

SECTION 1

TRENDS AND PROBLEMS OF DEVELOPMENT OF THE SPHERE OF USE OF INFORMATION CONTROL SYSTEMS AND TECHNOLOGIES

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STATE, TRENDS AND PROSPECTS FOR THE DEVELOPMENT OF INFORMATION CONTROL SYSTEMS AND TECHNOLOGIES IN VARIOUS SECTORS OF THE ECONOMY AND TECHNOLOGY

The experience of the leading countries of the world shows that success in the social and economic activities of the state in the current conditions of globalization of the world economy is primarily ensured by the extent of the scientific, production, technological, information, and communication support in the country, as well the level of competitiveness of national science-intensive products through to the introduction of the latest information management systems and technologies (ICST).

State target programs and programs for developing economic sectors in the use, implementation, and creation of the latest ICST for individual organizations and spheres of public life of Ukraine are targeted at carrying out measures directed at effective cooperation between Ukraine and the European Union [1].

The main factors of economic growth and development of European countries are 17 key areas that were adopted at the UN Summit on Sustainable Development 2030. In particular, «Goal 9» refers to «Building resilient infrastructure, promoting inclusive and sustainable industrialization and innovation» [2] in the creation of the latest ICST, which are effectively used in organizations, manufacturing enterprises, associations, and business centers, open a fast path for the development of the national economy, as well as ensure efficient functioning of many related industries, since this market is an effective tool for integration into the world economic space due to its significant features, in particular the development of world information and communication technologies and high-tech production systems.

The IT sphere is especially important for Ukraine now in the context of the general economic crisis and military risks. Therefore, domestic and foreign IT companies open a fast path for the development of the national economy, ensuring the functioning of many related science-

intensive industries, since this market, despite the limitation of investment resources, is a fairly effective tool for the development of the latest products – information management systems (ICS) for various purposes in the fields of economics, technology, medicine, and education, and also allows for rapid integration into the world economic Space.

«Information Control Systems and Technologies» as an educational and professional program (EPP) at the second (master's) level of higher education in the specialty 122 «Computer Science», field of knowledge 12 «Information Technologies» of the «Kyiv National Economic University named after Vadym Hetman» is focused on the synthesis and improvement of the efficiency of ICS design solutions and their components, development, improvement, and maintenance of systems using modern information technologies in the economy, science, technology, education, industrial and infrastructure facilities of the national economy, in particular, these are production and economic enterprises, banking institutions, social infrastructure, international IT companies, business IT sphere, financial and industrial groups, concerns, holdings. It is aimed at training *a new generation* of IT specialists who will have deep theoretical and practical training in the use of innovative information technologies, mathematical and computer modeling of processes and phenomena, methodologies of design, optimization, system analysis, and acceptance management decisions, analysis of knowledge and data of large arrays capable of solving non-standard tasks, making optimal decisions, generating original and effective ideas, applying modern research tools in specific conditions, taking into account modern challenges and principles of humanization of the digital sphere [3]. The scientific component of the EPP «IUST» specialty 122 «Computer Science» is focused on developing and implementing real ICS projects, students' participation in domestic and international conferences, circles of IoT technologies, artificial intelligence components, and programming systems.

1. Relevance and problems of ICS development

Research should focus on developing ICS capable of quickly responding, adapting, and preventing consumer demands to external conditions, as well as quickly reconfiguring the production of various batches of high-tech products. Integrating knowledge and technology, taking into account safety, social responsibility, and vitality, is a prerequisite for accelerating the transformation of European industry and the Ukrainian economy. The knowledge economy is based on new

knowledge that has an information basis and is embodied in innovations, which, in highly developed economies, through the latest technologies and relevant products, ultimately provide the dominant weight of GDP growth. Therefore, the problem of introducing innovative information technologies into the process of designing ICS for various purposes remains relevant.

Advantages of ICS:

Improved decision-making: The ICS provides managers with timely and accurate information, allowing them to make more informed decisions. ICS can provide insights into trends, patterns, and opportunities to help managers identify problems, evaluate alternatives, and make the best decisions for their organizations.

Increased efficiency: ICS automates many routine tasks, such as data entry, processing, and reporting, reducing the time and effort required to perform these tasks manually. This allows employees to focus on more valuable tasks, improving the overall efficiency and productivity of technological processes or organizations.

Improved communication and collaboration: ICS allows employees to share information and collaborate more effectively both within and between departments, businesses, and associations. This improves communication and coordination, reduces errors and delays, and improves the overall productivity of the organization.

Advanced strategic planning: ICS provides senior executives with the necessary information to develop and execute effective strategic plans. By analyzing data and information from a variety of sources, managers can identify opportunities and threats, evaluate different scenarios, and make informed decisions about the future direction of their organizations.

Competitive advantage: ICS provides organizations with a competitive advantage, allowing them to respond faster and more efficiently to changes in the market and customer needs. Using data and information, organizations can identify new opportunities, develop innovative products and services, and improve overall customer satisfaction.

2. Classification of information control systems

The classification of ICS is carried out according to the following classification criteria, which are shown in Fig. 1:

1. Level of management.
2. Scope of use.
3. Source of information.

4. Method of access to information.
5. Organizational level.
6. Type of intelligent information systems.
7. Type of interaction of objects in specialized computer systems.

Level of management	• Operational • Tactical • Strategic
Scope of use	• Financial activities • Marketing activities • Production activities • Personnel activities • Logistics activities
Source of information	• Internal source • External source • Combined source
Method of access to information	• Online • Offline • Mobile • Cloud
Organizational level	• Departmental • Organizational • Cross-organizational
Type of intelligent information systems	• Systems with communicative abilities • Expert systems • Self-learning systems • Adaptive systems • Hybrid Intelligent System (GIS)
Type of interaction of objects in specialized computer systems	• The Internet of Things (IoT) • The Internet of Everything (IoE) • The Internet of Nano Things (IoNT) • Internet of Mission Critical Things (IoMCT) • The Internet of Mobile Things (IoMT) • The Industrial Internet of Things (IIoT)

Figure 1. ICS classification based on different classification features

Source: Developed by the author

2.1. Based on the level of management, ICS can be classified into three categories depending on the level of management that uses them:

An operational ICS is a type of information system that supports day-to-day operations and decision-making at an organization's operational level. It provides real-time information about operational activities such as sales and inventory levels, order processing, and production schedules. The primary purpose of the operating ICS is to improve the efficiency, productivity, and quality of operations. Examples of operating ICS are sales and inventory management systems, production planning systems, customer service systems, etc.

A tactical ICS is a type of information system that supports decision-making at the tactical or middle level of an organization's management. Provides insights into key performance indicators such as sales, costs, and customer satisfaction. The primary purpose of tactical ICS is to help managers monitor performance, identify trends, and make tactical decisions. Tactical ICS provides aggregated data and reports that middle managers use for monitoring productivity and decision-making. Examples of tactical ICS are supply chain management systems, human resource management systems, and sales and marketing systems.

A strategic ICS is a type of information system that supports decision-making at the strategic level of an organization. It provides information about the organization's external environment, market trends, and long-term goals. The main goal of a strategic IMS is to help top managers make strategic decisions that determine the direction and future of the organization. It aids in identifying new opportunities, managing risk, and allocating resources to achieve long-term goals Organization. Examples of strategic IMS are business intelligence systems, enterprise performance management systems, and strategic planning systems.

2.2. Based on the scope of use. The ICS supports several categories of functional levels in the organization's field of activity and helps to improve decision-making, increase efficiency, and optimize work. The ICS must integrate all functional areas of activity to ensure the smooth flow of information and decision support throughout the organization. There are the following types of ICS depending on their functional scope of use:

Financial activities. To support decision-making in financial management and accounting functions, the ICS helps to monitor financial performance, analyze financial data, and make informed decisions about budgeting, resource allocation, and investments. The financial ICS provides aggregated data and reports on financial

transactions, assets, liabilities, and equity. Examples of ICS in the field of financial and economic activity are general Ledger systems, accounts payable systems, and accounts receivable accounting systems.

Marketing activities. ICS in marketing activities helps track the marketing process's effectiveness, analyze marketing data, and make informed decisions about product development, pricing, promotion, and distribution. Marketing ICS provides aggregated data and reports on marketing activities such as sales, customer behavior, advertising, and market research. It allows marketing managers to track the performance of marketing campaigns, identify growth opportunities, and make informed decisions. A few examples of marketing IMS are sales analysis systems, customer relationship management systems, and market research systems.

Production activities. ICS in the field of production activities helps to monitor production productivity, analyze production data, and make informed decisions on production planning, inventory management, quality control, and resource allocation. A manufacturing ICS provides aggregated data and reports on production activities, such as production schedules, inventory levels, quality control, and resource utilization, enabling production managers to monitor the efficiency of production processes, identify areas for improvement, and make informed decisions. Examples of ICS in the field of production activities are inventory management systems, production management systems, product quality control systems, etc., and fixed assets management systems of the enterprise.

Personnel activities. The ICS in the field of HR organization is designed to manage human resource information and processes such as hiring, training, payroll, performance evaluation, and employee benefits. It enables organizations to automate HR processes, increase efficiency, and streamline administrative tasks about employee data, allowing them to make informed decisions and support strategic business goals. Examples of using HR ICS are employee data management systems, compliance management systems, and performance management systems.

Logistics activities. ICS in the field of logistics activities is designed to manage and optimize logistics processes and supply chain management in an organization. ICS assists in managing logistics operations such as purchasing, transportation, inventory, and warehouse management and enables organizations to automate logistics processes, increase efficiency, and reduce costs. It provides logistics professionals with access to accurate and up-to-date information on inventory levels, order status, and shipping information

and maintains strategic business goals. Examples of logistics ICS are procurement management systems and warehouse management systems.

2.3. Based on the source of information. ICS can be classified based on the nature of the origin of the source of the information they process and manage:

Internal source. The ICS processes and manages the organization's information, as well as helps manage its internal operations by providing accurate, relevant, and timely information to support decision-making and business operations. By automating and streamlining internal processes, organizations can save time and resources, reduce costs, and increase productivity in enterprise resource planning, customer relationship management, and inventory management.

External source. The ICS processes and manages information from external sources outside the organization. The primary purpose of an external system is to help organizations collect, analyze, and interpret information about the external environment to make informed decisions and gain a competitive advantage. Examples of ICS are market research, economic analysis, and monitoring of social networks.

Combined source. The ICS functions within the framework of internal and external information flows in a single information space of a given subject area to obtain, process, and optimize all the main aspects of the organization's management activities. Examples of ICS tasks are operational planning of resources (financial, human, material) for the production of goods (services), operational management of the implementation of plans (including supply, sales, and contract management), etc.

2.4. Based on the method of access to information, it is possible to classify into the following categories of ICS work:

The online mode of operation of the ICS provides users with real-time information through web applications. It allows users to access the system from anywhere, anytime, and from any device that has an Internet connection. The system uses a client-server architecture, where the server provides data and services, and the client accesses and interacts with the data through a web browser. Examples of online systems are business intelligence systems, dashboards, and customer relationship management systems.

Offline – the system provides information in the form of reports, documents, and other printed media. It generally does not require an internet connection to access the information, and users can access the information offline. Examples of offline systems that organizations can use are directories, reports, and newsletters.

Mobile ICS provides users with real-time information using mobile devices such as smartphones and tablets. The mobile system allows users to access the system from anywhere, anytime, and on any mobile device with an internet connection. The system uses a client-server architecture, where the server provides data and services, and the client accesses and interacts with the data through a mobile application. Examples of mobile ICS are mobile business intelligence systems, mobile dashboards, mobile supply chain management systems, etc.

Cloud ICS provides information and services to users through a cloud computing platform. The system uses a client-server architecture, where the server provides data and services, and the client accesses and interacts with the data through a web application. Cloud-based ICS allows users to access the system from anywhere, anytime, and any device with an internet connection. Some examples are cloud-based ERP, cloud-based SCM, and cloud-based HRM.

2.5. Based on the organizational level. ICS are classified based on their relationship to other ICs in the organization. Organizational information deals with the organization's environment where organizational goals are achieved. ICS can be classified based on the attribute – organizational level since they are designed to support specific functions and operations in a particular department, the entire organization (enterprise), or between several organizations (associations):

Departmental sign. Departmental ICSs designed for the operation of an organization's department are information systems that are designed to support the information needs of individual departments of an organization and focus on the specific needs of any particular department or function within the organization, such as production, marketing or accounting, marketing, or production. The purpose of the systems is to provide department leadership with the information they need to make better decisions, improve efficiency, and achieve their department's goals. ICS typically perform tasks related to department activities, such as sales, customer, financial, inventory, or production data. Examples of departmental ICS are sales management information systems, marketing management information systems, and Accounting Management Information Systems.

Organizational feature. ICS (organization-wide) or information systems that combine and manage data from different departments and functions of the entire organization. This includes the so-called corporate information systems (CIS) to provide a comprehensive view of the organization's activities and facilitate decision-making at the strategic level. CIS is designed to process large amounts of data,

integrate various information systems and databases, and provide information in a format that is easy to use and understand. CIS can contain modules for multiple functions such as finance, accounting, human resources, marketing, and operations, and can integrate external data such as market trends, competitor analysis, and economic indicators. CIS is aimed at large companies and can support geographically remote nodes and networks. They usually have a hierarchical client-server structure with server specialization. During the development of such systems, the same database servers can be used to develop group information systems.

Cross-organizational trait. ICS of this level allows different organizations (production associations, corporations, etc.) to exchange information and cooperate in business processes. ICS facilitates the exchange of data and information between organizations, allowing them to work together more efficiently and effectively. ICS across organizations is particularly important in today's business environment, where many organizations operate in complex networks of suppliers, customers, partners, and other stakeholders. By sharing information and collaborating on business processes, organizations can improve their agility, responsiveness, and competitiveness. The most common servers for corporate systems are Oracle, DB2, Microsoft SQL Server, SAP, and document management systems. CIS includes, for example, the systems of such organizations as the Open Joint Stock Company «Ukrtelecom», «Ukrzaliznytsia», the National Bank of Ukraine, the Unified Automated System for Urban Passenger Transport Management in Kyiv, which combines four autonomous systems: dispatch control of urban public transport, management of route facilities, automated traffic and parking management. Surveillance cameras will be used to ensure the efficient operation of the electronic traffic controller at intersections. Examples of systems on an inter-organizational basis are supply chain management systems and the production of high-tech products at the corporate level, such as the Antonov enterprise, customer relationship management system, electronic data interchange, etc.

2.6. Based on the types of intelligent information systems. Intelligent information systems allow building programs of expedient activity to solve the tasks assigned to them based on a specific situation that is currently developing in the environment. At the same time, intelligent systems must remain operational in case of unforeseen changes in the properties of the controlled object, control goals, or the environment (be adaptive).

Types of intelligent information systems for various purposes are widely considered in the literature [4], in particular,

- **Systems with communicative abilities** (intelligent databases, natural language interfaces, hypertext systems, contextual reference systems, cognitive graphics);

- **Expert systems** (classifying, pre-recognizing, transforming, multi-agent);

- **Self-learning systems** (inductive systems, neural networks, precedent-based systems, information repositories);

- **Adaptive systems** (CASE-technologies, technology components).

The paper analyzes intelligent information systems that use modern technologies, in particular, **a hybrid approach to the construction of such systems:**

- **Hybrid Intelligent System (GIS).** GIS is usually understood as a system in which several methods are used to solve a problem, as a rule, from different classes to solve management and design problems. Various artificial intelligence (AI) methods are widely used in GIS [5]. GIS is a multitude of AI tools, where each tool – neural networks, fuzzy logic, evolutionary algorithms – plays a role.

GIS allows you to use the advantages of traditional technologies and methods of ICS design, overcoming some of their shortcomings and limitations, and can more effectively solve complex problems in the context of growing technologies such as AI, Big Data, ML, AutoML, DLd in the practice of ICS design:

A model for combining paradigms for the use of rules and use cases.

This model allows you to improve the efficiency of exception handling without complicating the rule set. Thus, each component deals with what it is best focused on: rules deal with generalizations of the subject area, and precedents deal with individual atypical cases. This technology involves looking for precedents that are analogous to the current case if it is an exception to the rule. This approach requires that the database of use cases be indexed according to the rules to which they are exceptions. The algorithm assumes the following order: first, rules are applied to solve the current problem, as a result of which some solution is formed. Then, the library of use cases is reviewed for exceptions to the relevant rule, shown in Fig. 2.

This model can be used in complex production systems of process control systems and the defense sector [6]. In production systems, the construction of a database is identified with an extended set of rules,

the completeness of coverage of the tasks of the subject area, and the correctness of the system's functioning.

Popular algorithms and methods combined in such systems are:

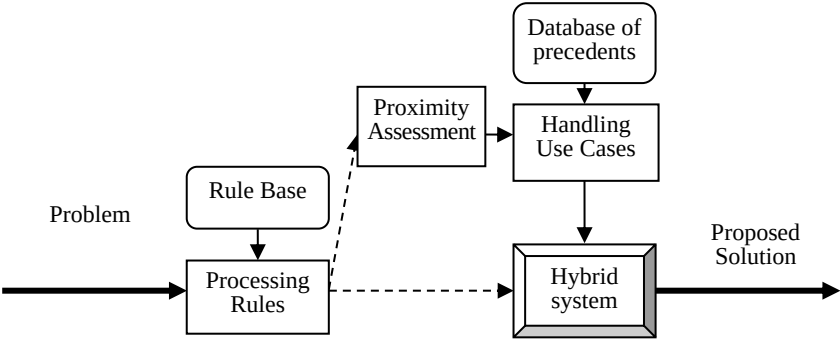


Figure 2. Architecture of hybrid use of rules and use cases

Source: Developed by the author

A hybrid combination of technologies, rules, and neural networks in IIS.

A hybrid approach to building knowledge-oriented ICS can solve an important problem of learning a system. After all, knowledge-oriented ICS is mainly built for subject areas characterized by the need to update and expand knowledge in knowledge-intensive industrial areas. With this in mind, GIS should contain a module that allows you to upload new knowledge to the system and edit old knowledge. Of increasing interest is the automated acquisition of knowledge (self-learning), or the creation of new concepts or rules based on existing data and knowledge, checking them for indisputability with existing ones and inclusion in the knowledge base. The collection and storage of expert knowledge is best done by a knowledge-oriented system, but it does not adapt to change immediately. Neural networks, on the other hand, are not very good custodians of expert experience, but they can be trained to prolong learning. Neural networks can sift through large amounts of data and find cause-and-effect relationships that will help them adapt to changes in their environment.

The neural network approach is especially effective in expert evaluation tasks because it combines a computer's ability to process numbers with the brain's ability to generalize and recognize.

So, like neural network algorithms and systems with fuzzy logic, expert systems are technology used in a knowledge-oriented system. These systems are also capable of learning, that is, of forming their knowledge base based on examples from the subject area.

Neural Networks + Expert Systems. The most popular example, which has its name, is **neural expert systems** or communicative expert systems. The combination of data-driven learning and human experience (expert knowledge) is often used to improve financial forecasting and medical diagnosis. The combined use of the expert system and the apparatus of artificial neural networks provides the necessary flexibility and self-learning based on knowledge; at the same time, the knowledge obtained from experts allows for significantly simplifying the structure of neural networks, reduces the number of neurons and network connections—general overview of GIS [7].

Neural Networks + Fuzzy Logic (Fuzzy Neural Networks) [8]. Classical fuzzy systems have the disadvantage that in order to formulate logical rules and membership functions, it is necessary to involve objective subject matter experts, which is quite difficult to ensure. The concept of fuzzy neural networks (or adaptive fuzzy systems) involves the implementation of logical proof based on the apparatus of fuzzy logic. Still, its necessary components are a set of appropriate linguistic rules, and the optimal form of membership functions is selected in the process of training a neural network based on experimental data. To do this, the fuzzy control module is presented in the form of a multilayer neural network, and an error inverse propagation algorithm is used. A fuzzy neural network typically consists of four layers: the input variable phasification layer, the activation condition value aggregation layer, the fuzzy rule aggregation layer, and the output layer. The architecture of fuzzy neural networks such as ANFIS and TSK is currently the most widespread; these networks are universal approximators. The advantages of adaptive fuzzy systems, such as the ability to obtain new knowledge and transparent interpretation of accumulated knowledge, have made these systems today the most promising and effective tools for «soft» computing.

Neural Networks + Genetic Algorithms. The combination of these technologies involves the selection of inputs for the neural network in the form of natural selection and training of the neural network by selecting adequate parameters at two stages: to search for general parameters of the neural network (the number of hidden layers and neurons) and at the final stage of training (to find all values of the neural network weights and activation functions). Genetic algorithms are used to improve neural networks already created and trained using any

algorithm. Experts have divided how neural networks are supported by genetic algorithms into three types, namely: the use of genetic algorithms to select functions or transform the function space used by a neural network, the use of genetic algorithms to select learning rules or parameters that control the learning of a neural network, and the use of genetic algorithms to analyze a neural network.

It is worth noting that neural networks are also used to support genetic algorithms. For example, a hybrid system was developed in which a genetic algorithm played two roles: finding a set of favorable parameters that the heuristic procedure uses to create highly efficient breakpoints and finding a set of heuristic selection rules to find the minimum path. The parameters encoded in the chromosome to find breakpoints are the initial set of assignments that heuristics try to improve. The parameters encoded on the chromosome to find the minimum path determine the select-insert heuristics (e.g., «nearest neighbor», «cheapest insert», etc.) for each breakpoint. This approach has also been used to solve the problems of the traveling salesman [9].

Machine learning systems. Unlike knowledge-based systems, they do not require clear rules but rely on statistical models and algorithms that learn from the data. Such systems include those that use supervised learning, unsupervised learning, or reinforcement learning. The advantages of machine learning systems are their adaptability, that is, the ability to improve over time as new data sets arrive, as well as the ability to search for non-obvious patterns and relationships. The main application areas of such systems are stock markets and spam filtering. That is, those areas where it is important to analyze large amounts of data and find patterns for making a decision or providing conclusions [10]. Automated machine learning (AutoML) provides methods and processes to make machine learning accessible to non-machine learning experts, improve the efficiency of machine learning, and accelerate research in the field of machine learning.

Deep learning system. These systems are inspired by the complex architecture of the human brain. They use artificial neural networks that mimic brain structures to learn from huge amounts of data, especially good at tasks related to big data, such as images and natural language. Deep learning methods in the hierarchy of AI systems are believed to be part of machine learning systems and have a huge impact on the development of modern AI.

Deep learning methods include those based on the unattended learning architecture of pre-trained networks, convolutional neural networks, recurrent neural networks, and recursive neural networks [11].

Different types of neural networks are used for different use cases and data types. For example, recurrent neural networks are commonly used for natural language processing and speech recognition. In contrast, convolutional neural networks (ConvNets or CNNs) are most widely used for classification and computer vision tasks. Convolutional neural networks now provide a more scalable approach to image classification and object recognition problems, using the principles of linear algebra, in particular matrix multiplication, to identify patterns in an image.

Recursive neural networks (RvNN) are a special type of deep learning that can work with structured inputs, such as parse trees in natural language processing or molecular structures in chemistry. The network processes input recursively, combining information from child nodes to form a representation for parent nodes. RvNN is mainly used in some NLP tasks, such as analyzing the mood of the interlocutor. RvNN processes parsing trees by assigning vectors to each word or phrase based on information from its child nodes, allowing the network to capture hierarchical relationships and dependencies within a sentence [12].

A recurrent neural network (RNN) is a type of artificial neural network that uses sequential or time-series data. These deep learning algorithms are typically used to solve ordinal or temporal tasks such as speech translation, natural language processing (NLP), speech recognition, and image captions; they're included in popular apps like Siri, voice search, and Google Translate. Like direct and convolutional neural networks (CNNs), recurrent neural networks use training data for training. They are distinguished by their «memory» because they take information from previous inputs to influence current inputs and outputs. While traditional deep neural networks assume that inputs and outputs are independent of each other, the output of recurrent neural networks depends on the previous elements in the sequence. While future events can also be useful in determining the output of a particular sequence, unidirectional recurrent neural networks cannot account for these events in their predictions.

The «Dropout» method is one of the key examples of the application of deep learning systems. Deep neural networks with a large number of parameters are very powerful machine learning systems. Large networks are slow to use, making it difficult to combat overfitting by combining the predictions of many large neural networks during testing. Screening is a method of solving this problem.

The key idea is to randomly remove elements (along with their connections) from the neural network during training. This prevents the

elements from co-adapting excessively. During the training, samples are screened out from an exponential number of different «thinned» networks. During testing, it is easy to approximate the effect of averaging the forecasts of all these thinned networks by simply using one unbranched network that has less weight. It has been shown that the screening method significantly improves the performance of neural networks in the tasks of guided learning in the fields of vision, speech recognition, document classification, and obtaining results on reference datasets [13].

Deep learning in ICS development. Deep learning has become widespread in a variety of fields, including ICS. Its ability to learn complex patterns based on big data provides the potential to improve functionality and efficiency. Deep Learning:

- enables businesses to build predictive models to predict future trends, behaviors, and outcomes. Deep learning models can analyze vast amounts of data, identifying patterns and making accurate predictions. Recommender systems, which are widely used in e-commerce, streaming media, and personalized marketing, use deep learning algorithms to suggest relevant products, movies, music, and content to users based on their preferences and behaviors;

- optimizes supply chain operations by forecasting demand, optimizing inventory levels, and improving logistics. It can analyze historical data, market trends, and external factors to improve decision-making and streamline operations;

- is crucial for fraud detection and strengthening cybersecurity measures. Deep learning models can analyze large amounts of data in real-time, identifying patterns, anomalies, and potential threats. They are used to detect credit card fraud, detect network intrusions, detect malware, and filter spam, among other tasks. Deep learning models continuously learn from new data, increasing their ability to detect new threats and improving threat detection [14].

Machine Learning + Situation-Based Reasoning. Improving the process of combining defined patterns with logical rules for navigation and decision-making. An example of such a system would be personalized learning systems, which combine learning models with field-specific knowledge to tailor learning content to the individual needs of users. There is also an interesting study on the application of hybrid intelligent methods to model the diffusion of light hydrocarbons in bitumen in the road sector. According to the analysis, the combination of methods such as ANFIS (Adaptive Neuro-fuzzy Inference System) and PSO (Particle Swarm Method) is best suited for analysis compared to ANFIS+GA and ANFIS+R2 [15].

Coevolutionary algorithms can be considered part of synergistic systems. In coevolutionary algorithms, two or more populations of individuals evolve together. Their adaptability is determined by how well they interact and cooperate, not just their performance. This interdependence forces populations to adapt and learn from each other, leading to new and effective solutions. The behavior of the coevolutionary algorithm depends on the interaction between individuals. In this case, individuals are not evaluated in terms of an explicit fitness function but rather in terms of direct interactions between individuals taken from populations. Traditional evolutionary algorithms assess an individual's fitness objectively, regardless of the population context in which it is placed. Coevolutionary algorithms work the same way as traditional algorithms, except that fitness assessment is not objective but subjective: an individual is evaluated through interaction with other individuals in the evolutionary system. Two types of interaction have been developed: cooperative and competitive.

Cooperative coevolutionary algorithms are often used in situations where a problem can be naturally decomposed into subcomponents. Individuals present such subcomponents and are evaluated in a series of interactions with other individuals to form complete solutions. The fitness of a subpopulation is an assessment of how well it «cooperates» with other species to produce reasonable solutions. Cooperative-coevolutionary algorithms have been successful in various fields, such as production planning, optimization of functions, design of artificial neural networks, and painting of premises. An example of the application of a cooperative coevolutionary algorithm can be its use in multi-agent systems (MAC) to improve the interaction between agents.

Competitive coevolution occurs either within a single population engaged in «competitive games» or between multiple populations. Competitive co-evolution has several types of interactions. To gain shared resources and space, they compete with each other. Competitive co-evolution of a single population has been successfully applied to the iterative prisoner's dilemma, chase, and evasion, as well as to the search for reliable game strategies [16]. An example of the application of these systems is robot control training, where several robots can jointly develop their movement and coordination strategies to perform complex tasks. Also, computer players (computer-controlled players) with artificial intelligence in competitive games can change their strategies to become more unpredictable and efficient.

2.7. Based on the types of interaction of objects in specialized computer systems.

The Internet of Things (IoT) is a technology where physical objects are interconnected with each other through the Internet and can identify themselves. It is a huge network with a combination of different sensor devices such as RFID, GPS, etc., which are used to identify, manage, and control devices [things connected to an IoT platform where we can collect and share any information through machine-to-machine (M2M) communication. The Internet of Things (IoT) consists of an Arduino/Raspberry Pi IoT board, an RF module, a sensor module, an access point (Wi-Fi/4G/3G), an IoT server, and a cloud point. Communication with each other is carried out through an IP address without human intervention [17, 18].

The Internet of Everything (IoE) is an extension of IoT made up of people, things, and processes, with data spanning business and industrial processes. The exchange and collection of information takes place from machine to machine (M2M) or person-to-person (P2P) or person-to-machine (P2M), where in the case of IoT, it is only for things. In IoE, it stands for the Internet for Everything/Everyone [19].

Internet of Nano Things (IoNT) – refers to nanocomponents in an integrated circuit, where miniature sensors are connected to each other via a nanonetwork to receive data from objects. Nanodevices with nanocomponents are integrated into a single device to perform multiple tasks. It will work according to how we connect devices over the internet. The main differences between the Internet of Things (IoT) and the Internet of Nano Things (IoNT) are that nanocomponents will not be achievable in IoT [20].

Internet of Mission Critical Things (IoMCT) – The Internet of Mission Critical Things (IoMCT) is driven by the convergence of detection, communication, computing, and control. The main goal of IoMCT is to improve the use of network surveillance. IoMCT technology is approaching critical events such as military operations, border patrols, search and rescue, and monitoring and surveillance of critical objects [21].

The Internet of Mobile Things (IoMT) is a technology for mobile devices that uniquely identifies owners, their locations, and security of use. It gains scalability in mission-critical missions of subjects and surveillance objects [22].

The Industrial Internet of Things (IIoT) is a network of intelligent and connected industrial components that are deployed to achieve high performance with reduced operating costs through real-time monitoring, efficient management, and control of industrial processes, assets, and operations [23]. IIoT devices connect wirelessly to internal networks as well as to the global Internet. These devices

represent a new stage of automation – collecting unprecedented amounts of data from all aspects of the process and sharing it with a central server. This data allows you to analyze and take action that has not been seen before, resulting in increased efficiency and productivity. Implementing IIoT technologies is a key element of Industry 4.0 initiatives, manifested in the strategies of «smart» industrial facilities.

3. Identification of basic trends in innovative technologies in ICS

In connection with the high rates of development of information technologies, the classification of ICS, the introduction of the principles of hybridization, and the integration of methods and technologies into ICS, it is necessary to determine the basic trends of innovative technologies that are used in the methodology for designing various types of ICS and with the help of which organizations, the production sector of the economy, as well as in the technical and educational spheres and modern medicine can effectively stay and compete in business thanks to the real-time efficiency of using them provided by such a current information technology industry.

3.1. Trend 1. The Impact of AI Innovation on ICS

Development and implementation of machine learning algorithms. AI continues to rank at the top of emerging technologies.

Artificial intelligence (AI) is defined as the science and engineering aimed at creating intelligent machines, information systems, their components, and computer algorithms and programs [24–26]. Breakthroughs in AI have been driven by the development of two key areas: machine learning (ML) and deep learning (DL).

Machine learning is a fundamental technology in AI that allows systems to learn and improve based on experience without explicit programming for each task. This is achieved through algorithms that analyze large amounts of data by identifying patterns and using them to make informed decisions or predict future events.

One of the key advantages of machine learning is its ability to improve itself: the more data a system analyzes, the more accurate its predictions and decisions become. However, ML algorithms need access to large amounts of structured, well-organized data to work effectively. Unstructured or poorly organized data can significantly reduce the efficiency of algorithms, leading to an increase in the importance of deep learning being able to work effectively with such data.

With the availability of large amounts of data, machine learning has become an integral part of decision-making and efficiency processes in many industries, including finance, manufacturing, healthcare, and many others.

Deep learning, a subfield of machine learning, uses multi-layered artificial neural networks to mimic the human brain, allowing the system to learn with incredible accuracy. DL effectively solves tasks that are difficult for traditional ML algorithms, such as speech recognition, image recognition, and automatic translation. Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, in their 2015 article in the journal *Nature*, describe how deep learning has become a key element of modern AI, allowing systems to learn efficiently from large amounts of data and solve complex problems that were unattainable by other machine learning methods [27].

Automated Machine Learning (AutoML) in ICS. The main breakthrough in machine learning will be related to automated machine learning. Despite its value, machine learning is resource-intensive and takes time to develop training models. AutoML helps developers and researchers derive highly efficient predictive models. This allows them to identify the best hyperparameters, neural architectures, preprocessing, and even entire data processing pipelines for the existing dataset and metric [28].

This is especially useful in ICS, where you need to adapt to new data and requirements quickly. For example, using AutoML to analyze sensor data in production allows you to optimize production lines, predict equipment failures, and improve product quality. For instance, Siemens uses AutoML to analyze large amounts of data from its turbines, significantly reducing downtime and increasing equipment efficiency. Other examples are using AutoML algorithms in medicine to analyze medical images, predict the course of diseases, and personalize treatment. For example, Google Health uses AutoML to improve diagnosing diabetic retinopathy by automating the process of analyzing retinal images. In banking and asset management, AutoML helps analyze financial markets, predict lending risks, and optimize investment portfolios. JPMorgan Chase uses AutoML technologies to develop algorithms that aid in risk management and identifying new investment opportunities.

Improving the efficiency of programming and improving the quality of ICS applications. AI can make a significant contribution to enhancing software development. Software companies that want to keep up with the times actively use AI technologies: ML – on methods of building algorithms, DL – focuses on data classification; Natural language processing (NLP) – specializes in speech recognition

technologies in the development of ICS applications, which allows for effective communication with the user, automation of routine tasks and ensuring a high level of security.

Apps face numerous security challenges, from malware attacks and data breaches to privacy and user authentication issues. These security challenges not only threaten user data but also affect trust in app developers. Integrating AI into the application development lifecycle can significantly improve security measures. Starting with the design and planning phases of ICS design, AI can help predict potential security flaws. AI algorithms can identify vulnerabilities developers may miss during the coding and testing phases. The implemented neural networks can provide suggestions and recommendations in the coding process, which leads to an increase in the efficiency of ICS implementation, as well as the process of testing, prototyping, scaling, and versioning systems. Software quality assurance plays an important role in the software development life cycle when testing and scaling applications and significantly reduces unforeseen problems when implementing applications in ICS [29].

Improving ICS security. Organizations collect and accumulate large amounts of data that need to be protected. AI identifies patterns [24] that allow security systems to learn and improve continuously. AI contributes to improving cybersecurity by searching for undetected threats, detecting anomalies by analyzing the basic behavior of users and servers, and improving the security of systems through network policy and network topography.

Therefore, to ensure the security and confidentiality of the data collected for AI purposes, a robust architecture for the functioning of the ICS should be created: first, AI is changing data management because it relies on data for training and data to improve system performance; secondly, much of the data may be confidential and, if fraudulent, may lead to identity theft; third, the problem with AI is ambiguity, which can occur due to the use of complex algorithms that lead to layering of variables and a delay in identifying data on server platforms. AI allows you to effectively predict potential problems, which contributes to the stable functioning of the system and provides recommendations for solving them.

3.2. Trend 2. Cloud Computing – Improving ICS Efficiency

ICS is used to store and analyze a large amount of data needed to perform various tasks of organizations and companies, as well as to help managers develop and implement a business plan.

Cloud technologies have emerged as a response to business needs to reduce IT deployment and scaling times and have opened up a range of functionalities for businesses: expanding business markets both geographically and in terms of more fully reaching new customer segments, especially such as small/medium-sized businesses, as well as entering new fast-growing vertical markets.

The main impacts of cloud technologies on ICS are as follows:

Use of available IT infrastructure. Cloud computing provides customers with the flexibility to customize the power of their computer systems, allowing them to scale up or down resources to meet their needs. This adaptability contributes to the growing demand for cloud solutions, allowing businesses to optimize IT resource costs. Cloud computing offers significant economic benefits for companies, including reduced costs for managing and maintaining IT infrastructure. The study presented at the 2018 International Conference on Information Technology highlights that cloud-based solutions allow companies to reorient their IT needs, offering both quantitative and qualitative advantages compared to purchasing and operating their own IT systems [30]. This allows for a more in-depth analysis of the cost and benefits of using cloud computing for enterprises.

Cloud computing can significantly reduce the cost of managing and maintaining IT infrastructure, particularly through the possibility of using hybrid cloud solutions. This allows companies to reduce the cost of purchasing and maintaining complex equipment.

The growing demand for cloud platforms and services is driving the development of networking links between the information systems of different companies, contributing to the creation of more integrated and efficient digital ecosystems.

Global technology leaders such as Google Cloud, Microsoft Azure, and Amazon Web Services demonstrate the active use of global public clouds. There is a growing demand for hybrid cloud services, requiring data centers to ensure continuity and «connectivity» to act as digital hubs.

Tech giants like Amazon and Microsoft are investing heavily in hybrid cloud computing.

The cloud computing market offers a wide range of services for various business sectors, including B2C, B2B, and B2G, demonstrating the flexibility and adaptability of cloud technologies to a variety of business needs.

Increasing the scalability of business projects. The service provider quickly updates cloud storage systems and applications that

use cloud computing to ensure scalability and save a significant amount of time. For a business company, it is critical to be able to quickly scale up or down operational operations and meet storage requirements to guarantee smooth business operations. Therefore, there is no need to purchase and install ICS hardware and software to perform the update process.

The article «Adaptive scaling of Kubernetes pods» considers scalability as the ability of a resource or application to expand to meet growing needs. In the context of cloud computing, automatic scaling algorithms are becoming increasingly important. This paper proposes adaptive autoscaling «Libra», which automatically determines the optimal set of resources for a single container or group and then manages the horizontal scaling process. If the load or environment changes, Libra adapts the resources for the container and adjusts the horizontal scaling process accordingly [31].

There is also a dynamic scaling model based on queue theory to scale virtual container resources and meet customer service level agreements (SLAs) while keeping scaling costs low. The goal is to improve the utilization of virtual computing resources and meet SLA constraints regarding CPU utilization, system response time, system failure rate, number of tasks in the system, and system throughput [32].

Instead of building their IT infrastructure, they need to communicate with dozens of equipment suppliers, integrators, and companies that support the IT infrastructure; the client needs to communicate only with the cloud service provider. The general trend towards shortening the supply chain is also evident despite the need to integrate cloud services from different providers. In its turn, a cloud platform that provides self-service tools can bring in a large pool of customers with minimal service maintenance costs. Cloud technologies have created the basis for the development of other technologies, such as mobility, social networks, and big data, which in turn have led to the creation of companies with new business models such as Uber, Netflix, Airbnb, and others – that are changing the rules of the game in their sectors of the economy.

Modern realities have accelerated the digital transformation of businesses and countries around the world and strengthened the priority of cloud technologies, which help optimize infrastructure costs and quickly increase capacity for large-scale projects.

3.3. Trend 3. Big Data in ICS

Digital transformation involves significant technological developments such as AI, machine learning, the Internet of Things,

and big data (IoT). The proliferation of IoT-connected devices is projected to increase dramatically, with an estimated 25.44 billion devices expected by 2030, up from 10.07 billion in 2021. This surge in connected devices is a notable source of a growing big data reservoir. Machine Learning Tools and AI are ready to play a key role in analyzing the flow of big data coming from colossal data centers. They will manage the operation of these systems, identify hidden connections in the data, and efficiently store and extrapolate information. IDC predicts that global data will grow by about 61 % annually. By 2025, this figure will reach 175 zettabytes. [33]. Today, Big Data helps solve various problems in many areas, including finance, industry, energy, retail, medicine, tourism, ecology, entertainment, etc. Thanks to the processing and analysis of a large amount of data, representatives of government, business, science, ICS developers, and IT companies improve the quality of goods and services and develop business. In Ukraine, big data is used by mobile operators. For example, Big Data technologies make it possible to determine which roads Ukrainians travel more often.

Expanding Big Data Research Methodology

Big Data Analysis Methods:

Classification is used to predict consumer behavior in specific market segments. This method allows companies to tailor their marketing strategies and products to the needs of their target audience.

Cluster Analysis is used to group objects according to similar characteristics. This aids in the identification of natural divisions in the data, simplifying further analysis.

Crowdsourcing is used to collect data from a wide network of sources. This approach allows for the involvement of a large number of people in the collection of information, providing diversity and volume of data.

Data Mining – allows you to discover previously unknown but valuable information from large data sets. This facilitates informed decision-making in various fields of activity.

Machine Learning – includes the creation of models capable of self-learning and efficient information processing. The use of neural networks opens up new opportunities for data analysis.

Signal Processing – is used to recognize and analyze signals against background noise, which is critical in many technical and scientific applications.

Data Integration – allows you to combine heterogeneous data into a single format, simplifying their analysis and processing. This is especially true when working with audio, video, and text files.

Unsupervised Learning – is used to identify complex relationships in data without predefined labels or categories.

Data Visualization – transforms analysis results into clear and attractive visual representations, such as graphs and animations, contributing to a better understanding of information.

The application of analytics is the key to maximizing the value of big data. Accordingly, big data analytics is seen as the analysis of large and diverse data sets, including structured, semi-structured, and unstructured information from various sources, ranging in size from terabytes to zettabytes. Big data analytics reflects the challenges associated with data that is too large, too unstructured, and too fast to be managed by traditional methods. Due to technological developments and the increasing amount of information that enters and leaves companies daily, faster and more efficient means of evaluating such data have become necessary. Thanks to standard methodologies and data management and analysis infrastructures, datasets of this type can no longer be easily analyzed. Therefore, new tools and methodologies specializing in large-scale data analytics are needed, as well as the necessary systems for storing and managing such data.

Application of decision support technologies based on Big Data. The development of big data has a significant impact on everything from the information itself and its acquisition and processing to the final judgments obtained. Therefore, the Big Data, Analytics and Solutions (B-DAD) framework was proposed, including tools and methodologies for big data analytics in decision-making. The framework reflects various large-scale storage, management, and governance tools, analytical tools, and techniques, as well as tools for mapping and evaluating many adoption processes Solutions. A Big Data environment requires magnetic, flexible, deep (MAD) analytical capabilities that differ from the traditional enterprise data warehouse (EDW) context. First, typical EDW methods prevent the inclusion of new data sources until they have been cleaned and integrated. Due to the ubiquitous presence of data nowadays, the big data ecosystem must be magnetic and thus encompass all data sources, regardless of their quality. Big data storage should also allow analysts to create and modify data quickly, given the growing volume of databases and the complexity of data analysis. This requires a flexible database that can synchronize physical and logical content with rapidly changing data. After all, since modern data analysis uses a complex statistical methodology and analysts need to analyze large amounts of data by digging, a big data warehouse must also be thorough and have a smart, algorithmic working mechanism.

A wide range of innovative technologies and trends in working with Big Data: Initially, the set of approaches and technologies included tools for massively parallel processing of indefinitely structured data, such as NoSQL DBMS, MapReduce algorithms, and Hadoop project tools. Later, big data technologies began to include other solutions that provide similar capabilities for processing ultra-large data sets, as well as some hardware.

MapReduce is a model of distributed computing in computer clusters that was introduced by Google. According to this model, the application is divided into a significant number of identical elementary tasks that are performed on the nodes of the cluster and then naturally reduced to the final result.

NoSQL Not Only SQL, not just SQL, is a general term for various non-relational databases and repositories and does not mean any specific technology or product. Conventional relational databases are well suited for fairly fast and uniform queries, and on complex and flexibly constructed queries typical for big data, the load exceeds reasonable limits, and the use of DBMS becomes inefficient.

Hadoop is a freely distributed set of tools, libraries, and frameworks for developing and executing distributed applications that run on clusters of hundreds or thousands of nodes. It is considered one of the fundamental technologies used in most data collection.

R is a programming language for statistical data processing and working with graphics. It is widely used for data analysis and has become a standard for statistical applications.

Teradata, EMC, and others offer hardware and software systems designed to process big data. These complexes are supplied as ready-to-install telecommunication cabinets containing a cluster of servers and control software for massively parallel processing. This sometimes includes hardware solutions for analytical processing in RAM, in particular, SAP's Hana hardware and software complexes and Oracle's Exalytics complex, even though such processing is not initially massively parallel, and the amount of RAM of one node is limited to several terabytes. In addition to the NoSQL, MapReduce, Hadoop, and R technologies considered by most analysts, McKinsey also includes Business Intelligence technologies and relational database management systems with SQL Big Data support in the context of being suitable for processing big data.

Expanding the scope of implementation of big data technologies:

A study of the forecast of the Earth's climate change. The quest for understanding requires an unprecedented influx of data from an

extensive network of scientific observatories located both on Earth and in its atmosphere. This includes not only data from these observatories, but also enormous contributions from ocean research, earth sciences, meteorological research centers, and, interestingly, from the enigmatic realms of nuclear research spanning events from the Big Bang to the current age of the universe;

Search for innovative medical solutions. The role of big data in healthcare is poised for significant growth, with the potential to accelerate medical discovery by consolidating vast volumes of global medical records. The impact of big data goes beyond medical breakthroughs. It improves the staffing of healthcare facilities, automates the processing of electronic medical records, and allows you to receive real-time notifications about the condition of patients. The basis of the medical infrastructure can be the ICS of data exchange between research institutions and medical institutions, both public and private, to optimize the process of treatment, rehabilitation, and life support of patients. The transformative impact of big data in healthcare is evident, from groundbreaking research to pandemic management, cardiovascular disease treatment, and organ and tissue transplantation, marking a significant step towards improving global healthcare;

The development of urban IT ecosystems based on big data is created as cluster associations of stakeholders around common interests and economies of scale, particularly co-financing of educational and infrastructure initiatives of higher education institutions. Technological and computing resources in such an ecosystem are closely related; monitoring and managing physical processes are carried out using IoT technologies. Traditional Engineering Models harmoniously coexist with computer ones. Example: at KNEU named after Vadym Hetman, one of the main directions of the University's strategic objective until 2025 is the formation of effective digital educational, scientific, and economic activities of the University's IT ecosystem. In order to adequately respond to changes in the market of educational services, it is also necessary to develop an integrated information system for managing the quality of educational activities of KNEU named after Vadym Hetman, the main purpose of which is to study the process of educational and scientific activities, monitoring and targeting end users to identify their requirements, assessing the degree of compliance of the quality of educational services with market needs. Overall, the Big Data ecosystem consists of various components that work together to enable efficient storage, processing, and analysis of big data. This includes not only technologies such as Hadoop, Spark, and NoSQL databases but

also other tools and solutions such as ETL tools (Extract, Transform, Load), data management systems, analytical platforms, IT infrastructure and cloud computing services, ICS design technologies and methodologies;

The intersection of the application of unmanned driving technologies and big data. The use of Big Data technologies plays a key role in improving automated vehicle management and training. This process involves collecting, processing, and analyzing vast amounts of data from a variety of sources, such as sensors, cameras, and other systems installed on the vehicle. Using this data allows for more accurate and efficient driving systems that can predict potential road hazards and optimize driving routes.

One example of the application of Big Data in automated driving is the development of in-depth training models for autonomous driving, based on data obtained from simulations and real-world operating conditions. A study conducted by Symphorien Karl Yoki Donzia and others found that the use of deep learning models such as YOLO based on convolutional neural networks (CNNs) can significantly improve the ability of autonomous vehicles to recognize and respond to dangerous situations on the road in advance, through the analysis of big data collected from various sources [34].

The use of big data is not limited only to improving the direct management of vehicles but also contributes to the effective training of autonomous systems. For example, methods based on Model predictive control (MPC) and big data analysis make it possible to optimize the lateral control of autonomous vehicles, improving their ability to follow a given route with high accuracy [35].

Integrating Big Data and unmanned driving technologies opens new opportunities to improve autonomous vehicles' safety, efficiency, and reliability. In particular, using big data allows for developing systems capable of adapting to changing traffic conditions, anticipating potential hazards, and optimizing routes in real-time. This approach not only increases traffic safety but also helps reduce transportation costs and environmental impact.

Expanding the services of business companies with the help of big data. New trends in the social sphere involve the integration of all critical aspects of business operations: advertising, supply chain management, customer support, social media management, social services management, etc. Data integration is vital for a variety of purposes, including analysis, reporting, and business intelligence. Sources can range from social media pages and ERP applications to customer logs, financial reports, emails, presentations, and employee-

generated reports. This integration strategy encompasses a wealth of data, ranging from customer bank transaction records, interaction patterns with internet query landing pages, geographic data, and video feeds from multiple supermarket branches to provided suggestions and customer survey feedback. Regardless of the complexity of the data, the latest analytics tools are ready to process it in real time, providing previously unattainable insights. The Transformative Impact of Big Data goes far beyond simple data analysis. It shapes the way we work, make decisions, and innovate. Netflix's system was one of the early proponents of big data analytics, but in the future, the list of organizations willing to harness the full potential of data-driven decision-making is growing.

Big data is also penetrating local retail, where another segment of DaaS providers is used – Data as a Service, which is a cloud-based software tool designed to work with data, such as to manage data in a data warehouse or analyze data using business intelligence. It is provided by SaaS software-as-a-service. DaaS is based on the concept that its data product can be made available to the user on demand, regardless of the geographical or organizational dependency between the supplier and the consumer. Big Data is widely used in retail by centers like Vodafone (Ukraine), ATB-Market, Silpo chains, etc.

3.4. Trends 4. Development of the Internet of Things (IoT) in specialized computer systems

The Internet of Things (abbreviated as IoT) is a new stage in the development of the Internet, which significantly expands the possibilities of collecting, analyzing, and distributing data that users can turn into information and knowledge. To define IoT more precisely, it is a global infrastructure for the information society that enables the provision of more complex services by connecting (physical and virtual) things with each other based on existing and functionally evolving interoperable information and communication technologies [36, 37].

The application of numerous IT solutions to improve traditional operational technologies (OT) has created a whole class of solutions commonly referred to as the Industrial Internet of Things (IIoT). Gartner's Industrial Internet of Things Standard Reference Architecture consists of three parts (Figure 3) [38].

Edge includes traditional OT hardware such as sensors and actuators, as well as an IIoT gateway that performs a multitude of tasks, such as data filtering, aggregation and storage, analytics, device

management, access control, and communication with networks and applications.

A cloud platform is typically a platform-as-a-service (PaaS) that integrates data storage and analytics, event processing, process orchestration, network communication, and other functions.

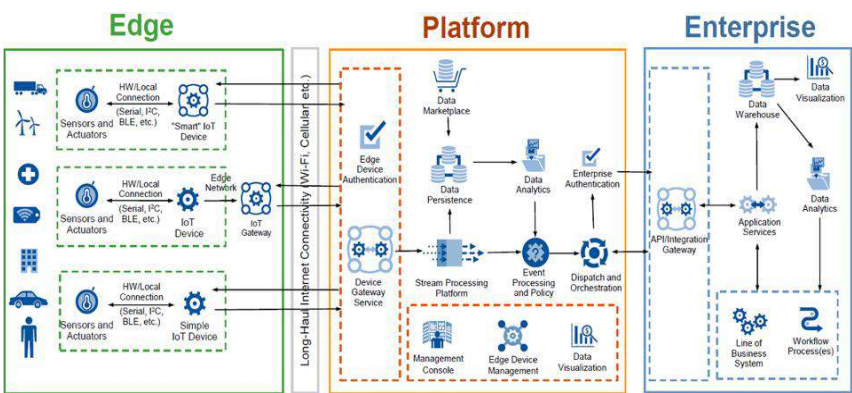


Figure 3. Gartner IIoT Standard Reference Architecture

Source: [38]

The enterprise supports server-side software and applications such as databases, data warehouses, web services, etc.

This optimized architecture bypasses traditional hierarchical levels and allows data to be exchanged directly from physical devices to cloud services or to consolidate communication through an IIoT gateway to the cloud. In IoT deployments, data is not limited to traditional hierarchies, and in fact, data no longer lives entirely within the enterprise.

IIoT is a key component of Industry 4.0, the fourth industrial revolution characterized by a combination of digital, physical, and biological technologies. It is a revolution in traditional industries, facilitating the shift from manual and time-consuming processes to automated, data-driven operations. With IIoT, equipment performance can be monitored, failures can be predicted, logistics can be optimized, product quality improvements, and more. It's about creating the smartest, efficient, and profitable industrial operation, or in other words, OT. IIoT is a subset of IoT that specifically deals with industrial applications. It focuses on improving industrial processes and operations through data-driven insights. IIoT includes more complex

systems, stringent security requirements, and mission-critical operational controls. It's about improving efficiency, productivity, and safety in industries such as manufacturing, energy, and transportation. While both IoT and IIoT are powered by similar technologies such as sensors, connectivity, and data analytics, the key difference lies in their application and impact. The Internet of Things improves our daily lives by making our homes, cities, and devices smarter. IIoT, on the other hand, is transforming industries by revolutionizing how businesses operate and compete.

The development of IoT and IIoT technology architecture is based on the use of the following basic principles [39]:

- the ubiquitous typical Y.2060 communications infrastructure;
- global identification of each object of a given subject area;
- the target's ability to send and receive data using a personal area network or the Internet;

The development of IoT architecture can be supplemented with the use of

- principles of adaptability to each development of a specialized computer system, scalability, hybridization, and security of systems.

The latter principle is becoming increasingly widely used in specialized computer systems in various subject areas. In particular, Cisco Systems has developed a Cisco IoT model at the level of the security environment (Fig. 4).

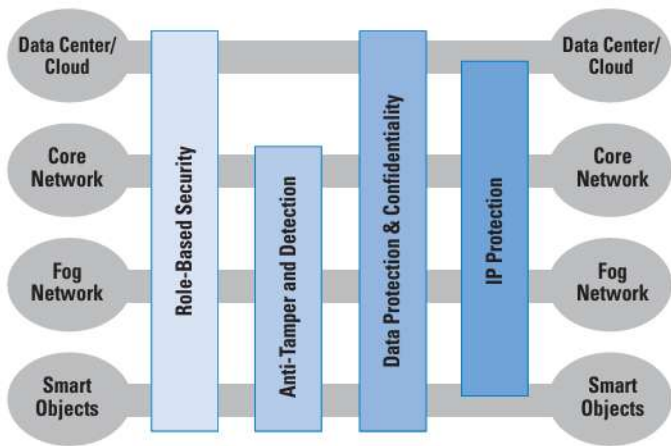


Figure 4. Cisco Security Model

Source: [40]

With this four-tiered architecture, Cisco's security model defines four common security capabilities spanning multiple layers:

- Role-based security;
- Protection from interference and detection of interference;
- Data protection and privacy;
- Secure Internet protocols.

Also, a user's sensitive personal information cannot be compromised, so data security is a key issue to overcome. There is a possibility that IoT networks are also at risk of attacks, so hardware security is an equally important component of IoT architecture development.

A typical architecture for IIoT describes the arrangement of digital systems so that they together provide network and data connectivity between sensors, IoT devices, data storage, and other layers. Thus, the IIoT architecture should have the following components [41], Fig. 5.

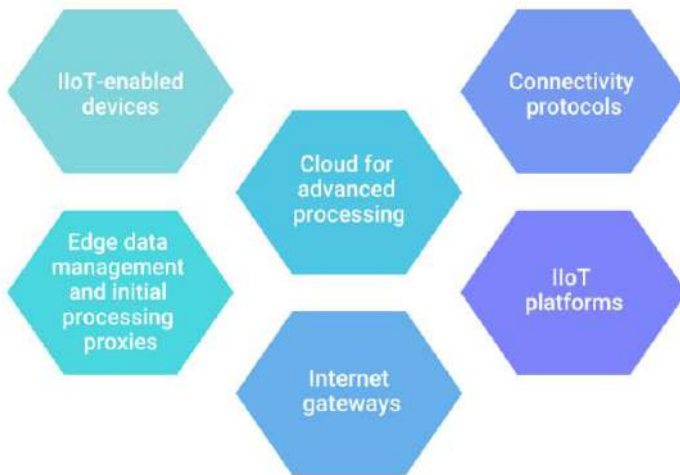


Figure 5. Typical IIoT architecture

Source: [41]

Advanced IIoT platforms. Industrial Internet of Things (IIoT) systems play a critical role in coordinating, monitoring, and managing operations throughout the value chain. They provide device data management, analytics, data visualization, and integration of AI features, working from edge devices and sensors to cloud computing

and back again. This allows for fully connected, transparent, automated, and intelligent factory settings, improving manufacturing processes and efficiency [42].

The Industrial Internet Reference Architecture (IIRA) serves as a standard for the development of complex IIoT systems, promoting a systematic approach to development that includes feedback and iterations. It recommends adapting IIoT projects to the specific needs of business sectors, such as energy, healthcare, transportation, and government services [43].

Today, the Industrial Internet of Things (IIoT) is a strategic asset for large corporations and a key offering from leading cloud service providers, including Microsoft and Amazon Web Services (AWS). IIoT expands opportunities for industry in the areas of advanced data analytics and cloud computing, improving equipment maintenance, industrial operations efficiency, supply chain management, and personnel safety. The use of IIoT enables enterprises to achieve higher operational efficiency, increase productivity, and better manage industrial assets and processes through product customization, intelligent monitoring of production processes, and predictive and predictive maintenance of industrial equipment [44].

When modeling industrial facility processes, studies related to implementing the concept of a digital twin of an industrial facility, which is a complete virtual copy of a physical object for the entire life cycle of project management, from ideas to decommissioning and curtailment of production, are acquired. The necessary infrastructural conditions for implementing a given concept, including IIoT and the material base for processing large data volumes, are determined.

Given the security and privacy challenges accompanying IIoT implementation, it is important to implement advanced data protection and network security technologies. Developing and implementing robust authentication, data protection, and access control mechanisms are critical to securing IIoT devices and protecting against cyber threats [45].

Predictive data on the use of IIoT technologies. Accenture conducted an extensive study, «Winning with the Industrial Internet of Things» [46]. As part of this study, a survey of 1,400 senior executives in many countries around the world (736 of them CEOs) was conducted. The report, released as a result of the study, claims that the contribution of the Industrial Internet of Things to global manufacturing by 2030 could be about \$ 14.2 trillion. However, this one potential growth is at risk because neither companies nor governments are doing enough to create the necessary conditions for the widespread adoption of new digital technologies.

IoT and IIoT challenges in ICS.

The Internet of Things has a significant impact on ICS. However, face-to-face interaction and professional activities can decrease significantly as IoT usage increases. Smart environments, smart objects, and devices bring significant lifestyle changes as people become more adaptable to technology and intelligence. As more devices connect to the internet, the quality of services may decline accordingly, highlighting the need to improve the relevant IT infrastructure. In addition, the security and confidentiality of data and big data are critically important to consider in IoT technology, which can seriously jeopardize the stable operation of the ICS. The interoperability of different types of devices that connect to each other through a single IoT platform is another issue that needs to be considered when designing an ICS, which can be solved by using the standard protocols and platforms of different IoT devices in the ICS.

4. Prospects for the development of ICST

4.1. Information Aspect of the Development of ICST Programs

The National Informatization Program, which is regulated by the Law of Ukraine «On the National Informatization Program» [47], forms a set of tasks, programs, projects, works on informatization aimed at the development of the information society through the concentration and rational use of financial, material, technical and other resources, production and scientific-technical potential of the state, coordination of the activities of state bodies, local self-government bodies, as well as enterprises, institutions, organizations regardless of ownership. The National Informatization Program is formed and implemented in accordance with the Concept of the National Informatization Program [48]. It is aimed at the formation of the national infrastructure of informatization, informatization of priority areas of the economy, informatization of socio-economic development processes, solving problems of information society development, increasing the efficiency and effectiveness of public administration, national security and defense, democratization Society.

A comprehensive and balanced solution to the problems of socio-economic development is possible only on a modern information-analytical, system-technical base, with the help of situational centers for providing information support for the functioning of the public sector of the economy, conducting a balanced budgetary, credit and tax policy, the emergence of knowledge-intensive industries in

strategically important areas [3]. ICST will provide scientific approaches to solving social problems of society. This direction of informatization is based on the creation of databases and knowledge, as well as means of their processing, focused on effective informatization of state statistics bodies and accurate forecasting of the processes of socio-economic development, in particular, information and reference systems of the labor market, goods and services, quality control of consumer goods and others with their subsequent use for the formation of information systems for the management of given economic objects and processes.

Prospects for further research will be to study the problems of developing a system of cooperation between education, science, business, and the state on the basis of the active application of a systematic approach to the development, implementation, and commercialization of innovative information technologies on the concepts of Industry 4.0 technologies. Informatization of education will be aimed at the formation and development of the intellectual potential of the nation, improving the forms and content of the educational process, the introduction of computer methods of teaching and testing, which will make it possible to solve the problems of education at the highest level, taking into account world requirements. Among them are the individualization of education, the organization of systematic control of knowledge, the ability to take into account the psychophysiological characteristics of each child, etc. The results of the informatization of education should be:

- development of human information culture (computer education);
- development of the content, methods, and means of teaching to the level of world standards;
- shortening the term and improving the quality of education and training at all levels of training;
- integration of educational, scientific and industrial activities;
- improvement of education management;
- staffing of all areas of informatization of Ukraine through specialization and intensification of training of relevant specialists.

Also, today in Ukraine, the processes of digital transformation in management and administration are important, especially in the context of the introduction of e-government and digitalization of public services, which are key elements of modern information policy. These processes aim to improve the efficiency, accessibility, and transparency of management and administration through the use of information technology. They cover a wide range of activities and initiatives, from the development of electronic reporting and

permitting platforms to the registration of property rights. Digitalization of public services is about digitizing service delivery processes, making them faster, more efficient, and more user-friendly. This includes the development of electronic platforms for reporting, obtaining permits, registration of property rights, electronic appeals of citizens, electronic auctions, etc.

4.2. Technological Aspect of the Development of ICST Programs

The technological aspect of the development of ICST programs covers a wide range of innovations aimed at improving the efficiency, reliability, and accessibility of information processes in various fields of activity. This aspect includes the development and implementation of emerging technologies such as artificial intelligence, machine learning, Big Data, blockchain, the Internet of Things, cloud computing, and others that enable the transition to more automated, intelligent, integrated, and specialized management systems.

Big data technologies make it possible to collect, store, process, and analyze huge amounts of unstructured and structured data. It provides insightful insights to improve decision-making, streamline processes, and develop new products and services.

Blockchain technologies offer a new approach to ensuring the security, transparency, and negotiability of data in various fields, including finance, logistics, law, and public administration. They can be used to create decentralized databases, smart contracts, and voting systems [49, 50].

The Internet of Things integrates physical objects with the Internet infrastructure, enabling real-time data collection, sharing, and analysis. It finds applications in smart homes, Industry 4.0, smart cities, and healthcare, contributing to improving efficiency and quality of life.

Cloud computing provides flexibility, scalability, and cost savings by providing Internet access to computing resources and services. They enable organizations to quickly adapt to changing market demands and optimize IT infrastructure costs.

The technological aspect of ICST will continue to focus on integrating these innovative technologies to create more intelligent, automated, and interconnected systems. The main areas of research and development are improving artificial intelligence algorithms, ensuring data security, developing standards for IoT, introducing the latest industrial technologies and IIoT, optimizing cloud platforms, and expanding blockchain capabilities.

4.3. Organizational aspect of the development of ICST programs

The organizational aspect of the development of ICTS programs encompasses a wide range of interrelated elements, including the management structure, decision-making processes, organizational culture, and the interaction between people and technology. The development of ICT requires an integrated approach, which includes the analysis and optimization of organizational processes, the adaptation of the culture and management structure to the new requirements of the digital era, as well as the development of strategies for the effective integration of information systems into all aspects of the organization's activities.

The development of ICT requires businesses to review and adapt their organizational structure and management processes. This includes creating agile structures that can quickly adapt to changes in technology and market conditions, as well as developing mechanisms to manage knowledge and information within the organization effectively. Successful implementation of ICT also depends on the culture of the organization. Organizations must foster a culture that fosters innovation, is open to change, and supports continuous learning. This includes developing training and development programs for employees to ensure they are prepared to handle new technologies and systems [51].

The development of ICT also requires organizations to manage knowledge effectively [52]. This includes the development of systems for collecting, storing, processing, and analyzing data and information, as well as mechanisms for sharing knowledge among employees.

The organizational aspect of the development of information management systems and technologies is key to achieving success in today's business environment.

Conclusions

1. A classification of information control systems has been carried out in the context of state programs of informatization, development, and implementation of innovative information technologies in the process of designing information control systems, where new promising classes of information control systems have been identified: intelligent information systems (hybrid systems) and specialized computer systems (Internet of Things).

2. Positive trends in the development and implementation of innovative information technologies, in particular artificial intelligence

technologies, cloud computing, «big data», and the Internet of Things in the architecture of information control systems in various organizations, manufacturing enterprises, technical facilities, higher education institutions, medicine, are highlighted. Despite the long-term war in the country, there are favorable conditions and the need for the organization of dynamic digitalization of all spheres of public relations and informatization of priority areas of high-tech production in the defense, social, and state spheres of management.

3. The informational, technological, and organizational aspects of the development and implementation of ICST programs in various sectors of the economy and technology are considered. Aspects aim to improve the efficiency, accessibility, and transparency of management of organizations, manufacturing enterprises, and the social sphere. The technological aspect of the development of ICT programs will continue to focus on the implementation of the principles of hybridization and integration of methods and the development of approaches to the use of innovative technologies to create more intelligent, automated, specialized, and interconnected systems. The main areas of research and development are the improvement of artificial intelligence algorithms, ensuring data security, and the introduction of the latest IIoT industrial technologies. Organizational architectural solutions for ICTS programs include the creation of flexible structures that can quickly adapt to changes in technology and market conditions, as well as the development of mechanisms for effective management of knowledge and information within the organization.

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