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SMART ANALYTICS TOOLS FOR SUPPORTING MANAGEMENT DECISIONS IN THE FIELD OF PRODUCTION SYSTEM MANAGEMENT AT ENTERPRISES IN THE CONTEXT OF SUSTAINABLE DEVELOPMENT

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ABSTRACT

This article addresses the growing importance of smart analytics as a technical tool and fundamental intellectual asset ensuring sustainable development, resilience, and competitiveness of enterprises under digital transformation. The paper examines the Smart Data Adaptive Cycle (SDAC) model, which offers a continuous closed-loop decision-making process in a digital manufacturing environment. The model integrates informational, financial, and cognitive components using self-learning mechanisms and the human-in-the-loop principle. The purpose of the work is to examine the specifics of ensuring sustainable development in an enterprise through managerial decision-making using smart analytics tools in the management of production systems. The study applies general and specialized methods, including a scenario-based approach to determine the relationship between information entropy and economic value added (EVA), a case study for empirical validation of the SDAC model at a metallurgical enterprise, discounting for economic feasibility, and a systematic approach to constructing the conceptual model. A comparative scenario analysis of ex-post, partial, and full SDAC models was conducted. The main results show that the SDAC model integrates information theory and value-based management (VBM) into a single adaptive cycle. The findings demonstrate that entropy analysis allows for the formalization of uncertainty in the production environment (BANI context), providing a quantitative ex-ante risk assessment that is more effective than traditional retrospective methods. Empirical modeling confirms that integrating smart analytics into production management enables the maximization of EVA. Practical testing at a metallurgical enterprise demonstrated the model's ability to reduce equipment downtime to 8.2%, defect rates to 3.6%, and carbon emissions to 190 kg CO_2/t, while increasing labor productivity. The conclusions confirm the effectiveness of the SDAC model as a tool for improving managerial decision-making and ensuring sustainable enterprise development. Future research includes scaling the model to other sectors and integrating it into approaches for assessing nonlinear extreme events (black swan events).

Keywords: strategic management, digital transformation, business analytics, Industry 4.0, operational efficiency, innovative technologies, smart economy, production systems management, ESG metrics, competitiveness

JEL Classification: C63, D81, M11, M15, Q01

INTRODUCTION

The development of industrial enterprises in the context of Industry 4.0 is marked by unprecedented turbulence, driven by both global challenges and local crises. Smart technologies and analytical tools are the technical foundation of digitalization and a key component of targeted management of business development in the context of sustainable development. Under such conditions, traditional management methods based on retrospective (ex-post) data analysis are found not to be sufficiently effective. Smart technologies, artificial intelligence (AI), and decision support systems (DSS) are becoming key elements of enterprises' strategic architecture, enabling a shift from reactive measures to proactive modeling of the future state of production systems. Smart analytics, as an integrated analytical mechanism, combines methods for processing big data with financial verification of management decisions, which is critical for minimizing management uncertainty. The transformation of management processes creates the conditions for aligning current management decisions with sustainable development goals, enhancing the resilience of production systems, and ensuring their long-term viability. The relevance of this study arises from the need to formalize analytical procedures and integrate them into a single adaptive cycle that would ensure a balance between economic efficiency, innovation, and adherence to the principles of sustainable development in a highly uncertain environment (BANI context).

LITERATURE REVIEW

Modern researchers are placing significant emphasis on smart manufacturing through the use of big data analytics, the Internet of Things, and artificial intelligence in SSM. Organizational Enablers of Sustainable Manufacturing and Industrial Ecology include Manufacturing Costs, Power Consumption, Waste Management, Operational Safety, Digital Transformation, Life-cycle Assessment (LCA), Design for Remanufacturing, and Industrial Symbioses. The author also classifies the following as Technological Enablers of Smart Manufacturing: Vision Systems and Instrumentation, Big Data Analytics and Artificial Intelligence, Internet of Things, Edge and Cloud Computing, Cyber-physical Systems, Digital Twins and Simulations, Smart Process Planning and Optimization, Advanced Robotics, Data Visualization, and Predictive and Prescriptive Maintenance (Chinnathai, 2023).

This study was followed by a paper (Lin, 2024), which demonstrated that smart manufacturing plays a crucial role in the circular supply chain (CSC), ensuring product quality and durability. High-quality products last longer, reducing the need for frequent replacements and thereby supporting CSC's goal of minimizing resource extraction and waste generation. Furthermore, advanced smart manufacturing technologies (AI and machine learning algorithms, the Internet of Things, and advanced visualization technologies) can identify materials suitable for recycling or reuse at the end of their life cycle, thereby enhancing the sustainability of the supply chain.

The study (Magableh, 2024) systematized the impact of information systems on the development of smart manufacturing to achieve sustainable development goals (SDGs). The author applied the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology and demonstrated that blockchain technology, the Internet of Things (IoT), and Industry 4.0 can support sustainable development across various sectors of the economy.

The achievement of the SDGs is ensured through the implementation of reconfigurable manufacturing system (RMS) practices and the latest Industry 4.0 technologies. All of these studies emphasize the central role of managerial decision-making, which is a fundamental function of management not only in production processes but also in the enterprise as a whole (Pansare, 2023).

Stayetsky (2025) proposed using Big Data, AI, and DSS to support management decisions aimed at achieving economic sustainability, adaptability, and long-term competitiveness for enterprises. The shift from intuitive approaches to data-driven management ensures sounder strategic and operational decisions, reduced managerial uncertainty, and increased business flexibility in an unstable external environment. Developing this approach, Shpak & Kis (2022, 2024) view the "smart enterprise" as the result of integrating digital technologies, information and analytical systems, and modern management mechanisms into a unified management system. The authors argue that the use of analytical tools and digital technologies improves the efficiency of business process management, the adaptability of enterprises, and the formulation of development strategies in the context of Industry 4.0. Filippov & Yangulov (2024) view digital and analytical tools as the foundation for the digital transformation of strategic enterprise management. The authors demonstrate that these tools transform management from reactive to proactive and enable management decisions to be aligned with corporate sustainability goals.

Therefore, when managing innovative changes and business transformations in the context of Industry 4.0, smart analytics is not only a decision-support tool but also a foundational element of the management architecture. "Smart Enterprise" is becoming a conceptual hub for the implementation of smart technologies. For example, P.G. Pererva et al. (2024) argue that effective management of innovative changes in the context of Industry 4.0 requires the development of a comprehensive analytical toolkit that combines digital analytical modules, a system of key performance indicators (KPIs), and mechanisms for adapting to external risks. We agree with the need to integrate analytics into the management cycle, formalize the SDAC stages, and implement mandatory financial verification of management decisions. This approach allows smart analytics to be viewed as a tool for ensuring a balance between an enterprise's efficiency, stability, and innovation, which aligns with the logic of sustaining the development of production systems.

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Similar conclusions regarding the use of not only individual digital tools but also of integrated approaches to building management systems (including DSS, predictive models, and dashboards) to enhance the adaptability and functional flexibility of enterprises were reached by G.B. Svinaryova & D.K. Tkach (2025).

Knyazeva et al. (2024) proposed adding digital asset indicators and measures of the effectiveness of online tools to the toolkit for assessing economic resilience in the context of digitalization. This approach allows for the expansion of the system of financial indicators in smart analytical models, which is consistent with the use of financial metrics as key input parameters. S.V. Onishchenko et al. (2024) argue that digital business transformation improves financial resilience and contributes to the achievement of sustainable development goals by improved resource productivity, adaptation to changes in the external environment, and integration with environmental and social dimensions.

Bashynska et al. (2023) argue that the smartification of enterprises in the context of digital transformation is based on the integration of digital technologies, data analytics, and tools for evaluating the results of smart projects, which improves the efficiency of production system management and ensures that management decisions are based on sound reasoning. The study also emphasizes the role of digital transformation in ensuring the sustainable development of enterprises through improved resource efficiency and enhanced competitiveness and adaptability of production systems to changes in the external environment. This approach lays the groundwork for implementing the SDAC concept, proposed in the study, at the level of production systems; this will ensure that financial verification of results is integrated into every stage of the analytical cycle and establish a methodological foundation for the use of smart analytics as a tool for improving management efficiency, reducing management risks, and achieving the enterprise's sustainability goals.

Megits et al. (2022) formalized a set of indicators to assess the development of five components of the innovation ecosystem (business, society, government, science/education, and environment) and developed a decision tree to select a scenario for digital transformation depending on the institutional context. This approach provides a foundation for organizing data sources and identifying responsible stakeholders at the Sense SDAC stage. Although this work is primarily focused on the meso/macro level, the proposed indicators and scenario algorithm can be used as input parameters for developing enterprise-level scenarios (data preparation for Diagnose) and as a benchmark for the preliminary assessment of digitalization options in terms of expected benefits. This proves the usefulness of the model for formalizing input data in NPV-oriented comparisons of scenarios.

Sak & Shepelyuk (2023) systematized a set of diagnostic methods (coefficient analysis, horizontal/vertical analysis, factor analysis, rating systems) and proposed benchmark values for key financial ratios. This has made it easier to use Diagnose SDAC at the micro level of the enterprise. The proposed tools allow for the reduction of a large array of financial and operational metrics into a compact set of key factor indicators that can be converted into cash flows for NPV/EVA calculations and serve as the basis for making investment decisions on smart initiatives. Also, the authors emphasized the need to adapt the methodologies to the size of the enterprise and external shocks, which is important for the Confirm stage.

Generalization of the above theoretical and methodological approaches allows for the interpretation of smart analytics as a multi-level analytical and managerial tool, able to simultaneously ensure the financial balance, efficiency of current business processes, and strategic resilience of production systems and align economic, innovation, and management goals of sustainable development. In addition to the theoretical approaches discussed above, domestic research is increasingly interpreting smart analysis as a holistic system of management decision support, which ensures alignment of strategic and operational decisions with the objectives of financial resilience, balance, and sustainable development of enterprises in a turbulent economic environment and amid growing uncertainty. It is this understanding of smart analytics that lays the theoretical groundwork for the transition from a conceptual understanding of its role to the justification of specific methodological decisions on its practical implementation in the management of production systems.

The results obtained confirm that smart analytics and management decision-support systems are primarily used to formalize management processes and quantitatively evaluate the performance of enterprises. At the same time, there is a lack of systematization in the issue of stepwise integration of analytical procedures with the financial verification of management decisions and sustainable development goals within a single analytical cycle. This makes it appropriate to justify an SDAC-based methodological approach that ensures a structured implementation of smart analytics and the incorporation of financial evaluation criteria at every stage of the analytical process.

The review of recent publications confirms the relevance of the issue under study and demonstrates the urgent need to formalize analytical procedures and integrate them into the management decision-making process to ensure the sustainable development of enterprises.

AIMS AND OBJECTIVES

The aim of this study is to examine the capabilities for ensuring sustainable development at the enterprise level through management decisions, using smart analytics tools to manage the enterprise’s production systems.

To achieve this aim, the following objectives were set and accomplished:

1. To develop a conceptual framework (SDAC – Smart Data Adaptive Cycle) that integrates real-time information flows, financial performance metrics, and cognitive decision-making processes into a unified adaptive management cycle.
2. To formalize decision-making under uncertainty by applying Shannon entropy theory to quantify volatility in production environments, thereby enabling more structured and data-driven risk management.
3. To integrate economic efficiency filters (specifically Economic Value Added – EVA) into the smart analytics loop, ensuring that technological and operational interventions are verified against their long-term financial viability.
4. To establish a “human-in-the-loop” mechanism that balances the precision of AI-driven predictive analytics with strategic management intuition, allowing for flexible adaptation of operational parameters in turbulent environments.
5. To validate the proposed methodology through an empirical case study of a metallurgical enterprise, comparing the effectiveness of traditional management models versus the proposed smart analytics-based approach across key sustainability indicators (productivity, resource efficiency, and carbon emissions).
6. To synthesize an integrated Sustainability Index (SI) that combines economic, environmental, and social performance criteria, providing a quantitative basis for assessing the overall sustainability impact of management decisions.

METHODS

The study employed general scientific and specialized methods of the scenario-based approach to determine the relationship between changes in information entropy and changes in economic value added under various management approaches; a case study with analytical generalizations in the empirical validation of a model for adaptive smart analytics of a metallurgical enterprise’s operations; discounting to assess the economic viability of an intellectual solution; a systematic approach to build a conceptual model of the SDAC adaptive smart data analytics cycle; and a comparative scenario analysis for ex-post, partial SDAC, and full SDAC management models.

The SDAC (Smart Data Adaptive Cycle) model is based on the concept of cyclically converting “raw” data into strategic decisions. The method is built on three key components. First, Shannon entropy is used to quantify the uncertainty of a system's states ($H = -\sum p_i \ln p_i$), which allows risks to be identified at an early stage, before they affect operational efficiency. Second, intellectual verification (EVA/NPV) means that every management decision is subject to a “filter” of financial performance, which prevents “investment traps” where technological innovations have no real economic effect. Third, the adaptive-cognitive loop (Sense–Diagnose–Act–Confirm) enables the system to learn from the results it obtains, thus minimizing the time lag between detecting an anomaly and resolving it.

The study uses a comprehensive methodological approach to the analysis and support of managerial decision-making in industrial logistics systems. The proposed methodology is based on the integration of digital technologies for monitoring production processes, predictive analytics tools, and methods for the economic evaluation of alternative management scenarios. This approach enables a comprehensive analysis of the functioning of an enterprise's logistics systems and enhances the relevance of management decisions in an environment of high economic uncertainty.

Today, production systems that operate within the framework of Industry 4.0 are characterized by a high level of complexity and the need to take into account a significant number of interrelated parameters. These circumstances create the basis for multi-criteria decision-making analysis (MCDA), which allows for the evaluation of alternative management decisions by taking into account economic, technological, and risk-oriented criteria. This method is used in management systems for modern industrial complexes and digital logistics systems (Da Silva et al., 2023).

Furthermore, recent research in the field of production planning emphasizes the need to use analytical models capable of integrating economic, environmental, and social aspects of sustainable development into the management decision-making process. This requires the use of data analysis methods and decision-support models that provide a comprehensive assessment of the operational efficiency of industrial systems (Zarte et al., 2022).

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The research methodology involves integrating data from digital monitoring of production and logistics processes, their further analysis using predictive analytics tools, and the economic evaluation of alternative management scenarios. The general logic of the proposed approach is illustrated in Figure 1, which shows the interrelationships between the main components of the management decision support system.

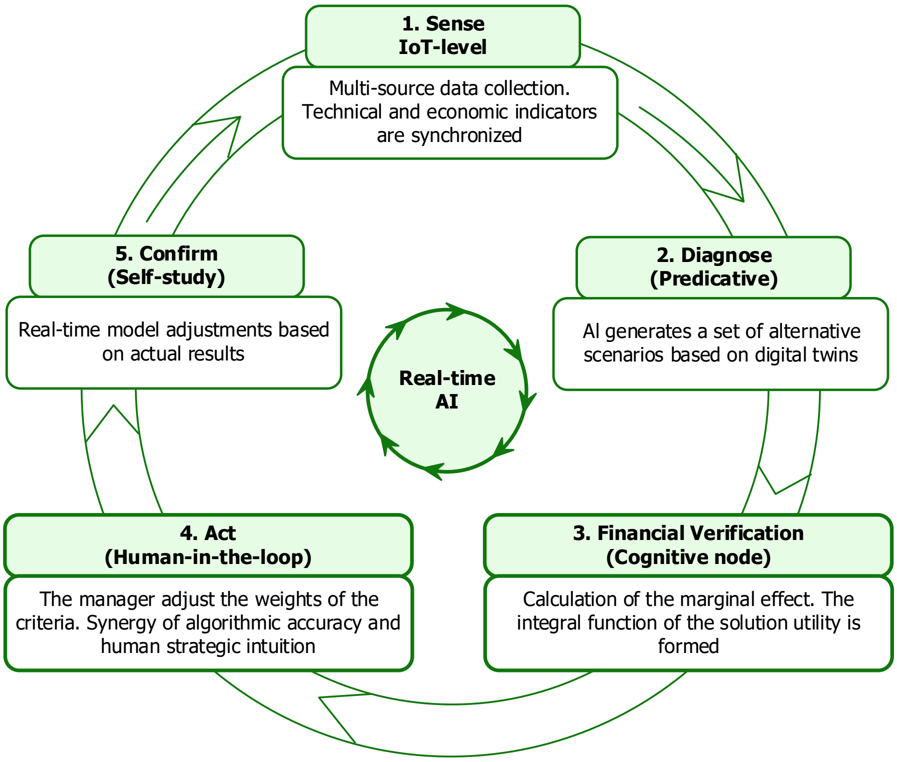

Figure 1. Conceptual model of the SDAC adaptive smart data analytics cycle.

The first stage involves building a research database by integrating the operational data that characterize the functioning of the enterprise's production and logistics systems. In today's environment, this integration is achieved through digital monitoring technologies and Internet of Things (IoT) systems, which enable the collection of information on production process parameters, material flow, resource utilization, and other operational metrics in real time. The use of digital technologies in production management systems enhances the transparency of an enterprise's operations and lays the groundwork for the use of analytical tools for forecasting and optimizing logistics processes (Lin et al., 2024).

Based on the integrated data, an analytical database is created, which is used for further modeling of management scenarios. This study employs a predictive analytics approach, which involves the use of statistical and analytical methods to identify patterns in the functioning of the logistics system and predict the potential consequences of alternative management decisions. Recent studies highlight the growing role of artificial intelligence and data analysis tools in industrial enterprise management systems, in the assessment of logistics risks and in the optimization of production processes in particular (Kozenkov & Kaut, 2024).

The analytical phase yields several possible management scenarios, each characterized by different parameters of the logistics system's operation, resource costs, and expected economic outcomes. To quantitatively compare the alternative scenarios, an integrated performance function is used that takes into account a set of key performance indicators for the enterprise's logistics system (1):

$$E_j = \sum_{i=1}^{n} w_i * x_{ij} \quad (1)$$

where E_j is the integrated effectiveness of the j-th management scenario; x_{ij} is the weight coefficient of the indicator's significance; n is the number of evaluation criteria.

The use of an integrated function makes it possible to account for the combined impact of economic, logistical, and operational factors on the overall efficiency of the system and to identify the most rational management decision.

The next stage of the study is an economic assessment of alternative management scenarios. At this stage, the results of the predictive modeling are converted into financial and economic indicators, which makes it possible to determine the economic feasibility of each management decision. The economic effectiveness of a management scenario is defined as the difference between the expected benefits of optimizing logistics processes and the costs of implementing the corresponding management measures (2):

$$R_j = B_j - C_j \tag{2}$$

where: R_j is the economic outcome of implementing the scenario; B_j is the expected benefits of implementing the management decision; C_j is the total costs required to implement the scenario.

The use of economic evaluation of management scenarios makes it possible to integrate the results of operational analysis with the company's financial performance indicators. Today's models of enterprise management are increasingly placing emphasis on the indicators of economic security and sustainable development; these allow for assessing not only the short-term effectiveness of management decisions but also their long-term strategic impacts (Tiutchenko et al., 2024).

Thus, the proposed research methodology combines digital monitoring technologies, predictive analytics tools, and methods for the economic evaluation of management scenarios. Integration of these elements enables the creation of a comprehensive management decision-supporting system designed to improve the efficiency of industrial logistics systems and reduce the enterprise's operational risks.

RESULTS

The SDAC smart analytics-based model of adaptive cycle of production system management offers a continuous closed-loop of management decision-making in a digital production environment and includes five interconnected stages.

Stage 1. Data collection and synchronization (IoT level). It involves the continuous collection of multi-source data covering production parameters (temperature, speed, load, equipment wear), energy performance indicators, logistics and resource flows, as well as financial variables (production costs, expenses, and downtime losses). A key feature of this stage is the integration of technical and economic indicators into a single database, where the data is synchronized, creating a foundation for further financial analysis.

Stage 2. Predictive and prescriptive analytics. It uses machine learning, time series analysis, scenario-based forecasting, and digital twins of production processes. The analytics module not only generates forecasts of events (such as equipment failures, cost overruns, or delays) but also offers a range of alternative management scenarios. The key point is that, from the outset, each scenario is prepared for further economic evaluation, rather than being merely limited to technical optimization.

Stage 3. Assessment of financial and economic implications (cognitive node). It involves marginal analysis of management decisions, assessing the effect on cash flows, analyzing risks and uncertainties, and comparing short-term and long-term effects. An integrated utility function for a decision is formed, taking into account financial efficiency, system stability, and its adaptability to external changes.

Stage 4. Making a management decision (human-centered cognitive logic). A cognitive interaction develops between the system and the manager. The system suggests scenarios that explain cause-and-effect relationships, while the manager adjusts the weights of the criteria (risk, profitability, sustainability) in accordance with strategic priorities. This implements the principle of human-in-the-loop management, where automated insights are combined with managerial judgment.

Stage 5. Real-time adjustments and self-learning. After the decision is implemented, the results are recorded and compared with the forecast values, the model parameters are adjusted, and the decision-making rules are updated. A self-learning cognitive loop is formed, which improves the quality of subsequent managerial cycles and ensures the system's dynamic adaptability.

1. The scientific novelty of the SDAC model does not lie in individual technical procedures, but rather in the systematic integration of informational, financial, and cognitive components into a single adaptive loop. The key elements of this novelty include the following:

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2. economic interpretation of data at the collection level. Unlike traditional approaches, where IoT data is viewed as an isolated technical dataset, the SDAC model forms it as an economically interpretable stream that immediately provides managerial value and is synchronized with financial variables;
3. priority of economic rationality over technical KPIs. Solutions are optimized not by technical efficiency indicators (uptime, OEE), but by economic rationality criteria (EVA, NPV) under conditions of uncertainty, which allows combining financial logic with cognitive risk assessment;
4. transformation of management logic. The management process shifts from a reactive response to events (Ex-post) to a proactive shaping of the desired future state of the production system (Ex-ante) through self-learning mechanisms and the reduction of information entropy;
5. Integration of the human factor into the analytical loop. Implementing the human-in-the-loop principle ensures a balance between the system's algorithmic accuracy and the manager's strategic intuition, which is critical in environments characterized by high uncertainty.

Table 1 summarizes the differences between traditional approaches and the proposed model.

Table 1. Systematic comparison of classical analytical paradigms and the cognitive-adaptive approach.

Criterion	Traditional approaches	Proposed model
Type of analytics	Reactive / Predictive	Cognitive-adaptive
Role of finance	Secondary role	Key role
Management logic	KPI-oriented	Economically rational
Human factor	Minimized	Integrated
Time response	Periodic	Real-time
Adaptation	Limited	Self-learning

The author's view is that, unlike traditional production management systems, where decisions are mainly based on historical data (ex-post analysis), the adaptive-cognitive loop proposed in the SDAC model implements a management logic focused on proactively responding to potential deviations and risks.

The key scientific advantage of the model is the minimization of information entropy in the management decision-making process. By combining predictive modeling and financial verification:

- uncertainty regarding the future states of the production system is reduced;
- the transparency of the cause-and-effect relationships between technological parameters and financial results is improved;
- transition from reactive to adaptive and predictive management is ensured.

The SDAC model offers several advantages. First, it complements and extends the cognitive loop of smart analysis, creating a formalized adaptive loop, in which a management decision is viewed as the result of integrating data, forecasts, and economic rationality within a dynamic production environment. Second, it reflects the logic of adaptive control of a production system under conditions of high uncertainty and dynamic external changes. Third, it demonstrates high relevance in a BANI environment (Brittle, Anxious, Non-linear, Incomprehensible), which requires a shift toward adaptive leadership and flexible strategic architectures capable of functioning under conditions of nonlinear dynamics and high uncertainty (Uhl-Bien & Arena, 2018). The above is consistent with the methodological approaches of chaos theory (Kozenkova et al., 2025), which takes into account nonlinear interactions and sensitivity to initial conditions in the generation of early warning signals and in scenario-based modeling of crisis situations.

From the standpoint of complex systems theory and an organization's dynamic capabilities, a key prerequisite for effective management in a BANI environment is the ability to identify weak signals in a timely manner, adapt management decisions, and transform informational complexity into economically interpretable results (Teece et al., 1997). Within the framework of SDAC, the logic behind neutralizing the key characteristics of the BANI environment is summarized in Table 2.

Table 2. Mechanisms for neutralizing the characteristics of the BANI environment in the SDAC model.

BANI characteristics	Neutralization mechanism in the SDAC model
Brittle	Early detection of subtle signs of degradation in production systems based on real-time IoT data and predictive analytics (Ayvaz & Alpay, 2021; Zhang et al., 2020; Yu et al., 2022), which is consistent with approaches to management in complex adaptive systems (Taleb, 2012)
Non-linear	Use of scenario-based and predictive modeling to account for threshold effects, feedback loops, and cascading changes, as confirmed by research in the fields of nonlinear dynamics and risk-based decision making (Sterman, 2020; Turgay & Aydin, 2025)
Incomprehensible	Transformation of complex stochastic and technical data into financially interpretable metrics (NPV, EVA, NV), consistent with modern approaches to value-based management and decision analytics (Moholkar & Choudhari, 2024; Lassi et al., 2024; Saidov, 2025)

Thus, SDAC serves not only as a technological platform but also as a methodological tool for complexity management, through combining principles of information theory, concepts of dynamic capabilities, and finance-oriented management. This reduces systemic fragility and enhances the economic resilience of production systems in the BANI environment, where uncertainty and nonlinearity become not only sources of risk but also opportunities for creating added value.

After the cognitive loop of smart analytics has been examined as a tool for the cyclical alignment of data, models, and management actions in production systems, the next logical step is to move on to evaluating the quality and reliability of the management decisions themselves. At this point, the concept of information entropy comes to the fore, which is a key metric of uncertainty that allows a quantitative assessment of the degree of chaos, incompleteness, or redundancy in the information upon which decisions are based. While the cognitive loop provides the structure of the process, information entropy serves as its "thermometer"– it indicates the extent to which the data obtained can be used to develop well-grounded, consistent, and effective management strategies.

In the context of production system management, information entropy characterizes the level of uncertainty with regard to possible system states and the outcomes of management decisions, and is calculated using Shannon's classic formula (Cover & Thomas, 2006). To formalize this, the entropy model will be used, which allows assessing the level of uncertainty in the managerial decision-making system. The information entropy of the system is determined by (3):

$$H = -\sum_{i=1}^{n} p_i log p_i \ , \qquad (3)$$

where: p_i is the probability of the i-th state occurring in the production system.

The use of smart analytics tools as part of the Smart Decision Analytics Center (SDAC) architecture enables the updating of probability distributions for system states based on production data streams, predictive models, and financial and analytical assessments:

$$p_i^{SDAS} = f(D_{IoT}, M_{pred,} F_{eval}), \qquad (4)$$

where: D_{IoT} is data from sensor systems and production monitoring; M_{pred} is predictive analytics models; F_{eval} is financial and analytical mechanisms for assessing management decisions.

Reducing the information entropy of the management system contributes to improving the economic efficiency of the enterprise's operations. Within the framework of a value-oriented approach, this effect can be reflected through a change in the economic value-added indicator (5):

$$\Delta EVA = a * \Delta H, \qquad (5)$$

where: ΔEVA is the change (increase) in Economic Value Added; α is the sensitivity coefficient (or impact coefficient); ΔH is the change in weighted average cost of capital.

The calculation of economic value added is performed using the classical value-based management model (6):

$$EVA = NOPAT - WACC * IC \qquad (6)$$

where: NOPAT is net operating profit after tax; WACC is the weighted average cost of capital; IC is the enterprise's invested

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capital.

Thus, the integrated efficiency of using smart analytics tools in the SDAC system can be represented as a generalized function (7):

$$SDAC = \gamma_1 \Delta H + \gamma_2 EVA, \tag{7}$$

where: λ1 and λ2 are weighting coefficients that reflect the effect of the informational and economic components on the overall efficiency of the system.

The proposed model allows for a quantitative assessment of the impact of smart analytics systems on the effectiveness of production process management and formation of the enterprise's economic value. To comprehensively assess the impact of smart analytics systems on the development of a manufacturing enterprise, it is advisable to consider not only economic outcomes but also the environmental and social indicators of the system's performance.

The integrated model for assessing the sustainability of a production system is presented in the form of an integrated index. The integrated sustainability index of a production system can be expressed as a weighted function (8):

$$SI = w_1 EVA - w_2 EC - w_3 CO_2 + w_4 LP, \tag{8}$$

where: SI is the integrated sustainability index of the production system; EVA is the enterprise's economic value added; EC is energy consumption per unit of output; CO_2 is carbon emissions intensity; LP is labor productivity; w_1, w_2, w_3, w_4 are the weighting coefficients of the respective indicators.

In this model, the economic component shows the financial efficiency of production activities, the environmental component reflects the level of resource efficiency and environmental impact, and the social component shows the effectiveness of the use of labor resources.

Given the sustainable development index obtained, the overall performance of the SDAC system can be expressed as:

$$SDAC_{eff} = \gamma_1 \Delta H + \gamma_2 SI, \tag{9}$$

where: ΔH is the decrease in the information entropy of the management system; SI is the integrated sustainable development index; λ1, λ2 are the weighting coefficients for the influence of the information and sustainable development components.

Thus, the proposed model makes it possible to assess the effectiveness of using smart analytics tools not only in terms of economic performance but also in the context of achieving the sustainability goals of industrial enterprises.

The proposed mathematical framework makes it possible to formalize the impact of smart analytics tools on the effectiveness of production system management. Reducing information entropy in the management decision-making system means reducing uncertainty regarding the possible states of the production process, which enhances the soundness of management decisions.

Within the SDAC architecture, this transformation is achieved through the integration of production data streams, predictive analytics tools, and financial and economic mechanisms for evaluating management alternatives. As a result, a more accurate probability distribution of the possible states of the production system is obtained, which directly contributes to a reduction in management information entropy.

Reducing information uncertainty creates the conditions for improving the economic performance of the enterprise. Within the framework of a value-oriented approach, this effect manifests itself through an increase in the economic value-added indicator. Thus, the use of smart analytics systems contributes to increasing the efficiency of production resource management, optimizing operating costs, and improving the financial results of the enterprise.

At the same time, today's approaches to evaluating the performance of industrial enterprises take into account not only economic results but also the environmental and social aspects of development. In this context, the proposed model integrates indicators of economic efficiency, resource efficiency, and effectiveness of the use of labor potential.

The use of an integrated sustainability index makes it possible to assess the impact of management decisions on the formation of an enterprise's economic value, the reduction of the production resource intensity, and an increase in labor productivity. This approach provides a more comprehensive assessment of the performance of the production system and is consistent with modern concepts of sustainable industrial development.

Thus, the use of the SDAC system creates the conditions for improving both the economic efficiency and the overall resilience of production systems in the face of high external uncertainty.

Due to the high dispersion of the system's state probabilities and delays in the feedback loop, $E_{cost,t}^{Ex-post}$ remains significantly limited, which leads to an underestimation of the overall economic value of the management cycle. In the SDAC model, on the contrary, thanks to proactive shaping of the information environment, reducing entropy and increasing the accuracy of forecasts, a significant improvement in both expected effects and resource efficiency is achieved. This is formalized as a strict relationship: $NV_{smart} > NV_{trad}$, which not only states the economic advantage of adaptive Ex-ante management, but also quantitatively confirms the hypothesis that information rationality is a source of added value creation in complex production systems. Thus, a comparative analysis shows that the shift from reactive to intelligent management has not only methodological but also measurable financial justification.

The proposed set of formulas makes a significant contribution to the development of the theory and methodology of smart management, establishing a rigorous quantitative link between the principles of information theory and financial performance. First, it introduces a new metric for the smart component of decision-making, i.e., the Net Value of Smart Decisions (NV_{smart}), which quantifies the economic value created through the reduction of information entropy and proactive adaptation. Second, the framework formalizes the causal impact of smart analytics on financial performance, moving from general considerations to a parametric model based on discounted cash flow theory and information entropy. Third, the proposed model integrates three previously loosely connected fields of knowledge: information theory, financial analysis, and systems management – to achieve sustainability goals, which provides a foundation for interdisciplinary research into complex production systems. Fourth, thanks to its clear operational structure and measurable variables, the model is empirically validated and can be tested in real-world industrial settings. Thus, the integration of cognitive, informational, and economic dimensions facilitates the transition to a scientifically grounded, data-driven approach to smart management in complex socio-technical systems.

The relationship between a decrease in information entropy and an increase in financial performance can also be visualized. Figure 2 shows a hypothetical (or model) relationship illustrating how each additional percentage point of reduction in uncertainty (entropy *H*) achieved through the use of smart analytics correlates with an increase in the net present value (*NPV*) or economic value added (*EVA*) of the project.

The figure presents model-based scenarios (ex-post management, partial SDAC, and full SDAC) and is used to visualize the economic logic of value creation through smart analytics rather than to report empirical point estimates. These data are of a modeling nature and serve to provide a conceptual illustration of the impact of a reduction in information entropy on an enterprise's financial performance. A direct positive correlation has been identified between the extent to which information uncertainty is reduced through the use of smart analytics tools and the increase in the economic efficiency of the production system. The findings confirm the study's hypothesis that investment in smart analytics systems, which are designed to minimise uncertainty, is strategically sound and generates significant economic value added. The graph therefore illustrates the logic behind value creation through smart analytics within the proposed model, rather than empirical point estimates.

The empirical validation of the proposed adaptive smart analysis model was carried out using the case study method, with analytical generalization based on the example of a representative metallurgical enterprise located in one of the industrial centres of eastern Ukraine. The selected enterprise is a typical representative of the industry, as it carries out the full production cycle (from raw material processing to the manufacture of finished products) and operates in an environment of heightened macroeconomic and operational uncertainty characteristic of many industrial enterprises in Ukraine; it could therefore serve as a prototype model or a model for testing the results of the theoretical research.

The following assumptions were made for the purposes of this study: the production system is capital-intensive and energy-intensive; a significant proportion of operating costs is attributable to unplanned equipment downtime and high levels of defects; management decisions are traditionally based on ex-post analysis of retrospective data; the enterprise operates under conditions of limited access to financial, material, and human resources, in an unstable regulatory and market environment.

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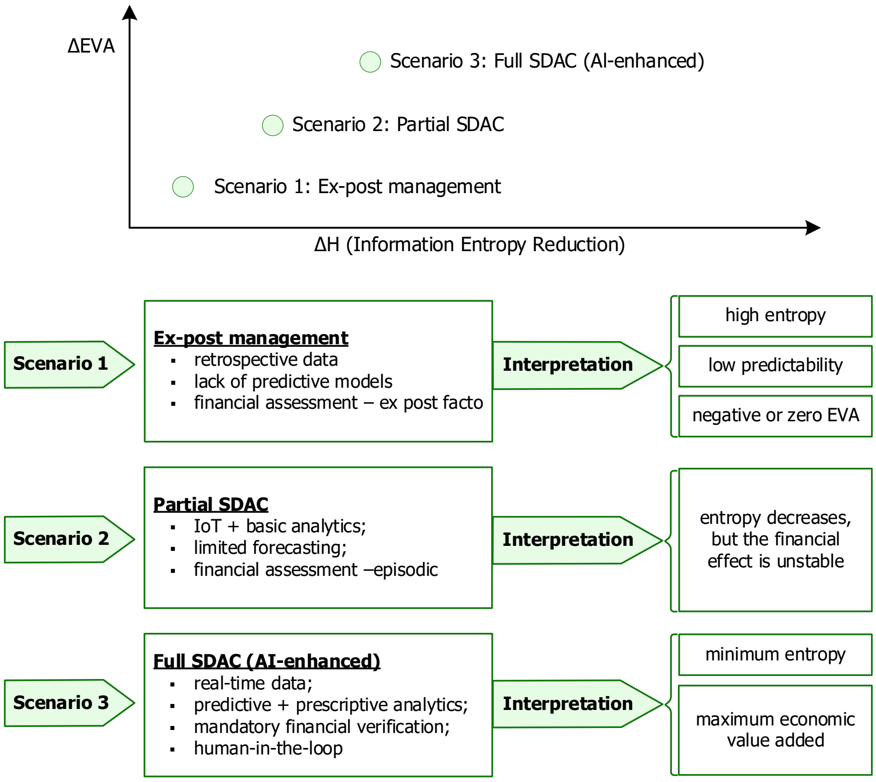

Figure 2. A scenario-based approach to determining the relationship between changes in information entropy (*ΔH*) and changes in economic value added (*ΔEVA*) under different management approaches. Note: The figure illustrates model-based scenarios (ex-post, partial SDAC, and full SDAC) rather than empirical point estimates and is used to visualize the economic logic of value creation through smart analytics

The numerical parameters used in the calculations are model-based but representative: they reflect the average industry-wide structure of costs, revenues, and operational characteristics of full-cycle metallurgical enterprises. The data do not contain confidential financial statements of any specific enterprise and do not violate trade secret requirements.

A three-year planning horizon (n = 3 years) was used to assess the economic effectiveness of implementing smart analytics. The discount rate was set at r = 18%, taking into account both industry-specific risks (business cycles, energy dependence) and macroeconomic instability. The high discount rate was due to significant military and macroeconomic risks.

Investment parameters: the initial capital expenditure for implementing the SDAC architecture to ensure the sustainability of the production system amounts to ($Cinv$) UAH 12.0 million; annual operating expenses for maintaining smart analytics systems ($Coper$) amount to UAH 1.5 million per year.

Expected economic benefits: annual cost savings resulting from reduced downtime, fewer defects, and sustainable resource use ($E_{cost,t}$) are estimated at UAH 8.0 million per year; additional revenue from improved operational efficiency (ΔR_t) is estimated at UAH 4.0 million per year.

The projected total annual effect ($E_{total,t}$) is UAH 12 million, and the net value of the smart analytics solution (NV_{smart}) is UAH 9.6 million.

A positive NV_{smart} score confirms the economic viability of investing in smart analytics to achieve sustainable development goals, even in the face of high uncertainty and limited resources.

One of the most important areas in the mitigation of adverse climate change and promotion of sustainable development is investment in decarbonization. These solutions are designed to reduce carbon dioxide emissions by transitioning to renewable energy sources and improving the energy efficiency of production operations. Achieving the set goals is possible through the exchange of knowledge and experience, technological support, and investment in projects that will help reduce dependence on fossil fuels (Ivanova, 2025).

The investment parameters and expected benefits of implementing the SDAC architecture are determined by structuring the costs of the investment and operational components, which are summarized in Table 3.

Table 3. Investment parameters and expected benefits of implementing the SDAC architecture, UAH million. Note: The expenses are classified as investment in the enterprise's intellectual capital aimed at improving the adaptability of management processes.

Parameter	Value	Description
Cinv (initial capital expenditure)	12.0	Investment in the deployment of IoT infrastructure, smart analytics platforms, data integration, and staff training
Coper (annual operating expenses)	1.5	Costs for system support, model updates, maintenance, and development of smart analytics competencies

The expected economic effect, linked to the Sustainable Development Goals, is projected to result from the implementation of the SDAC system. This is a generated comprehensive effect that should be structured according to the three dimensions of sustainable development (ESG) (Table 4).

Table 4. Expected economic effect of implementing SDAC architecture for sustainable development goals, UAH million.

Sustainability metrics	Effect	Mechanism for achieving	Link to the Sustainable Development Goals
Economic	Annual cost savings (Ecost,t) = 8.0	Optimize equipment operating modes, prevent unplanned downtime, and reduce defects	Improving production resource efficiency
Economic	Additional annual income (ΔRt) = 4.0	Faster decision-making, improved product quality, and increased competitiveness	Sustainable productivity growth
Environmental	Reduced energy consumption per unit of product	Accurate load forecasting, adaptive management of energy flows	Reducing resource intensity
Environmental	Reduced CO_2 emissions	Optimize manufacturing processes, minimize overproduction and waste	Reducing the carbon footprint
Social	Increased labor productivity	Automate routine tasks, support decision-making, reduce cognitive load	Creating conditions for quality work and professional development

An integrated assessment of economic feasibility is based on the net value of the smart analytics solution (NV_{smart}) and is calculated using equation (10):

$$NV_{smart} = \sum_{t=1}^{n} \frac{E_{cost,t}+\Delta R_t}{(1+r)^t} - (C_{inv} + \sum_{t=1}^{n} \frac{C_{oper}}{(1+r)^t}, \quad (10)$$

The calculation results showed that the total discounted effect amounts to UAH 26.10 million; total costs (capital and operating) amount to UAH 16.5 million; NV_{smart} = UAH 9.6 million.

The positive NV_{smart} value confirms the economic viability of investing in smart analytics, even in conditions of high uncertainty. This creates a synergistic effect: financial performance (growth in EVA) is achieved not through the extensive use of resources, but by improving the intellectual quality of management decisions, which is consistent with the paradigm of sustainable development.

When determining quantitative results, we recommend adhering to the concept of decoupling, which reduces the dependence of economic growth on the amount of raw materials and energy consumed, as well as on environmental impact. According to (Tiutchenko S., 2024), an enterprise's economic capacity for growth requires a simultaneous combination of economic, social, and environmental development. The authors recommend assessing this indicator using a three-component decoupling index, which should combine measures of financial, social, and environmental decoupling.

To assess the impact of smart analytics tools on the enterprise's performance, a scenario analysis of the production system's development was conducted. The resulting values for key economic, environmental, and social indicators are presented in Table 5.

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Table 5. Comparative assessment of the economic, environmental, and social indicators of the production system's performance under various scenarios of development.

Indicator	Scenario 1: Ex-post management	Scenario 2: Partial SDAC	Scenario 3: Full SDAC (AI-enhanced)
Economic indicators			
Production cost, UAH/ton	18 400	17 600	16 900
Operating costs, UAH million /year	220	210	202
Additional revenue, UAH million /year	–	2.0	4.0
Net operating profit after tax (NOPAT), UAH million	42	48	55
Economic value added (EVA), UAH million	–6	–1	+5
Equipment downtime, %	14.5	11.2	8.2
Environmental indicators			
Defect rate, %	5.8	4.6	3.6
Energy consumption per unit, kWh/ton	500	450	400
Carbon emission intensity, kg CO2/ton	250	220	190
Social indicators			
Labor productivity, tons/employee	100	115	130
Dominant management logic	Reactive (Ex-post)	Hybrid (Predictive + selective financial verification)	Proactive (Ex-ante SDAC)

The results of the scenario analysis indicate that the integration of smart analytics tools into production management has a significant positive impact on the enterprise's performance. With the increasing use of analytics tools, there is a decrease in equipment downtime and production defects, indicating improved efficiency in the management of production operations.

Simultaneously, the enterprise's operating expenses are being reduced, and its financial performance is improving. This is reflected in the change in the economic value-added indicator. While the enterprise reports a negative EVA in the baseline scenario, the full-scale implementation of the SDAC system results in the generation of positive economic value added.

Another important outcome is the improvement of the environmental performance of the production system. Among other things, the implementation of smart analytics tools helps reduce energy consumption per unit of output and lower carbon intensity. This is due to the ability to more accurately predict production parameters and optimize equipment operating modes. Furthermore, there is an increase in employee productivity at the enterprise, which is attributed to a reduction in unproductive time losses and a more efficient use of production resources.

Thus, the results of the analysis confirm that the implementation of the SDAC architecture contributes to improving the economic efficiency of the enterprise's operations and, at the same time, creates the conditions necessary for ensuring the sustainable development of production systems.

The results obtained confirm the relevance of using smart analytics systems as a tool for improving the economic efficiency and environmental performance of industrial enterprises.

Scenario 1 represents a traditional ex-post management approach based on retrospective data analysis. Scenario 2 describes a partial implementation of the SDAC adaptive cycle, characterized by the use of IoT data and predictive analytics, with episodic financial validation of management decisions. Scenario 3 involves the full deployment of SDAC, including real-time data integration, AI-powered predictive and prescriptive analytics, and mandatory financial validation of decisions.

The results obtained demonstrate that smart analytics based on the SDAC adaptive cycle provides a significant reduction in information uncertainty in the process of making management decisions; it also offers transformation of information gain (ΔH) into financial value added (EVA), increased operational and financial resilience of the production system in the face of external shocks, and paradigmatic transition from reactive (ex-post) to proactive (ex-ante) management. Empirical testing confirms the universality and scalability of the proposed approach. The model is not tied to the specifics of an individual enterprise and can be applied to a wide class of industrial systems operating in conditions of high complexity and dynamic uncertainty to help enterprises achieve sustainability goals.

DISCUSSION

The research proved that the use of smart analytics tools allows for effective management decisions concerning the sustainability of an enterprise's production process and its achievement of sustainable development goals. However, it should be noted that the application of this integrated analytical mechanism is not confined to the processing of large-scale datasets and the use of smart analytics for managerial decision-making. Chinnathai (2023) notes that for process management, it is advisable to use tools such as Disco for process analysis, Matlab SimEvent for discrete-event modeling, artificial intelligence in Matlab for energy consumption forecasting, and Grafana and e-KPI dashboards for process visualization. The scientist proved that structuring the digital lifecycle helps enterprises implement sustainable smart production by optimizing the flow of energy-intensive processes. The SDAC model proposed in this study mitigates the main negative characteristics of the BANI world and is a complexity management tool that combines information theory, the concept of dynamic capabilities, and financial management.

We support the findings of Lin (2024), who noted that it is advisable to integrate the UNISONE framework, which is based on the principles of the circular supply chain (CSC), with advanced smart manufacturing technologies. The practical outcome is improved operational efficiency and the creation of a sustainable production system that significantly minimizes waste.

According to Pansare (2023), different practices of reconfigurable manufacturing systems (RMS) have different weights in achieving the United Nations' Sustainable Development Goals (SDGs). The author proposed to determine these weights using the Step-wise Weight Assessment Ratio Analysis (SWARA), while the Weighted Aggregated Sum Product Assessment (WASPAS) was used to determine the priority of performance indicators. The resilience of the developed structure was tested using sensitivity analysis in five different organizations, which proves the high practical significance of this study.

A study by Magableh (2024) used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The authors proved the most effective role of information systems in supporting smart analytics business in such economic sectors as urban planning and development, tourism, supply chains, integrated manufacturing and Industry 4.0, business and commerce, and healthcare. Among the types of information systems to support sustainable development, the authors distinguish Transaction Processing System (TPS), Office Automation System (OAS), Knowledge Work System (KWS), Management Information System (MIS), Decision Support System (DSS), and Executive Support System (ESS). These results prove that support for management decisions regarding production management can be provided by a much wider range of information systems.

Batwara's (2023) view on the use of Value Stream Mapping (VSM) as a standard Lean tool for identifying and reducing waste is worth discussing. Applying the PRISMA methodological approach, as did Magableh (2024), the author proved that the manufacturing sector consumes a significant amount of non-renewable resources and generates waste, which raises concerns about the sector's ability to respond to sustainable development challenges. The second most important sector is business, management, and accounting. Particularly important for this study is the result related to the categorization of tools. All tools and methods used to eliminate waste and improve the process in VSM have been classified into four categories: Lean Too (TAKT time, Pull system (Kanban), Supermarket, 5S, Kaizen, Single minute exchange of die (SMED), Poka-yoke, Cellular manufacturing, Total productive maintenance, Just in time, 5 Whys, Continuous improvement, Heijunka box), green tool (Life Cycle Assessment (LCA), life cycle cost analysis (LCCA), Quality function deployment (QFD)), digital tool (RFID, Radio Frequency Identification, virtual reality to facilitate waste identification and disposal in a dynamic environment) and a management tool (engagement in business processes and training). Of particular importance for this study is the result obtained by A. Batwaraa (2023) regarding the definition of categories of analytical indicators that can be used in mapping the current and future state of enterprises. The author identified the following analytical indicators: value added time (VAT), material consumption, energy consumption, steam consumption, carbon emissions, greenhouse gas emissions, cost analysis, employee satisfaction assessment, and level of digitalization. These findings can be used in the process of selecting production system indicators before and after the implementation of the SDAC model (see Table 3).

A limitation of this study is the use of data from a single metallurgical enterprise, which limits the possibility of direct extrapolation of the results to other industries. In addition, the model is based on the assumption of a certain distribution of random variables, which in conditions of extreme military uncertainty requires further verification using larger data samples and taking into account nonlinear effects ("black swans"), which can significantly affect the sustainability of production systems.

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CONCLUSIONS

The article proposes solving a relevant scientific and applied problem of ensuring sustainable development of an enterprise when making management decisions by using smart analytics tools in managing the enterprise's production systems. The article addresses a relevant scientific and practical challenge of ensuring the sustainable development of an enterprise through management decision-making with the use of smart analytics tools for the enterprise's production management.

A conceptual SDAC (Smart Data Adaptive Cycle) model has been developed to integrate the principles of information theory and value-based management (VBM) into a single adaptive cycle. It has been proven that the use of entropy analysis allows formalizing the uncertainty of the production environment (BANI context), providing a quantitative assessment of risks at the decision-making stage (ex-ante), which is much more effective than traditional retrospective methods.

The proactive management toolkit has been mathematically substantiated. Empirical modeling has shown that integration of smart analytics into the production management structure allows maximizing the EVA indicator. The estimated intellectual value of the management solution (NPV_{smart}) for the tested enterprise is UAH 9.6 million, which confirms the financial feasibility of implementing smart analytics tools even in conditions of high market volatility.

The role of smart analytics as a driver of sustainable development has been identified.

The basis for the strategic transformation of the industry has been formed.

Practical testing on the example of a metallurgical enterprise demonstrated the model's ability to reduce equipment downtime to 8.2%, the defect rate to 3.6%, and carbon emissions intensity to 190 kg CO_2/t, simultaneously increasing labor productivity. This allows enterprises to move from reactive crisis management to strategic planning focused on long-term viability and socio-economic responsibility.

Prospects for further research include scaling the proposed SDAC model to enterprises in other sectors of the economy and integrating it into the system of methods for assessing nonlinear extreme events (black swan events). It is advisable to develop methods for dynamic entropy analysis, which will increase the adaptability of industrial systems to global macroeconomic shocks.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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ІНСТРУМЕНТИ СМАРТАНАЛІЗУ ПІДТРИМКИ УПРАВЛІНСЬКИХ РІШЕНЬ У ЦАРИНІ УПРАВЛІННЯ ВИРОБНИЧИМИ СИСТЕМАМИ ПІДПРИЄМСТВА В КОНТЕКСТІ СТАЛОГО РОЗВИТКУ

У статті обґрунтовано зростання значущості розумної аналітики як технічного інструмента й фундаментального інтелектуального активу, що забезпечує сталий розвиток, стійкість і конкурентоспроможність підприємств в умовах цифрової трансформації. Розглянуто модель Smart Data Adaptive Cycle (SDAC), яка пропонує безперервний замкнений процес ухвалення управлінських рішень у цифровому виробничому середовищі. Модель інтегрує інформаційні, фінансові та когнітивні компоненти, використовуючи самонавчальні механізми та принцип «людина в циклі». Мета роботи полягає в дослідженні особливостей забезпечення сталого розвитку підприємства через управлінське ухвалення рішень із використанням інструментів розумної аналітики в управлінні виробничими системами. У дослідженні застосовано загальні та спеціалізовані методи, зокрема сценарний підхід для визначення взаємозв'язку між інформаційною ентропією та економічною доданою вартістю (EVA), кейс-стаді для емпіричної валідації моделі SDAC на металургійному підприємстві, методи дисконтування для оцінки економічної доцільності, а також системний підхід до побудови концептуальної моделі. Проведено порівняльний сценарний аналіз моделей ex-post, часткового та повного SDAC. Основні результати показують, що модель SDAC інтегрує принципи теорії інформації та управління на основі цінностей (VBM) у єдиний адаптивний цикл. Отримані результати свідчать, що ентропійний аналіз дозволяє формалізувати невизначеність у виробничому середовищі (BANI-контекст), забезпечуючи кількісну оцінку ризиків на етапі ухвалення рішень (ex-ante), що є ефективнішим за традиційні ретроспективні підходи. Емпіричне моделювання підтверджує, що інтеграція розумної аналітики в управління виробництвом забезпечує максимізацію EVA. Практичне випробування на металургійному підприємстві продемонструвало здатність моделі знижувати простої обладнання до 8,2%, рівень дефектів до 3,6% і викиди CO_2 до 190 кг/т при одночасному підвищенні продуктивності праці. Висновки підтверджують ефективність моделі SDAC як інструмента підвищення якості управлінських рішень і забезпечення сталого розвитку підприємств. Перспективи подальших досліджень передбачають масштабування моделі на інші сектори та інтеграцію її в підходи до оцінювання нелінійних екстремальних подій (подій типу «чорний лебідь»).

Ключові слова: стратегічний менеджмент, цифрова трансформація, бізнес-аналітика, Industry 4.0, ефективність діяльності, інноваційні технології, смартекономіка, управління виробничими системами, ESG-показники, конкурентоспроможність

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