LatIA. 2025; 3:344
doi: 10.62486/latia2025344
ISSN: 3046-403X

ORIGINAL

AI evolution and its role in transforming the automation of commercial activities

La evolución de la IA y su papel en la transformación de la automatización de las actividades comerciales

Mykhailo Lukash[1], Yevhenii Chuprun[2], Oksana Lysak[3], Anatolii Husakovskyi[4], Kyrylo Hanhanov[5]

[1]Pryazovskyi State Technical University, Department of Management and Marketing. Dnipro. Ukraine.
[2]Warsaw University of Technology Business School. Warsaw, Poland; National Aviation University. Kyiv. Ukraine.
[3]Dmytro Motornyi Tavria State Agrotechnological University, Department of Economics and Business. Melitopol. Ukraine.
[4]Independent Contractor (IT). Ukraine.
[5]Interregional Academy of Personnel Management. Kyiv. Ukraine.

Cite as: Lukash M, Chuprun Y, Lysak O, Husakovskyi A, Hanhanov K. AI evolution and its role in transforming the automation of commercial activities. LatIA. 2025; 3:344. https://doi.org/10.62486/latia2025344

Submitted: 09-06-2024 **Revised:** 01-01-2025 **Accepted:** 22-05-2025 **Published:** 23-05-2025

Editor: Misael Ron

ABSTRACT

This article examined the impact of artificial intelligence (AI) on the automation of business processes, focusing on how intelligent systems enhanced management efficiency and operational optimization. Special attention was given to cognitive neuro-fuzzy models and their role in transforming business processes in the digital era. The study was timely, considering the exponential growth of data and the complexity of modern organizational structures, which demanded fast, accurate, and adaptive management solutions. AI technologies provided such capabilities, while companies that failed to adopt them risked losing competitive advantage amid ongoing digital transformation. The study aimed to develop and justify a conceptual approach to automating business processes through AI. To achieve this, two primary methods were applied: cognitive modeling using semantic M-networks to reflect human imaginative thinking in process structures, and reinforcement learning to optimize processes based on feedback mechanisms. The methodology combined theoretical literature analysis, mathematical modeling, and empirical examination of real business processes. The findings demonstrated that integrating AI significantly improved overall business process efficiency by reducing complexity, costs, and feedback loops, while enhancing control, regulation, and financial outcomes. The M-network model illustrated how AI adapted processes to dynamic environments and supported decision-making through visualized cognitive maps. Future research directions included advancing cognitive learning algorithms to handle larger datasets, designing adaptive AI interfaces tailored to individual user behavior, and exploring AI's influence on cross-functional collaboration to foster comprehensive digital management ecosystems.

Keywords: Artificial Intelligence; Business Process Automation; Cognitive Modelling; Semantic Networks; Neural Networks; Decision Support Systems; Procurement Optimization.

RESUMEN

Este artículo examinó el impacto de la inteligencia artificial (IA) en la automatización de los procesos empresariales, enfocándose en cómo los sistemas inteligentes mejoraron la eficiencia de la gestión y la optimización operativa. Se prestó especial atención a los modelos neurodifusos cognitivos y su papel en la transformación de los procesos empresariales en la era digital. El estudio fue oportuno, considerando el crecimiento exponencial de los datos y la complejidad de las estructuras organizativas modernas, que exigían soluciones de gestión rápidas, precisas y adaptativas. Las tecnologías de IA proporcionaron estas capacidades, mientras que las empresas que no las adoptaron perdieron ventajas competitivas en el contexto de la transformación digital. El objetivo del estudio fue desarrollar y justificar un enfoque conceptual para automatizar los procesos empresariales mediante tecnologías de IA. Para ello, se aplicaron dos métodos principales: el modelado cognitivo con redes semánticas M para reflejar el pensamiento imaginativo humano en la estructura de los procesos, y el aprendizaje por refuerzo para optimizar los procesos mediante el análisis de retroalimentación. La metodología combinó el análisis teórico de la literatura, el modelado matemático y el examen empírico de procesos empresariales reales. Los resultados demostraron que la integración de la IA mejoró significativamente la eficiencia general de los procesos, reduciendo la complejidad, los costos y los bucles de retroalimentación, y mejorando el control, la regulación y los resultados financieros. El modelo de red M ilustró cómo la IA adaptó los procesos a entornos dinámicos y apoyó la toma de decisiones mediante mapas cognitivos visualizados. Las futuras líneas de investigación incluyeron el perfeccionamiento de los algoritmos de aprendizaje cognitivo, el desarrollo de interfaces adaptativas basadas en el usuario y el estudio del impacto de la IA en la colaboración interfuncional.

Palabras clave: Inteligencia Artificial; Automatización de Procesos Empresariales; Modelado Cognitivo; Redes Semánticas; Redes Neuronales; Sistemas de Apoyo a la Toma de Decisiones.

INTRODUCTION

In the era of rapid technological progress, when digital transformation covers all areas of activity without exception, companies operating in the dynamic environment of the digital economy face the need to constantly update management approaches to take into account rapid changes in both the internal and external business environment, which leads to an increasing role of innovations, in particular artificial intelligence (AI), as a tool for automating and optimizing key business processes.

The growing volume of information, financial, and logistics flows caused by deep digitalization and high level of market competition requires companies not only to be prompt in decision-making, but also to improve forecasting accuracy, adaptability of strategic planning, and efficiency of management initiatives implementation, which is made possible by the introduction of new generation AI systems.(1,2)

Given the increasing complexity of modern digital infrastructures and the high degree of interdependence of business processes, the integration of artificial intelligence into management mechanisms is becoming particularly relevant, as it is intelligent technologies that allow analysing large amounts of data in real time, identifying hidden relationships between operational indicators, forming reliable predictive models, and automatically adapting management processes to new environmental conditions.

Of particular value in this context are machine learning algorithms that can effectively solve the tasks of forecasting, optimization, classification, and performance evaluation, which makes them fundamentally important for the development of automated solutions in business management.(3) Therefore, the development of AI-based automated control systems is becoming not only relevant, but also strategically necessary, as it ensures the company's overall efficiency, sustainability, and innovation capacity in the long run.

The aim of this article is to develop a conceptual approach to business process automation using artificial intelligence technologies based on the integration of cognitive modeling, neural network structures with fuzzy logic, and reinforcement learning mechanisms to achieve high adaptability, efficiency of management decisions, and flexibility in the transformation of business processes.

Literature review

The transformation of business processes in the context of the rapid development of digital technologies, including the use of artificial intelligence, is at the center of scientific discussions. Some researchers focus on practical mechanisms for reengineering business processes using specific digital technologies, demonstrating an increase in the efficiency of companies' operations. For example, Bruno(4) notes the growth of sales efficiency due to the digital rethinking of logistics procedures based on reengineering, and Chai(5) reveals the potential of information and communication technologies to restructure companies' internal business models using computer networks.

A number of authors, including Abbasi et al.,(6) Mangal et al.,(7) Nandhini & Nandhini,(8) focus on the use of artificial intelligence and machine learning algorithms to improve the accuracy of business process management, which allows to reduce costs, reduce the time for developing solutions and achieve greater flexibility in adapting to changes in the market environment. In turn, studies on automated customer relationship management, in particular using predictive analytics systems, confirm that the use of such technologies allows companies to personalize offers, optimize marketing campaigns, and increase customer satisfaction.(9,10)

A separate area of literature focuses on the integration of cognitive approaches to artificial intelligence modelling. In particular, researchers such as Caspary et al.,[11] Shah[12] emphasize the importance of taking into account cognitive processes in creating hybrid models of artificial intelligence that combine algorithmic accuracy with human decision-making logic. Such processes actively stimulate the development of the concept of cognitive learning of neural networks, which involves the integration of elements of thinking, context analysis, situational response, and emotional adaptation into the algorithmic basis of business decisions.

Other researchers, including Selvam et al.,[13] and Sheth,[14] propose algorithmic approaches to supporting management decisions by integrating business process indicators with the creation of customer value through the prism of analytics based on big data and artificial intelligence. For their part, Pandy et. al.,[15] Pelz-Sharpe & Mullen,[16] consider the introduction of cross-functional ERP-based systems as an example of effective integration of ICT into the internal structure of companies, which contributes to the integrity of management and accelerates digital transformation.

A separate group of researchers is made up of scientists who are actively developing the concept of a company's digital twin as a symbiosis of analytics, forecasting, and automation based on artificial intelligence. Thus, Oyekunle and Boohene[17] propose a five-dimensional model of a digital twin that includes simulation, data analysis, standardization, and integration of information flows, which creates the foundation for the makeTwin platform. Similarly, Sarker[18] presents a digital twin platform for managing business processes in supply chains based on the principles of flexible integration and adaptive management.

Among the modern studies that combine the concept of digital transformation with artificial intelligence tools, it is worth mentioning the research by Adorno,[19] and Filippucci et. al.,[20] who introduce the concept of a digitally inclusive finance (DIF) system, considering it as a strategic direction for modernizing corporate governance, taking into account socio-economic factors. In turn, Daclin et al.[21] and Kussainov et. al.[22] developed a mathematical model to assess the scale of the digital economy and the level of innovation activity of companies, which allows quantifying the effectiveness of digital changes caused by the introduction of intelligent technologies.

Thus, a critical analysis of the literature shows that at the intersection of machine learning, cognitive modelling, and digital business process management, a new scientific paradigm is being formed that goes far beyond a purely technological approach and requires a comprehensive rethinking of automation methods, taking into account strategic, organizational, and behavioural factors in the context of modern company management in the digital age. The purpose of the article is to form a methodological basis for ensuring high-quality automation of business processes in the environment of companies based on the introduction of AI technologies.

METHOD

The study uses a mixed-method research design that combines elements of qualitative cognitive modeling with quantitative performance diagnostics to study and evaluate the role of artificial intelligence (AI) in the automation of commercial activities. The type of research is applied and exploratory, as it not only investigates existing AI-based solutions in business process automation but also proposes and empirically tests an original cognitive neuro-fuzzy model based on semantic M-networks.

The data set consists of real business processes taken from a Ukrainian trading company, with a particular focus on the operational stages related to the generation of commercial offers and purchasing decisions. The sample includes a target subset of ten key business processes that were most critical to the company's value chain, selected through expert assessment and suitability for AI implementation.

Data collection was conducted in two stages: (1) primary data was obtained through expert interviews and observation of processes in the company's operational departments, while (2) secondary data was collected from internal digital records, ERP system logs, and performance reports. Particular emphasis was placed on obtaining real-time process traces and performance metrics before and after AI integration. A cognitive modelling method is used to create semantic M-networks that reflect the relationships between objects and processes of a company, integrating human imaginative thinking with the algorithmic logic of artificial intelligence, which contributes to a deeper understanding of the structure of business processes and their further optimization through neural networks with fuzzy logic. This approach proved to be effective for analysing complex systems where traditional methods do not take into account all variables, providing the ability to decompose processes into components and determine their significance through thresholds and linkage weights that reflect the company's real-world management contexts.

For the second part of the results, which focuses on modelling AI-based business process improvement, a reinforcement learning method was used to form the basis for automatic process reconstruction and optimization by analysing feedback in the form of "rewards" or "penalties" depending on the achievement of target indicators, such as cost reduction or efficiency improvement. The method proved valuable for adapting models to the dynamic conditions of the company, demonstrating the ability of AI to gradually improve processes, as evidenced by fluctuations in the integrated performance indicator.

https://doi.org/10.62486/latia2025344 ISSN: 3046-403X

RESULTS

Image of AI implementation to ensure formative automation of key business processes

Graph models implemented in the form of semantic networks have significant potential to stimulate imaginative thinking of company employees, which is especially valuable in the context of studying the development of artificial intelligence and its impact on business process automation, since classical analytical methods based on integro-differential equations are often insufficient to accurately reflect real conditions and take into account numerous variables that affect processes in a company.(23) The proposed model of cognitive neuro-fuzzy systems integrated into the automation of business processes using artificial intelligence suggests that the limitations of traditional approaches to modelling complex tasks can be overcome or significantly reduced by taking into account human imaginative thinking in the interaction between humans and AI systems.

This study considers an improvement of the concept of M-automata and networks, which aims to integrate the imaginative thinking of company employees into the management system of automated business processes, where the semantic M-network acts as a static structure that displays objects (i-models) and the relationships between them, contributing to a better understanding of processes.(24) The peculiarity of describing the functioning of i-models allows us to interpret the M-network as a neural network, where information is presented through the decomposition of complex objects into components, each of which is associated with a specific neuron or group of neurons that reflects their content in the context of the company's business processes (figure 1).

It is important to emphasize that such a representation of a neural network in the format of a semantic graph is actually a process of its training based on cognitive images, which we call cognitive neural network training, which differs from the traditional training of classical neural networks based on input-output samples. In this approach, the process of cognitive learning for automating a company's business processes consists of two stages: first, a set of objects is formed with their significance determined through the thresholds of neural-like elements, and then the relationships between these objects are established by assigning link weights that correspond to the setting of synaptic weights in the neural network.

The assignment of synapse weights and thresholds for i-models in the M-network is a complex and creative process that depends on the specifics of the company's business processes and requires expert assessments, while each object in the M-network corresponds to a fuzzy concept formed on the basis of these assessments and expressed through the values of weights and thresholds.

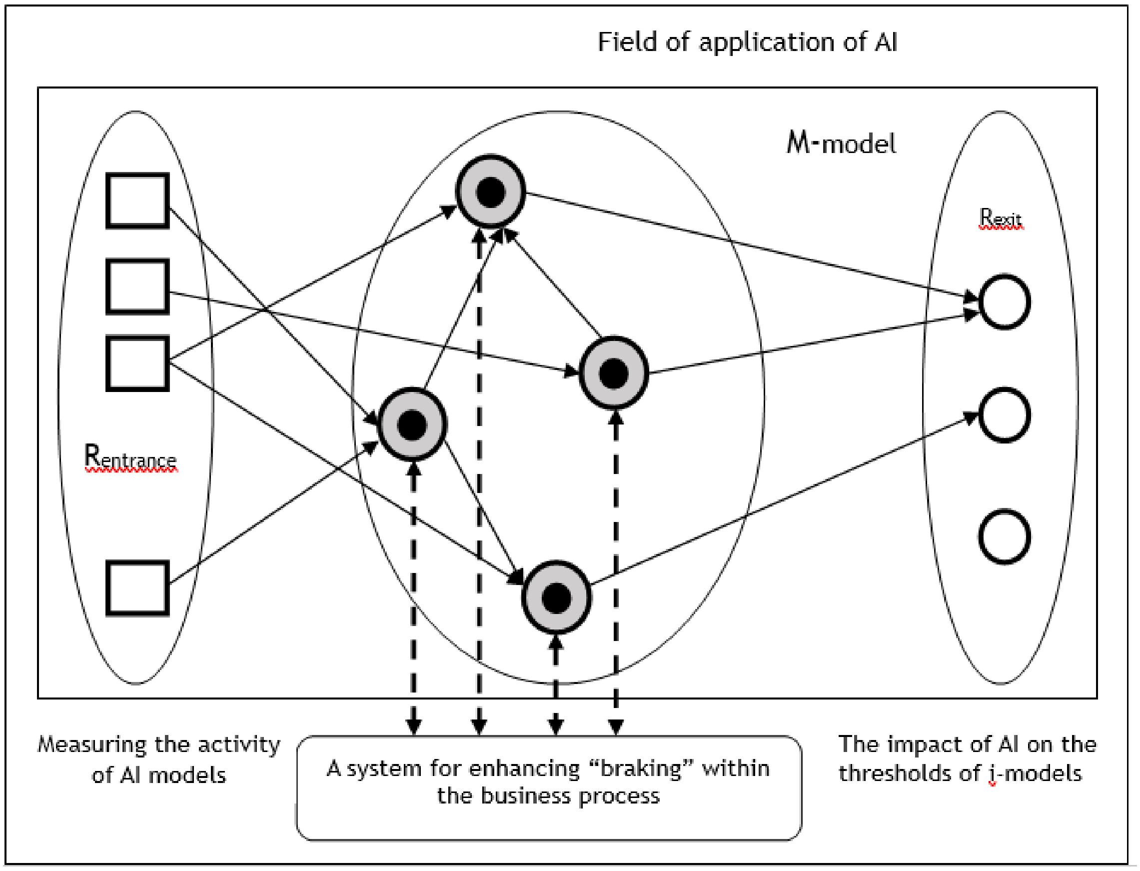

Figure 1. Semantic neural "M-network" as a basis for further automation of business processes

This makes it possible to mathematically describe the M-network using the fuzzy logic apparatus, considering it as a neural network by structure and as a fuzzy system by principle of operation, where the output layer acts as an aggregator and defuzzifier, summarizing fuzzy data from neurons, and the parameters of the middle layer neurons representing objects are fuzzy values with a membership function determined by the "reinforcement-inhibition" mechanism.[25]

Based on the analysis, it is possible to outline the conceptual foundations of the functioning of the so-called M-network in the context of artificial intelligence and its application in the field of automation of management decisions and business processes. If we consider an M-network as a cognitive neural structure capable of semantic interpretation and transformation of symbolic information, its architecture takes the form of a graph in which nodes (vertices) represent individual objects or business events, and inter-node connections represent relationships or cause-and-effect dependencies between them.[26,27]

Within such a model, an important function is performed by the system of regulation of cognitive activity, which is based on the principle of "amplification-inhibition", where the excitation of i-models (information models) of individual process elements depends on their relevance or priority in a particular management context. The control algorithm functions in such a way that elements that demonstrate an increased level of cognitive activation (i.e., significance) receive a lower perception threshold, which allows them to "outrun" other elements in the process of automated analysis or decision-making.

As a result of this influence, the original semantic structure is transformed into a subgraph that includes the most active objects and relationships that are critical to the current business situation. If we add a visual indication of the level of its activity to each node of this cognitive graph in the form of a numerical value, colour, saturation, or special marking, we get a so-called visualized cognitive map of the business process, which reflects priorities, risks, bottlenecks, or potential growth points in real time.[28]

Thanks to such a representation, a company's manager or analyst is able to read the current state of the system at both conscious and subconscious levels, assess the dynamics of changes, and make strategic or tactical decisions based on a deep semantic understanding of the context. Since the cognitive M-network operates in a continuous analysis mode, it is able to store and broadcast information about changes in the situation over time, thereby ensuring self-learning and adaptation of management models to new challenges.[29]

In addition, the dynamic updating of the significance of individual graph elements, represented through numerical indicators, symbols, visual markers, annotated links, or other semiotic means, allows building flexible AI-based business intelligence systems that can show the user the most relevant information in real time, form a context for making informed decisions, and bring the business process management system to a new level of cognitive automation.

Given the specifics of building the initial cognitive network, which is formed as a multi-level hierarchy of neural ensembles with subsequent reflection in the structure of the semantic graph, the company has a unique opportunity to manage the level of detail of visualized business processes based on the goals of management analysis, as well as taking into account the cognitive characteristics of information perception inherent in a particular manager or analyst.[7,30]

In this regard, it is advisable to use proven mechanisms for training classical neural networks, which allow you to adjust the parameters of the cognitive model so that it adequately reflects the behaviour of a business object or process. At the same time, such a model does not require a complete reflection of the internal semantic structure, which reduces computational complexity without losing managerial value (figure 2).

The process of creating such a model, based on the development of artificial intelligence and its impact on the automation of a company's business processes, is essentially a complex procedure of cognitive compaction of information about the objects of management, which is achieved by training a neural network based on a specially prepared data sample adapted to the needs of the company.[31,32]

The synthesis of a neural network for business process automation is accompanied by certain difficulties, since it is impossible to determine in advance exactly which network architecture will be most effective in ensuring the correct transformation of input data into output results that meet the goals of a specific task related to the optimization of the company's activities and procurement optimization.[33]

Within the scope of the study, attention should be paid to the practical analysis of the implementation of artificial intelligence tools in the field of automated software testing. In this context, particular focus is placed on the integration of AI solutions into the validation processes of business workflows that are actively transforming under the influence of digital technologies. The use of neural networks and machine learning algorithms for automatic test scenario generation, test case prioritization based on risk-oriented analysis, and for detecting flaky tests, which is one of the key challenges in CI/CD,[18] was considered.

A separate focus should be placed on the impact of AI on adaptive testing of dynamic user interfaces that change in response to user behavior or business rules. In real-world projects, such as HR management platforms, financial services, and e-commerce solutions, systems have been tested in which AI agents are used to make decisions in real time. These cases have identified new requirements for QA infrastructure, including the need for continuous self-learning of verification models and the creation of environments for secure A/B testing of AI modules.

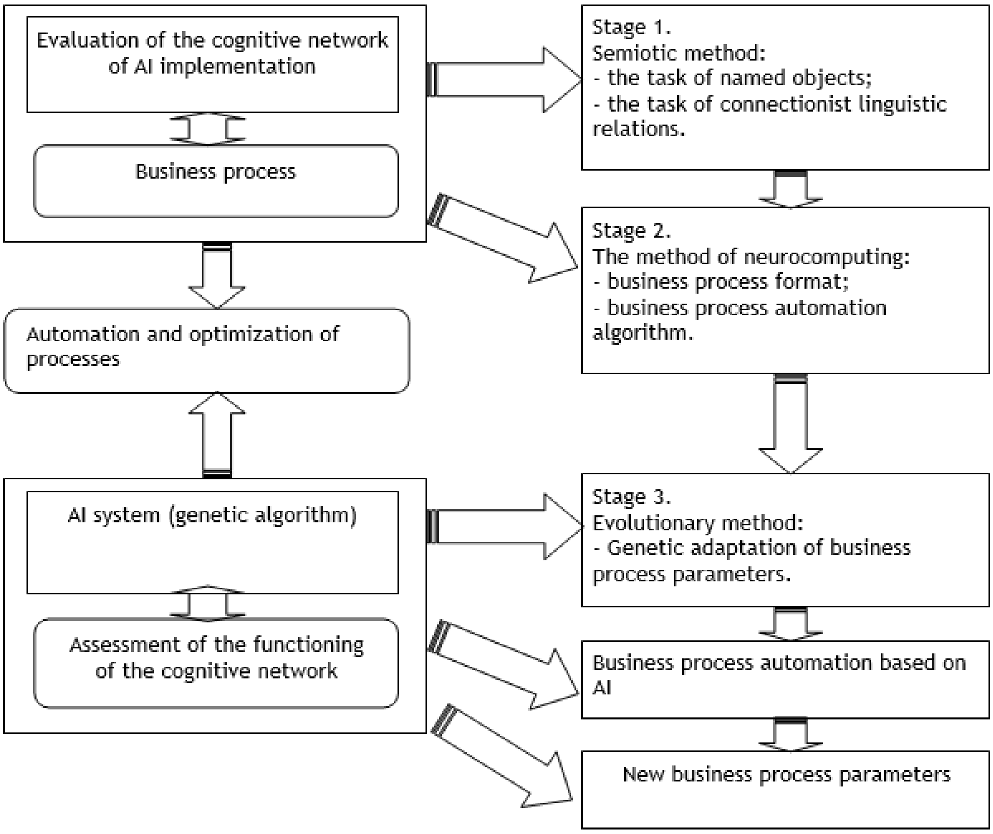

Figure 2. Stages of training cognitive neural networks in the process of automating company business processes using artificial intelligence

In addition, it is always necessary to determine the effectiveness of GPT-based tools for generating test documentation, transforming requirements into natural language tests, and generating test reports for stakeholders without a technical background. Such tools have reduced the time needed to prepare test cases, reduced the number of human-related errors, and made QA processes more transparent for the business.

Modeling the improvement and automation of a company's business process based on an AI model

The initial stage in the process of introducing artificial intelligence into business process automation is the intelligent recognition of the main elements of the company's process activities and the construction of its visual digital model, which is a prerequisite for further analysis, optimization, and automatic management improvement.[34] Recent studies recognize multifunctional software libraries that combine algorithmic precision with artificial intelligence capabilities as the most effective tools for this task (figure 3).

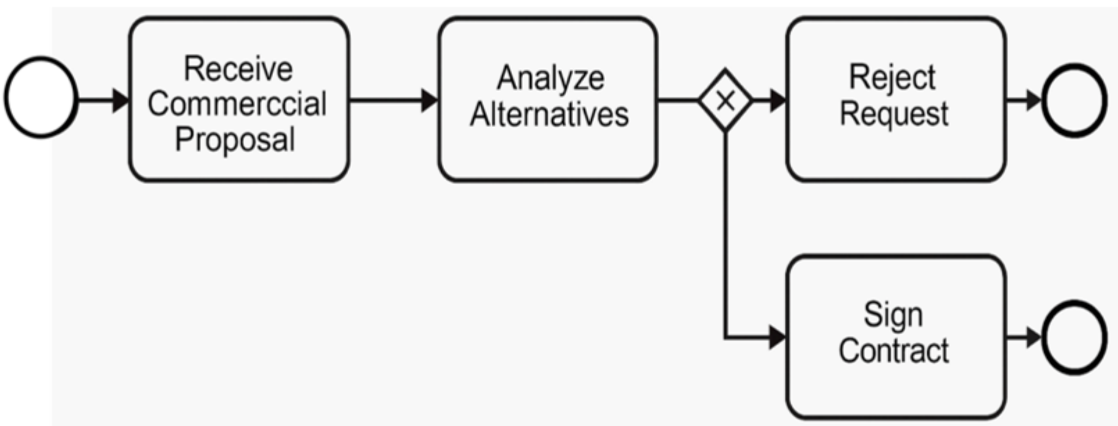

Figure 3. An example of business process automation for a trading company

The next critical stage is the calculation and interpretation of process quality indicators, which allows a deep assessment of the efficiency of the business system. The author's proposed approach to assessing management effectiveness uses both expert evaluation and analytical algorithms, which together form a holistic integral index of business process quality (table 1).[35]

Table 1. Metrics for assessing the impact of artificial intelligence on business process automation

Indicator	Designation	Normative value	Calculation method	What it shows
1. Complexity of the hierarchical structure	P1	≤ 0,7	The ratio of the number of decomposition levels to the sum of the types of automated processes	Shows the degree of complexity of the hierarchical structure of business processes in the context of AI implementation
2. The level of control with the help of AI	P2	> 0,9	The ratio of the number of business process classes to the number of AI systems that manage them	Shows the efficiency of business process management using artificial intelligence
3.Probability of successful automation	P3	> 0,7	It is determined based on the following factors: AI qualification, resources, planning, risk management	Shows the likelihood of successful completion of automated business processes with the set goals
4. Expenditure of resources for automation	P4	< 1	Ratio of the amount of resources used to the results of automated processes	Shows the efficiency of resource use when automating business processes with AI
5. Regulation of automated processes	P5	≥ 1	Ratio of the number of regulations to the number of classes of automated business processes	Displays the degree to which AI-supported business processes are regulated by relevant documents
6. Financial result of automation	P6	≥ 1	Ratio of revenue from automated processes to the cost of their implementation	Displays the financial efficiency of business processes automated by AI.
7. Connectivity of automated processes	P7	< 1	Ratio of the number of gaps to the sum of classes of automated business processes	Determines the level of AI integration into process models (process or problematic)
8. Average looping during automation	P8	< 0,3	The ratio of total time to the number of completed cycles in fractions of one	Shows the time required to complete one cycle of an automated process using AI
9. Average length of the automated path	P9	< 7,7	The ratio of the sum of the number of steps to the number of possible paths in the process	Shows the average number of steps to complete an automated business process with AI

The calculation is based on a specialized formula that takes into account both the positive and negative impacts of individual indicators on overall efficiency. The integral indicator of business process quality is calculated using the following formula:

$$E = -P1 + P2 + P3 - P4 + P5 + P6 - P7 - P8 - 0{,}1 \times P9, \qquad (1)$$

where E – is an integral indicator of business process diagnostics;

P_i – is the value of impact assessment metrics.

When the value of the quality index exceeds 0,1, it indicates proper performance and compliance of the process with the expected results.

Automation of business processes involves the use of reinforcement learning, where artificial intelligence constantly analyzes the results of its actions through a reward-punishment system. When the system achieves key performance indicators, such as cost reduction (P4) or overall productivity (E), it receives a positive reinforcement signal. On the contrary, it is when deviations from the norms lead to negative ratings.

The AI algorithm carefully evaluates each step of the business process, awarding points for achieving the target parameters: positive marks are awarded for reducing production cycle time (P8<0,3) or reducing operating costs (P4<1), while violations of the established norms are punished with penalty points. This type of continuous feedback system allows AI to iteratively adapt its actions, gradually optimizing all business processes.

Here is the business process of drawing up a "commercial offer" for a trading company before automated actions (figure 4).

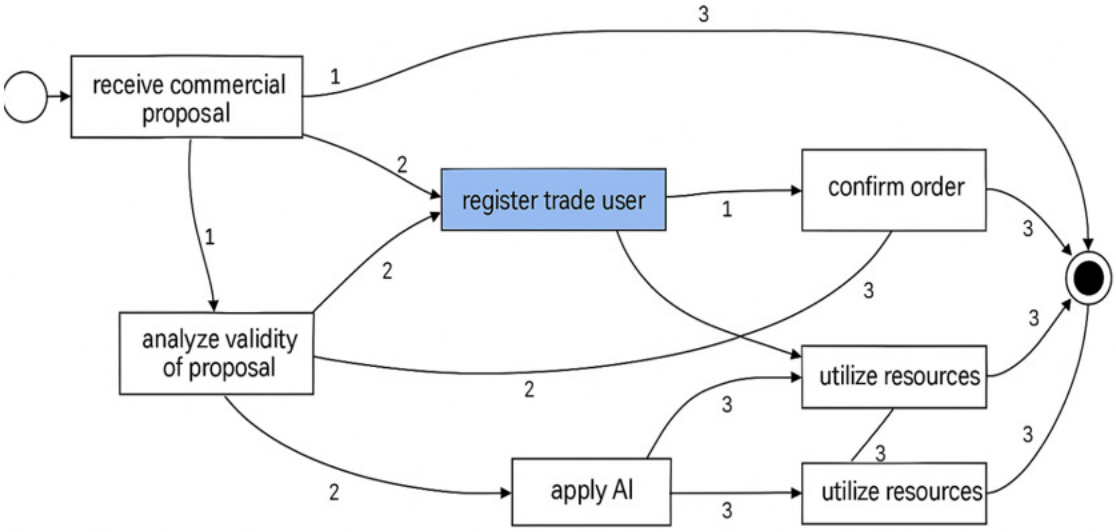

Figure 4. Business process of making a “commercial offer” for a trading company before automated actions

The identified discrepancy indicates a violation of the sequence of operations, possible deviations in the decision-making logic, or ineffective actions that reduce the overall efficiency of the process. Table 2 shows the values of the key quality metrics that were calculated during the study for the business process “commercial offer” and and procurement optimization as the basis for building an integrated assessment of the effectiveness of its functioning.

Table 2. Actual values of metrics for assessing the impact of artificial intelligence on the automation of the business process “commercial offer”

Indicator	Designation	Actual value
Complexity of the hierarchical structure	P1	0,2
The level of control with the help of AI	P2	0,6
Probability of successful automation	P3	0,9
Expenditure of resources for atomation	P4	0,9
Regulation of automated processes	P5	1,1
Financial result of automation	P6	0,2
Connectivity of automated processes	P7	1,1
Average looping during automation	P8	0,7
Average length of an automated path	P9	9

Let us calculate the current integral quality indicator of the business process “commercial offer”.

$$E = 0{,}2 + 0{,}6 + 0{,}9 - 0{,}9 + 1{,}1 - 0{,}7 - 0{,}1 \times 9 = -1{,}0$$

The actual value of efficiency (E = -1,0) indicates a low level of efficiency of business process automation under current conditions. A negative value indicates that negative factors (high resource costs, connectivity, looping, and path length) prevail over positive factors (control, probability of success, regulation, financial result). This may be the result of insufficient optimization of processes using artificial intelligence.

The use of artificial intelligence (AI) to automate a company’s business processes is based on a step-by-step approach. First, key elements of processes (stages of a commercial offer) are identified using machine learning algorithms such as classification and recognition. The data obtained is transformed into a digital model that reflects the structure and sequence of actions. The next step involves analysing quality indicators (table 1), such as structure complexity (P1) or control level (P2), which allows us to assess the effectiveness of existing business processes.

The study revealed significant deviations between the actual and normative state of processes in a trading company. The actual efficiency index (E) was -1,0, while the minimum permissible value was 0,1. There were also violations of the sequence of operations (P9 = 9 instead of the norm < 7,7), insufficient control by AI (P2 = 0,6 instead of > 0,9), and excessive looping (P8 = 0,7 instead of < 0,3), which indicates suboptimal decision-making and the presence of unnecessary actions that reduce the overall productivity of the business process.

Of particular importance in the analytical module is the detection of anomalies in deviations from the normative business process model, which may indicate the presence of bottlenecks, inefficient links, or deviations from standard procedures that reduce the overall productivity and accuracy of the organization. In this context, artificial intelligence, in particular machine learning models, make it possible to predict with high accuracy the probability of successful completion of processes, determine the cyclicality of actions, identify critical points, and assess the impact of specific actions on quality indicators.(36,37)

The fourth stage involves the automatic reconstruction of the business process, which is implemented using reinforcement learning methods that allow not only to model optimal trajectories of process development, but also to constantly improve them by analysing feedback in the form of "rewards" or "penalties" for achieving or not achieving target results.(38) In this case, self-adaptive models are created that gradually improve their efficiency in accordance with changes in internal and external conditions.

The analysis of empirical data for the reporting period revealed a significant deviation between the actual business process model and the regulated (reference) process, which indicates insufficient compliance of current management practices with company standards.(39) Most of the expert metrics remained within the normative values, but algorithmic indicators related to the depth of cycles, the efficiency of transitions and the load on individual elements negatively affected the overall efficiency index, which amounted to -0,2, which does not meet the recommended range for the stable functioning of the system.

In order to address the identified shortcomings, another stage of digital reengineering was implemented, focused on identifying hidden anomalies in processes related, in particular, to the stage of approval of a commercial offer within the loyalty program, which, according to the analysis, proved to be critical in terms of reducing the quality of management decisions.

By introducing automated management of the general outline of the business process "commercial offer" for a trading company, we will both change the structure and give a new assessment of the metrics of the impact of artificial intelligence on the automation of this business process (figure 5).

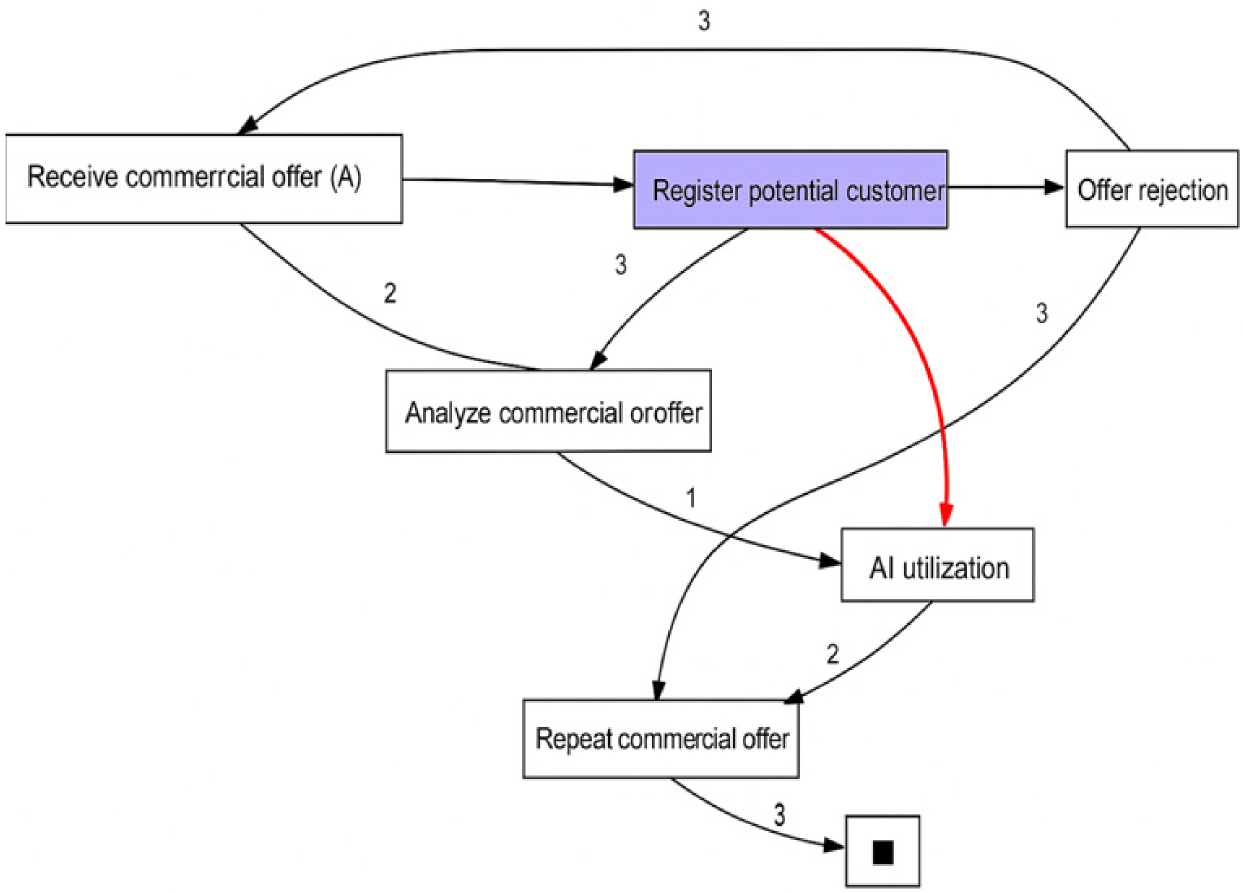

Figure 5. Modification of the business process "commercial offer" in the work of a trading company to perform automated actions

The new calculations of the values of the evaluation metrics after the business process improvement, based on formula (1), are shown in table 3.

Table 3. Updated values of the metrics for assessing the impact of artificial intelligence on the automation of the business process "commercial offer"

Indicator	Designation	Actual value	Updated value
Complexity of the hierarchical structure	P1	0,2	0,1
The level of control with the help of AI	P2	0,6	0,95
Probability of successful automation	P3	0,9	0,98
Expenditure of resources for automation	P4	0,9	0,7
Regulation of automated processes	P5	1,1	1,5
Financial result of automation	P6	0,2	1,2
Connectivity of automated processes	P7	1,1	0,8
Average looping during automation	P8	0,7	0,4
Average length of an automated path	P9	9	6

Let us calculate the integral quality indicator for the improved business process "commercial offer":

$E = -0,1 + 0,95 + 0,98 - 0,7 + 1,5 + 1,2 - 0,8 - 0,4 - 0,1x6 = 2,03$

The updated efficiency value (E = 2,03) demonstrates a significant improvement due to the optimization of indicators. A positive value indicates that the implementation of advanced AI solutions contributes to increased control, probability of success, regulation, and financial efficiency, while reducing complexity, resource consumption, connectivity, looping, and process length. The difference between the actual (-1,0) and updated (2,03) values (ΔE = 3,03) emphasizes the potential of AI to transform business processes.

Thus, we can state that the development of artificial intelligence and its targeted application for business process automation can significantly increase efficiency, as evidenced by the transition from a negative to a positive value of the E indicator.

DISCUSSION

The study confirmed the significant potential of AI in automating business processes, in particular in optimizing the structure, improving the accuracy of management decisions, and adapting to changing market conditions. The use of cognitive neuro-fuzzy models forms the basis for combining human imaginative thinking with the algorithmic logic of machine learning, which distinguishes this approach from traditional automation methods.

The results are consistent with the findings of Gu[3] and Dalsaniya & Patel,[1] which emphasize the role of machine learning in creating flexible business models. The proposed methodology makes it possible to overcome the limitations of classical neural networks that do not take into account the semantic and cognitive aspects of management. In contrast to the research of Mangal et al.,[7] which uses a linear input-output architecture, the M-network model reflects business processes as a dynamic interaction of i-models with adaptive weighting relationships that meet current management goals.

The key innovation is the use of the "reinforcement learning" principle to prioritize elements of business processes under high load, which becomes the basis for automatic filtering and visualization of the most important information, and reduces time and analytical resources compared to traditional methods.[9,12] Reinforcement learning has also been proven to be effective for the automatic reconstruction of business processes. This makes it possible to create a self-adaptive management system capable of responding quickly to external and internal changes. Although similar approaches were considered by Patrício et al.,[38] their solutions did not integrate cognitive structures, which is a key advantage of this study.

The practical value is confirmed by the improvement of the efficiency indicator of the business process "commercial offer" from -1,0 to 2,03. This is in line with the findings of Oyekunle and Boohene[17] on the need for dynamic assessment and flexible customization of systems based on analytics.

However, the proposed approach is characterized by deeper detail (division of metrics into expert and algorithmic) and the ability to detect hidden anomalies that are not captured by standard methods. Compared to the work of Caspary et al.,[11] the integration of the cognitive component (modelling the thinking of managers) provides a better interpretation of anomalies and increases the efficiency of their elimination.

The scientific contribution is the combination of semantic modeling, cognitive learning, fuzzy logic, and machine learning, which forms an integrated approach to automation. Unlike studies that focus on either data processing[39] or information architectures,[15] this paper proposes a holistic model that considers both technical and behavioural aspects. In practice, the M-network model can become a tool for improving the efficiency of business processes in companies that implement digital transformation without losing flexibility. This is especially true in an environment of instability, when decisions should be based not only on data but also on cognitive mechanisms that ensure quick response.

CONCLUSION

It is substantiated that the concept of integrating artificial intelligence into the automation of business processes is based on the use of cognitive neuro-fuzzy models that combine objective data and subjective perceptions of employees. The use of semantic M-networks allows representing key aspects of management in the form of graph structures, which facilitates analysis and decision-making.

This study presents an integrated approach to digital business process reengineering based on the use of artificial intelligence technologies and machine learning algorithms for automated modelling, evaluation, and improvement of management procedures. The proposed methodology covers the full cycle of digital reengineering, including the creation of a virtual map of a business process based on real digital traces of the company's activities, calculation of quality metrics, detection of anomalies in the performance of operations and automatic reconstruction of the process logic in order to adapt it to the current conditions of a highly dynamic business environment.

The study also outlines the key conditions for the successful implementation of the digital reengineering model, including the availability of sufficient data on the execution of processes, the accuracy of recognizing their elements, and the ability to flexibly integrate AI models into the company's existing infrastructure.

REFERENCES

1. Dalsaniya A, Patel K. Enhancing process automation with AI: The role of intelligent automation in business efficiency. Int J Sci Res Arch. 2022;5(2):322–37. https://doi.org/10.30574/ijsra.2022.5.2.0083

2. Rajagopal NK, Qureshi NI, Durga S, Ramirez Asis EH, Huerta Soto RM, Gupta SK, et al. Future of business culture: An artificial intelligence-driven digital framework for organization decision-making process. Complexity. 2022;2022:7796507. https://doi.org/10.1155/2022/7796507

3. Gu S. Exploring the role of AI in business decision-making and process automation. Int J High Sch Res. 2024;6(3):94-102. https://doi.org/10.36838/v6i3.15

4. Bruno Z. The impact of artificial intelligence on business operations. Glob J Manag Bus Res D Account Audit. 2024;24(D1):1-8. https://doi.org/10.34257/GJMBRDVOL24IS1PG1

5. Chai J. Artificial intelligence and its impact in the business world. Bolivia: Universidad Nur; 2024. https://www.researchgate.net/publication/381092836

6. Abbasi M, Nishat RI, Bond C, Graham-Knight JB, Lasserre P, Lucet Y, et al. A review of AI and machine learning contribution in predictive business process management (process enhancement and process improvement approaches) [Preprint]. arXiv; 2024. https://doi.org/10.48550/arXiv.2407.11043

7. Mangal A, Gupta P, Goel O. The role of RPA and AI in automating business processes in large corporations. Int J Novel Res Dev. 2023;8(3):e784–e799. https://www.ijnrd.org/papers/IJNRD2303502.pdf

8. Nandhini AA, Nandhini A. Automation of business process through artificial intelligence (AI): A study with special reference to selected industries in Coimbatore district of Tamil Nadu. J Orient Inst. 2022;71(6):60–6. https://www.academia.edu/101010930/

9. Khabbaz R. The role of artificial intelligence in enhancing business process management systems and its implications. Middle East Conf Sci J. 2022. https://mecsj.com/uplode/images/photo/The_Role_of_Artificial_Intelligence_in_Enhancing_Business_Process_Management_Systems_and_its_Implications.pdf

10. Rane N, Choudhary S, Rane J. Artificial intelligence-driven corporate finance: Enhancing efficiency and decision-making through machine learning, natural language processing, and robotic process automation in corporate governance and sustainability. SSRN Electron J. 2024. https://doi.org/10.2139/ssrn.4720591

11. Caspary J, Rebmann A, van der Aa H. Does this make sense? Machine learning-based detection of semantic anomalies in business processes. In: Francescomarino CD, Burattin A, Janiesch C, Sadiq S, editors. Business Process Management – 21st Int Conf, BPM 2023, Utrecht, Netherlands, Sept 11–15, 2023. Proceedings. Vol. 14159. Cham: Springer; 2023. p. 163–79. https://doi.org/10.1007/978-3-031-41620-0_10

12. Shah W. Federated learning and privacy-preserving AI: Safeguarding data in distributed machine learning. ResearchGate; 2022. https://doi.org/10.13140/RG.2.2.36659.44324

13. Selvam P, Dornadula VHR, Madhur P, Kotehal PU. Application of artificial intelligence in business operations and its impact on organisational performance: An empirical study. Afr J Biol Sci. 2024;6(6):6812–20. https://doi.org/10.33472/AFJBS.6.6.2024.6812-6820

14. Sheth H. The impact of automation on business process efficiency and accuracy: Enhancing operational performance in the digital age. Iconic Res Eng J. 2021;4(12):317–21. https://www.irejournals.com/paper-details/1702757

15. Pandy G, Jayaram V, Krishnappa MS, Ingole BS, Ganeeb KK, Joseph S. Advancements in robotics process automation: A novel model with enhanced empirical validation and theoretical insights. Eur J Comput Sci Inf Technol. 2024;12(5):64–73. https://doi.org/10.37745/ejcsit.2013/vol12n56473

16. Pelz-Sharpe A, Mullen M. A simple guide to successful business process automation. OpenText; 2024. https://www.opentext.com/assets/documents/en-US/pdf/a-simple-guide-to-successful-business-process-automation-wp-en.pdf

17. Oyekunle D, Boohene D. Digital transformation potential: The role of artificial intelligence in business. Int J Prof Bus Rev. 2024;9(3):e04499. https://doi.org/10.26668/businessreview/2024.v9i3.4499

18. Sarker IH. AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems. SN Comput Sci. 2022;3(2):158. https://doi.org/10.1007/s42979-022-01043-x

19. Adorno OA. Business process changes on the implementation of artificial intelligence [Master's thesis]. São Paulo: University of São Paulo; 2020. https://doi.org/10.11606/D.12.2020.tde-08042021-011316

20. Filippucci F, Gal P, Jona-Lasinio C, Leandro A, Nicoletti G. The impact of artificial intelligence on productivity, distribution and growth: Key mechanisms, initial evidence and policy challenges. OECD Artif Intell Pap. 2024;(15). https://doi.org/10.1787/8d900037-en

21. Daclin N, Mallek-Daclin S, Zacharewicz G. Generative AI for business model generation (GAI4BM): From textual description to business process model. In: Proc 10th Int Food Operations Process Simul Workshop (FoodOPS 2024); 2024. https://doi.org/10.46354/i3m.2024.foodops.013

22. Kussainov K, Goncharuk N, Prokopenko L, Pershko L, Vyshnivska B, Akimov O. Anti-corruption management mechanisms and the construction of a security landscape in the financial sector of the EU economic system against the background of challenges to European integration: Implications for artificial intelligence technologies. Econ Aff (New Delhi). 2023;68(1):509–21. https://doi.org/10.46852/0424-2513.1.2023.20

23. Makedon V, Budko O, Salyga K, Myachin V, Fisunenko N. Improving strategic planning and ensuring the development of enterprises based on relational strategies. Theor Pract Res Econ Fields. 2024;15(4):798–811. https://doi.org/10.14505/tpref.v15.4(32).02

24. Pisoni G, Moloney M. Responsible AI-based business process management and improvement: Observations from financial domain cases. SSRN Electron J. 2024. https://doi.org/10.2139/ssrn.4822711

25. Żywiołek J, Gupta SK. Call for chapters: Artificial intelligence as a business management tool (AIBMT-2024) [Internet]. ResearchGate; 2024. https://doi.org/10.13140/RG.2.2.31829.03046

26. Arsawan IWE, Suhartanto D, Koval V, Tralo I, Demenko V, Azizah A. Enhancing the circular economy business model towards sustainable business performance: Moderating the role of environmental dynamism. J Infrastruct Policy Dev. 2024;8(5):Article 3321. https://doi.org/10.24294/jipd.v8i5.3321

27. Dumas M, Fournier F, Limonad L, Marrella A, Montali M, Rehse JR, et al. AI-augmented business process management systems: A research manifesto. ACM Trans Manag Inf Syst. 2023;14(1):1–19. https://doi.org/10.1145/3576047

28. Moderno F, Smith J, Taylor L. Robotic process automation and AI: A resource-based enhanced future. Strateg Dir. 2024;40(1):23–4. https://doi.org/10.1108/SD-12-2023-0160

29. Kampik T, Warmuth C, Rebmann A, Agam R, Egger LNP, Gerber A, et al. Large process models: A vision for business process management in the age of generative AI. KI Künstl Intell. 2024. https://doi.org/10.1007/s13218-024-00863-8

30. Rana NP, Chatterjee S, Dwivedi YK, Akter S. Understanding the dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. Eur J Inf Syst. 2022;31(3):364–87. https://doi.org/10.1080/0960085X.2021.1955628

31. Khatniuk N, Shestakovska T, Rovnyi V, Pobiianska N, Surzhyk Y. Legal principles and features of artificial intelligence use in the provision of legal services. J Law Sustain Dev. 2023;11(5):1–18. https://doi.org/10.55908/sdgs.v11i5.1173

32. Yakovenko Y, Shaptala R. Intelligent process automation, robotic process automation and artificial intelligence for business processes transformation. In: Globalisation Processes in the World Economy: Problems, Trends, Prospects. Baltija Publishing; 2024. p. 496–521. https://doi.org/10.30525/978-9934-26-378-1-20

33. Amaugo O. Impact of AI adoption on business process automation and competitiveness in manufacturing industry in Nigeria. Int J Res Innov Soc Sci. 2024;8(3). https://dx.doi.org/10.47772/IJRISS.2024.803398S

34. Avanesova N, Tahajuddin S, Hetman O, Serhiienko Y, Makedon V. Strategic management in the system model of the corporate enterprise organizational development. Econ Finance. 2021;1(9):18–30. https://doi.org/10.51586/2311-3413.2021.9.1.18.30

35. Makedon V, Myachin V, Plakhotnik O, Fisunenko N, Mykhailenko O. Construction of a model for evaluating the efficiency of technology transfer process based on a fuzzy logic approach. East Eur J Enterp Technol. 2024;2(13(128)):47–57. https://doi.org/10.15587/1729-4061.2024.300796

36. Makedon VV, Kholod OH, Yarmolenko LI. The model of assessing the competitiveness of high-tech enterprises based on the formation of key competencies. Acad Rev. 2023;2(59):75-89. https://doi.org/10.32342/2074-5354-2023-2-59-5

37. Soni N, Sharma EK, Singh N, Kapoor A. Artificial intelligence in business: From research and innovation to market deployment. Procedia Comput Sci. 2020;167:2200–10. https://doi.org/10.1016/j.procs.2020.03.272

38. Patrício L, Varela L, Silveira Z. Integration of artificial intelligence and robotic process automation: Literature review and proposal for a sustainable model. Appl Sci. 2024;14(21):9648. https://doi.org/10.3390/app14219648

39. Tayab A, Li YW. Robotic process automation with new future trends. J Comput Commun. 2024;12(6):12-24. https://doi.org/10.4236/jcc.2024.126002

FINANCING
The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Conceptualization: Yevhenii Chuprun.
Data curation: Mykhailo Lukash.
Formal analysis: Oksana Lysak.
Research: Mykhailo Lukash.
Methodology: Oksana Lysak.
Project management: Anatolii Husakovskyi.
Resources: Kyrylo Hanhanov.
Software: Kyrylo Hanhanov.

Supervision: Mykhailo Lukash.
Validation: Yevhenii Chuprun.
Display: Kyrylo Hanhanov.
Drafting - original draft: Anatolii Husakovskyi.
Writing - proofreading and editing: Yevhenii Chuprun.