regarding task assignment.

Based on information about task priority $p(t)$ and complexity $s(t)$, as well as information about available time $a(e)$ and current workload $w(e)$ of performers, a set D is formed containing data on tasks and performers. The elements of D are pairs (t, e) supplemented with characteristics that allow evaluation of task execution efficiency and the level of professional development. The set D is randomly divided into K non-overlapping subsets $\left\{D_k, k=\overline{1,K}\right\}$ of approximately equal size.

For each subset D_k, an analysis is performed aimed at determining the current workload $w(e)$ of each performer, evaluating task complexity $s(t)$ and priority $p(t)$, and calculating the aggregate workload of each performer. The result is an informational object $R(D_k)$ in the form of an analytical report containing, among other things, information about the number of tasks assigned to each performer or group of performers, the composition of the subset of tasks, their execution time, complexity, priorities, as well as potential overload of employees and their available resources sufficient to execute new tasks.

The analytical reports $R(D_k)$ obtained for all subsets are combined into a general result, a report R_{total}, which represents recommendations for task allocation taking into account workload balancing and task complexity. The resulting report R_{total} is displayed in the graphical user interface of the software for the manager, enabling the latter to make the final decision regarding task assignment to performers. The algorithm under consideration performs the collection and structuring of data on tasks and performers, as well as primary workload analysis, which allows it to be regarded as a possible tool within decision support systems, providing recommendations to a manager responsible for task allocation and personnel management.

2.6. Neural network based workload adjustment algorithm

When considering the production planning problem as a multi-objective optimization problem, the authors of [24] justified that the implementation of traditional task allocation systems may be limited due to the restricted set of fixed criteria used in them. To overcome this limitation and enable consideration of additional factors that are difficult to formalize, such as order priorities or equipment specifics, a hybrid algorithm was proposed that combines traditional optimization methods with plan adjustment using neural networks. The neural network based corrector used in the algorithm is based on two types of artificial neural networks (ANNs): a multilayer perceptron (MLP) [25] and a self-organizing map (SOM) by Kohonen [26].

An important feature of the algorithm is the grouping of performers into types of work centers and tasks into task groups. All tasks from the set T are grouped according to their relevance to work center types R using the Kohonen SOM trained via a self-organization algorithm. For each task t, a work center type $R(t)$ is determined that can execute it in the shortest time. Tasks are combined into groups $G(t)$, where each group corresponds to the type of work center most suitable for executing tasks of this category. Based on historical data and predefined expert rules, an MLP-type ANN is trained, which dynamically adjusts task priorities $p(t)$, the distribution of tasks among groups $G(t)$, and the selection of performers, taking into account available time $a(e)$ and workload $w(e)$. After the correction stage, tasks from the set T are assigned to performers from E in such a way as to minimize total completion time, balance workloads $w(e)$, and preserve task priorities $p(t)$ and available time constraints $a(e)$.

The algorithm also incorporates certain constraints. For example, not all tasks may be assigned to any performer, and a decisive assignment mechanism is possible: if a task belongs to a high-priority order, it may be rigidly assigned to a specific performer regardless of optimality according to other criteria.

2.7. Heuristic front based algorithm

Based on the analysis of the problem of optimal allocation among performers within a project consisting of tasks connected by dependencies representable as an acyclic directed graph, [27] proposes a heuristic algorithm that allows finding an acceptable allocation of tasks within given time limits while minimizing the project execution cost. The algorithm is based on the principle of front based execution, according to which tasks are sequentially assigned to performers based on task labor intensity and performer availability.

For formalization, additional definitions are introduced: $D(t)$ is the set of predecessor tasks for task t; $R(t) \subseteq E$ is the set of performers capable of executing task t; and the labor intensity $s(t, e)$ of task t depends on the specific performer e. The front of tasks at step k, denoted F_k, represents a subset of tasks from T whose predecessor tasks have already been completed, that is, $D_k(t) = \emptyset$. Tasks from F_k become candidates for allocation. For each task $t \in F_k$ and each performer $e \in R(t)$, the start time of task t by performer e is calculated as:

$$x(e) = \max\left(y_k(e), \max_{t' \in D(t)} y(t')\right) \tag{8}$$

and the completion time is determined as:

$$y(e) = x_k(e) + s(t, e), \tag{9}$$

The task is assigned to the performer e^* for whom $y_k(e)$ is minimal. For this performer, the values of $a(e^*)$ and $w(e^*)$ are updated, and for the task the start time $x(t) = x_k(e^*)$ and completion time $y(t) = y_k(e^*)$ are fixed. Allocation of tasks from the set F_k continues until it is exhausted.

After assigning all tasks from the current front F_k, a new front F_{k+1} is formed, including tasks whose predecessor tasks have now been completed, that is, $D_{k+1}(t) = \emptyset$, and which require allocation. At the same time, the completion times of already assigned tasks for performers are updated as $y_{k+1}(e) = y_k(e)$. The formation of new task fronts continues until all tasks from the set T have been allocated.

After allocation of all tasks, feasibility and optimality are verified. Feasibility consists in checking compliance with directive deadlines $d(t)$ for each task, that is, $y(t) \leqslant d(t)$. Optimality is assessed using an objective function whose minimization reduces the total project execution cost:

$$f = \sum_{e \in E} \sum_{t \in T} p(t) x(t,e) \big(d(t) - y(t,e) \big). \tag{10}$$

If the generated plan is feasible and optimal, the project schedule is formed and the total cost is evaluated. Alternative allocation variants are generated by different assignments of performers to tasks. The first front, consisting of tasks without predecessors, is determined by complete enumeration of all possible assignments. Subsequently, for each new task, all available performers are considered, and execution times are calculated taking into account workload and task dependencies. Thus, different variants correspond to different combinations of assignments $x(t, e)$, and the optimal one is selected by comparing the resulting combinations using the objective function that ensures the minimum project cost.

2.8. Iterative task delegation algorithm

When considering an approach to automating the task delegation process in project management, [28] proposed a model based on the use of iterative algorithms operating on data regarding employee experience, availability, and preferences stored in a NoSQL-type database. The main objective of developing such an algorithm was to reduce the involvement of the project manager in routine task allocation and to improve assignment quality through analysis of accumulated data. The authors present an iterative task delegation algorithm based on task keywords $K(t)$ and rating indicators of performer e. If the standard algorithm fails to assign a task due to insufficient data, a backup assignment mechanism is applied, taking into account the set of professional skills and preferences of performers.

The algorithm operates as follows. When a new task $t \in T$ is added, its keywords $K(t)$ are extracted. For each keyword $k \in K(t)$, performers $e \in E$ with the highest rating $R(e, k)$ are identified, and their ratings are summed to form an overall rating $R_s(e)$ for each performer. A list of performers ranked in descending order of $R_s(e)$ is formed. This list is then sequentially processed to check whether the current performer is available and capable of accepting the task, taking into account their workload $w(e)$ and available time $a(e)$. If a suitable performer is found, the task is assigned to them.

If no suitable performer is found, a backup algorithm is triggered. It uses professional skills $Q(e)$ and personal preferences $L(e)$ of the performer to compute a combined rating:

$$R_c(e) = Q(e) \cdot w_q + L(e) \cdot w_l, \tag{11}$$

where w_q and w_l are weights determining the relative importance of skills and preferences, respectively. The most suitable performer is then selected in a manner analogous to the selection based on $R_s(e)$. If the task remains unassigned after this stage, it is marked as requiring manual assignment. Such tasks are assigned by the project manager after algorithmic processing of the entire set of tasks T.

2.9. Task delegation algorithm based on a multi-agent system

In [29], an algorithm for planning, decomposition, and delegation of tasks in an unstructured decentralized environment is presented, where agents possess limited information about their own capabilities and the capabilities of other agents. The described approach to task allocation using a multi-agent system is based on the assumption that each agent may partially execute a task and delegate the remaining parts to other agents. The approach relies on a recursive task decomposition algorithm based on applied artificial intelligence methods, which allows a task to be decomposed into subtasks, enabling the agent to execute those subtasks it can implement independently and delegate the remaining subtasks to other agents. Such an assignment process continues recursively until the entire task is distributed or a stopping condition is reached. The algorithm operates under conditions of incomplete information about the capabilities of all agents and supports partial planning, allowing planning with abstract actions that are later replaced with specific steps through delegation.

An iteration of the performer assignment algorithm for a task t proceeds as follows. First, it is verified whether the task is primitive, that is, does not require further decomposition. If so, among the performers E, a performer e is identified for whom condition (4) holds and the competency sufficiency condition $C(t) \subset C(e)$ is satisfied. If such a performer is found, the task is assigned to them; otherwise, the task is marked as unresolved.

If the original task t is not primitive, the agent invokes a decomposition function $D(t)$, which returns the set of its subtasks $\left\{t'_k, k = \overline{1, K}\right\}$. For each subtask t', if the condition $C(t') \subset C(e)$ is satisfied, the agent e assigns the subtask to itself, updating its workload according to (5). If the condition is not satisfied, the subtask is delegated to another agent $e' \in E$ possessing a sufficient set of competencies for its execution, that is, $C(t') \subset C(e')$. Delegation of subtasks continues until all subtasks are assigned or an additional stopping condition is reached.

As an additional development of the algorithm, a two-phase mechanism may be used. In the first phase, the agent requests readiness from other agents to execute the subtask, and in the second phase, the subtask is transferred to the performer who first confirms the ability to execute it.

2.10. Adaptive expectation based algorithm

The systematization of approaches aimed at improving the efficiency of crowdsourcing using applied artificial intelligence methods, conducted in [30], made it possible to identify three key directions: task delegation, performer motivation, and quality control. For each of these directions, an updated taxonomy was proposed, and limitations and development prospects were analyzed. Based on this analysis, the authors proposed an algorithm for delegating complex tasks using the WMST (Weighted Multi-Skill Tree) model [31], which is employed to evaluate performer skills. The purpose of developing this algorithm was to provide a procedure for assigning tasks to performers with optimal skill matching and workload balancing.

For each performer e, a WMST model is preliminarily constructed to assess their competencies $C(e)$. During allocation of the task set T, for each task t, a performer e is selected who satisfies three conditions: correspondence of competencies $C(t) \subset C(e)$; sufficiency of execution resources $A(e) \geqslant S(t)$; and minimal current workload $W(e)$. The last condition is aimed at balancing the overall workload of the entire performer set E. If the selected performer is temporarily unavailable, the algorithm revises the assignment by selecting a new performer satisfying the above conditions.

3. Comparative analysis of algorithms

The comparative analysis of task allocation algorithms was carried out according to a number of criteria allowing for a comprehensive evaluation of their effectiveness and practical applicability. The degree of consideration of competencies reflects the extent to which the correspondence between performer characteristics and task requirements is taken into account, thereby determining the algorithm's ability to ensure optimal allocation based on professional skills and experience.

Adaptability to changes characterizes the flexibility of the algorithm and its ability to adjust decisions when the composition of performers changes, execution conditions are modified, or new tasks appear. Data requirements indicate the volume, structure, and accuracy of input information necessary for correct algorithm operation. Robustness to incomplete or noisy data determines the reliability of the algorithm under conditions of uncertainty and informational distortions. Transparency and explainability of decisions are associated with the interpretability of obtained results and the possibility of analyzing the reasons influencing the selection of a specific performer. Computational complexity characterizes the amount of computational resources and time required to obtain a solution, while scalability reflects the algorithm's ability to maintain efficiency as the number of tasks and performers increases. Implementation cost includes the total organizational, software, and hardware expenses associated with deploying and maintaining the algorithm. Finally, orientation toward personnel development reflects the potential of the algorithm to support employee qualification enhancement, identify competency gaps, and contribute to forming an optimal structure of labor distribution.

The analysis of *Table 1* shows that different algorithms possess specific advantages and limitations, which determine their areas of practical application. The main recommendations for selecting an appropriate approach are presented below.

The **Round-robin** algorithm described in Section 2.1 represents a simple and transparent method applicable under conditions of relatively uniform workload. It is effective in situations requiring rapid and low-cost task allocation with limited input data and high demands for explainability.

The **assignment matrix method** described in Section 2.2 is recommended when detailed task data are available and high transparency of decision-making is important. However, this approach demonstrates lower robustness to noisy data and limited scalability.

Table 1.

Algorithm comparison by key criteria

No.	Criterion	Round Robin (2.1)	Assignment Matrix (2.2)	Genetic Algorithm (2.3)	Heuristic Greedy (2.4)	RSP (2.5)	ANN Corrector (2.6)	Front-Based (2.7)	Iterative (2.8)	MA Approach (2.9)	WMST Model (2.10)
1	Competency consideration	None	Lim	Lim	None	Lim	Lim	Lim	Lim	Lim	Lim
2	Adaptability	Low	Med	High	Low	Med	High	Med	High	High	High
3	Data requirements	Min	High	Med	Min	Med	VH	Med	Med	High	High
4	Robustness to imperfect data	High	Low	Med	Med	High	Med	Med	Med	High	Med
5	Transparency	Full	High	Low	High	Med	Low	Med	Med	Low	Low
6	Computational cost	Low	High	High	Low	Med	High	Med	Med	High	High
7	Scalability	High	Lim	High	High	High	Med	Med	High	High	Med
8	Implementation cost	Low	High	Med	Low	Med	VH	Med	Med	High	High
9	Personnel development focus	None	Part	Yes	None	Part	Yes	Part	Part	Yes	Yes

Legend: Limited – Lim, Minimal – Min, Medium – Med, Very High – VH, Partial – Part.

The **genetic algorithm** described in Section 2.3 is advisable for solving complex optimization problems with multiple constraints. Its advantage lies in high adaptability to changing conditions and the ability to search for globally optimal solutions. At the same time, it requires significant computational resources and time costs.

The **heuristic (**greedy) **algorithm** described in Section 2.4 is oriented toward rapid solution generation under limited data availability and high dynamics. Its advantage is high execution speed and low computational complexity; however, the solutions obtained are generally far from optimal.

The **RSP method** described in Section 2.5 demonstrates robustness when working with incomplete and noisy data. It provides a compromise between randomness and optimality, making it applicable under uncertainty conditions.

The **ANN based corrector** described in Section 2.6 shows high effectiveness in self-learning systems designed to process large data volumes. This makes it applicable for forecasting and adaptive management, although its implementation requires significant resources and high computational capacity.

The **front based algorithm** described in Section 2.7 provides balanced results under conditions of moderate task complexity. Its main advantage lies in its universality, making it applicable when there are no strict requirements for optimality or robustness.

The **iterative algorithm** described in Section 2.8 is recommended when the solution needs to be gradually refined. This approach is effective in dynamic environments, allowing step-by-step improvement and adaptation to changes.

The **multi-agent (MA) approach** described in Section 2.9 is most appropriate for systems involving interaction among multiple participants or subsystems. It is effective under high environmental variability and for collective-type tasks.

The **WMST based algorithm** described in Section 2.10 is applicable to long-term strategic planning in large-scale systems. It provides high adaptability and robustness but requires significant resources for implementation and maintenance.

Conclusion

The results of the analysis of ten task allocation algorithms published over the past twenty years allow us to conclude that modern approaches, despite their considerable diversity, still possess a number of significant limitations that constrain their application as universal tools within systems for automation and optimization of business processes. The primary reason for this lies in the fact that most of the examined algorithms are based on formal processing of quantitative characteristics, such as employee workload, time expenditures for task execution, or task priorities, while excluding from consideration the individual competencies of performers. Taking into account only quantitative characteristics may lead to situations in which task assignments are made without sufficient regard for the correspondence between actual skills and possible employee preferences, which may negatively affect overall project performance.

At the same time, approaches characterized by greater flexibility and adaptability, supporting practical personnel management in complex projects, require that performer competencies be considered not as scalar, binary, or simple numerical parameters, but as multidimensional characteristics, individual components of which influence the quality, speed, and reliability of task execution in different ways. However, modern task allocation algorithms either insufficiently incorporate this factor or introduce it into their models in a simplified manner, without adequate mathematical and logical substantiation. This indicates an existing need for the development of new, more advanced task allocation methods that would organically combine standard formally quantifiable indicators with competency analysis as a key element of decision-making.

Thus, despite the existence of a number of new solutions in the field of automated task management, the creation of algorithms capable of comprehensively taking into account not only temporal and workload indicators but also professional skills of employees remain a challenging problem. Such approaches could serve as innovative tools for improving efficiency in task allocation, ensuring minimization of erroneous decisions and increasing employee motivation. ■

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About the authors

Timofey Yakovlevich Shevgunov

Candidate of Sciences (Technology);

Associate Professor, Moscow Aviation Institute (National Research University), 4 Volokolamskoe Hwy., Moscow 125993, Russia;

Associate Professor, Department of Business Informatics, Graduate School of Business, HSE University, 26–28 Shabolovka St., Moscow 119049, Russia;

E-mail: shevgunov@gmail.com

ORCID: 0000-0003-1444-983X

Anna Alexandrovna Kroshilina

Master's student, Department of Business Informatics, Graduate School of Business, HSE University, 26–28 Shabolovka St., Moscow 119049, Russia;

E-mail: ankrosh@vk.com

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Digital twinning in smart agribusiness: Towards a conceptual and methodological framework for organizational digital modelling

Olga Mikhailovna Pisareva [a]
E-mail: om_pisareva@guu.ru

Vyacheslav Arkadievich Alexeev [a,b]
E-mail: va_alekseev@guu.ru

Dmitry Vladimirovich Stefanovsky [a]
E-mail: dv_stefanovskiy@guu.ru

[a] State University of Management, Moscow, Russia

[b] Rabus LLC, Moscow, Russia

Abstract

At the present stage, the achievement of the set strategic goals of ensuring Russia's economic independence and technological leadership is associated with the development and implementation of domestic information and cognitive technologies. The country's agro-industrial complex, which is undergoing a complex process of digital transformation with the expansion of the use of robotic technology and intelligent systems, plays a special role in solving the basic tasks of maintaining state sovereignty. The development of platform solutions in agricultural production faces serious limitations and constraints on the effective application of the "digital twin" concept, due to unresolved issues regarding the conceptual and institutional justification for their construction for organizational systems. In this regard, the aim of this study is to substantiate proposals for defining the concept of a digital model of an agricultural enterprise and the formation of a possible option for describing the economic system and basic business processes for conducting full-cycle smart agriculture. The application of content and logical analysis methods, and reengineering technology, allowed us to appropriately define a reference digital model of an enterprise in the agricultural sector and present a possible design for a digital model of the economic system of a smart agricultural enterprise. Definitions of the concepts of "digital model" and "digital twin" for organizational systems are proposed, clarifying existing definitions in terms of reflecting the variability of the description of the organization's business model when displaying the entities of "business architecture" and "business processes" as separate structural elements and the contour of subjective perception of information when making decisions. The structure of a digital model of an agricultural enterprise's economic system in a networked precision farming environment is substantiated, taking into account changes in the composition and role of production factors in a data economy. We demonstrate the need to reflect in this model elements and relationships that address the requirements of ensuring environmental neutrality and social responsibility in full-cycle agricultural production. We recommend using the information image of a digital twin of an agricultural enterprise to design the structure and fill the model of the economic system with data based on regulated forms of planning and reporting documentation when building a digital platform to support management decision-making. The digital twin ontology description scheme expands our understanding of the theoretical foundations of the methodology and tools for designing and developing information models of objects and processes for business systems.

Keywords: digital transformation, digital platform, digital standards, digital model, agriculture, smart agricultural enterprise, factors of production, artificial intelligence, robotic devices

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Introduction

Scholarly and public discourse consistently associate the current historical phase with an intensifying transformation of the global order. For Russia, with the expanding spectrum of threats to both scientific and everyday consciousness, the current historical stage is firmly associated with an actively unfolding process of global order transformation. For Russia, the expansion of national security threats amid worsening demographic distress acutely raises the issue of ensuring technological independence and achieving technological leadership.

In addressing fundamental tasks related to strengthening the country's economic sovereignty – while prioritizing population preservation – the agro-industrial complex (AIC) plays a particularly critical role, as it is oriented toward fully satisfying domestic demand for traditional food commodities in the required volume and quality. However, as noted in [1], since 2014 the problem of the Russian economy's dependence on imported technologies – including those needed for the digitalization of the AIC—has intensified: according to estimates by the Russian Ministry of Agriculture for 2014, approximately 95% of specialized agricultural information technologies (IT) were supplied by foreign software developers. Prime Minister Mikhail V. Mishustin's address at the plenary session of the Xth "Digital Industry of Industrial Russia" conference on June 3, 2025, painted a contradictory picture of the current state of software import substitution. He observed that over the past five years, the IT sector's average annual growth has been four times greater than that of the overall GDP. This rapid expansion has occurred alongside a 1.5-fold increase in corporate digitalization spending and a 3.5-fold rise in the purchase of Russian software licenses. Despite these positive trends, the adoption of domestic solutions in the critical area of design and simulation systems remains limited, with their market share barely exceeding 50%. This gap is highlighted by the existence of 412 types of foreign software that still lack Russian-made analogs. The Prime Minister's remarks therefore underscore an urgent need to strengthen the national centers of competence responsible for driving progress in software engineering and digital transformation.

Digital transformation (DT) in the AIC – already underway in agriculture – involves not only the deployment of robotic machinery (RM), artificial intelligence (AI), and information systems (IS), but also the refinement of governance mechanisms for ecologically neutral and socially responsible full-cycle agricultural production. Modernizing the agribusiness model within a data-driven economy necessitates a management system commensurate with the new technological paradigm. Digitalization of technological and managerial processes for economic, social, and regulatory actors within this production system is implemented through the concept of the "digital twin," which enables the projection of routine and situational decision-making scenarios into a virtual environment via an information model (IM) to support the formulation and adoption of managerial decisions regarding operational and strategic activities. In fact, the approach to developing digital twins has been known since the late twentieth century [2], having already demonstrated significant achievements and secured a reputable position in both research and engineering practice [3]. Nevertheless, substantial barriers impede its broad application in advancing national platform-based solutions within the digital economy. First, there are gaps in the institutional and conceptual foundations for constructing digital twins of organizational systems (OS); second, there is a lag in the development of domestic business modeling software – a domain directly relevant to the task under consideration. These identified gaps hinder the resolution to scientific and practical problems concerning the advancement of methodologies and toolsets for developing and deploying enterprise digital twins aligned with the requirements of the data economy, as well as the creation of domestic digital platforms (DP) for organizational management, including those for smart agricultural enterprises (SAE). This renders it timely to address the problem of refining business modeling methodology and tooling, thereby defining the objective of the present study: to substantiate the proposals for conceptualizing the digital model of an agricultural enterprise and to formulate a potential framework for its representation through the construction of schemas depicting the organization and execution of business processes in smart farming.

1. Theoretical and practical aspects of societal digitalization based on information technologies

Issues concerning the refinement of the normative and theoretical foundations for developing methods and tools of information modeling are extensively addressed in publications by both domestic and international scholars and practitioners, drawing upon the evolution of approaches within computer science disciplines and the implications of legal regulation in the IT domain. Research papers [4, 5] substantiate the importance of scrutinizing platform-based solutions in digital agriculture, emphasizing the necessity of an interdisciplinary approach when implementing projects aimed at creating and deploying intelligent IS in the operational and managerial activities of agricultural enterprises. Typologies of digital products designed for production and management technologies in the agro-industrial complex (AIC) are proposed in publications [6, 7]. The genesis of conceptual frameworks and software tools for designing information systems and sector-specific platform solutions is described in articles [8, 9]. The implementation of artificial intelligence (AI) methods, cognitive modeling, and knowledge management is discussed in research papers [10, 11]. The emergence, evolution, and future prospects of the digital twin concept are characterized in publications [12, 13], while issues related to improving the methodology and toolsets for their construction are addressed in works [14, 15]. Methodological aspects of developing digital twins in the context of economic activity are presented in articles [16, 17]. International experience regarding the application of digital twins in smart agriculture is reviewed in works [18, 19]; a comparative analysis of the effectiveness of digital twin deployment in agribusiness is provided in article [20]; and the design of a precision farming management system for protected cultivation based on digital twins with predictive control modeling support is detailed in publication [21].

Research paper [22] notes that the principle of minimizing labor expenditures required to sustain socio-economic systems of various types constitutes one of the foundational principles of civilizational development and represents a fundamental condition for the quality of societal progress – a principle that naturally extends to managerial activity as well. Within this context, three revolutionary periods in the development of management theory and practice can be distinguished [23]: the first stage – the organizational revolution of the late 19th to early 20th century – associated with the division and specialization of managerial functions (data accumulation); the second – the computer revolution of the mid-20th century – linked to the automation of management processes (information accumulation); and the third – the cognitive revolution, which emerged in the late 20th century and is currently unfolding – driven by the advancement of intelligent management technologies (knowledge accumulation and utilization).

Any management system employs an informational representation generated by an integrated set of characteristics of the managed object (MO): qualitative and quantitative, structured and unstructured, deterministic and uncertain.

Under conditions enabled by computer technology – based on discrete computational architectures and capabilities for data collection, transmission, and storage – the informational representations of managed and managing subsystems, along with their environment, become digital models (DM) of real-world entities and phenomena.

As is often the case in theoretical inquiry, the original idea for identifying and explaining a given phenomenon typically emerges significantly earlier than the formal adoption of the corresponding term in scholarly literature. This is also true of the concept of the "digital twin". In substantive terms, the digital twin concept is associated with Michael Grieves, who in 2002 introduced his approach to creating a virtual space in publication [24], inspired by David Gelernter's 1991 notion of describing physical objects within a "mirror world" of computer-generated and processed informational representations [25]. In the early 1990s, this methodological proposition—promising from the standpoint of informatics theory –

gained recognition among specialists but remained unrealized due to the absence of suitable information technologies and software. With advances in computing and communication technologies, these earlier proposals have since gained renewed momentum, enabling their productive implementation within distributed environments of integrated information systems and universal digital services (DS).

2. Evolution of tools and standards for information system design and modeling

The history of automation began roughly in the mid-twentieth century, when information-based control systems were first actively deployed in defense-related domains and subsequently extended to economic and administrative spheres. During this period, initial attempts were made to develop standardized descriptions of individual entities and phenomena, including those related to design, technological, production, and managerial activities (e.g., CAD/CAE, CAM/DCS, MES/MES, ERP/ERP). Naturally, the first regulatory frameworks for information modeling and design emerged in the leading nations of competing socio-economic systems – the USSR and the USA: GOST 24.104-85 "Unified System of Standards for Automated Control Systems. Automated Control Systems. General Requirements" (implemented in 1987, updating a generation of standards dating back to 1976); and NIST Special Publication 500-167, "Information Management Directions: The Integration Challenge" (issued in 1988). In the former, the architecture of the managed object (MO) was defined by the set of functions providing informational support to the management process [26]. In the latter, a five-level MO model was employed, designed to organize, plan, and construct an integrated set of interrelated and ordered architectures for selective informational descriptions of management layers [27]. Ultimately, both approaches converged on conceptual constructs later identified as belonging to the domain of enterprise business architecture.

The current era of automation in production and management is defined by distributed digital infrastructures, which emerged around the turn of the millennium. Centered on data storage and processing facilities, these systems are fueled by the exponential growth of global internet traffic and data, driven by a proliferation of connected and autonomous intelligent devices (IDs), especially mobile ones. The first international ISO standards for information modeling of objects from a life-cycle management perspective were adopted somewhat later: for engineering design in 2002 (ISO/IEC 15288 "Systems and software engineering – System life cycle processes") [28]; for architectural and construction design in 2012 (ISO/TS 12911 "Framework for building information modelling (BIM) guidance") [29]; and for industrial enterprise information systems design in 2017 (IEC PAS 63088:2017 "Smart manufacturing – Reference architecture model Industry 4.0 (RAMI4.0)") [30]. A digital model is distinguished from a classical information model by its use of discrete data formats, which allow for the computer-based implementation of functions that describe an entity's elements, relationships, and representations. Classical information models, by contrast, are confined to the documentary registration of these components through registries and procedural regulations tailored to various organizational forms.

The domain of developing and applying digital models already has institutionalized requirements – based on synthesized conceptual approaches, instrumental capabilities, and practical experience – for digital descriptions of three classes of objects: designed/produced products (items), designed/constructed buildings (facilities), and operating/emerging production enterprises:

- GOST R 57700.37-2021: "Digital product model – a system comprising mathematical and computer models, along with electronic product documentation, describing the structure, functionality, and behavior of a newly developed or operational product across various stages of its life cycle" [31] (based on ISO 23247-1:2021 [32]);
- GOST R 58439.1-2019: Information Model (IM) – "a collection of structured and unstructured information containers serving as a single, authorita-

tive source of project (asset) information across all or selected life-cycle stages” [33], i.e., the IM of a project during its construction phase and the IM of an asset during its operational phase (based on ISO 19650-1:2018 [34]);

- GOST R 59799-2021: reference or reference architecture model – an IM of a physical-world industrial object defining its reference architecture, “represented as a multi-layered (multi-tiered) cube that maps technical objects (assets) as hierarchical levels, enabling their description and traceability throughout their life cycle, accounting for their placement within technical and/or organizational hierarchies” [35] (based on IEC PAS 63088:2017 [30]).

However, as noted by researchers and developers, a fully consolidated and normatively stabilized terminological system for information modeling of real-world entities and processes has not yet been established [36]. An overview of the scope and application of digitalization standards based on the digital twin concept and IoT technologies is provided in the analytical report “Standardization strategy on IoT and Digital Twin – ISO/IEC JTC 1/SC 41” [37].

Turning to the definitions introduced in ISO 23247: “Digital Twin of a Product – a system consisting of a digital product model and bidirectional information links with the product (when the product exists) and/or its components” [32]. It should be noted that this standard includes additional provisions elucidating the conceptual content of the term, leading to the following interpretation: a digital twin is understood as a digital model of “a specific physical element or process, connected to live data streams, which ensures convergence between physical and virtual states at an appropriate synchronization rate” [32].

Considering the general characteristics of the aforementioned concepts and the key features of purposeful activity by agents engaged in social relations, and applying notations and formalization practices established for managing commercial enterprises [38] and information resources [39], we may refine the definitions of “digital model” and “digital twin” as follows:

- a digital model of an organization is a system comprising mathematical and computational models, analytical and heuristic algorithms, as well as electronic templates and documents, representing – within a computer-based data storage and processing environment – a comprehensive schema of the organization’s structure and operations, grounded in descriptions of its business architecture (assets and resources), business processes (regulations and procedures), and IT infrastructure (software and data);
- a digital twin of an organization is a system composed of a digital model of the organization and supporting software equipped with functional components designed to accumulate, process, visualize, analyze, monitor, and forecast – over a required and permissible time horizon – the necessary information to generate a sufficient set of performance indicators for characterizing organizational activity and substantiating managerial decisions based on data and knowledge extracted from the organization’s digital environment.

A distinctive feature of the proposed definition of “digital model of an organization,” compared, for instance, with the interpretation used in [39], is the explicit separation of structural components describing the entities “business architecture” and “business processes.” This distinction is significant, as applied digital modeling inherently involves natural variability in representing many-to-many (“m:n”) relationships among entities within the digital model’s construct, depending on the specific business configuration of the organizational system. Similarly, the refined definition of “digital twin,” compared with the generalized formulation presented in [12], shifts emphasis away from modeling automatic interaction and data exchange between physical and virtual environments toward describing the subjective perception of information within the organization’s management subsystem when justifying and making decisions to regulate its operations and development in terms of target and control performance indicators. Given their electronic form and purpose – namely, the management of a specific business system – the concepts of “digital model” and “digital twin” of an organization must be invariant with respect to the architecture of the existing ensemble of computing, communication, storage, power, and other infrastructure ensuring uninterrupted operation of information systems, and must also align with the catalog of supported information resources and software products. We also note the critical importance of evaluating DT initiatives through the lens of the RAMI 4.0 enterprise reference architecture model [30]. Technological progress is continuous and dynamic; consequently, the normative provisions of IEC PAS 63088:2017 – developed under the “Industry 4.0” paradigm and serving as the basis for the Russian standard GOST R 59799-2021 – can already be considered outdated. Herein lies a fundamental consideration: practical digitalization projects launched under the “Society 4.0” and “Industry 4.0” paradigms are now being implemented amid a transition – from “Society 5.0” (human-centered automation) toward “Society 6.0” (intelligence-driven automation) – in accordance with the logic of continuous innovation. The integration of vast volumes of digital data and knowledge via AI models and methods in Industries 5.0 and 6.0 necessitates an expansion of the conceptual worlds of digital models (DMs). Beyond the representation of the physical world in the information world – alongside the status world, models world, and archive world – a predictive world (or future world) must emerge, integrating forward-looking projections derived from accumulated data and knowledge, as anticipated (predicted by methods embedded within the models world) states of the business system.

The anticipated and empirically assessed effects of digitalization in the national economy – including the agro-industrial complex (AIC) – are linked to the intensification of labor substitution by capital, directed toward acquiring fixed assets such as robotic machinery (RM) and intelligent devices (IDs), as well as intangible assets: databases, knowledge repositories, and digital solutions. Collectively, digital transformation in the AIC will enable timely and targeted adaptation to changing conditions across the full production cycle, effectively neutralizing operational differences between open-field and protected-environment cultivation by accounting for the heterogeneous characteristics of dispersed agricultural lands and facilities across leading subsectors (crop production, livestock farming, etc.) [40].

3. Conditions and directions for the formation of digital agriculture

The enhancement of agricultural systems is being pursued through the prioritization of digital transformation (DT) in agribusiness, based on the widespread deployment of technical equipment and software solutions aimed at robotizing and intellectualizing production and management technologies within the agro-industrial complex (AIC). The full realization of opportunities and potential inherent in digital innovations is contingent upon the appropriate synchronization of structural and functional transformations in the system and mechanisms governing interactions among economic agents of diverse types (differing legal organizational forms and behavioral models of economic actors within the business environment).

Table 1 characterizes the adaptation of business-system, production, and management models in the AIC under the influence of digital technologies and artificial intelligence (AI) applied to agricultural systems (including both open-field and enclosed production facilities: farmland/fields and agricultural buildings/structures).

The technological dimensions of transforming the economic system (ES) of full-cycle agricultural production under contemporary conditions are defined by the role of key innovation-driven trends in AIC development, implemented on an integrated basis and shaped by advances in information technology (IT):

1) production-related (smart production);

2) organizational (smart management);

3) sector-specific:

a) bioengineering – smart genetics;

b) agrarian – smart farming;

c) environmental – organic and green agriculture.

Table 1.

Directions for the implementation of the digital transformation project for an agricultural enterprise and their characteristics

Areas and directions of digitalization of the agro-industrial complex	Key substantive tasks
Transformation of the agribusiness model (business system)	Innovation focus (market positioning) Social responsibility (political motivation) Environmental neutrality (generational continuity)
Transformation of the agricultural production model	Specialized rationality (product range localization) Technological sufficiency (completeness of operations) Technical autonomy (fleet optimization)
Transformation of the agricultural management model	Dynamic proactivity (market situation assessment) Operational adaptability (condition monitoring) Comprehensive effectiveness (impact assessment)

A pivotal aspect in describing production systems within information modeling standards is the consideration of the entire set of assets belonging to a real economic entity that are engaged in value creation processes. *Figure 1* illustrates a possible scheme for describing the networked operational environment of a smart agricultural enterprise. Here, it is fundamentally important to treat agricultural production within the AIC as an open system embedded in a complex web of external relationships – including regulatory interactions with public authorities at relevant levels – and to reflect the full agricultural cycle, incorporating closing-loop and waste-utilization technologies necessary to meet requirements of ecological neutrality and to harmonize stakeholder relations through the fulfillment of social responsibility commitments within the agribusiness's operational locality, thereby supporting comprehensive regional development and the creation of high-tech, well-paid jobs (including those needed to retain young talent in the AIC).

Digital transformation enables the mechanization and automation of agricultural production to be addressed at a qualitatively new level, significantly expanding the scope for effective deployment of autonomous robotic machinery and equipment (in both stationary and mobile configurations) and trusted AI (in the development of IS and IT), most rationally achieved through platform-based integration [1]. Contemporary organizational-technical solutions are radically reshaping the model and environment of agribusiness; however, the primary objective lies in ensuring solution flexibility for implementing both universal and specialized agricultural robotic and intelligent devices (IDs) [41], thereby helping overcome budgetary constraints in DT projects through rational and efficient customization aligned with the profile and scale of individual agricultural producers' operations.

It is essential to recognize that historically, information modeling standards were first developed primarily for technical systems (TS). A distinguishing feature of organizational systems (OS) is the active role of subjective factors, which impart flexibility and variability to the mechanisms implementing pur-

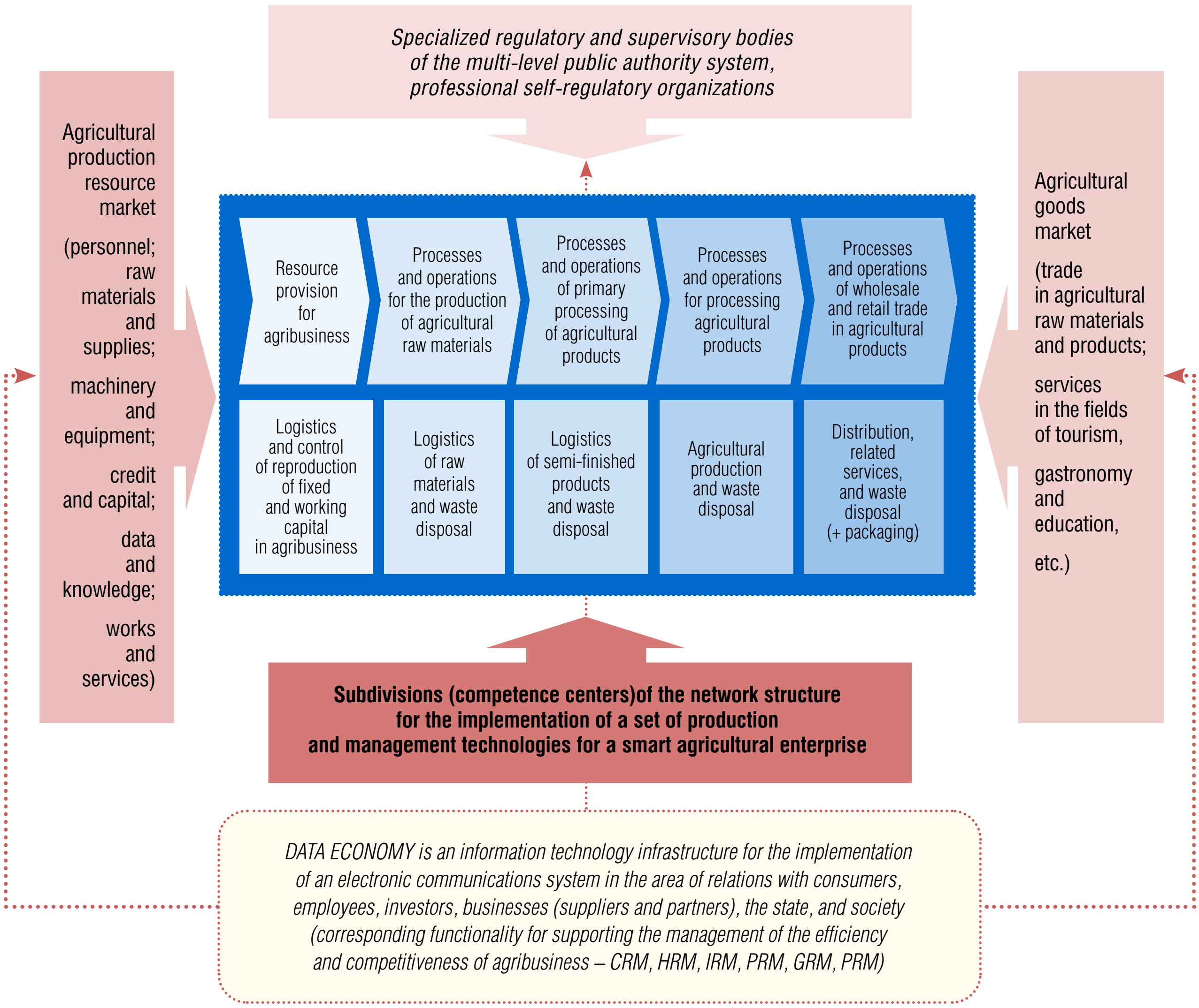

Fig. 1. Diagram of the process of creating added value for a full-cycle agricultural enterprise in a digital environment.

poseful activities — oriented toward an anticipated and necessary outcome of the system's core functionality, yet permitting both situational adjustments and fundamental shifts in originally planned courses of action. The inherent uncertainty of agricultural conditions necessitates built-in temporal buffers to respond to abrupt impacts from climatic and environmental factors that may devalue outcomes of previously completed seasonal operations and require rapid rescheduling of subsequent technological tasks on fields that retain productive potential. Accordingly, a digital model, reflecting and accounting for the goals and tasks of the managing subsystem — as the integrative and "animating" component of the OS — must be oriented toward decision support systems (DSS), whose components embody the governance mechanism for OS development within an uncertain socio-relational environment populated by numerous active agents, each possessing distinct motives, orientations, and objectives [42].

Integrating the core characteristics of the concepts discussed above and accounting for the distinctive features of agricultural activity, we propose the following definition: the digital model of the economic system of a smart agricultural enterprise constitutes a unified computerized framework providing an electronic description of its structure and operations across organizational units that jointly participate in the production process – transforming available resources using existing production capacity, including robotic and intelligent systems integrated into economic circulation and data and knowledge activated within the digital environment – into agricultural outputs intended for both production and consumer markets, subsequently sold at quality-adjusted competitive prices sufficient to cover total costs (investment, production, management, and commercial) while achieving an acceptable return on equity for the agribusiness owner.

In our view, when extending the traditional interpretation of the term "economic system" in agriculture – as presented, for example, in publication [5] – it is crucial not only to consider technical and technological aspects of the transition to precision farming but also to explicitly emphasize the role of data and knowledge within the digital environment of an agricultural organization as a factor enhancing the efficiency of both traditional and innovative production inputs. Building upon the refined understanding and attributes of the general concept of DM, the definition proposed above for the DM ES of a smart agricultural enterprise can be regarded as relevant to the realities of conducting agribusiness in a digital environment. This definition adequately captures the role of robotic and intelligent systems as components of fixed assets, and incorporates the maintenance of digital databases and knowledge repositories into the enterprise's reproduction processes as the foundation for making informed, timely decisions in precision agriculture.

Accordingly, the priority lies not merely in highlighting the absence of information modeling standards for general-purpose organizational systems, but rather to stress the critical need for their adaptation – specifically, the explicit inclusion of digital data and specialized knowledge as production factors integrated into production and management technologies based on robotic and intelligent systems. From a theoretical standpoint, and adhering to the four-level notation of managerial aspects outlined in GOST R IEC 62264-1-2014 "Enterprise Control System Integration" [43], a holistic DM construct must encompass the next hierarchical level of OS description detail. Beyond specifying core parameters such as production scheduling, material usage, transportation, delivery logistics, inventory levels, and operational production control, it is also necessary to define characteristics of tactical management mechanisms (pertaining to corporate market positioning, Level 5.1, rhythm: annual and shorter) and strategic management mechanisms (pertaining to regulating the company's investment cycle, Level 5.2, rhythm: annual and longer).

Within the scope of this study, the structured electronic description of an agricultural enterprise focuses specifically on DM ES – conceived as a theoretical representation of a real production (economic) entity whose objective function is to deliver market-demanded products in a manner and volume that yield stakeholders an acceptable financial return. Moreover, given contemporary trends toward multifunctional rural development models [44, 45], a crucial dimension of information modeling involves examining the full agricultural production cycle under conditions of robotic and intelligent device deployment, while adhering to norms and regulations concerning ecological neutrality and social responsibility within the agribusiness's operational area. We now proceed to elaborate on the challenge of constructing a digital model of the economic system of a smart agricultural enterprise, with a specific orientation toward the adoption of profitable closing-loop technologies in agribusiness.

4. Constructing the digital model of the economic system of a smart agro-enterprise

Among the principal drivers transforming the economic sphere of society is the activation of new elements within the composition of production factors:

incorporating information and knowledge as digital components in the description of a firm's capital and resources enables a precise specification and differentiation of the roles played by traditional and innovative production factors under conditions of digital transformation. In the data/knowledge economy, intellectual capital within the digital space of business interactions contributes to the generation of additional value by the enterprise's aggregate capital, which is engaged in a new mechanism of information exchange with business partners.

The generation and utilization of data and knowledge in the digital environment entail substantial capital and operational expenditures. Moreover, projects integrating these assets into organizational and technological-administrative processes exhibit diverse financing models for developing the requisite corporate IT infrastructure. The degree of integration among the processes of creating, accumulating, and consuming digital informational and knowledge-based assets may vary significantly — from full self-provisioning to complete outsourcing. Specifically, an economic agent may: (1) independently develop and expand the digital infrastructure of smart agricultural production while accumulating necessary data for its databases and knowledge repositories; (2) partially utilize only selected external services for data and knowledge provision, along with processing and integration services, embedding them into internal agricultural business processes based on robotic and intelligent technologies.

Digital standards and formats for describing data and knowledge define — within the category of intangible assets — both general/global and specific/local resources supporting production activities, conceptualized as labor-associated components of an organization's intellectual capital (i.e., employees as competent bearers and skilled users of digital production factors in the knowledge economy). *Figure 2* presents a generalized schematic of the agricultural enterprise's economic system (ES), highlighting the regeneration mechanism for information and knowledge as intellectual production factors.

Figure 2 illustrates the expansion of material, energy, financial, and informational flows through cognitive linkages along the business value-creation chain.

The schematic employs the following notations:

I&K denotes the agricultural enterprise's data and knowledge repository;

$X_{I\&K}$ represents consumed informational resources from the business environment ($X_{I\&K} = P(I\&K)$);

$Y_{I\&K}$ denotes produced informational outputs ($Y_{I\&K} = S(I\&K)$).

The traditional "black box" model of an ES — describing a production entity through input-output transformation and feedback-based regulation — has been extended by explicitly including data and knowledge on precision farming among input resources and by reflecting their use in formulating managerial interventions (decisions) to sustain the effectiveness of agribusiness digital transformation.

Figure 3 presents a scheme that characterizes the composition and interconnections of core and supporting business processes within a smart agriculture system. It should be noted that in the digital economy, data and knowledge as commodities possess two key properties:

1) non-depletability in production,

2) non-rivalry in consumption.

Consequently, in the value-creation chain depicted in *Fig. 3*, the output of the ES — measured in terms of agricultural output volume and associated service delivery — includes an increment in the overall utility derived from financial investments in the reproduction of information and knowledge.

The widely accepted approach to business process reengineering allows the value-creation process within an agricultural enterprise (as shown in *Fig. 3*) to be elaborated in detail, using crop production as an illustrative example. The interrelationships among all types of business processes depicted in the sche-

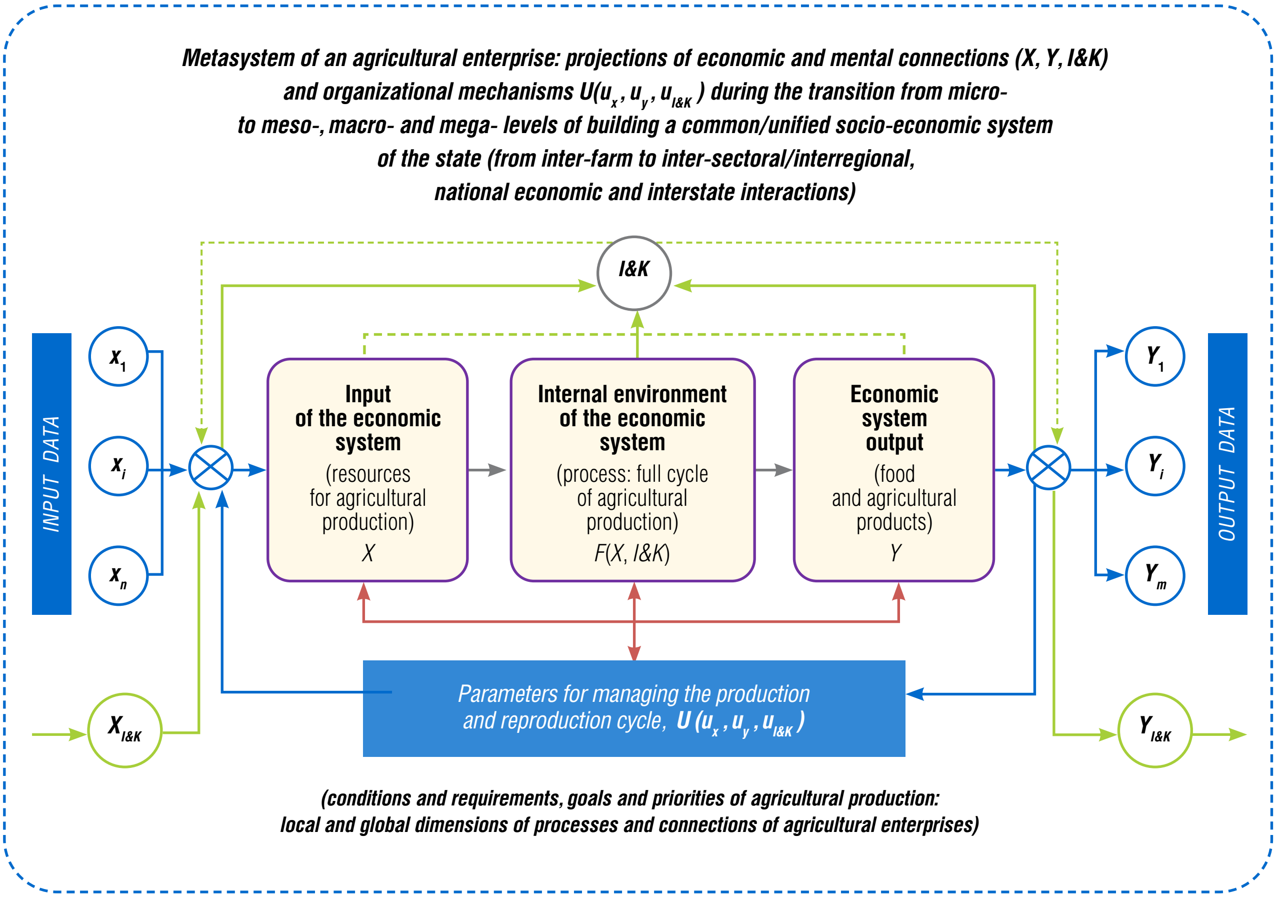

Fig. 2. Schematic description of the economic system of a smart agricultural enterprise: a cybernetic approach in the context of digital transformation.

matic reflect the overarching logic of executing full-cycle agricultural operations, including waste utilization across stages of agro-raw material processing into agricultural products. Notably, the requirement of ecological neutrality extends to wholesale and retail distribution channels, particularly within the enterprise's own trading network, where traceability of digitally tagged packaged/batched shipments facilitates waste management in commerce.

The development of a digital model of the economic system is conceptually and functionally tied to defining the business model of a smart agricultural enterprise – specifically, its business architecture and business processes – which serves as the foundation for subsequent construction of a digital platform supporting production and management technologies.

The architecture of the DM ES is directly dependent on the adopted management model governing the SAE's operations and development. Therefore, the DM of any organizational system, including those in the AIC, is determined by the set of managerial tasks addressed across management functions, as well as by the procedures governing decision formulation and implementation. Unlike RAMI 4.0 – which focuses primarily on production – the upper-level DP management functionality supports the formation of ensembles and cascades of decisions for organizing and regulating the full spectrum of business processes:

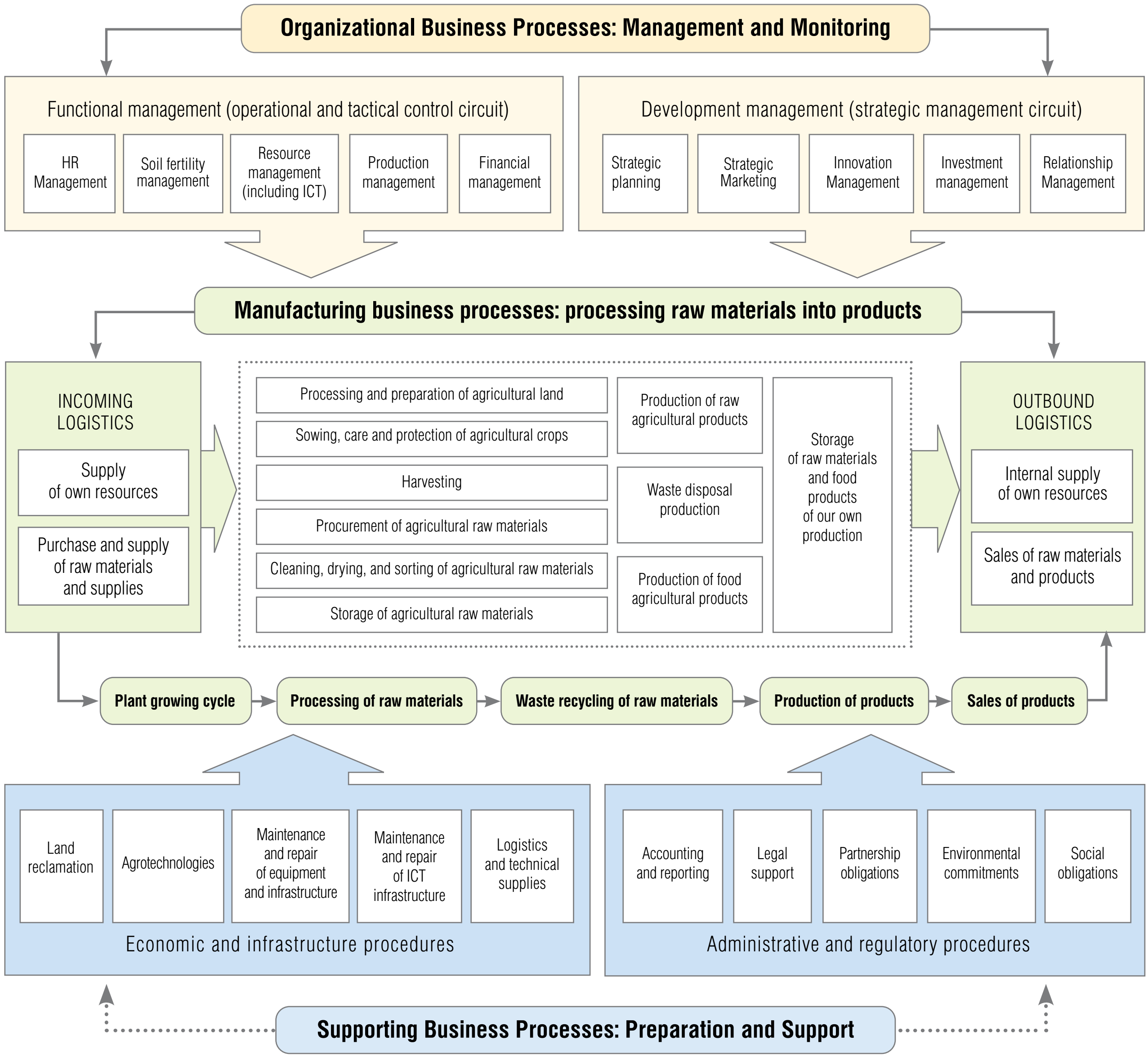

Fig. 3. Composition and relationships of the main business processes of a multi-agricultural enterprise at the stages of the full cycle of agricultural production.

technological, operational, enabling, auxiliary, administrative, and others. The content and parameters of managerial tasks predetermine the composition of methods and models embedded in the DP's knowledge base for designing decision-making solutions across strategic, tactical, and operational planning horizons of agribusiness activity.

Figure 4 presents a characterization of the informational-algorithmic support structure for the DM ES of an agricultural enterprise, implemented within the periodic procedure of ex post and ex ante evaluation of agribusiness performance, based on an electronic representation of the ES framed in terms of key financial planning and reporting documents.

A high-level representation of the functional blocks of the DM ES of an SAE enables a comprehensive overview of the entire spectrum of full-cycle agricultural management tasks but does not reveal the nature of entities and relationships within individual structural components. For instance, it is crucial to emphasize that, given the distributed interaction mechanisms among owners of electronic data – from soil sensors to remote sensing systems for farmland, as well as their processing centers (see the "Data import" block in *Fig. 4*) – the use of the DM ES as the basis for constructing an SAE DP necessitates adherence to a multi-domain organization of digital services supporting a federated data storage and computational governance infrastructure. Analysis of the proposed architectural concept for the ES and DP of an SAE demonstrates that the platform solution for smart farming must be developed primarily with consideration for the heterogeneous nature of data and algorithms employed in the agribusiness management system within the digital environment. Therefore, while adhering to traditional IS design principles – modularity, adaptability, and scalability – it is essential to incorporate the requirement of multimodal activation regimes for the DM ES within the SAE DP, implying domain-oriented, decentralized ownership of services, data, and knowledge.

The developed DM ES and the prototype SAE DP can be regarded as the foundation for constructing a modeling complex serving as the analytical component of the knowledge base for a digital platform supporting AIC production and management technologies under conditions of ecological neutrality and social responsibility throughout the full agricultural cycle. The primary objectives of creating a full-cycle digital model of agricultural production include:

- formulating and evaluating alternative agricultural production plans based on forecasts of weather-climatic and financial-economic conditions affecting the execution of seasonal operations and agribusiness activities;
- analyzing, forecasting, and planning agribusiness operations and development in light of local and global market dynamics and agricultural commodity trends;
- analyzing, optimizing, and adapting digital transformation project/program designs for the agricultural enterprise in alignment with target and contextual characteristics of agribusiness development during DP deployment within the regional AIC ecosystem.

The core tasks addressed through the DM ES of an SAE within the agribusiness development management framework reflect the functional dimensions of leveraging the productive potential of accumulated data and structured knowledge regarding the preparation and execution of seasonal field operations, with optimization of procurement and sales activities. Knowledge extraction will be more complete and more accurate when based on updated and verified indicator values derived from successive generations of digital datasets capturing the full production cycle. A critical element here is the formulation of a coherent set of requirements for information-technological and information-analytical support tailored to the diverse user base of an integrated agricultural enterprise information system (agroholding/agrocluster), including channels for external informational and cognitive communication. When constructing an effective multimodal and multi-modular upper-level SAE DP within a networked business environment, the primary requirement is the establishment of an integration mechanism for functions and data originating from external platforms [38]. Within the paradigm of DT project implementation, it is imperative to follow the logical progression from service integration to platform integration – a shift that aligns with the objective of distributing responsibility for high-quality digital resources among multiple owners, grounded in the federated principle of domain-based DP IS infrastructure design.

Conclusion

The strategic guidelines and priorities of national development render it timely to assess the current state of the conceptual and institutional foundations of business-system information modeling in Russia.

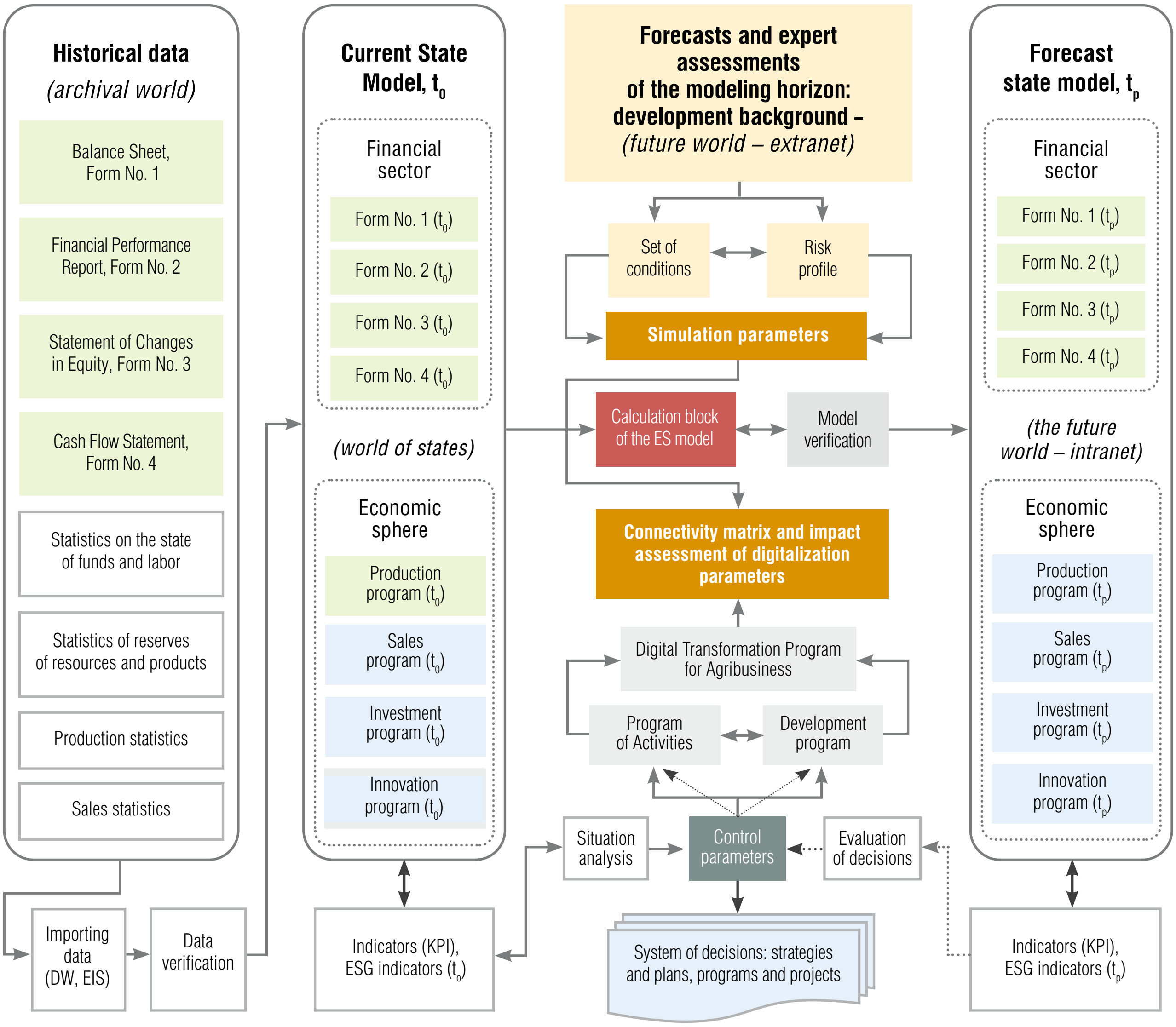

Fig. 4. Scheme of information and algorithmic support of the digital model of the economic system of a smart agricultural enterprise in the projection of the description of the architecture of the digital platform for supporting production and management technologies.

Analysis of existing challenges has revealed that high-technology sectors of the economy consistently outpace the prevailing frameworks of regulatory standardization, as innovative solutions frequently emerge outside the boundaries of established norms — including in critically important sectors of the national economy such as agriculture. Modernization of the domestic agro-industrial complex through contemporary information technologies and digital platforms is hindered by the lag in mechanisms for unification and standardization of integrated information systems designed to support precision farming technologies, thereby complicating efforts to ensure national food security and technological sovereignty.

Within the scope of this research, a series of interrelated tasks was formulated and addressed in the following domains:

1) identification of distinctive features and definition of parameters for standardizing the development of digital twins for organizational-type economic systems;
2) determination and justification of the structure of the digital model of an agro-industrial complex enterprise;
3) specification of the process model for organizing smart agricultural operations under conditions of digital transformation;
4) formulation and substantiation of recommendations for utilizing the digital model of the economic system of a smart agricultural enterprise in constructing a digital platform for managing the full cycle of agricultural production to support core decision-making functions.

The findings of this study may inform the development of provisions for a national standard or regulatory framework governing the creation of digital twins for agro-industrial complex enterprises and organizations, thereby extending the scope of standardization beyond information modeling of technical systems to encompass the construction of digital models of general-purpose organizational systems. ■

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About the authors

Olga Mikhailovna Pisareva

Candidate of Sciences (Economics); Associate Professor;

Head of the Department, Department of Mathematical Methods in Economics and Management, Director, Institute of Information Systems, State University of Management, 99 Ryazansky Ave., Moscow 109542, Russia;

E-mail: o.m.pisareva@gmail.com

ORCID: 0000-0002-6042-2657

Vyacheslav Arkadyevich Alexeev

Candidate of Sciences (Economics);

Deputy Director, Rabus LLC, 4 Teterinsky Ln., Moscow 109004, Russia;

Researcher, Engineering Project Management Center, State University of Management, 99 Ryazansky Ave., Moscow 109542, Russia;

E-mail: va_alekseev@guu.ru

Dmitry Vladimirovich Stefanovsky

Candidate of Sciences (Technology);

Head of the Department, Department of Information Systems, State University of Management, 99 Ryazansky Ave., Moscow 109542, Russia;

E-mail: dv_stefanovskiy@guu.ru