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A SYSTEM-ORIENTED VIEW ON THE USE OF ARTIFICIAL INTELLIGENCE IN ENTERPRISE BUSINESS FUNCTIONS AND ITS IMPACT ON ECONOMIC EFFICIENCY

СИСТЕМНИЙ ПІДХІД ДО ВИКОРИСТАННЯ ШТУЧНОГО ІНТЕЛЕКТУ В БІЗНЕС-ФУНКЦІЯХ ПІДПРИЄМСТВА ТА ОЦІНКА ЙОГО ВПЛИВУ НА ЕКОНОМІЧНУ ЕФЕКТИВНІСТЬ

Summary. The purpose of the article is to systematize the use of artificial intelligence technologies in enterprise business functions and to assess their impact on economic efficiency. The authors classify AI technologies by functional complexity and develop a matrix linking technology types with ten key enterprise functions, expected benefits, and implementation complexity. The scientific novelty lies in the structured integration of technology types, functional areas, and efficiency effects within a unified framework. The results show that the impact of artificial intelligence differs across functions and is expressed in different forms, including cost reduction, production productivity growth, and improved decision-making quality. The findings have practical relevance for enterprises planning future artificial intelligence adoption in terms of technology use per function.

Keywords: artificial intelligence, business functions, digital integration, efficiency, technology type.

Анотація. Метою статті є систематизація використання технологій штучного інтелекту в основних бізнес-функціях підприємства та оцінка їх впливу на економічну ефективність. У роботі здійснено класифікацію сучасних технологій штучного інтелекту за рівнем функціональної складності та розроблено структуровану матрицю відповідності між типами технологій, сферами їх застосування у десяти ключових функціональних напрямах підприємства, очікуваними ефектами та складністю впровадження Авторський внесок полягає у формуванні системного підходу до аналізу використання штучного інтелекту в економічних процесах підприємства, що дозволяє поєднати класифікацію технологій із функціональною структурою організації та результатами її діяльності. Наукова новизна дослідження полягає у поєднанні типології сучасних технологій штучного інтелекту з оцінкою їх практичного значення для різних функціональних напрямів підприємства у межах єдиної аналітичної моделі, що враховує очікувані економічні ефекти, а також рівень складності впровадження. У результаті дослідження встановлено, що вплив штучного інтелекту на економічну ефективність має диференційований характер залежно від функціонального напряму. В адміністративних процесах та напрямів, що стосуються взаємодії із клієнтом або надання сервісу, основні ефекти пов'язані зі зниженням витрат і підвищенням продуктивності, тоді як у маркетингу, дослідженнях та виробництві, використання штучного інтелекту сприяє підвищенню точності прогнозування, оптимізації процесів, скороченню часу розробки продукції та покращенню якості управлінських рішень. Складність впровадження технологій штучного інтелекту також відрізняється залежно від функціонального напряму. Найменша складність характерна для адміністративних процесів та маркетингу, де можливе використання готових рішень без істотної перебудови внутрішніх інформаційних систем. Натомість у виробництві, логістиці, фінансах та кібербезпеці впровадження потребує глибшої інтеграції з існуючою інфраструктурою. Практичне значення результатів полягає у можливості застосування запропонованої систематизації для прийняття обґрунтованих рішень щодо впровадження технологій штучного інтелекту з урахуванням завдань та функціональних потреб окремих департаментів підприємства.

Ключові слова: штучний інтелект, функціональні напрями підприємства, цифрова інтеграція, ефективність, види технологій.

Problem statement. The recent surge of artificial intelligence (AI) tools has significantly changed how enterprises organize and manage their economic processes. These technologies are increasingly embedded across multiple departments, influencing decision-making, operational efficiency, and value creation. They are no longer limited to isolated pilot projects. As a result, enterprises face the challenge of understanding which AI technologies are relevant for specific business functions, how they are applied in practice, and what benefits they can realistically generate.

Existing studies often focus on individual technologies or isolated use cases despite extensive discussions on AI adoption, without providing a structured overview that links AI tool types to specific departments and performance outcomes. This creates a gap between the increased adoption of AI solutions and the ability of enterprises to make informed decisions regarding their implementation.

The purpose of this study is to classify and systematize AI technologies used in enterprises, identify their application across key business functions, and analyze the benefits associated with their adoption. To achieve this purpose, the paper applies analytical and comparative research methods based on secondary data sources, including corporate reports and industry research publications. The result allows for a better understanding of AI contribution to efficiency improvements across different functional areas.

Analysis of recent research and publications. Existing research has shown that AI turns into one of the significant drivers of enterprise digital transformation affecting both operational and strategic activities. AI-driven models, AI-driven models, in particular, machine learning (ML) and deep learning (DL), illustrate better forecast accuracy, scalability, and responsiveness in demand forecasting and inventory optimization compared to the traditional supply chain methods (Saha R. et al., 2024) [1]. Multiple studies outline the role of AI and ML in decision support enhancement. For example, AI ML-based decision support systems enhance the analytical capabilities and contribute to faster data-driven managerial decisions including procurement and sourcing decisions (Balkan D. & Akyuz G. A., 2025) [2]. Other works focus on certain automation technologies like robotic process automation that has proven efficiency in automating routine marketing processes, data entry, and report generation, improving operational efficiency, and free resources for more strategic tasks (Wilson G. et al., 2024) [3].

At the same time, research findings show the practical value of AI adoption varies across enterprise functions: for example, administrative and service-oriented processes tend to benefit mainly from efficiency gains and cost reductions, while other functions related to research and development (R&D), marketing, and production get more value from innovation, personalized design of products, and processes. Moreover, studies keep pointing to data readiness as a critical element in AI implementation, pointing out that technological will not lead to measurable practical benefits if not aligned with organizational preparedness (Wilson et al., 2024). [3].

However, the literature also reveals a lack of framework that systematically links a specific AI technology type with enterprise functions and associated benefits across various departments. Most studies have focused on either standalone technologies or use cases that are not integrated into a comparative model. This points to a research gap in the systemization of diverse applications of AI tools in understanding their relevance and benefits, along with assessing the complexity of implementation in a unified manner.

The aim of the article is to develop a system-oriented view of the use of artificial intelligence in enterprise business functions by identifying how different AI technology types are applied across key functional areas. The other goal is to compare the nature of the benefits they generate and examine how implementation complexity varies depending on the operational context. On this basis, the article will propose a structured analytical framework that integrates all the aforementioned aspects into a unified perspective, providing a comprehensive basis for evaluating expected impact of AI integration in business practice.

Methodology. The study employed a qualitative analytical research design based on the analysis of secondary data sources, including reports from major technology companies, industry publications, and studies conducted by international business schools and professional organizations. The analysis was done in several stages. First, relevant sources were selected based on their focus on enterprise AI adoption. Qualitative data regarding AI application areas was extracted during the next step and systematized into a matrix that maps AI technologies to ten key enterprise business functions.

Methods of analysis included classification, comparison, and synthesis. AI technologies were grouped by type, and application areas were evaluated in terms of implementation complexity and expected benefits. Additionally, documented enterprise examples were used to illustrate practical outcomes of AI adoption. The study focused on synthesizing existing empirical evidence to provide a structured and comparative overview of AI usage in enterprise economic processes and its impact on efficiency.

Summary of the main research material. To better understand the current state and future development prospects of artificial intelligence technologies, it is necessary to consider their classification according to the level of functional complexity. This classification will help systematize existing knowledge and identify the areas of future research and development.

A modern classification of artificial intelligence technology types is presented in Figure 1.

Artificial intelligence is commonly divided into three general levels: Narrow AI, General AI, and Super AI. Among these, Narrow AI represents the current technological reality [4]. It is designed to perform specific tasks within a limited context (one or several tasks within a specified fields) and does not have abstract reasoning capabilities. All modern basic artificial intelligence systems belong to this category.

Two functional subtypes can be distinguished within Narrow AI. The first one includes reactive machines, which operate exclusively on current input data and don't have any memory or learning mechanisms. A good example of such technology is the chess-playing system Deep Blue, which calculates moves based on predefined algorithms. In an economic context, this category includes basic

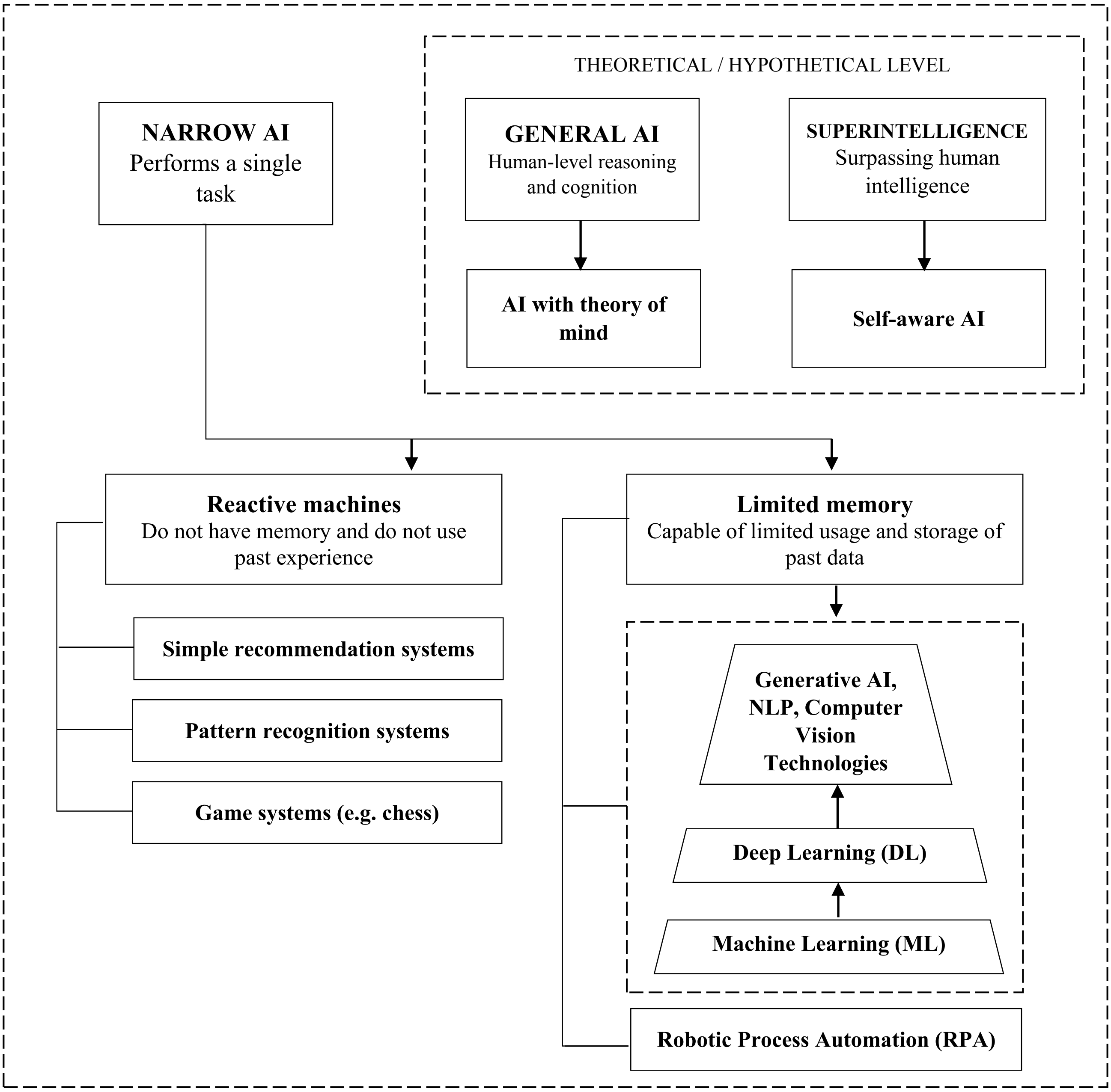

Figure 1 – Modern classification of AI technology by functional levels

Source: [4–7]

recommendation systems that do not take user history into account. Also we can add elementary image recognition systems into reactive machines category – as they classify objects without constructing deeper contextual understanding [4].

The second subtype comprises systems with limited memory, which form the foundation of modern artificial intelligence technologies. These systems are capable of analyzing and storing past data, experience, modeling dependencies, and learning from historical information [4]. This group can be visualized in a hierarchical structure. Machine learning lies at the base. It prominently emerged in the 1990s, enabling systems to identify patterns in data without explicit programming. On the next level we have deep learning, which gained significant momentum in the 2010s and relies on multi-layer neural networks to recognize complex patterns in speech, images, and human behavior.

Several highly functional artificial intelligence systems have been developed recently using the approach of deep learning. Such systems are increasingly being used by different kinds of enterprises. Such systems include generative artificial systems that have the capability to produce images or text (for instance, GPT for texts and DALL-E for images), Natural language processing (NLP) systems that have the capability to analyze human language, and computer vision systems. These systems, though restricted by memory, have the partial potential for autonomy.

Robotic Process Automation (RPA) represents a similar but somewhat different direction. Although robotic systems are also based on limited memory AI, the main difference is their capability to interact with the physical environment by moving, avoiding obstacles, etc., and adapting their behavior real-time [5].

General AI and Super AI currently remain in the hypothetical domain. General AI is envisioned as a future system capable of understanding intentions, emotions, and beliefs of others, having the so called "theory of mind." [4]. Such systems would be able to transfer knowledge across domains and learn without fixed instructions. Self-aware AI is an even more distant concept. In theory it would fully understand its own existence and can potentially surpass human intelligence. At present, these concepts remain subjects of scientific debate rather than a real technology within the closest dozens of years.

The process illustrated in Figure 2 includes five key stages that demonstrate how an enterprise gradually moves from establishing a technical foundation to achieving measurable results.

The process begins with the formation of basic conditions for digital interaction, when the enterprise ensures technical readiness to work with digital data. This includes establishing digital document management, creating data structures, updating software, and configuring integration between information systems. The enterprise cannot proceed to subsequent phases without this stage, since the effective use of artificial intelligence requires access to structured, up-to-date data available in digital format [8].

Additional implementation of artificial intelligence tools relates to the use of particular algorithms and technology in tackling individual tasks. It starts with preliminary testing, which, if successful, can move towards automation of particular processes, developing smart decision support systems, or building new, simpler, work processes. At this stage, the enterprise receives first benefits from automation.

As the use of artificial intelligence tools becomes more prominent, the enterprise gradually changes its internal organization of work, the structure of departments, and approaches to planning. This stage is also marked by changes in corporate culture, as analytics, automation, and technological flexibility become integral parts of everyday activity, while employees adapt to new conditions. The need for adaptation leads to a revision of internal regulations, job responsibilities, motivation systems, and reporting practices [11]. This stage is critically important for avoiding internal resistance to change and achieving organizational compatibility with new technologies. It is important to note that on this stage in particular, the enterprise can identify bottlenecks in AI technology usage and make adjustments where necessary.

The result of these changes is a deeper transformation of business processes. Tasks that were previously performed manually become automated, which significantly reduces execution and decision-making time. Management becomes simpler due to the use of data and systems that automatically generate reports and recommendations. Duplication of operations is eliminated, and functional units begin to operate in a coordinated manner within a unified digital environment (with interaction often taking place in new formats). At the same time, the enterprise begins to approach its products or services differently, with new, more user-friendly service formats emerging, based on automation and gathered data.

Practical results of all previous changes are evaluated at the final stage. They can appear in the form of cost reductions, increased speed of operations, growth in workforce productivity, reduction of errors, customer experience improvement of, and growth of financial performance indicators, among others. Since efficiency is one of the key indicators of enterprise performance, this stage allows for substantiating the relevance and depth of AI tools implementation within the enterprise. The usage of modern artificial intelligence tools in enterprise economic processes is becoming increasingly systemic, covering various departments and functions. The next section analyzes

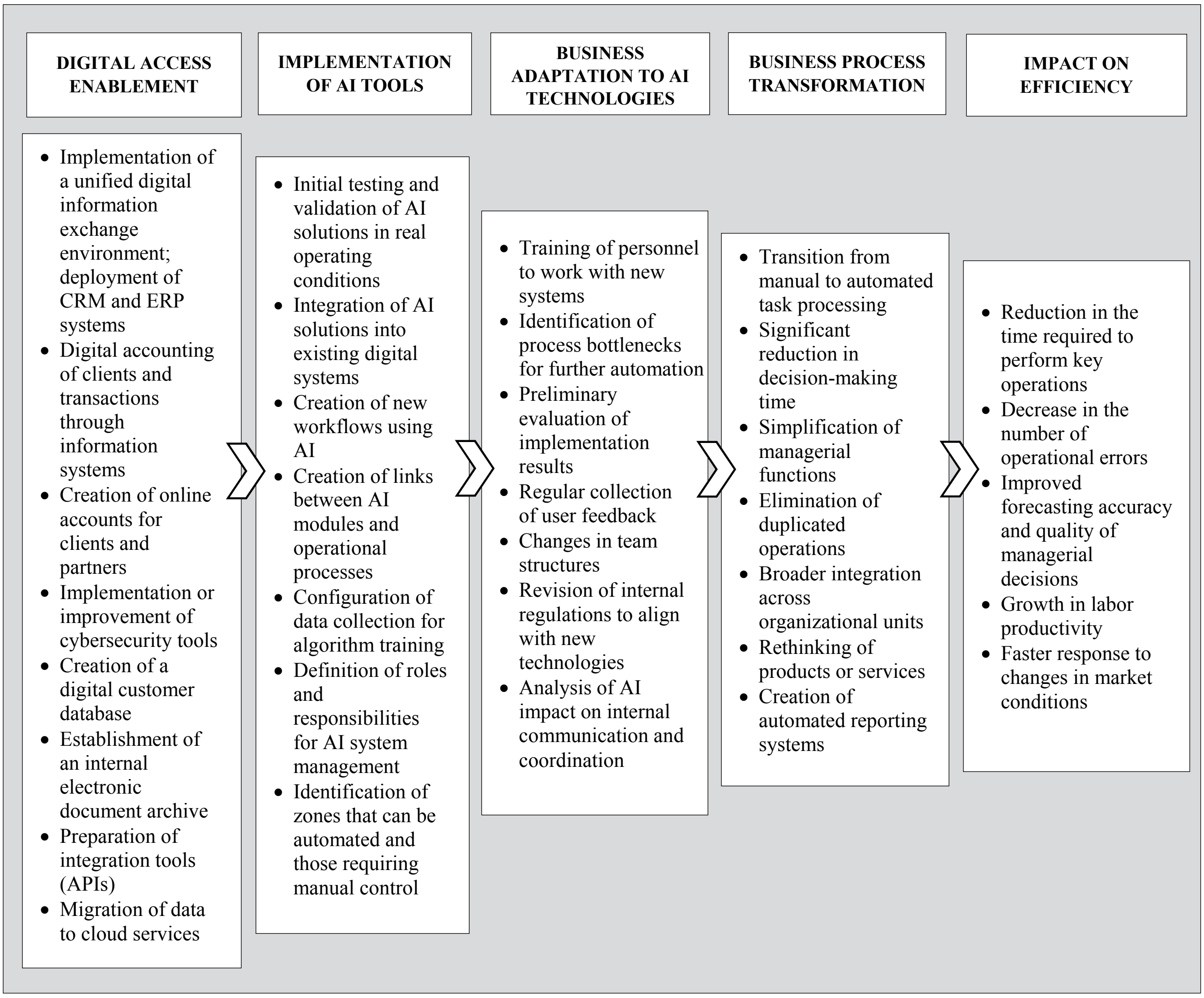

Figure 2 – Structure of the artificial intelligence implementation process in enterprise activity

Source: [8–11]

which technologies are commonly used by enterprises, the purposes for which they are applied, and the potential benefits that help clarify the relationship between specific technologies and their impact on efficiency.

Reports from major technology companies such as SAP [12], Hewlett-Packard [13], IMD [14], and Microsoft [15] were used for the analysis, as well as publications from the well-known technology outlet CIO [16]. Ten main areas of technology implementation were identified, including customer service, marketing and sales, analytics, human resource management, logistics, finance, document management, production, R&D and innovation, and cybersecurity.

The results of the analysis are presented in Tables 1 and 2.

The breadth of technology application across different departments is explained by the tangible advantages they already provide to enterprises. Each area of activity relies on a specific combination of technologies rather than focusing on a single type. Most of the technology types presented in Figure 1.1 are used, including ML & DL; NLP; RPA; computer vision; and generative artificial intelligence. The most popular technologies available are machine learning and deep learning, which have commonly been employed as powerful analytics techniques to build forecasting models, classification models, anomaly detectors, and trend predictors. Generative artificial intelligence stands at the top in areas where human creativity is required, like marketing, R&D, and innovation. In addition, it is used to reduce the workload of personnel involved in customer-facing activities.

Table 2 outlines the potential benefits and implementation complexity of AI adoption across enterprise functions.

From the perspective of implementation complexity, application areas can be conditionally

Table 1 – AI application by enterprise function and technology type

Function	Area of usage	Technology (type, name/example)
Customer service	– Automation of customer interaction – request handling, communication	– NLP – chatbots, virtual assistants, call processing – Generative AI – automatic creation of responses, customer offers
Sales and marketing	– Personalized recommendations – Analysis of customer behavior – Creation of promotional materials and communications	– Generative AI – creation of texts, images, creatives – NLP – review analysis for personalized offers and communication – ML/DL – customer segmentation
Analytics	– Business analytics – Forecasting and evaluation of KPIs – Competitive environment analysis	– ML/DL – analytics of large data volumes, scenario modeling – NLP – market monitoring
Human resources	– Automated recruitment and candidate assessment – Scheduling interview dates – Initial basic interview – Onboarding of new employees – Workforce workload planning -Employee performance evaluation	– ML/DL, NLP – CV screening algorithms – ML/DL – platforms for automated interviews and tests; analytics platforms for results
Logistics	– Collection and analysis of large datasets to predict demand – Optimization of delivery routes – Identification of bottlenecks in the supply chain	– ML/DL – overall supply chain management, forecasting – ML/DL – smart inventory management
Finance and accounting	– Automatic invoice processing, payment management – Financial flow forecasting – Detection of fraudulent transactions – Management of credit and investment risks	– RPA – invoice processing – NLP – automated report generation – ML/DL – default prediction, fraud detection, investment success prediction
Document management & administration	– Automatic form filling – Document processing and sending – Intelligent classification, sorting, and archiving of documents – Monitoring of administrative process execution and reporting	– NLP – extraction of key data from large document volumes – RPA – automation of routine document processing – Computer vision – recognition and structuring of images and scanned copies
Production	– Predictive maintenance of equipment – Analysis of final products	– IoT – sensors collecting machine operating parameters – Computer vision – analysis of products at the line output – RPA – robots performing a specific production task
R&D / Innovations	– New product design – Generation of new ideas; search for new formulas and products – Prototype creation – Experiment modeling	– Generative AI – idea generation; creation of prototypes and designs – ML/DL – modeling of development results – NLP – patent database analysis
Cybersecurity	– Real-time threat detection – Monitoring inbound traffic to digital resources – Fraud prevention	– ML/DL – anomaly detection, transaction analysis – RPA – intrusion detection

Source: [12–16]

divided into three levels: low, medium, and high. The lowest level of complexity is typical for administrative and marketing processes, as well as certain document management activities, where artificial intelligence can be rapidly integrated through ready-made platforms (for example, chatbots or NLP-based automated document processing systems). These solutions do not require large-scale changes to the internal IT infrastructure and can demonstrate quick results. This is confirmed by successful examples such as Chobani company, where the introduction of artificial intelligence into document management reduced the time spent on report preparation by 75 %, as well as German public authorities that processed more than 2.7 million documents in just three weeks thanks to artificial intelligence [12].

Operational domains such as production, logistics, and finance have greater complexity of

Table 2 – AI Potential benefits and implementation complexity by function

Function	Potential benefits for economic efficiency	Implementation complexity
Customer service	– Reduced workload (and/or costs) for the support department – Shorter response time – Increased customer satisfaction	Low
Sales and marketing	– Increased sales/conversions – Higher ROI of advertising campaigns – Reduced content creation costs, more accurate targeting	Low
Analytics	– Improved grounding of strategic decisions – Faster decision-making – Reduced time spent on analytics – Proactive KPI management	Low
Human resources	– Reduced recruitment time – Lower risk of inefficient hires – Higher employee engagement and retention	Medium
Logistics	– Reduced warehousing storage costs – Reduced excess inventory – Faster logistics cycle	Medium
Finance and accounting	– Improved accuracy of financial forecasting and budgeting – Reduced manual labor costs – Lower financial and investment risks	Medium
Document management	– Reduced administrative workload and staff time costs – Improved document processing accuracy – Fewer errors, faster internal document flow	Low/Medium
Production	– Reduced downtime – Lower maintenance and repair costs – Increased equipment reliability	High
R&D / Innovations	– Shorter product development time – Increased number of successful ideas – Optimization of the research process	High
Cybersecurity	– Reduced response time to threats – Detection of complex attacks – Increased enterprise-level cybersecurity protection	High

Source: [12–16]

AI implementation, requiring more sophisticated integration with ERP systems or forecasting platforms. Even higher complexity is observed in production and cybersecurity, where systems must adapt to strict accuracy requirements and operate under high risk, for example in fraud detection and cyber threat identification.

An interesting observation comes from the differing nature of potential benefits. In administrative and service functions the primary effect is associated with increased speed, cost reduction, and decreased employee workload, while in R&D, marketing, and production AI predominantly creates new value in the form of innovations, personalized products, and new communication creatives. Documented examples include the use of generative artificial intelligence in pharmaceutical compound design, electronics design, consumer product design, and the creation of personalized marketing materials by large multinational companies such as Carlsberg, AstraZeneca, BMW, Coca-Cola, Pfizer, and Johnson & Johnson.

The use of artificial intelligence in the real business environment has led to both cost reductions and revenue growth. Based on data from the Artificial Intelligence Index Report 2025 by McKinsey, it was determined that the most significant cost reductions from artificial intelligence implementation occurred in customer service (49 % of respondents reported cost reductions), supply chain & inventory management (43 %), and software development and innovation (41 %). Artificial intelligence also demonstrated substantial potential as a income booster. Companies most frequently reported revenue increases from the use of AI in marketing and sales (71 % of respondents), supply chain management (63 %), and again in customer service (57 %) [17]. This may indicate that artificial intelligence achieves the greatest impact in areas where processes can be standardized, scaled, or quickly adapted.

Conclusions. The analysis confirms that artificial intelligence in enterprise economic processes is applied across multiple business functions using a structured set of technologies. It is expected that enterprises would use a combination of various AI tools depending on various functional objectives, nature of the data, and implementation complexities.

The application of AI technologies in ten specific functions in an enterprise points to a prominent role of machine learning and deep learning technologies in analytical and forecasting functions, which ultimately lead to better decision-making in functions such as analytics, logistics, finance, and supply chain management. NLP technologies are seen as more applicable in functions that deal extensively with text-based operations, such as customer service, document management, and administration. Generative artificial intelligence is most applicable in functions requiring creative and innovative activity, such as marketing, research and development, and product design, where it supports content creation, idea generation, and personalization. RPA and computer vision technologies play a supporting role in production, administrative workflows, and cybersecurity tasks.

The study also reveals that the benefits of artificial intelligence adoption differ across enterprise functions. For administrative and service-oriented activities, key impacts relate to aspects of improved efficiency, cost reduction, faster execution of routine activities, and lowered employee workloads. However, in terms of activities like innovation, marketing, and production, creation of new value can be seen with reference to improved product designs, efficiency, and customer involvement.

Analysis of implementation complexity suggests that AI adoption is most straightforward in administrative processes, marketing, and document management, as the tools can easily be integrated without making substantial changes in internal systems. For production processes, logistics, finance, and cybersecurity, the AI adoption would be complex, requiring the integration of high levels of precision.

Overall, the results of the study demonstrate the significance of the systematization of artificial intelligence technologies when it comes to their perceived importance for enterprise use. Thus, associating particular types of artificial intelligence tools with complexity and benefits can help to better understand the influence on the enterprise efficiency.

In administrative and service-oriented processes, the main effects are associated with efficiency gains, cost reduction, faster execution of routine tasks, and decreased employee workload. In contrast, functions related to innovation, marketing, and production are more likely to generate new value through improved product design, process optimization, and enhanced customer engagement.

Analysis of implementation complexity indicates that AI adoption is most accessible in administrative, marketing, and document management processes, where ready-made solutions can be integrated without significant changes to internal IT infrastructure. Production, logistics, finance, and cybersecurity require more complex processes, where integration with existing enterprise systems and high accuracy requirements increase technological and organizational demands.

Overall, the results of the study highlight the importance of structured systematization of AI technologies when assessing their relevance for enterprise use. Linking specific AI tool types to business functions, implementation complexity, and expected benefits provides a clearer understanding of how artificial intelligence affects enterprise efficiency.

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