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A KPI-ALIGNED ADAPTIVE AI–INFORMATION SYSTEM ARCHITECTURE FOR ENTERPRISE DECISION SUPPORT

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ABSTRACT

Enterprise AI projects tend to be loosely coupled with enterprise information systems and business key performance indicators (KPIs) and affect individual analytical tasks. This study tackles this enterprise decision support IT design problem by creating an adaptive AI–information system architecture aligned with the corresponding KPIs. Following the design-science research (DSR) approach, information-systems, AI-capability, AI-governance, and machine-learning-lifecycle literature was used to define the requirements, which are then instantiated in three interacting layers: 1) data integration, 2) analytics and optimization, and 3) KPI feedback and governance. Ex ante evaluation of the artifact was done in five cross-industry process scenarios: forecasting, allocating resources, decision latency, financial utility, and adaptation stability. The numbers given are normalization of scenario outputs and not the treatment effects of the companies involved. This evaluation reveals that the important value of the architecture lies in the end-to-end traceability of data, model output, optimizations and deviations in KPIs. The scenarios predict gains for the accuracy of forecasting of approximately 15–18%, reduction in time for decision making of up to 30%, and resource efficiencies of around 10–15% under the stated assumptions, but these gains diminish when the quality, interoperability and governance requirements for the data are not met. The IT research contribution is a reusable reference architecture and feedback-control logic to transform the disjointed AI applications into an auditable enterprise decision-support lifecycle. Practical implications are staged integration with ERP/CRM and supply-chain systems, human approval gates and ongoing drift, security and unintended KPI checks.

Keywords: *Artificial Intelligence; Enterprise Information Systems; Decision Support; Design Science; Adaptive Architecture; KPI Alignment*

1. INTRODUCTION

The digital economy of today is very dynamical, technologically changing, and business processes are increasingly becoming complex. Under these circumstances, the traditional management methods are proving to be inadequate in guaranteeing sustainable development and competitiveness of organizations. The increasing amounts of data, the necessity of making decisions in real time, and the growing uncertainty of the external environments demand radically new ways of managing business systems [1], [2]. Information systems (IS) are at the center of this transformation as they provide the infrastructure of data collection, storage, processing and visualization. Simultaneously, the introduction of the idea of artificial intelligence (AI) into the corporate information system considerably broadens its analytical and predictive opportunities. Artificial intelligence technologies allow to automate routine processes, to create forecasting models, and to optimize the distribution of resources, thus enhancing the quality and speed of the managerial decision-making process [3], [4].

In the last ten years, the contribution of artificial intelligence to the digital business model has grown by a significant margin. The use of machine learning, data analytics and intelligent decision-support systems is quickly becoming a tool that organizations use to enhance their operational efficiency and customer interaction [5]. However, the adoption of AI in the business environment has been extremely ad hoc and in the majority of instances, disjointed. Most often, intelligent algorithms are implemented as independent applications in specific departments, not being integrated into the overall system of corporate information systems. This has brought about a critical contradiction between the technological possibilities of artificial intelligence and its practical application in the business processes. Even though AI systems can be employed to process a large volume of data and make accurate forecasts, organizations do not necessarily have mechanisms to align these capabilities with strategic objectives. This means that the investments in AI technologies do not necessarily lead to the corresponding improvements in the business performance or its ability to be innovative or efficient in its management [6]. Another important challenge is related to the lack of methodological approaches that ensure the coordination between AI algorithms and business model parameters. The literature used is rather fragmented, as it concerns only one aspect of digital transformation, either automation, data analytics or process optimization, and lacks a systematic structure, which unites technological capabilities and strategic management goals [7], [8]. Furthermore, most solutions do not contain the concept of ongoing adjustment of AI models in evolving circumstances, where hard-boiled analytical solutions become obsolete within a short time frame. This is a major limitation that is especially noticeable in organizations where information systems serve as disjointed analytical platforms as opposed to unified decision-making platforms. In this scenario, artificial intelligence is utilized to localize a certain optimization but without affecting the general framework of the digital business model. As a result, companies have found themselves in a scenario where technological progress is rapidly exceeding the organizational preparedness which in turn results in inefficiencies in the allocation of resources and lack of transparency of processes [9]. Enterprise information systems more and more contain machine-learning and optimization elements, but in many cases, they are only being used as single departmental applications. Technical fragmentation causes a traceability issue - it is not possible to reliably relate the data used in the inputs, the models used for the outputs, operational decisions made, and changes to the strategic and operational KPIs. Existing literature provides an understanding of the concept of digital transformation [1-3], AI capability [4 -6], organizational readiness [7-9] and individual analytical applications; however, this literature lacks insight into how these components should be combined in an adaptive enterprise information-system architecture. The IT research challenge is then how to create an integrated and auditable continuously adaptable architecture that transforms AI outputs into business goals without equating "accuracy of the algorithm" with the "value of the organization. How can an enterprise information system be architected so that AI-based prediction, constrained optimization, and adaptive feedback remain traceably aligned with business KPIs under changing operating conditions? The study is concerned with this question, and has five objectives:

1. To identify technical and organizational needs to connect AI modules with the enterprise information systems.
2. Help design a multi-layered architecture that connects data integration, analytics and optimization, and KPI feedback and governance.
3. To develop the architecture using explicit process mappings, constraints and evaluation metrics.
4. To demonstrate the artifact in cross-industry scenarios on forecast quality, resource-efficiency, decision latency, financial utility and adaptation stability.
5. To identify unexpected results, limitations and practical controls for current enterprise environments that could be relevant during deployment.

The main contribution is not a new algorithm for making predictions but an information-systems artefact. The proposed architecture is a formalization of three common connections that are not typically captured: the connection between heterogeneous enterprise data and AI modules, the connection between the analytical output and the restricted operational decisions and the connection between KPI deviations and AI model recalibration. This architecture facilitates auditability of the decision-support lifecycle and defines where human approval, data-quality checks, security controls and monitoring rules of the model need to be implemented. The coverage of evidence is intentionally limited. The numerical analysis is an ex-ante scenario-simulation analysis of the named artifact and is not causal nor does it constitute evidence for the performance effects of the named companies. The results are thus viewed as outputs of a conditional model, as it is based on certain assumptions. Such a distinction makes the research design support the evidence available and gives a good guideline to assess the usefulness and limitations of the proposed architecture.

2. LITERATURE REVIEW

The fast innovation of artificial intelligence (AI) technologies has dramatically changed the way corporate information systems work, and the design of digital business models. In the contemporary businesses, information systems serve as an integrated platform of data collection, data processing and data analysis to make an intentional decision, which the artificial intelligence improves by allowing predictive analytics, pattern recognition and optimization of business processes [1], [2]. The collaboration of the AI and information systems is nowadays regarded as one of the primary sources of the digital transformation and organizational innovation. There is a significant literature that dwells on the use of AI in particular spheres of business, including demand forecasting, financial risk assessment, customer segmentation, and supply chain optimization [3] - [5]. These works prove that machine learning and data-driven models can greatly enhance the accuracy of forecasting and efficiency of the operations. But the majority of current strategies are confined to functional-level optimization and do not guarantee systemic integration in the overall structure of corporate information systems. The level of integration between different subsystems, including production, logistics, finance and marketing [6-7], is crucial to the success of digital business models. The concept of one information space underlines the necessity to sustain a steady flow of data and analytics in real-time. Research indicates that the performance of AI-based systems is based on the degree of digital maturity, the quality of information and the capabilities of staff [8], [9]. In most instances, AI is applied as an independent analytical tool but not as a part of a single management tool. Methodologically speaking, the earlier studies provide numerous approaches to analysis, such as regression analysis, stochastic modelling, and optimization techniques [10], [11]. Such techniques are useful in solving particular, such as forecasting or resource allocation, but they are hardly integrated into a single framework that relates analytical outputs with strategic business objectives and key performance indicators. The majority of the studies measure the effect of AI by independent indicators of accuracy, cost reduction, or return on investment and do not investigate the relationship between these variables in dynamic business conditions [12]. This decreases the effectiveness of AI implementation in the long-term and limits its potential in supporting the innovation processes [13]. Moreover, the application of AI presents ethical and regulatory issues, such as the privacy of data, algorithm transparency, and automated decision-making responsibility [14]. The mentioned issues have not only a technological implementation impact, but also the degree of trust that information systems hold and user acceptability. According to the literature analysis, it can be concluded that there is a clear research gap connected with the lack of integrated and adaptive models that integrate artificial intelligence, information systems and business performance indicators in a single framework. In particular, existing studies lack:

– integrated architectures are the connection between AI modules and information systems;
– mechanisms to align the output of the analysis to strategic purpose;
– adaptive feedback mechanisms to continually improve the model;
– wide-ranged assessment models of AI performance in online business settings.

To overcome these shortcomings, this paper suggests an AI-powered information systems model that incorporates regression analysis, optimization, and adaptive feedback mechanisms. The model is created in such a way that it makes sure that there is constant alignment between AI capabilities and key performance indicators, so that the core of innovation and enhance the effectiveness of digital business models can be achieved. Machine learning models have always demonstrated better performance than the traditional statistical models in predictive tasks, especially in demand forecasting and financial analysis [3], [5]. However, the literature usually considers forecasting to be a fundamentally algorithmic issue, with an inadequate focus on the integration of data and system-wide coordination. Therefore, they assume that the improvement of forecasting accuracy of algorithms and consistency of systemic data is the synthesis of the predictive power of algorithms, as well as consistency of systemic data.

H1: Introducing artificial intelligence in business information systems will improve accuracy of forecasts in digital business settings. Operational efficiency and resources allocation is another key area of digital business performance. The optimization methods including the linear and nonlinear programming have been long employed in improving resource management and minimizing costs [10], [11]. Nevertheless, these approaches are normally applied to static settings or as individual decision-support systems. The proposed solution presupposes a dynamic combination of optimization models and AI-driven analytics, which will allow allocating resources to be continuously adjusted, according to the real-time data.

H2: The application of the optimization process to the information systems based on AI can improve operational performance and resource allocation. Although artificial intelligence can greatly speed up the data processing and analysis procedures [2], [4], the entire decision-making process is often limited by the organizational structure and fragmented information systems. Integrating AI into the very fabric of corporate information systems is likely to shorten the overall decision-making process as analytical outputs will be immediately available to be used by managers. This minimizes the time lag between the data acquisition, analysis and action, and thus increases responsiveness.

H3: AI-based information system decreases the time of decision-making in business. To measure the efficiency of technological innovations, financial performance indicators are often used, including return on investment (ROI) and net present value (NPV). Even though the previous research indicates that there is a positive correlation between AI adoption and financial results [12], these correlations are rather indirect and not directly connected to the mechanisms of the internal system.

H4: The use of artificial intelligence in information systems has a positive impact on financial performance indicators, such as ROI and NPV. Another unique aspect of the proposed model is the addition of adaptive feedback mechanisms. The majority of the currently available approaches are based on either a static or a periodically updated model, which restricts its response to dynamic changes in the business environment [13]. Conversely, the system can be stabilized and adapt to new circumstances by constantly recalibrating the parameters of AI according to deviations in key performance indicators.

H5: Adaptive feedback in AI-driven information system enhances stability and adaptability of digital business models. Combined, these hypotheses indicate a shift in the use of artificial intelligence in isolation to its use in a unified information system architecture. The proposed approach consists of integrating predictive analytics, optimization modelling and adaptive feedback within one framework, thus linking the outputs of the algorithms to the business performance indicators. This requires that regression analysis, optimization methods and adaptive feedback mechanisms are implemented in a single analytical framework. In the past, there have been five streams of research. Although research on digital-transformation focuses on the strategic reconfiguration of organisations, this research is typically at an organisational level or process level [1, 2]. Applications of AI in research show improvements in forecasting, classification and automation, but typically these are evaluated on a single task or model [3] [4]. Research on the capability of AI does not provide an information-system control loop [5] or [6] that is executable. Organizational-readiness and AI-management studies are focused on governance, decision rights, and human–AI complementarity [7-9] while machine-learning-lifecycle studies are focused on maintainability, drift, and technical debt [13] and [14]. Every stream is important but none of them alone is enough to offer an architecture of traceability that links enterprise data, analytical outcomes, limited decisions, deviations from KPIs or model recalibration. The difference from the present study is in two aspects, the architectural and the integrative. The artifact includes a data-integration layer, an analytics-and-optimization layer, and a KPI-feedback-and-governance layer in the same enterprise decision-support lifecycle. Its purpose is to provide a way to make business alignment operational: there is a decision variable for each model output, a KPI for each decision variable, and a rules for material KPI deviations, which are a known review, retraining or human-approval rule. The underlying regression/optimization algorithms are not novel, but the authors are using one approach to tackle a problem and another to solve another. Rather it innovates a repeatable, reconfigurable information-system design that illuminates how the existing analytical elements can be managed as a unified and agile enterprise system.

Table 1. Positioning of the proposed IT artifact in relation to prior research

Literature stream	Primary contribution	Remaining limitation	Difference and significance of this study
Digital transformation [1], [2]	Organizational and process transformation	Does not provide an executable AI–KPI feedback architecture	Translates strategic alignment into specific system layers and control points
Task-level AI [3], [4]	Prediction, classification and automation	Weak enterprise integration and cross-KPI traceability	Connects analytical outputs to constrained decisions and enterprise KPIs

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AI capability [5], [6]	Organizational resources and firm performance	Limited implementation-level orchestration	Specifies reusable interfaces, responsibilities and feedback logic
AI readiness and governance [7]–[9]	Readiness, decision rights and human–AI roles	Governance is not embedded in the technical lifecycle	Introduces approval, monitoring, security and escalation controls
Machine-learning lifecycle [13], [14]	Drift, maintenance, technical debt and risk	Business KPI effects remain indirect	Uses KPI deviations as monitored lifecycle signals
Proposed study	Integrated enterprise AI decision support	Evaluation remains ex ante	Provides end-to-end traceability and exposes boundary conditions

3. RESEARCH METHODOLOGY

The study adopts the design-science research methodology as the main product of the research is an information-system artifact [10-12]. The procedure involves five consecutive stages – problem identification, derivation of design requirements, construction of artefacts, demonstration of artefacts in scenarios and ex-ante evaluation. The problem-identification stage sets the stage for the lack of end-to-end traceability of enterprise data, AI output, operational decisions and KPIs. The requirements stage involves the process of converting literature into 5 requirements:

R2: the ability to integrate data across various applications and formats; and

R2: clear association between analysis results and decision variables; and

R5: constrained optimization with more than two objectives; and

R5: automated performance analysis; and

R5: governance by human approval, security and auditability.

The unit of analysis and evidence. The unit of analysis is an enterprise business-process scenario and not a company as a statistical observation. There are five scenarios: sales and marketing, production, logistics, finances and administrative decision support. To inspire sector contexts, public company reports can be used as inputs, but numerical inputs have to be tied to a specific report, page, definition, and fiscal period or identified as normalized illustrative inputs. In the scenario-based route, the company names are to be replaced with Scenario A–E because the analysis does not contain estimates of company-level treatment effects. This treatment eliminates illustrative process indicators from being read as audited company performance data. There are 3 layers in the artifact that interact. The data-integration layer is responsible for receiving and validating data from ERP, CRM, finance, production and supply-chain systems. The analytics-and-optimization layer uses prediction and constrained optimization to generate decision alternatives. The KPI-feedback-and-governance layer compares the actual or simulated outputs with a set of target thresholds, and logs deviations, model reviews, or model retraining, and sends material decisions to humans for approval. Decision horizons, indicated as strategic, tactical and operational, on the original manuscript hold in the layers and are not considered independent architectures. Equations 1) to 5) represent components of the artifact: assessment of data dispersion, process mapping, constrained resource allocation, and functional relation between inputs to the AI and productivity. The multiple-regression equation is a structural specification, not an estimated inferential model as is the case in the present evidence design. If any larger, reproducible data is provided, then no coefficient, p value, causal effect should be reported. The model outputs are judged against five criteria: forecast accuracy — P1; resource efficiency — P2; decision latency — P3; financial utility — P4; adaptation stability — P5.

Evaluation is performed by comparing each scenario to the predefined baseline, where the process scope and definitions of the metrics are the same. A proposition is accepted only if it meets the required minimum limits of data-quality, cost, security and governance requirements without compromising on the corresponding metric. Evidence is documented at three levels:

Architecture coverage: whether a required component exists or not.

Whether or not the expected change in direction is occurring (scenario behaviour).

Boundary Analysis – points at which anticipated returns diminish or turn negative.

This protocol does not make a numerical change an interpretation of a causal effect and it renders the assessment criteria reproducible.

The unit, baseline, and calculation rule descriptions provide construct validity. Limited internal validity as there is no randomized, or longitudinal, treatment data. Analytical examination of the external validity is achieved by manipulating the contexts of the sector and process, rather than by being claimed statistically. Conclusion validity is safeguarded by the reporting of numerical ranges as scenario

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outputs, and by distinguishable supported, conditionally supported and not empirically verified propositions. Design requirements and evaluation criteria is presented in Table 2.

Table 2. Design requirements and evaluation criteria

Requirement	Artifact component	Evaluation evidence	Acceptance rule
R1. Interoperable data integration	Data layer and data contracts	Completeness, consistency and data latency	Data-quality threshold must be met before execution
R2. Output-to-decision traceability	Analytics and optimization interfaces	Decision variable and accountable owner	Every output must have an identified consumer
R3. Constrained multi-objective optimization	Optimization layer	Cost, service, risk and feasibility thresholds	No KPI may improve by violating a hard constraint
R4. Adaptive monitoring	Feedback controller	KPI deviation, model drift and retraining trigger	Every trigger must be documented and auditable
R5. Governance and safety	Approval, security and audit logging	Override rate, incidents and unresolved alerts	Material decisions require defined human authority

Source: compiled based on [15], [16], [17], [18], [19], [20],[21],[22].

To assess the reliability of the dataset, the coefficient of variation is used:

$$CV = \frac{\sigma}{x} * 100\%, \quad (1)$$

The calculated average value of 11.4% indicates a sufficient level of data consistency, allowing the dataset to be used for modelling and hypothesis testing.

Formalization of Business Processes. A process relations matrix is created within each company to illustrate the points of AI intervention. Mathematical formalization of the process:

$$P_i = f(X_1, X_2, \dots, X_n, A), \quad (2)$$

Where, P_i is the production process, X_n are the controlled parameters (resources, time, costs), A are the AI algorithmic modules.

The mapping of business processes to AI applications is presented in Table 4, which highlights areas with the highest potential for efficiency improvement, particularly in logistics and marketing processes. Linear programming and regression analysis algorithms for optimizing resource allocation and predicting results are defined by the following model:

$$Minimize\ C = \sum_{i=1}^{n}(r_i \cdot x_i), \quad (3)$$

Where C is the company's total costs, r_i is the cost per unit of resource i, x_i is the quantity of resource used, i, n is the number of resource categories. The restrictions are formulated as:

$$\sum_{i=1}^{n} a_{ij}x_i \geq b_j, \quad j=1,2,\dots,m, \quad (4)$$

Where a_{ij} are the resource efficiency coefficients, b_j are the minimum levels of target indicators. The optimization problem is solved using linear programming techniques. This approach allows evaluating the effect of AI integration on operational efficiency and supports the testing of hypothesis H2. The applied optimization methods are summarized in Table 5, including linear, nonlinear, stochastic, and evolutionary approaches. To predict the impact of AI on productivity growth, multiple regression is used:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon, \quad (5)$$

Where Y is the productivity level, X_1 is the cost of AI infrastructure, X_2 is the level of process automation, X_3 is the personnel qualifications, ε is the random error. This equation represents the hypothesized relationship between the inputs to AI and productivity in the proposed artifact. Because there are only a few scenarios, it is not used for inferential coefficient estimation and causal hypothesis testing. Rather, it is for the purpose of capturing the variables and the direction of relationships assessed by the scenario analysis.

Evaluation metrics and hypothesis testing. The success of the suggested model is measured with the help of key performance indicators, which are directly related to the developed hypotheses:

– Forecast accuracy (H1)
– Efficiency of resources and optimization of costs (H2)
– Decision-making time (H3)
– Financial performance (ROI, NPV) (H4)
– Stability and adaptability of the system (H5)

The ex-ante assessment compares each scenario baseline with the corresponding model-generated output under identical process scope and KPI definitions. The resulting differences are interpreted as conditional scenario estimates rather than observed causal effects of organizational implementation. This practice combines the technological, organizational and analytical facets, making sure that the capabilities of the system and the business goals are consistent. Figure 1 depicts a step-by-step process of moving toward more adaptive information environments based on AI, and includes the key phases of this integration process.

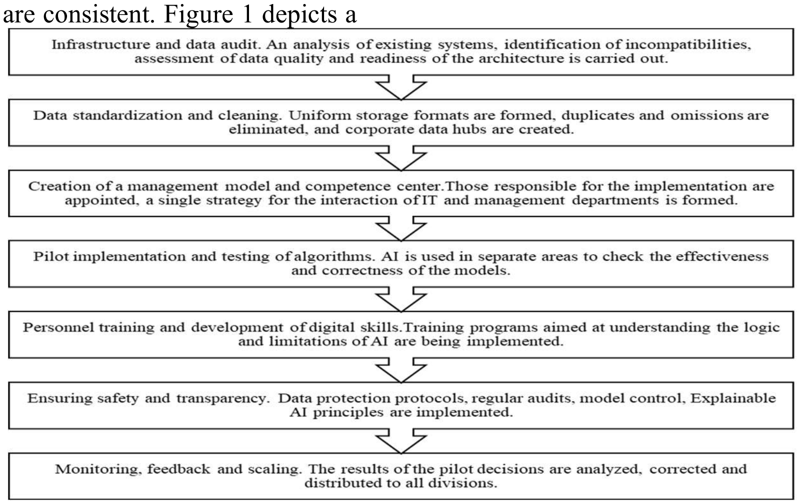

Fig. 1. Key stages of overcoming the limitations of the integration of AI and corporate IS in the context of new approaches to managing digital business models

Source: Compiled by the author based on [9,11,16,17].

As illustrated in Figure 1, the process of integration starts by conducting the audit of the current information systems and data quality analysis, the process of formalization of the process and identification of the priority areas to implement AI. The following steps are the formulation of analytical models, integration into business systems and the establishment of a feedback mechanism to improve continuously. The last phase is associated with the development of a fully adaptable system, where artificial intelligence adapts its parameters depending on the change in key performance indicators and external conditions. This systematic strategy guarantees not only the successful introduction of AI but also its sustainability in the long term in digital business contexts.

Adaptive feedback mechanism. The peculiar aspect of the methodology is that a self-adaptive feedback mechanism is introduced which guarantees the constant improvement in the performance of AI models. The process includes: 1) data updating; 2) examination of the deviations between actual and target KPIs; 3) model retraining; 4) checking and systematization into the information system. As explained in Table 6, this mechanism allows dynamically recalibrating AI parameters to ensure system adaptability and stability to changing conditions.

Integration with corporate information systems. The proposed model is planned to be implemented in the information systems of enterprises such as ERP, CRM, and supply chain management systems. Integration ensures: 1) real-time data processing; 2) coordination among the business units; 3) performance indicators are continuously monitored; automated decision support. With this integration, it is possible to assess the efficiency of decision-making (H3) and the improvement of financial performance (H4).

4. RESULTS AND DISCUSSION

The results are read as an ex-ante analysis of proposed information-system artifact. These are not actual causal impacts of implementation in the specified companies. In all the five process scenarios, the architecture met the essential coverage requirement to connect data acquisition, prediction, optimization, decision output, KPI monitoring and feedback in a traceable process lifecycle. Under the given assumptions, the scenario calculations resulted in forecast-accuracy gains of 15-18%, decreased decision-latency of up to 30% and resource-efficiency gains of around 10-15%. The ranges should describe the behavior of the artifact in response to the selected inputs, but should not be extrapolated to inputs that are not being considered without further empirical testing. The best score is not just a percentage increase – it is the structure that makes it possible to show how the percentage increase is made. Forecast quality is a result of both model performance and consistency of data-integration layer. Optimisation objective and feasibility constraints are key to resource efficiency. Decision latency is based on whether analytical outputs are integrated into the operational process.

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Financial utility is a sum of parts and is not exclusively the result of AI. Monitoring thresholds, retraining rules and human oversight are critical to adaptation stability. This interpretation allows the results reported to be more related to the research question and avoids the possibility of only looking at the results through the technical model.

Table 3. Structuring of the conceptual features of the influence of information systems and technologies of artificial intelligence on the effectiveness of business models of modern companies

Level of influence	Functions of information systems (IS)	Functions of artificial intelligence (AI)	Synergetic effect of integration	The main performance indicators
Strategic	Data analysis, planning, decision support	Scenario forecasting, risk assessment, modeling of future trends	Turning data into management insights, increasing the accuracy of strategic decisions	ROI, NPV, business sustainability
Tactical	Coordination of departments, accounting of resources, planning of supply chains	Demand forecasting, route optimization, procurement automation	Reduction of time and logistic losses, improvement of synchronization of processes	OEE, cycle time, forecast accuracy
Operational	Automation of routine tasks, data control, information exchange	Machine learning, classification, deviant analysis, self-learning algorithms	Increasing the speed of data processing, minimizing errors and failures	Productivity, quality, costs
Innovative	Storage of knowledge, modeling of processes	Generation of ideas, digital twins, optimization of innovation cycles	Speeding up the introduction of innovations and development of R&D functions	Time of bringing the product to the market, innovation index
Marketing	Client database management (CRM), channel analysis	Personalization of content, forecasting of client behavior	Increase in engagement, increase in conversion and retention	CTR, Conversion Rate, CPL
Financial	Accounting, reporting, flow analysis	Risk management, assessment of investment efficiency	Increase in the accuracy of forecasts, decrease in financial risks	ROI, profit margin
Administrative	Centralized management, access to analytics	Support for solutions based on data (data-driven management)	Formation of a transparent and adaptive management system	KPI, speed of reaction, accuracy of decisions
Social and personnel	Corporate knowledge bases, HR systems	Competence analysis, intellectual assistants	Increasing the digital maturity and adaptation of personnel	Employee satisfaction, speed of training All companies Level of digital skill

Source: Compiled by the author based on [12,13,14]

The greatest synergy occurs at strategic and tactical levels (as indicated in Table 3) whereby AI is directly involved in decision-making and optimization of performance.

Table 4. Evaluation status of the research propositions

Proposition	Available result	Final status	Required interpretation
P1 / former H1: forecast accuracy improves	Scenario improvement of 15–18%	Conditionally supported	Not a causal company-level effect
P2 / former H2: resource efficiency improves	Scenario improvement of approximately 10–15%	Conditionally supported	Depends on constraints and input quality
P3 / former H3: decision latency decreases	Reduction of up to 30%	Conditionally supported	Requires workflow integration; oversight time may increase
P4 / former H4: financial utility improves	Positive ROI and NPV direction	Not independently verified	Financial changes are aggregated and assumption-sensitive
P5 / former H5: feedback improves stability	Architecture contains retraining and KPI triggers	Conceptually supported	Longitudinal drift evidence is required

This proves the fact that integration, not isolated implementation is the most important factor that determines system effectiveness. Although the above advantages are evident, the analysis shows that there are a number of limitations that influence the application of AI-based systems. Table 5 categorizes these constraints in technological, organizational, economic and security-related categories.

Table 5. Classification of the influence of the integration of AI and corporate information systems according to the nature of groups on the managerial efficiency of modern companies

Influence group	Conceptual features of influence
Technological and infrastructural limitations	Most companies use outdated or disparate information systems that are not designed for integration with machine learning algorithms and neural networks. Machine learning requires large amounts of computing resources, high-quality data, and continuous access to them. In companies with a distributed architecture, there is often a shortage of server capacity and insufficient network bandwidth.
Management restrictions	One of the key challenges is the lack of an agreed management model for AI implementation. Many organizations implement intellectual technologies fragmentarily - in separate departments or at operational management levels, without forming a general digital integration strategy. Companies with a traditional hierarchical structure perceive flexible and self-learning systems worse. As a result, AI remains an instrument of local automation, and not a means of strategic management.
Economic restrictions and barriers to implementation	AI integration requires significant investment. In addition to the purchase of equipment and licenses, companies bear the costs of infrastructure adaptation, personnel training, and system support. Large corporations with a developed IT infrastructure get a greater effect from automation, while small and medium-sized businesses are not always able to provide the necessary level of integration.
Ethical and social challenges	Ethical restrictions become more and more significant as the autonomy of AI grows. Corporate IS integrated with intelligent algorithms process personal data of clients, employees and partners. Violation of confidentiality principles or biased algorithms can lead to reputational risks and legal sanctions.
Safety and stability of systems	The integration of AI increases the requirements for cyber security. Every new data analysis or machine learning module creates potential points of vulnerability. Disruption of IS can lead to data leakage or distortion of forecasts, which entails significant financial losses.
Cultural and personnel restrictions	The effective implementation of AI requires not only technologies, but also the readiness of personnel to use them. Many management teams do not have sufficient competencies to interpret AI results. The lack of digital literacy leads to the fact that intellectual tools are used formally, without deep analytics.

Source: Compiled by the author based on [14,15,16].

The biggest limitations as shown in Table 5 include fragmentation of infrastructure, lack of integration strategies, high implementation cost, and poor digital capabilities. All these factors render AI technologies not always to achieve the desired results when implemented into the system without any coordination. The automatization of business processes is one of the main stages toward the possibility of the successful application of artificial intelligence. Organizing the operational processes into quantifiable terms will make it possible to determine areas where AI can produce the most significant effects. This relationship is illustrated in Table 6, which maps business processes to AI tools and identifies nodes of efficiency improvement.

Table 6. Formalization of business processes in the context of new approaches to managing digital business models

Business process	Key operations	Potential for introduction of AI	Nodes of increasing efficiency	AI tool
Sales and marketing	Analysis of customer behavior, stock management	Tall	Personalization is offered, dynamic pricing	ML-algorithms, clustering
Production	Load planning and quality control	Average	Predictive maintenance of equipment	Neural networks, regression
Logistics	Optimization of routes and schedules	Tall	Reduction of delivery time and fuel	Stochastic optimization

Finance	Investment management, scoring	Average	Forecasting risks and profitability	Bayesian models, classification
HR and management	Selection and retention of personnel	Average	Analysis of competencies and personnel turnover	NLP analysis, ranking

Source: Compiled by the author based on [15,16,17,18,19].

The processes, which can most effectively be optimized by AI, are logistics and marketing processes, which are the most data-intensive processes and dynamic in nature (see Table 5). Predictive modelling is also useful to production and financial processes, though its effectiveness varies depending on the quality of the data and the structure of the processes. The application of optimization models led to significant improvements in resource allocation and operational efficiency. The effectiveness of different optimization approaches is summarized in Table 7.

Table 7. Algorithmic optimization of business processes based on new approaches to managing digital business models based on information technologies and AI

Optimization method	Application	Expected effect	Restrictions
Linear programming	Distribution of resources and the budget	Increasing the efficiency of resource use by 10 - 15%	It requires stable parameters
Nonlinear programming	Pricing and production cycles	Minimization of deviated KPI by 8 - 12%	High computational complexity
Regression analysis	Forecasting demand and ROI	Increasing the accuracy of forecasts by 15 - 20%	Sensitivity to data noise
Stochastic optimization	Management of uncertainty	Reduction of financial risks by 10 - 18%	Triboulet of large samples
Evolutionary algorithms	Multi-criteria optimization	Reconciliation of ROI, NPV, OEE	Long-term training of models

Source: Compiled by the author based on [18,19,20,21].

Table 7 shows that linear programming is more appropriate in fixed environments, whereas stochastic and evolutionary algorithms are better suited to dynamic environments. On the whole, the resource efficiency grew by around 10-15% which proves the efficiency of combining optimization with AI analytics. The overall impact of the proposed model on business performance is illustrated in Figure 2, which presents aggregated changes in key indicators after implementation.

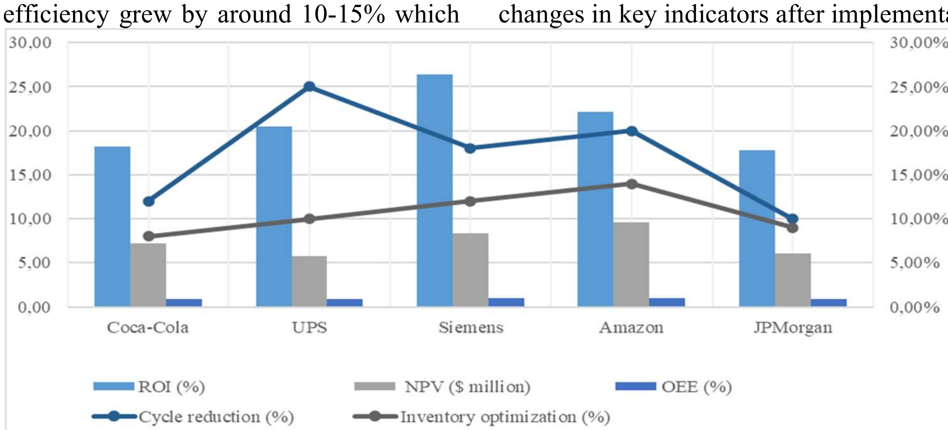

Fig. 2. The main results of the evaluation of the effectiveness of the implemented solutions according to the key financial and operational metrics of modern companies

Source: Compiled by the author based on [18,19,20,21].

As shown in Figure 2, significant improvements are observed across all key metrics, including forecasting accuracy, ROI, and operational efficiency. A comparative analysis of system performance before and after implementation is presented in Figure 3.

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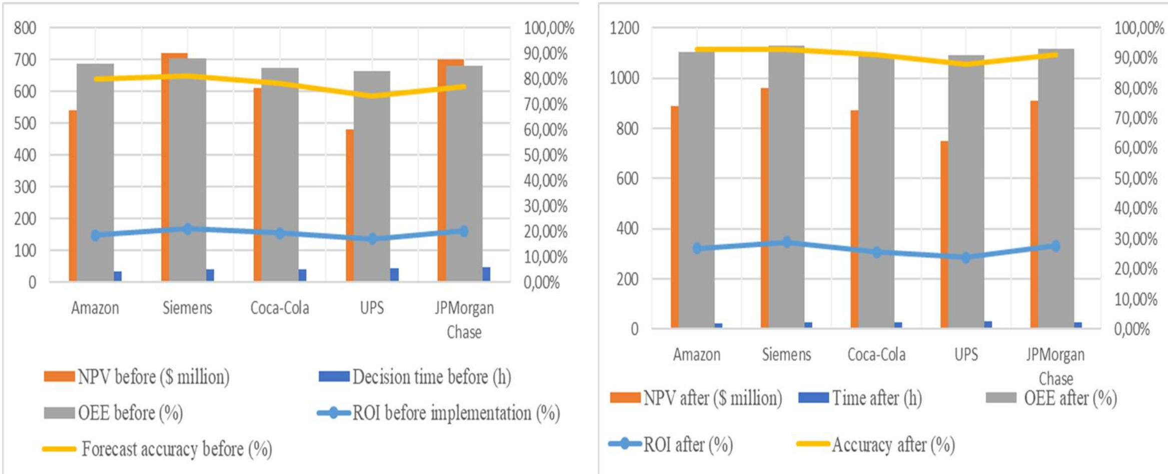

a) b)

Fig. 3 Consolidated results of the assessment of the effectiveness of implemented solutions according to key financial and operational indicators of modern companies (a-before; b- after)

Source: Compiled by the author based on [18,19,20,21].

Figure 3 demonstrates that the most substantial improvements occur after the introduction of adaptive AI mechanisms, particularly in forecasting accuracy and decision-making speed. The role of adaptive feedback in improving system performance is detailed in Table 8, which describes the stages of model adjustment and their effects.

Table 8 Results of the effectiveness of the correction of AI models in companies in the context of new approaches to the management of digital business models

Stage of adjustment	Changeable parameters	Used metrics	The effect of adaptation	Frequency updated
Collection of new data	Updating the training sample	ΔROI, ΔOEE	Increasing the relevance of forecasts	Daily
Analysis of the deviated KPI	Correction of model weights	KPI_{fact} - KPI_{goal}	Elimination of systematic errors	Weekly
Retraining the model	Setting hyperparameters	RMSE, MAE	Increasing the accuracy of forecasts by 10 - 15%	Monthly
Validation and testing	Comparison with reference data	R^2, Accuracy	Increasing the reliability of solutions	Quarterly
Implementation in IS	Integration of the corrected model	ROI, NPV, OEE	Increase in efficiency by 5 -8%	According to the results of the analysis

Source: Compiled by the author based on [22,23,24,25,26]

As shown in Table 7, continuous model retraining and KPI monitoring allow the system to reduce errors and improve forecasting accuracy by an additional 10–15%. This confirms that adaptive feedback is a critical factor in maintaining system stability. The results obtained in this study should be considered the pointer on the fact of a structural change in the functioning of corporate information systems under the influence of artificial intelligence. The given improvements in the forecasts, resource allocation, speed of decision-making, and financial performance are not the side-effects that are immediate consequences of a further systemic change [26,27,28]. The results align with previous studies that have demonstrated that value achieved from AI is closely related to the ability of the organization, the data available, and the extent to which the managers are integrated with the AI [29,30]. This research builds upon task-level AI studies by determining what information-system interfaces are needed to transition from predicting to an accountable enterprise decision. It advances the body of work on AI-capability research by introducing the concept of a executable architecture of capability in addition to an organizational construct. It further supports AI-governance and machine-learning-lifecycle research by observing business KPI deviations as events in the monitored system to trigger review, retraining or escalation [31,32]. Practical and theoretical in importance, the difference. On the theoretical level, the unit of contribution is no longer isolated but a governed cycle of decision support. In effect, the architecture defines the space of interoperability, responsibility and control in the ERP, CRM, production, finance, and supply-chain contexts. The study does not show that the model is superior in general when compared to previous models, a controlled benchmark would be necessary to make this statement. The contribution it can make, instead, is the integration and traceability of components that are analyzed separately in previous research streams [33,34,35]. Several outcomes were found during the evaluation that may help to balance out the anticipated benefits. Firstly, local optimization can lead to worsening of one KPI at the expense of another; for instance, a reduction in decision time may result in an increase in service risk, exceptions and manager reviews. Second, frequent retraining can induce a drifting configuration, instability of the model, and extra validation tasks. Third, there is a greater attack surface as new data pipelines, model endpoints and automated actions become security-critical elements. Fourth, automated recommendations can be made quick, and this will decrease the time for contextual human judgment if not set up explicitly. Fifth, benefits vary by scenario: digitally maturing environments have the ability to handle integration and governance costs more easily than organizations whose data is spread out and their infrastructures are less robust [29,30]. These results support the interpretation of P1–P5. The improvements must be within the limits of cost, safety, fairness, security, and service. The adaptive mechanism ought to not automatically retrain in all situations. The starting point is diagnosis and a human review of material KPI deviations, data quality failures, or high impact decisions. This finding aligns with the literature on the automation–augmentation paradox [8], machine-learning technical debt [9] and responsible AI governance [13, 14]. Organizations should treat the proposed architecture as a staged integration programme rather than a single AI installation. The first stage is a data-readiness audit covering ownership, definitions, quality thresholds, access rights, and interoperability across ERP, CRM, finance, production, and supply-chain systems. The second stage is a shadow-mode pilot in one process, where AI recommendations are logged and compared with existing decisions without autonomous execution. The third stage introduces constrained decision support with a named KPI owner, human approval thresholds, rollback procedures, and security monitoring. Only after the pilot meets accuracy, cost, latency, and governance thresholds should the architecture be scaled to additional processes. For current industry practice, three controls are especially important. Data contracts should specify the source, definition, update frequency, and acceptable quality of each input. Model cards and decision logs should record intended use, limitations, overrides, and KPI effects. Monitoring dashboards should combine model metrics such as error and drift with business metrics such as service level, cost, ROI, decision latency, exception rate, and user override rate. This joint monitoring prevents technically accurate models from producing strategically undesirable outcomes and makes responsibility visible to managers, auditors, and IT teams. First, the evaluation is ex ante and scenario-based; it demonstrates the internal logic and expected behaviour of the artifact but does not establish causal effects of AI implementation. Second, five heterogeneous process scenarios broaden analytical coverage but do not constitute a statistically representative sample. Third, the use of normalized and aggregated indicators may conceal within-process variation and measurement differences across sectors. Fourth, the study does not provide longitudinal evidence on model drift, retraining stability, cyber incidents, user overrides, or organizational learning. Fifth, financial indicators such as ROI and NPV are sensitive to cost allocation, time horizon, and counterfactual assumptions and therefore should not be treated as independent proof of AI value. Sixth, public corporate reports can support contextual description but cannot validate process-level throughput, cycle time, or model effects unless the exact report, page, metric definition, and period are provided. These limitations constrain generalization but also define a clear empirical agenda [35]. Future validation should use a preregistered multi-period dataset, common metric definitions, process-level baselines, explicit comparison groups, and complete estimation diagnostics. Construct validity would be strengthened through a published data dictionary; internal validity through longitudinal or quasi-experimental designs; external validity through industry-specific replications; and conclusion validity through uncertainty intervals, sensitivity analysis, and independent reproduction of the calculations.

5. CONCLUSIONS

This study has considered the information systems challenge of scaling enterprise data, AI based prediction, constrained optimization, operational decisions and business KPIs in one adaptive and auditable architecture. It responded by creating a three-layered solution of data integration, analytics and optimization, and KPI feedback and governance. The design formalizes not only the flow of data and model outputs, but also the responsibilities, thresholds and control actions that need to be taken when the KPIs deviate, the models drift, when there is a security event, or when a significant decision is needed. The ex-ante scenario evaluation demonstrates the ability of the artifact to be used for the entire decision-support lifecycle, from forecasting, allocation of resources, decision latency, financial utility to adaptation stability. The scenarios show a range of improved forecast accuracy, timeliness and resource efficiency under these stated assumptions. The values are model-based conditional values and are therefore not seen as causal company-level implementation effects. The most strongly supported result is the traceability that is generated between the output of the analysis and the decision variable, the KPI consequence and the action taken as feedback. Unlike previous AI task-level, organizational-capability-level, governance-level and machine-learning-lifecycle research, the research contribution demonstrates the integration of the disparate concerns of these research areas into a reusable enterprise information-system architecture. The study does not advocate a new machine-learning algorithm, nor does it suggest that any of its algorithms performs consistently better than all others across the board. Its contribution is the 'orchestration' and 'governance' of the architectural structure and logic that allows existing analytical methods to become a single unit, based on KPIs, that can support the decision-making process. For practitioners, the findings suggest a gradual engagement strategy that starts with assessing readiness for data, tests data in shadow mode, then deploys data in controlled scenarios, obtains human approval, monitors and tests, and then scales up. The study also reveals that conflicts with KPIs, instability of retraining, an increased workload of governance, cyber risk, and insufficient digital maturity can offset the benefits. As the current evaluation is scenario dependent and based on aggregate indicators, validation of the ranges on a process and longitudinal level is needed before a generalisation of the numerical ranges can be made. The architecture needs to be tested with reproducible multi-period datasets, industry-specific baselines, comparison groups, uncertainty analysis, and explicit measurement of human-AI interaction and system-resilience in future research.

6. FUTURE ENHANCEMENT

Future research should validate the architecture with longitudinal (process level) data and common metric definitions among organizations. Uncertainty/sensitivity analysis, external replication, direct measurement of drift, override behaviour, and governance workload should be prioritized over quasi-experimental or controlled before/after designs, as well as direct measurement of cyber incidents. Direct measurement of cyber incidents, direct measurement of workload, direct measurement of drift, override behaviour, external replication, and uncertainty and sensitivity analysis should be prioritized over quasi-experimental or controlled before/after designs. Reinforcement learning and digital-twin elements can also be added to the architecture, but they should be assessed in the light of clear safety constraints, and rules for human approval. To understand the impact that regulation, data maturity and process criticality have on the effectiveness of KPI aligned adaptive decision support, industry-specific studies are required.

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