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Predictive planning as a strategic risk management tool for the supply chains of oil and gas industry in Uzbekistan

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Abstract

This article discusses the challenges of strategic risk management in the supply chain operations of the oil and gas industry in Uzbekistan. Using the case of JSC ‘Uzbekneftegaz’, the study identifies critical weaknesses in the current material and technical supply (MTS) system, including a high level of import dependency, fragmented data, and a low level of digital maturity among suppliers. The need for a shift from reactive to predictive planning is supported by the use of digital tools and advanced analytics. The author proposes three innovative tools for predictive planning — PIRSP (Predictive Index of Risk of Supply Problems), PESI (Predictive Evaluation of Supplier Integrity), and DLI (Digital Literacy Index). These tools allow for a quantitative assessment of supply disruption risks, supplier resilience, and levels of digital integration. The paper concludes that predictive planning has a high potential to strengthen supply chain resilience, reduce operational costs, and enhance strategic agility for oil and gas companies.
Keywords: digitalisation, PIRSP, PESI, DLI, Uzbekneftegaz, import substitution, digital maturity

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预测性规划作为乌兹别克斯坦石油和天然气行业供应链中的战略风险管理工具

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简介

本文研究了乌兹别克斯坦共和国石油天然气行业物资技术保障（MTO）系统中的战略性风险管理问题。以乌兹别克石油天然气公司（AO "Uzbekneftegaz"）为例，分析了现行MTO模型的薄弱环节，包括对进口的高度依赖、数据碎片化以及供应商数字化成熟度较低等问题。论证了从被动应对转向基于数字技术与预测分析的前瞻预测性规划的必要性。研究提出了原创性的预测规划工具——PIRSP指数（供应链中断风险评估）、PESI指数（供应商稳定性评估）和DLI指数（数字化集成水平评估），这些工具可量化评估供应链中断风险、供应商韧性及数字化整合程度。研究结论表明，预测性方法在提升石油天然气企业供应链韧性、降低运营成本及保障战略适应性方面具有高度适用性。
关键词: 物资技术保障, 数字化, PIRSP, PESI, DLI, 乌兹别克石油天然气公司, 进口替代, 数字化成熟度

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Introduction

Against the backdrop of increasing volatility in global markets, technological transformation and geopolitical turbulence, the management of supply chains in the oil and gas industry is becoming one of the key areas of strategic management.

For decades, the oil and gas industry has remained the backbone of the global economy. However, 2024 has been marked by persistent unpredictability in energy markets. Experts point to three global trends: rising demand for energy, political uncertainty and uneven progress in the energy transition to alternative energy sources[1]. According to the International Energy Agency, growth in global oil demand slowed significantly in 2024: consumption increased by 0.8% compared with 1.9% in 2023. The main reasons for this slowdown are the completion of post-pandemic mobility recovery, slower industrial growth and the stronger impact of electric vehicles[2]. At the same time, experts forecast a 20% increase in global energy demand by 2040, driven by population growth to 9.2 billion and an expansion of the middle class from 3 billion today to 5 billion[3]. In response to these challenges, digital transformation – a profound rethinking of business processes based on modern digital technologies – is gaining increasing importance. This issue is particularly acute in developing economies such as the Republic of Uzbekistan, where the oil and gas sector plays a system-forming role. The purpose of this article is to demonstrate the potential of predictive planning as a tool of strategic risk management in the system of material and technical supply (MTS) of the oil and gas industry of Uzbekistan.

Joint-Stock Company *Uzbekneftegaz* (*Uzbekneftegaz JSC*) is the national energy leader of Uzbekistan. As a key element of the country's developed energy sector, the company has a diversified portfolio of assets and income sources and plays a crucial role in hydrocarbon production, petrochemical production and the export of refined petroleum products. *Uzbekneftegaz JSC* operates a unified risk management system (hereinafter, the URMS), which is a set of processes, methods and information systems aimed at achieving strategic and operational objectives through risk management. The URMS has been developed in accordance with the three lines of defense principle and covers the following areas:

- identification and categorization of risks (operational, strategic, financial, project-related, etc.);
- identification and assessment of risks by specialized units using brainstorming;
- development and implementation of risk management measures, including corrective and preventive actions;
- monitoring and review of risks and measures, including regular updating of the risk register;
- informing the governing bodies: risk data are submitted to the Management Board, the Supervisory Board and the shareholders;
- integration of risks into the company's strategic and operational planning.

On 1 March 2023, by decision of the Chairman of the Management Board, the company approved a new version of the Regulation on the Risk Management System. This document regulates the procedure for the assessment and minimization of production and economic risks and assigns responsibility for the implementation of risk-oriented approaches to the Risk Management Department within the Department for Business Development.

The governance structure of the URMS includes a risk management committee reporting to the Chairman of the Management Board. Its tasks include comprehensive risk assessment, development and implementation of measures, staff training, ensuring timely communication with senior management and maintaining the risk register.

Risk assessment is based on an approved matrix. Each month, structural units draw up and submit a list of potential risks, which are assigned a significance level: high, medium or low. Only the highest-category risks are included in the register, which is reviewed on a quarterly basis. At the end of 2023, the register comprised 58 business risks and 8 operational risks.

The company continuously monitors the implementation of measures and tracks emerging threats, which creates a solid foundation for integrating digital predictive models. Thus, the URMS provides the foundation for implementing digital and predictive solutions built on existing processes.

1. Research methodology

The methodological basis of this study is the use of systemic, process and risk-oriented approaches to the analysis and improvement of predictive planning processes in the supply chains of the oil and gas industry of the Republic of Uzbekistan. The research is grounded in the principles of strategic management, the digital transformation of logistics systems and the concept of sustainable development.

To achieve the stated objectives, the following methods were applied.

The method of comparative analysis was used to study international practice in the use of predictive planning tools and to compare them with the current state of planning and supply management processes at *Uzbekneftegaz JSC*.

[1] https://cdn.equinor.com/files/h61q9gi9/global/16ccbc5a098c3b971979118420c4f83ddee18fb4.pdf?annual-report-2024-equinor.pdf.
[2] https://www.iea.org/reports/global-energy-review-2025/oil.
[3] https://corporate.exxonmobil.com/-/media/Global/Files/research-and-development-highlights/Innovating-Energy-Solutions-R-and-D-brochure.pdf.

Economic and mathematical modeling was applied to construct the predictive indices PIRSP, PESI and DLI, which make it possible to quantitatively assess the level of logistics risks, the resilience of suppliers and the digital maturity of the MTS system.

SWOT analysis was carried out to identify the strengths and weaknesses of the current MTS planning system in the oil and gas industry of Uzbekistan, as well as to reveal potential threats and opportunities associated with the introduction of the predictive approach.

Expert surveys and interviews were used to collect qualitative data from specialists in logistics, IT and risk management at oil and gas enterprises, which made it possible to identify practical problems and needs in the field of digital and predictive planning.

Content analysis of regulatory and strategic documents made it possible to assess the degree of institutional readiness for the implementation of modern forecasting and risk management models.

The empirical base of the study includes statistical data of *Uzbekneftegaz JSC,* official reports of the Ministry of Energy of the Republic of Uzbekistan, industry analytics, as well as information from international organizations such as Accenture, *IBM, Equinor, IEA, Exxon Mobil* and others.

The author's concept of predictive planning as a tool for managing logistics risks developed in this study was tested in the form of the proposed Integrated Predictive Planning Cycle (IPPC) model and the author's indices for risk and resilience assessment tailored to oil and gas enterprises of Uzbekistan.

2. Core challenges facing the MTS system in the oil and gas industry

Classical supply planning methods often prove ineffective under high uncertainty, particularly in material and technical supply – an area that is especially vulnerable to disruptions and variability in lead times. The MTS system is affected by several systemic and operational challenges, including data fragmentation, limited integration between production and logistics units, and insufficient supplier transparency.

Material and technical supply is one of the key components of oil and gas companies' operations, as it directly affects the continuity of production, processing, transportation and capital construction. At the same time, in the oil and gas industry of Uzbekistan and other countries with an emerging digital economy, the MTS system faces a number of systemic and operational problems that hinder the achievement of strategic resilience and efficiency. The most critical of these are outlined below.

1. Fragmentation and low transparency of data. The MTS system often relies on fragmented data sources: separate ERP systems, Excel spreadsheets and manual reports. The absence of a single platform leads to duplicated orders, unreliable demand forecasts and longer approval times. Poor coordination between procurement, production and finance makes integrated control of supply chains impossible and complicates audits.

2. Weak supplier integration and insufficient digitalization. Despite the growth of electronic procurement, most suppliers, especially local ones, continue to use low-tech communication channels. This creates risks of delays in responding to inquiries, errors in documentation and an inability to integrate into automated procurement platforms (MDM, API, etc.). As a result, time lags between request and actual delivery increase, and overall process controllability declines.

3. Insufficient predictability of deliveries and a high share of unplanned procurement. Under conditions of unstable demand for spare parts, reagents, tubular products and equipment due to fluctuations in production and repairs, a significant share of procurement is carried out off-plan. This leads to a growing share of urgent purchases, stockouts for key items and unjustified growth of safety stocks. The system adapts poorly to changes in the schedule of production and investment programs.

4. Dependence on imports and weak development of local supplies of complex materials and equipment. Although local suppliers account for a high share in terms of number of counterparties, their share in total procurement value remains low (43% in 2023), especially in categories such as high-tech equipment and chemical reagents. This is due to the lack of production capacity among domestic manufacturers, technological lag, and difficulties in certifying and standardizing products in line with industry requirements. As a result, vulnerability to external risks rises, including exchange rate fluctuations, sanctions and disruptions in international logistics.

5. Low alignment between departments. In many cases, production, investment and procurement plans are not aligned in terms of timing and volumes. This results in untimely delivery of materials and equipment to sites, conflicts between cost centers and logistics services, and excessive bureaucratization of the approval process. The absence of a mature practice of integrated planning reduces adaptability to changes in the market environment and increases internal risks.

6. Shortcomings in supply risk management. Although Uzbekneftegaz JSC operates a unified risk management system, existing procedures often focus on identifying deviations that have already occurred rather than preventing them. Key limitations include the absence of quantitative assessment of the probability of disruptions (predictive indices are not used systematically), the fact that the digital maturity of suppliers is not taken into account in risk analysis, and weak linkage between risk assessment and safety stock planning. As a result, risks

are either underestimated or managed mainly through reactive response.

7. Shortage of competencies and staff overload. Procurement functions face a shortage of specialists in data analytics, ML, digital modeling, qualified buyers with sector-specific expertise, ERP integrators and IT architects. This limits the potential for implementing new digital solutions (including predictive planning), leads to calculation errors and reduces the adaptability of the system as a whole.

Observed disruptions in the supply of equipment and materials, as well as delays in well modernization or infrastructure construction, entail significant financial and production risks. All this necessitates a shift from reactive management to proactive planning based on predictive analytics and digital scenario modeling [Shmueli, Koppius, 2011].

3. Predictive planning: Essence and tools

3.1. What is predictive planning

Predictive planning is a management approach that uses forecasting models and machine learning algorithms to support proactive decision-making under uncertainty. Unlike traditional, reactive planning, which relies mainly on historical data and expert judgment, predictive planning focuses on future scenarios and allows companies to adjust their strategies before potential disruptions or risks materialize. In practice, predictive models can flag an emerging materials shortage 7–10 days in advance, which is critical for minimizing downtime[4].

At its core, the approach combines three elements: a forecasting model (based on Big Data, AI and ML), a layer of management logic (business rules, KPI, threshold values) and decision-making systems (automated S&OP resource planning systems). Predictive planning not only addresses the question of what is likely to happen – the focus of predictive analytics – but also suggests an optimal course of action that reflects available resources, constraints and strategic objectives.

Within the digital transformation of material and technical supply (MTS) in the oil and gas industry, predictive planning builds on a set of modern digital technologies. Of particular importance are blockchain, Big Data, the Internet of Things (IoT), Cloud Computing and artificial intelligence (AI) [Waller, Fawcett, 2013; Choi et al., 2018]. Together, these five technologies complement one another, compensate for individual limitations and help reduce labor and material costs while improving planning performance [Haiyan et al., 2019]. AI plays a central role in information exchange at all levels of an oil and gas enterprise and is increasingly seen as a defining feature of the oil and gas company of the future. It helps lower oil production costs, increase average output, streamline enterprise management and support both the economic and social development of the company [Wang et al., 2018]. Industry specialists report a 27% increase in production uptime due to AI-based predictive maintenance of equipment and a 26% improvement in asset utilization[5].

The current level of AI technology adoption in the various links of the value chain of the oil and gas industry, as well as the expected dynamics over the next three years, are presented in Table 1. As can be seen, the greatest progress in the use of AI is expected in the upstream and downstream segments, where the share of companies using AI will reach 85–93%. A particularly significant increase is projected in production (from 40 to 90%) and refining (from 41 to 93%). This points to the growing role of digital solutions in optimizing production processes, improving operational efficiency and reducing

Table 1
Implementation of AI in the Value Chain of the Oil and Gas Industry (%)

Sector	Activity	Current AI adoption	AI adoption in 3 years
Upstream	Exploration	44	89
	Drilling	28	85
	Production	40	90
Midstream	Transportation	28	85
	Storage	28	77
	Processing	30	85
Downstream	Refining	41	93
	Retail and Marketing	31	66

Source: https://www.ibm.com/downloads/documents/us-en/12fc84a1f2d95593.

[4] https://www.accenture.com/content/dam/accenture/final/accenture-com/document/Accenture-Decarbonizing-Energy-Full-Report-Digital-LDM.pdf .
[5] https://www.ibm.com/downloads/documents/us-en/12fc84a1f2d95593.

Table 2
PIRSP Interpretation Scale

PIRSP score	Risk level	Recommendations
0.00–0.30	Low risk	Standard planning
0.31–0.60	Medium risk	Enhanced monitoring, buffer stocks
0.61–1.00	High risk	Supplier diversification, safety stock, prequalification

Source: developed by the author.

costs. At the same time, the midstream segment, which includes transportation, storage and processing, also shows a steady increase in interest in AI, confirming companies' commitment to the digital transformation of the industry's entire logistics infrastructure.

3.2. Proposed predictive planning indices

In an environment of high market volatility, extended logistics chains and reliance on imported materials and equipment, traditional supply management methods do not provide adequate risk control. To quantify losses and integrate them into the overall assessment of MTS performance, this study proposes an integrated assessment model that combines factual data (costs, deviations, downtime) with predictive indicators of logistics risk.

Within this model, a Predictive Index of Risk of Supply Disruption (PIRSP) is developed. It reflects the aggregate probability of disruptions in the supply chain for a specific item based on objective and forecast parameters. PIRSP is a quantitative indicator designed to assess the probability and potential consequences of supply disruptions on the basis of predictive factors. The interpretation scale for PIRSP and an example of its calculation are presented in Tables 2 and 3, respectively. The index is used to:

– forecast the risk of shortages of materials and equipment;
– prioritize inventory;
– configure triggers in the procurement management system.

The PIRSP index is calculated as follows:

$$\text{PIRSP}_i = W_1 \times P_i + W_2 \times T_i + W_3 \times V_i + W_4 \times C_i + W_5 \times D_i, \quad (1)$$

where P_i is the probability of failure of supplier i (based on history, reputation and deviations). SAP data are used, including delivery date deviations (ME2N), penalty history and feedback, and this is modeled as a probability from 0 to 1;

T_i is the transit time of delivery (lead time variability), expressed as the coefficient of variation of delivery times. For example, if the standard deviation of lead time is 3 days and the average lead time is 10 days, the coefficient equals 0.3;

V_i is the volatility of consumption of the given item. It is calculated from the standard deviation of consumption over the period and may be replaced by a forecast error metric (e.g. MAPE);

C_i is the criticality of the item for the technological process. It is assigned manually or on the basis of ABC/XYZ analysis, where 1 means extremely critical (production downtime) and 0 means non-critical;

D_i is the share of a given supplier in the total procurement volume for this item. If 80% of purchases come from a single supplier, the risk is higher. It is calculated as the ratio of the volume purchased from that supplier to the total volume of purchases of the item;

Table 3
Example of Calculation for MRO Item 'Pump Station Filter'

Parameter	Notation	Value	Weighting coefficient	Weighted value
Probability of supply disruption	P_i	0.25	0.25	0.0625
Lead time variability	T_i	0.20	0.15	0.0300
Consumption volatility	V_i	0.15	0.15	0.0225
Item criticality	C_i	1.00	0.30	0.3000
Supplier share	D_i	0.90	0.15	0.1350
Total PIRSP	—	—	—	0.550

Source: author's calculations.

W_1 are weighting coefficients set by experts.

The PIRSP interpretation scale and an example of its calculation are presented in Tables 2 and 3, respectively.

Table 3 illustrates an example of calculating the Predictive Index of Risk of Supply Disruption (PIRSP) for the MRO item "Pump station filter." The calculation includes five key parameters: the probability of supply disruption, lead time variability, consumption volatility, item criticality and the supplier's share in the total supply volume. The aggregate weighted result is 0.55, which corresponds to a medium risk level. Recommended measures in this case include tighter control of delivery schedules, the creation of buffer stock and an assessment of alternative suppliers.

Integrating PIRSP into the MTS performance assessment system makes it possible to:

– identify potential bottlenecks before disruptions occur;
– minimize costs associated with unplanned deliveries and downtime;
– strengthen the justification of decisions within predictive and integrated planning;
– prioritize purchasing activities on the basis of forecast risks.

In the scientific literature and in supply chain management practice there is no established formula or model under the name PIRSP that combines predictive probabilistic approaches with a weighted integration of factors influencing the risk of supply disruption. The methods typically used in supply chain risk management (for example, FMEA, heat-matrix, supplier scorecards) rely on qualitative or semi-quantitative assessments and do not construct a composite numerical risk index based on parameters that can be calculated automatically. SAP Integrated Business Planning (IBP), Oracle SCM and similar systems do not offer a built-in index of this type; users must create it themselves on the basis of KPI and models. The PIRSP index can be implemented as a custom indicator in SAP IBP, SAP S/4HANA or via analytical dashboards in Power BI and SAP Analytics Cloud. The advantage of the PIRSP-based approach lies in its adaptability, the possibility of automatic recalculation and its integration into strategic and operational MTS planning processes.

Compared with existing logistics risk assessment methods such as criticality matrices, FMEA or supplier scorecard analysis, the proposed index is quantitative in nature, incorporates predictive parameters and can therefore be used as an element of intelligent supply chain management.

Thus, the predictive index of risk of supply disruption, PIRSP, represents a novel development that has no direct analogues in current logistics control systems. Its implementation enables oil and gas companies to assess supply chain vulnerabilities more accurately and to make well-founded decisions to ensure the reliability and continuity of MTS.

The Predictive Evaluation of Supplier Integrity (PESI) is a composite predictive indicator that evaluates the likelihood that a supplier will continue to meet its

Table 4
Main Components of the Index and Normalisation Methodology

Factor (S_i)	Assessment and normalization	Weight (w_i)
Delivery timeliness history	Share of on-time deliveries over the past 12 months (%). Normalization: 100% = 1.0, 80% = 0.8, etc.	0.25
Financial stability	Calculated via rating (e.g., D&B, SPARK, internal scores). Converted to a 0–1 scale using thresholds	0.15
Geopolitical/regulatory risk	GRI index, sanctions lists, political stability of the region. Direct normalization by risk level (low → 1)	0.10
Supplier price stability	Standard deviation of prices for this supplier over 6–12 months. The lower the deviation, the higher the score	0.10
Quality issues and claims	Share of orders with claims (%). Conversion: 0% = 1.0, 10% = 0.9, > 30% = 0.5 and below	0.15
Integration with SAP and digital system	Level of EDI/API integration, connection to SAP Ariba, availability of automatic exchange of orders/statuses	0.10
Logistics flexibility (response time)	Average response time to a new order (lead time reaction). Faster → higher score. Normalization: < 2 days = 1, > 5 days = 0.6	0.15

Source: author's calculations.

obligations in the future (over a 3–12 month horizon), taking into account:

- current logistics and financial characteristics;
- historical data;
- external factors (country, industry, sanctions);
- the supplier's level of digital integration and flexibility.

The index is particularly important in high-risk, fast-changing industries such as oil and gas, where the failure of even a single critical delivery can shut down a well or disrupt a drilling cycle. The main components of the index and an example of its calculation are presented in Tables 4 and 5, respectively. The PESI formula is as follows:

$$PESI = \sum_{i=1}^{n} \omega_i \times S_i, \sum \omega_i = 1, \quad (2)$$

where S_i is the normalized value of a stability indicator (0–1), ω_i – is the weight of the corresponding indicator, and, n is the total number of factors (6–8 are recommended).

When calculating PESI, additional indicators may also be considered, such as the supplier's ESG profile, its ability to adapt to force majeure (reserve lists, stock levels in the region) and the level of contractual discipline.

Table 5
Example of Calculation (Simplified)

Factor	Normalized stability score	Weight	Contribution
Delivery timeliness	0.90	0.25	0.225
Financial stability	0.60	0.15	0.090
Geopolitical risk	0.80	0.10	0.080
Price stability	0.50	0.10	0.050
Claims rate	0.85	0.15	0.128
Integration into SAP	0.40	0.10	0.040
Logistics flexibility	0.70	0.15	0.105
Total PESI	—	—	0.718

Source: author's calculations.

Potential implementation options in SAP: SAP Ariba Supplier Risk (connection via Supplier Scorecard); SAP SLP (Supplier Lifecycle Performance) as a supplier assessment module; SAP IBP (Integrated Business Planning) where PESI can be used as a KPI in scenarios; SAP BW/BI for reporting visualization with automatic scheduled PESI calculation. The main differences between PESI and its analogues, as well as the interpretation of PESI values, are presented in Tables 6 and 7, respectively.

Table 6
Differences Between PESI and Scorecards, Z-Score

Criterion	PESI (proposed index)	Existing approaches (Scorecards, Z-Score, etc.)
Predictive orientation	Yes (forward-looking)	No (backward-looking)
Multifactor structure	Yes – logistics, finance, digital integration	Often one-sided (finance or quality)
Assessment of digital maturity	Yes	No
Incorporation of external macro factors	Yes (sanctions, country)	Rarely
Use in SAP IBP	Yes (can be implemented as a KPI)	Partially (financial modules only)

Source: author's calculations.

Table 7
Interpretation of PESI Values

PESI	Interpretation	Recommendations
0.85–1.00	High stability	Recommended for long-term cooperation
0.70–0.84	Moderately high stability	Include in the core supplier pool
0.50–0.69	Moderate stability	Use with mitigation measures in place
< 0.50	Low stability	Review the contract, seek alternatives

Source: author's calculations.

PESI is a universal, flexible and scientifically grounded predictive index that reflects actual risks in supplier logistics, enables management decisions to be made in advance and provides the basis for an early-warning system for disruptions in MTS.

The Digital Logistics Index (DLI) reflects the level of digital maturity in a company's logistics operations, including warehousing, transportation, monitoring and planning. It is calculated as follows:

$$DLI = \frac{1}{n}\sum_{j=1}^{n} C_j \times W_j, \quad (3)$$

where $C_j \in [0,1]$ is the maturity level for the j-th component (assessed using a scale or checklist), $W_j \in [0,1]$ is the weight of the j-th component, and n is the number of components (for example, WMS, TMS, IoT, Big Data, e-SRM, AI-based planning).

An example of the index calculation is shown in Table 8. Let us assume that the digital maturity of logistics is assessed using five criteria, with a maximum score of 10 for each criterion.

Interpretation:

– DLI < 0.4 – low level of digitalization;
– DLI = 0.4–0.7 – transitional level;
– DLI > 0.7 – mature digital logistics.

Table 8
Example of DLI Index Calculation

Digitalization criterion	Criterion weight	Score (0–10)	Weighted score
Availability of an ERP system with a logistics module	0.25	8	8 × 0.25 = 2.00
Warehouse automation level (WMS, RFID)	0.20	6	6 × 0.20 = 1.20
Supplier integration via EDI/API	0.20	4	4 × 0.20 = 0.80
Use of predictive analytics (AI/ML)	0.20	3	3 × 0.20 = 0.60
Availability of a transport monitoring system (TMS, GPS, IoT)	0.15	7	7 × 0.15 = 1.05
Total	1.00		5.65

Source: developed and calculated by the author.

The DLI value of 5.65 indicates a medium level of digital maturity, where the company's logistics processes are partially automated but still lack deep integration with suppliers and advanced predictive analytics. This highlights the need to strengthen digital initiatives, primarily by deploying predictive AI tools and expanding integration with counterparties.

The system of indices proposed in this study forms the basis of the author's Integrated Predictive Planning Cycle (IPPC), which ensures continuous identification, forecasting and mitigation of logistics risks at the level of strategic management. This opens up new opportunities for shifting from reactive to proactive supply management, which is particularly important for high-risk industries such as oil and gas.

The Integrated Predictive Planning Cycle (IPPC) is an original conceptual model that represents a closed management cycle combining predictive analytics tools, risk assessment and digital supply chain management. The IPPC model is aimed at anticipatory risk management and at adapting the logistics system to changing internal and external conditions. Its primary objective is to ensure the resilience, adaptability and predictability of supply chains under conditions of uncertainty and digital transformation in the industry.

The model comprises six interrelated stages, each of which relies on specific predictive indices and digital tools (see the Figure).

Stage 1 – Digital diagnostics of the logistics system:

– assessing the current level of digitalisation of the company's logistics processes;
– calculating the Digital Logistics Index (DLI) to identify weaknesses in digital logistics maturity;
– determining the need for digital improvements (ERP integration, IoT, AI platforms).

Stage 2 – Predictive supplier assessment:

– building supplier profiles that take into account risk, reliability and stability;
– calculating the Predictive Evaluation of Supplier Integrity (PESI);
– ranking suppliers by the level of predictive stability;
– developing recommendations on adjusting the supplier base (expansion, diversification).

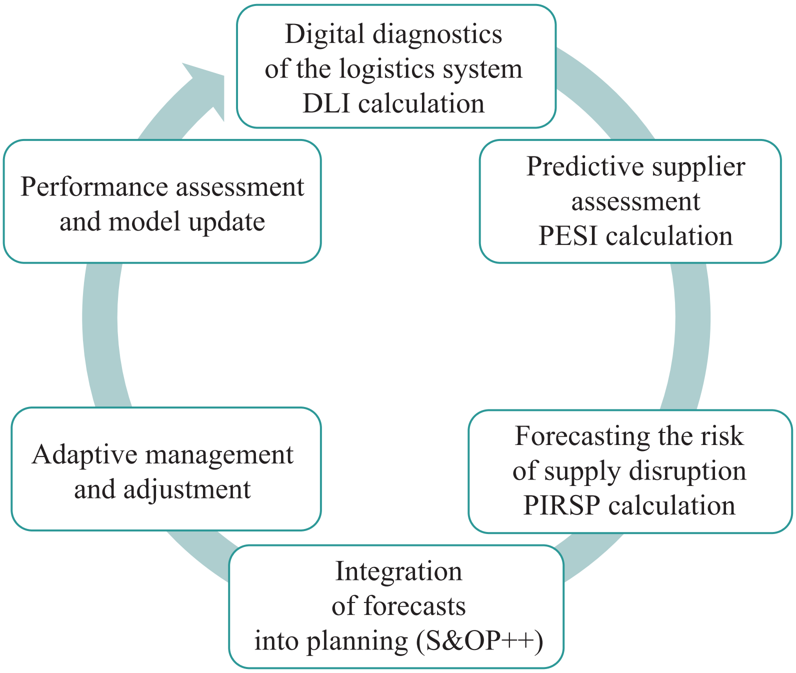
Stage 3 – Forecasting the risk of supply disruption:

– identifying external and internal threats to MTS stability;
– calculating the Predictive Index of Risk of Supply Disruption (PIRSP);
– conducting spatio-temporal risk analysis (geographical, seasonal and political factors);
– developing risk scenarios and performing scenario modelling.

Stage 4 – Integration of forecasts into planning (S&OP++). Embedding predictive planning into the integrated planning framework based on the Sales & Operations Planning (S&OP) concept is an objective necessity in the context of digital transformation of oil and gas companies [Zagrebelskaya, 2021]. S&OP as a process is not only about functional synchronisation but also about providing a platform for joint decision-making. S&OP becomes truly effective only when the decisions made within its framework are based on the future rather than the past [Hansali et al., 2021]. At this stage, the following tasks are carried out:

– extending the traditional S&OP cycle to incorporate predictive data;

Fig. Stages of IPPC



Source: author's calculations.

- developing optimal logistics and procurement strategies;
- forecasting demand for materials and equipment with regard to production and external data;
- using digital twins and machine learning algorithms to build scenarios.

Stage 5 – Adaptive management and adjustment:

- implementing mechanisms for automatic adaptation of logistics decisions to changing conditions;
- creating a risk dashboard;
- dynamically reconfiguring the supply chain based on forecasts.

Stage 6 – Final stage: performance assessment and model update:

- monitoring key indicators of supply chain resilience;
- recalculating the DLI, PIRSP and PESI indices on the basis of new data;
- adjusting model parameters and restarting the cycle.

The IPPC can be implemented both within an individual production and logistics unit (for example, in the Procurement Department of *Uzbekneftegaz JSC*) and as part of a corporate digital supply chain management platform. The model enables a shift from reactive management to preventive, strategy-driven decision-making, which is particularly important for companies that are highly dependent on imported resources and operate in an unstable external environment.

4. Preconditions for implementing the indices at Uzbekneftegaz JSC

Against the backdrop of its digitalization agenda, Uzbekneftegaz JSC is pursuing a strategy to introduce intelligent supply planning. In the company's 2025 procurement schedule[6] , expenditures are planned for the automation of MTS, including UZS 6.35 billion for the implementation of, and staff training in, a Master Data Management (MDM) system.

This creates preconditions for integrating predictive models into procurement, maintenance and production risk management processes. For example, developing a risk map using PIRSP makes it possible, at an early stage, to identify potential supply disruptions for equipment used at gas compressor stations, reduce downtime and lower the costs of urgent procurement.

To quantify the state of the MTS system, it is advisable to examine changes in inventories (Table 9). The most significant growth is observed in the following categories: petroleum products – from UZS 1,031 billion to UZS 1,633 billion (+58%), and materials and inventories – from UZS 992 billion to UZS 1,695 billion (+71%). At the same time, there is a reduction in work in progress (from UZS 208 billion to UZS 99 billion) and crude oil (from UZS 211 billion to UZS 40 billion), which may indicate the completion of part of production cycles and a transition to finished products.

[6] https://webdev.ung.uz/media/allfiles/files/7abf22aff0474158ac21907e481f1043.pdf

Table 9
Inventory of JSC 'Uzbekneftegaz' (billion UZS)

Inventory category	As of 31.12.2024	As of 31.12.2023
Petroleum products	1,633	1,031
Materials and inventories	1,695	992
Work in progress	99	208
Crude oil	40	211
Other	23	38
Total inventory	3,490	2,480

Source: https://webdev.ung.uz/media/allfiles/files/4284a385abaa4961814022f9c9180fd9.pdf.

This increase in inventories may be driven both by intensified procurement activity and by the need to hedge logistics risks, which in turn confirms the relevance of predictive planning as a means to reduce excessive reserves and improve the accuracy of procurement.

At the same time, an analysis of the procurement policy of *Uzbekneftegaz JSC* for 2021–2023 (Table 10) reveals substantial fluctuations in the share of procurement expenditures attributable to local suppliers. While local suppliers account for a very high share in terms of number of counterparties (97–99%), their share in total procurement value fell from 84% in 2022 to 43% in 2023. This may indicate:

– increased dependence on large foreign supplies under conditions of shortage,
– a low share of high-tech products provided by local manufacturers,
– the need to revise the system for assessing supplier risk and resilience.

Table 10
Share of Expenditures on Local Suppliers by JSC 'Uzbekneftegaz'

Indicator	2021	2022	2023
Total number of suppliers	2,681	2,935	3,897
Total procurement amount (billion UZS)	6,271.6	1,003.6	23,161.6
Total number of local suppliers	2,637	2,895	3,788
Procurement amount from local suppliers (billion UZS)	5,097.8	8,392	9,867.8
Share by number (%)	98	99	97
Share by amount (%)	81	84	43

Source: https://webdev.ung.uz/media/allfiles/files/6a53722d3e904f6db75e57e4c48ee8d2.pdf.

The procurement structure of *Uzbekneftegaz JSC* in 2023 also confirms active use of a wide range of procurement procedures. In total, 4,006 contracts were concluded for UZS 16,613.8 billion, including:

– 2,367 contracts totalling UZS 1,221.3 billion through electronic marketplaces, auctions, cooperation portals and electronic exchanges;
– 6 tender contracts (under Law ZRU-684) totalling UZS 105.6 billion;
– 209 contracts based on best-offer selection procedures totalling UZS 206.3 billion;
– 423 contracts with single-source suppliers totalling UZS 436.1 billion.

This diversity of procurement channels allows the company to respond flexibly to market conditions, but it also requires accurate forecasts and robust risk assessment when choosing a procedure. This reinforces the case for adopting predictive planning as a tool to optimize the company's procurement strategy. The trend also underscores the importance of implementing the PESI index as a predictive diagnostic tool for assessing counterparty reliability, as well as the need for digital monitoring of the geographic and operational diversification of procurement.

In the oil and gas sector, the introduction of predictive planning is particularly relevant due to:

– the high cost of supply disruptions (rig downtime, missed repair deadlines, contract penalties);
– dependence on imports of critical components;
– a high share of project-based supplies with long lead times and changing requirements;
– the need to factor in weather-related, geopolitical and technological risks.

5. Risks and limitations of implementation

Despite the high theoretical effectiveness of predictive planning in supply and risk management, its practical implementation is associated with a number of organizational and technological constraints. In the context of the transformation of the logistics model at *Uzbekneftegaz JSC*, these constraints may significantly affect the timing and depth of integration of predictive tools.

1. Limited and unstructured data

Predictive models require high-quality, complete and representative datasets. In the current document flow and reporting system, data are often:

– maintained in fragmented formats and systems (Excel, 1C, local databases);
– lacking a sufficient time horizon or indicators for seasonality analysis;
– not covering all risk categories (for example, contracts with new suppliers or risks of political instability in equipment-exporting countries).

This limits the applicability of machine learning and the development of robust forecasting models.

2. Low digital maturity of individual units

Despite automation initiatives (such as the implementation of MDM and the unified risk management system), many production and procurement units still operate within traditional paper-based processes. The absence of a unified IT infrastructure and integration between ERP systems reduces the effect of implementing AI algorithms and slows feedback on forecast results.

3. Shortage of competencies in analytics and risk management

Working with predictive tools requires specialists in data analytics, data science, applied mathematics and risk management. At the current stage, enterprises in the sector face:

– a shortage of qualified personnel;
– insufficient involvement of IT specialists in production processes;
– a lack of established cross-functional teams for implementing analytics in supply chains.

4. Organisational barriers and resistance to change

The transition from experience-based planning to predictive models is often perceived as a threat to stability or to managerial authority. Possible risks include:

– resistance from line managers and procurement staff;
– distrust of analytical results;
– delayed incorporation of model recommendations into managerial decisions.

5. Financial and regulatory constraints

Large-scale digitalisation requires investment in IT infrastructure, staff training and solution support. Under conditions of a limited budget and procurement procedures governed by the Law “On Public Procurement”:

– it is difficult to introduce modern SaaS solutions quickly;
– it is harder to respond flexibly to project needs (for example, to rapidly procure cloud capacity or data visualisation tools).

6. Risks of over-automation and model dependence

Despite the potential of AI, excessive reliance on automatic forecasts without expert validation may lead to erroneous decisions, especially in force majeure situations (sanctions, geopolitical shocks, pandemics, etc.). In addition, models lose accuracy over time without regular recalibration, which requires continuous monitoring and validation..

7. Legal and contractual risks related to suppliers

Predictive planning assumes the assessment of supplier risks. However, limited access to suppliers’ internal data and the legal framework of contracts (for example, the absence of penalty clauses for delays) may prevent effective influence on non-compliant suppliers, even when the system identifies a high risk level. The integration of predictive planning at *Uzbekneftegaz JSC* therefore requires not only technical modernisation but also organisational transformation. The most effective path is step-by-step implementation of pilot solutions followed by scaling, combined with active efforts to develop the digital competencies of personnel.

6. Conclusion and recommendations

Material and technical supply (MTS) in Uzbekistan’s oil and gas sector is undergoing active transformation and simultaneously facing the challenges of digitalization, global logistics risks and the need for sustainable import substitution [Zagrebelskaya, 2019]. The analysis of the current MTS system at Uzbekneftegaz JSC has revealed critical structural issues, ranging from fragmented data and dependence on external suppliers to weak integration of risk into planning and a shortage of digital competencies.

Predictive planning offers an effective response to these challenges. Unlike predictive analytics, which focuses on interpreting events that have already occurred, predictive planning makes it possible to construct forward-looking scenarios, estimate the probability of disruptions and rapidly adapt the supply strategy. The indices developed in this study – PIRSP, PESI and DLI – provide a practical pathway towards management based on predictive indicators by integrating risk assessment, supplier stability and digital maturity into a single decision-making framework.

IFRS-based financial data and operating performance indicators for 2021–2024 demonstrate the importance of shifting from a purely quantitative expansion of procurement to qualitative management of suppliers and risks. Substantial fluctuations in the share of local procurement, growth in inventories and the active use of diverse procurement procedures all underscore the need for more accurate, adaptive and digitally oriented tools.

To ensure supply chain resilience and achieve the strategic objectives of *Uzbekneftegaz JSC* through 2030, it is recommended to:

– implement a predictive planning system based on the PIRSP, PESI and DLI indices in a phased manner;
– integrate risk assessment results into procurement planning and safety stock formation;
– enhance suppliers’ digital maturity through cooperation programs and obligations to integrate with MDM;
– introduce KPIs based on predictive indices for procurement units;
– invest in staff training in data analytics and digital risk management.

In this way, predictive planning becomes not only a tool for minimizing operational risks but also a catalyst for a sustainable, digitally oriented transformation of the entire MTS system in Uzbekistan’s oil and gas industry.

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