UDC 330.1
JEL Classification: C00; C10; C38; D83
DOI: https://doi.org/10.32983/2222-4459-2025-2-181-195

FUNDAMENTALS OF INTELLECTUAL DATA ANALYSIS USING AND ITS CAPABILITIES IN THE KNOWLEDGE ECONOMY

© 2025 POLYAKOV M. V., KHANIN I. G., SHEVCHENKO G. Ya., BILOZUBENKO V. S., NAHORIANSKYI M. A.

UDC 330.1
JEL Classification: C00; C10; C38; D83

Polyakov M. V., Khanin I. H., Shevchenko G. Ya., Bilozubenko V. S., Nahorianskyi M. A.
Fundamentals of Intellectual Data Analysis Using and Its Capabilities in the Knowledge Economy

In the modern economy, knowledge has become a key factor in creating value, which increases the demand for and significance of methods for its production. Given the multiple increase in the volume of data containing useful but hidden information and the emergence of digital technologies that allow for processing this data to extract the information, one of the most important methods for acquiring knowledge has become intellectual data analysis (IDA). The aim of the research is to explain the fundamentals, capabilities, and characteristics of applying IDA in the knowledge economy, as well as to provide an overall assessment of its results. The necessity of IDA for acquiring knowledge has been substantiated, its essence has been clarified, and the fundamentals of its implementation have been summarized, including typical tasks that it addresses. Considering that modern approaches to IDA are based on the use of digital technologies, the main elements of the relevant infrastructure and IDA tools have been systematized, and their impact on effectiveness has been substantiated. Considering the purpose of IDA, a comprehensive evaluation of its results in terms of knowledge acquisition has been conducted, emphasizing its inherent limitations and role in this process. Practical applications of IDA have been identified, demonstrating its expanding role in the knowledge economy. The rise of the data economy, which is evolving and developing its own distinct characteristics, has been observed. The process through which data creates value and the fundamentals of understanding their usefulness have been explained. The gradual «enrichment» of data to unlock its usefulness through IDA has been demonstrated. In conclusion, general recommendations for the development of IDA within the knowledge economy, where it has become integral, have been formulated.

Keywords: *knowledge economy, data, knowledge, intellectual data analysis (IDA), typical tasks, digital infrastructure and tools, results of IDA, data economy, usefulness of data.*

Fig.: *1.* ***Tabl.:*** *4.* ***Bibl.:*** *24.*

Polyakov Maxim V. *– Doctor of Sciences (Economics), Associate Professor, Co-founder, NGO "Noosphere Association" (103-A Nauky Ave., Dnipro, 49000, Ukraine)*
E-mail: *info@noosphere.com*
ORCID: *http://orcid.org/0000-0001-7896-2486*
Researcher ID: *V-9971-2018*
Scopus Author ID: *57194904129*

Khanin Igor H. *– Doctor of Sciences (Economics), Professor, Professor of the Department of Enterprise Economics and International Business, National University of Water and Environmental Engineering (11 Soborna Str., Rivne, 33028, Ukraine)*
E-mail: *i.h.khanin@nuwm.edu.ua*
ORCID: *http://orcid.org/0000-0002-4221-2314*
Researcher ID: *AAM-7043-2021*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57203118329*

Shevchenko Gennadij Ya. *– Candidate of Sciences (Engineering), Associate Professor, Partner, NGO "Noosphere Association" (103-A Nauky Ave., Dnipro, 49000, Ukraine)*
E-mail: *gshevchenko@m.ht*
ORCID: *https://orcid.org/0000-0003-3984-9266*
Researcher ID: *V-9077-2018*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57211394013*

Bilozubenko Volodymyr S. *– Doctor of Sciences (Economics), Professor, Professor of the Department of International Economic Relations, University of Customs and Finance (2/4 Volodymyr Vernadsky Str., Dnipro, 49000, Ukraine)*
E-mail: *bvs910@gmail.com*
ORCID: *http://orcid.org/0000-0003-1269-7207*
Researcher ID: *V-9965-2018*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57211386386*

Nahorianskyi Mykola A. *– Senior Software Engineer, ServerBase AG (1 Kasernenstrasse, Bachenbülach, 8184, Switzerland)*
E-mail: *n.nagoryanskiy@gmail.com*
ORCID: *https://orcid.org/0009-0000-5396-1305*

УДК 330.1
JEL Classification: C00; C10; C38; D83

Поляков М. В., Ханін І. Г., Шевченко Г. Я., Білозубенко В. С., Нагорянський М. А.

Основи застосування та можливості інтелектуального аналізу даних в економіці знань

У сучасній економіці знання стали ключовим фактором створення вартості, що збільшує запит і підвищує важливість способів їх виробництва. Зважаючи на багаторазове збільшення обсягу даних, які несуть у собі корисну, але приховану інформацію та появу цифрових технологій, які дозволяють їх обробляти, щоб цю інформацію отримати, одним із найважливіших способів отримання знань став інтелектуальний аналіз даних (ІАД). Метою дослідження є роз'яснення основ, можливостей та особливостей застосування ІАД в економіці знань, а також загальна оцінка його результатів. Обґрунтовано необхідність ІАД для отримання знань, уточнено його сутність та узагальнено основи здійснення, зокрема типові завдання, які вирішуються. Враховуючи, що сучасні підходи до ІАД базуються на використанні цифрових технологій, систематизовано основні елементи відповідної інфраструктури та інструментів ІАД, обґрунтовано їх вплив на його ефективність. Враховуючи призначення ІАД, здійснено загальну оцінку його результатів з точки зору пізнання, що дозволило показати природну межу та роль у цьому процесі. Визначено напрями практичного використання ІАД, що доводить розширення його ролі в економіці знань. Відзначено появу «економіки даних», яка збільшується та набуває власної специфіки. Роз'яснено, яким чином з даних виникає цінність та основи розуміння їх корисності. Показано поступовість «збагачення» даних для вивільнення їх корисності в ході ІАД. У підсумку сформульовано загальні рекомендації щодо розвитку ІАД в економіці знань, частиною якої він став.

Ключові слова: *економіка знань, дані, знання, інтелектуальний аналіз даних (ІАД), типові завдання, цифрова інфраструктура та інструменти, результати ІАД, «економіка даних», корисність даних.*

Рис.: *1.* ***Табл.:*** *4.* ***Бібл.:*** *24.*

Поляков Максим Валерійович *– доктор економічних наук, доцент, співзасновник, ГО «Асоціація Ноосфера» (просп. Науки, 103-А, Дніпро, 49000, Україна)*
E-mail: *info@noosphere.com*
ORCID: *http://orcid.org/0000-0001-7896-2486*
Researcher ID: *V-9971-2018*
Scopus Author ID: *57194904129*

Ханін Ігор Григорович *– доктор економічних наук, професор, професор кафедри економіки підприємства і міжнародного бізнесу, Національний університет водного господарства та природокористування (вул. Соборна, 11, Рівне, 33028, Україна)*
E-mail: *i.h.khanin@nuwm.edu.ua*
ORCID: *http://orcid.org/0000-0002-4221-2314*
Researcher ID: *AAM-7043-2021*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57203118329*

Шевченко Геннадій Якович *– кандидат технічних наук, доцент, партнер, ГО «Асоціація Ноосфера» (просп. Науки, 103-А, Дніпро, 49000, Україна)*
E-mail: *gshevchenko@m.ht*
ORCID: *https://orcid.org/0000-0003-3984-9266*
Researcher ID: *V-9077-2018*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57211394013*

Білозубенко Володимир Станіславович *– доктор економічних наук, професор, професор кафедри міжнародних економічних відносин, Університет митної справи та фінансів (вул. Володимира Вернадського, 2/4, Дніпро, 49000, Україна)*
E-mail: *bvs910@gmail.com*
ORCID: *http://orcid.org/0000-0003-1269-7207*
Researcher ID: *V-9965-2018*
Scopus Author ID: *https://www.scopus.com/authid/detail.uri?authorId=57211386386*

Нагорянський Микола Анатолійович *– старший інженер-програміст, ServerBase AG (Kasernenstrasse, 1, Бахенбюлах, 8184, Швейцарія)*
E-mail: *n.nagoryanskiy@gmail.com*
ORCID: *https://orcid.org/0009-0000-5396-1305*

Modern economy, due to a number of its features, is called a «knowledge economy» (an «economy based on knowledge») because its general characteristic is the increasing importance of knowledge and knowledge capital, including human capital, in creating added value on one hand, and on the other hand, it serves as a foundation for creating an eco-knowledge structure of the economy that includes technologies, organizational models, and management decisions. This entire structure is tied to the generation and utilization of new knowledge to develop economic activities (business). As a result, along with a number of objective reasons (such as the complexity of consumer needs, increased regulatory requirements, heightened competition, the emergence of innovations, etc.), the demand for knowledge is continuously increasing, along with the importance of its sources and methods of production. In the economy, in addition to scientific and technological developments, there is an increasing need for knowledge about consumers, competitors, various economic systems, communities, and society and its functioning. Acquiring this knowledge has its own specifics and is often linked to processing extensive arrays of diverse data.

One of the most important ways to acquire new knowledge in contemporary conditions is through intellectual data analysis (IDA). On one hand, the development of the economy, the complexity of technological systems, and the advent of computer networks, sensors, measuring instruments, and so forth have led to a substantial increase in the volume of data, which collectively contains necessary and useful but hidden information. On the other hand, computer technology and digital technologies have emerged, enabling the collection, accumulation, and storage of this data. By applying relevant mathematical methods, they allow for its analytical processing to extract the useful information.

Observing the exponential growth of data volume in the economy and the expansion of data-related activities across all its sectors, it is no exaggeration to speak of a «data revolution» today [1–3]. However, it should be emphasized that, without IDA, obtaining meaningful information from this growing volume of data is impossible, especially considering its diversity. At the same time, it should be noted that IDA creates the conditions for revealing the value of data as a resource for acquiring knowledge, ensuring the effectiveness of data handling, and fostering the development of a data economy (or data-driven economy) [4].

At the same time, despite the widespread use of IDA in business and science, the understanding of its principles and purposes in the knowledge economy remains quite fragmented. Therefore, a more holistic view of the problems being addressed with its help, as well as the features, trends, and challenges of applying IDA in the economy, is required. It is important to develop a correct understanding of the capabilities and inherent limitations of IDA, along with a more comprehensive view of its results from the perspective of knowledge acquisition. This will help address distorted perceptions of IDA as merely a tool for obtaining knowledge, particularly from a business perspective, and improve its overall effectiveness.

For several decades, the concept of the knowledge economy has been used to describe a range of structural changes in the economy associated with the development of science and technology, intensive innovation, expansion of high-tech production, increasing importance of intellectual labor, and changes related to computing technology and networks, among other factors. As a result, new development trends emerged, and the economy gained qualitatively different characteristics, making the generation and utilization of knowledge crucial [5]. Digital technologies, which emerged from computer technology and networks, ushered humanity into a new era by transforming the «order of knowledge» – the conditions and methods of its production, transfer, and utilization – across all spheres of economic activity [6]. One of the most important features of the economy has become the expanded ability to operate with data [1], which simultaneously has become a more significant source of value [7]. The acquisition of knowledge based on data and, accordingly, the creation of new value is associated with the application of IDA [8].

The growth of data volume in the «digital world» has led to the emergence of enormous datasets, known as Big Data, which has created a demand for specialized digital technologies to work with these datasets, including analytical processing, on a new level [2; 9]. Big Data technologies have become an integral part of modern technological trends and have given rise to new production, logistics, energy, communication, and other systems [3; 10]. This includes the application of IDA to obtain the knowledge necessary for the normal operation and management of these systems, as well as the development of innovations that become increasingly data-driven [4; 10]. The challenge of using large volumes of accumulated data and extracting knowledge from it affects all sectors of the economy. However, this requires a proper understanding of IDA and its capabilities, which has led to the emergence of a new scientific branch – Data Science [11; 12]. The challenge of using large volumes of accumulated data and extracting knowledge from it affects all sectors of the economy. However, this requires a proper understanding of IDA and its capabilities, which has led to the emergence of a new scientific branch – Data Science [13].

Businesses operating at the edge of efficiency quickly recognized the potential of IDA, especially in the digital sector, and have extensively developed relevant activities that are now becoming routine. Many applications and variations of IDA have emerged, such as Data Analysis (Data Analytics), Data Intelligence, Business Analysis (Business Analytics), Business Intelligence [14; 15]. IDA has also found extensive application across various fields of scientific research, significantly altering existing research methodologies. Given the growing scale of data work in science, digital technologies have led to the emergence of a new research paradigm – e-science – which is increasingly data-driven and incorporates IDA as an integral component [3; 14]. Undoubtedly, the extent and outcomes of IDA application vary between business and science due to their differing goals and needs. In business, tasks are generally practical, fast-paced, and geared toward obtaining actionable, preliminary insights (though exceptions can occur), often leading to more superficial results. Conversely, science seeks in-depth exploration within specific fields to uncover fundamental truths. Consequently, while IDA is essential in scientific research, it represents only the initial stage of a more profound investigation [3; 11; 14; 15]. However, a common factor for both business and science is the increasing scale of IDA application, driven by the development and use of digital infrastructure and tools, which have become essential elements of analytical work [16; 17].

Although the review is far from exhaustive, it demonstrates the importance of considering IDA as a component of the knowledge economy. It also highlights the need for a systematic approach to understanding its essence, methodology, purpose, and economic effectiveness. It is critically important not only to grasp the significance, capabilities, and advantages of using IDA but also to understand its inherent limitations to apply it effectively in practice for knowledge acquisition. This will help address the contentious situations, especially in business, associated with inflated and irrelevant expectations of IDA, which are often the cause of complaints. Such issues cannot be resolved merely by increasing the volume of data analyzed or by boosting the computational power used for analysis; they require methodological clarifications.

The aim of the research is to clarify the fundamentals, capabilities, and specificities of applying IDA in the modern knowledge economy, and to provide a comprehensive assessment of its results.

In general terms, IDA refers to the field of data analysis based on the use of specialized mathematical methods for processing relatively large sets of diverse data. The aim is to uncover previously unknown hidden patterns (relationships, trends, etc.) that are interpretable and useful for practical application and/or further study to gain new insights. It is worth noting that IDA is employed when it is impossible to identify these patterns in large data sets using traditional analytical approaches, including statistical methods. Typically, the starting information for applying IDA is an experimental data table that records the results of observations of objects. The data sets in question are either an object-property table (OPT), where similar objects are characterized by specific attributes (properties) with corresponding parameter values, or a so-called training sample (TS) (dataset), which is essentially a verified OPT where the set of objects is pre-divided into specific classes. A large number of attributes (properties) allows for more comprehensive and detailed characterization of objects using diverse data. The similar objects that represent a specific domain knowledge and are analyzed can vary widely (e. g., specific consumers, companies, products, countries, advertising channels, periods, etc.), and are of interest for the development of economic activity (business). The methods used in IDA to find patterns are broadly referred to as Data Mining (DM), within which Machine Learning methods are increasingly distinguished. However, this distinction is not necessary for the purposes of this article.

Considering the potential of using IDA to study various objects and solve diverse structural and analytical tasks across virtually all sectors and areas of the economy, the research will be based on a systematic approach. The methodology of this research lies at the intersection of mathematics, statistics, computer science, control theory, economics, and business, and it may also extend to other fields of science and practice where IDA can be applied. In addition to employing general scientific methods of cognition (generalization, systematization, abstraction, induction and deduction, analysis and synthesis, analogy, comparison, formalization, modeling, classification, categorization), special analysis methods (logical, structural, functional), the descriptive research method, and interpretative methodology were also applied. The conceptual and guiding principles of this article are based on the concepts of the knowledge economy, the data economy, and, to some extent, the digital economy. In this regard, the features of the development of the Internet, electronic business and commerce, and several current technological trends have been taken into account. To describe the trends and assess the results of using IDA in the economy, the principles of modern economic theory, business administration, economic analysis, and decision-making theory have been used as the foundation.

The main issue in economy is making management decisions that must be well-grounded and lead to optimal outcomes. The basis for decision-making is relevant information, which, in this article, is understood in the broad sense defined by W. Shannon [18] as «...anything that reduces uncertainty about the outcome of a particular event». In economy, depending on the level of understanding and justification of a decision, information can be conventionally categorized into three types:

1 – «knowledge», which means information that is supported by observations (evidence), verified through practice, provides a comprehensive understanding of the nature of a particular phenomenon, and the causal relationships involved. This type of information is the most objective and reliable, thus enabling well-founded decisions;

2 – «assumption», which means information that is partially validated, does not provide a complete un-

derstanding of the phenomenon, and is less reliable. It allows for making assumptions about solving problems and making decisions;

3 – «opinion», which means information that is the least reliable, based on limited knowledge about the phenomenon and intuition, with a predominance of subjective views.

It allows for forming assessments and judgments (speculations, prejudices) of varying completeness, which are used to construct corresponding justifications and make decisions on this basis. Drawing clear boundaries between these types of information can often be challenging. However, this approach provides means to differentiate information based on its level of reliability, which impacts the quality of decisions made (*Fig. 1*). Transitioning from «opinion» to «assumption,» and then to «knowledge», involves qualitative leaps in understanding the subject area.

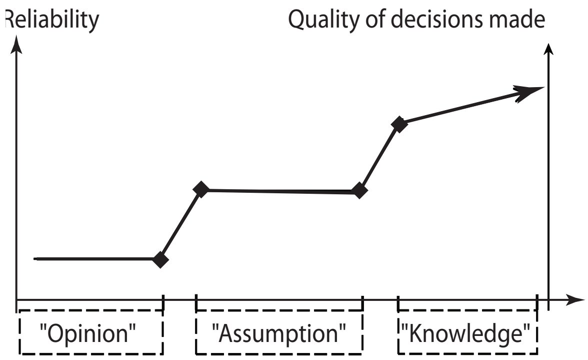

Fig. 1. The conventional link between the types of information distinguished by their level of reliability and the quality of decisions made

Thus, the quality of decisions improves as the reliability of information increases, moving from opinion through assumptions to knowledge, which is understood here as reliable information on which well-founded decisions can be based. This includes developing strategies, creating innovations, and establishing various competitive advantages. The enhancement of information reliability is directly related to data processing, the volume and diversity of which continue to expand. Even considering the significant volume and multidimensionality of data, it alone provides limited insight into specific situations. Any general analysis has substantial limitations (due to the size of datasets, memory distortions, difficulties in understanding and interpreting relationships between attributes, overlapping facts, and more). For decision-making, what is needed is not just the data itself but reliable information derived from it, which reveals the «black box» and reduces uncertainty. At the same time, the volume of the information obtained should be manageable enough to be processed, understood, and utilized effectively, which is a key factor for success. Therefore, the multidimensionality of experimental data and the inherent limitations of human analysis in identifying and extracting complex patterns necessitate the use of IDA, which is focused on transforming data into highly reliable information and drives the ongoing development of such systems. Moreover, IDA enables rapid data processing, which is crucial as the speed of obtaining necessary information often becomes a critical factor. Therefore, the ability to handle the increasing volume of data and effectively use it for insights and decision-making – through IDA – becomes an essential strategic competence for modern companies, regardless of the industry they operate in.

The application of IDA begins when a prepared dataset is available. Data represents human experience, perceptions of the surrounding reality, and the cognition (assessment) of its objects. It is formed based on observations, experiments, measurements, the functioning of information or technical systems, etc. Data can be collected by people or automatically using computer technology, sensors, measuring tools, and so on. Data is evaluated based on various criteria, including formalized appearance, structure, object attribute characteristics, interpretability, suitability for processing, and volume (in terms of the number of features and/or objects). Data can be of different types, such as numerical, categorical, ordinal, interval, and temporal. The content and quality of a specific dataset should be assessed in relation to the problem being addressed and its potential to produce satisfactory results. Nonetheless, this aspect often remains a weak point in data collection and analysis procedures. In some cases, the quality of datasets can be assessed using specialized mathematical approaches. The need for specific type (types) of data, as well as its structure, is determined by the specifics of the subject area (objects) being studied, the problem being addressed, and the suitability of the chosen indicators for the task.

Knowledge based on data can be seen as a form of «compression» that allows for handling larger volumes by summarizing all the experience gained from practical activities. Knowledge refers to stable patterns within a subject area (relationships, generalizations, patterns, trends) that create new meaning, provide understanding of phenomena, and enable specialists to make effective decisions and act within a given context. Knowledge gained from data through the application of IDA methods in economy is empirical. It reflects specific relationships between objects and the data that characterize them, as well as general patterns and trends within a particular field. In practice, probabilistic knowledge most often prevails, especially in the economy and social sphere. Based on this knowledge, technologies and organizational models are created, and social and technical processes are predicted and regulated.

Foundations of IDA. Thus, due to the limitations of statistical methods in the analysis of multidimensional datasets, especially heterogeneous ones, a number of specialized mathematical methods (Data Mining, DM) emerged in the second half of the 20th century. These methods enable the analysis of such datasets and have formed the foundation of modern IDA. Its purpose is to effectively analyze complex and large datasets that describe a domain knowledge to identify patterns within them. Given the nature of the data undergoing analytical processing, these patterns will henceforth be referred to as empirical regularities (ER).

The widespread application of Data Analytics in the economy is demonstrated by the emergence of new terms that emphasize its practical focus, such as: Data Analysis, Data Analytics, Data Intelligence, Big Data Analytics, Business Analysis, Business Analytics, Business Intelligence. In practice, this has led to the progressive development of a specific categorization, such as: Business Analysis (which essentially represents a broader understanding of IDA applied within the business sector, with relevant context and interpretation of results), Business Intelligence (which is more focused on studying the past, including descriptive and diagnostic analytics), and Business Analytics (which is more oriented towards understanding causes and justifying future actions, including predictive and prescriptive analytics).

Without IDA, which relies on computer technology, humans are unable to identify and establish patterns within large datasets. In addition to significantly expanding the computational capabilities for mathematically processing big datasets, specialized digital technologies enable tasks that are nearly impossible or impractical to perform manually. For instance, creating a 3D visualization of a large dataset to assess its quality, which aids in understanding the feasibility of solving the problem and formulating an analytical hypothesis. Digital technologies, which form the basis for specialized infrastructure and tools, create fundamentally new methods of IDA and, accordingly, new practical approaches to its organization and implementation.

Typical tasks addressed within the framework of IDA are presented in Table 1. The source of information for further analysis is a table of empirical data (OPT or TS), the formation of which often falls outside the competence of IDA specialist (Data Scientist, Data Analyst).

The choice of IDA methods in practice depends on the task and the nature of the data, and is a separate issue beyond the scope of this article. The main stages of IDA are: 1) collecting, structuring, and preliminary preparing of data; 2) constructing the feature space, including selecting the indicators that are most impor-

Table 1

Main typical tasks addressed within the framework of IDA

Task	General description
Clustering	Grouping objects based on similarity into relatively homogeneous groups (clusters) without predefined categories (known data structure); data is presented in the form of an OPT;
Classification	Determining the category or class to which a new object belongs based on a verified training dataset (TS);
Regression analysis	Predicting a continuous numerical value based on the analysis of relationships between variables; assessing the relationships between a dependent variable and one or more independent variables;
Dimensionality reduction	Transforming a dataset to reduce the number of variables by obtaining the principal ones for data compression, visualization, novelty detection, etc., while preserving important information;
Detection of associations	Searching for relationships between different variables in big datasets; identifying consistent combinations of attributes in specific objects, represented as rules;
Anomaly detection	Detecting rare, anomalous data or unusual patterns that deviate from the overall trend in the dataset, which may indicate errors or significant events;
Time series analysis	Analyzing data sequences to identify patterns over time, enabling the evaluation of past values and the forecasting of future values in the series;
Forecasting	Predicting future events or values in time series or other data sequences based on the analysis of historical data.

Source: compiled by the authors.

tant for describing the objects and solving the given task, constructing OPT or TS based on this, and verifying the latter; 3) preprocessing the dataset (cleaning, filling in missing values, standardizing delimiters, checking for outliers, etc.); 4) defining the aim and formulating the working hypothesis of the research (for some tasks, data quality assessment may be conducted to confirm the suitability of using a specific dataset); 5) selecting the appropriate method (algorithm, metrics) for analysis based on the specifics of the data and the task, performing the analytical processing of the dataset, and validating the results for their alignment with the initial hypotheses, interpretability, and usefulness; 6) interpreting the results, that is, explaining the meaning and significance of the identified empirical regularities (ER) in the context of the task being addressed; 7) practical application of the results (in the form of: justifying management decisions, adjusting existing approaches, modifying software algorithms, etc.). In many areas of the economy, business, and scientific research, IDA is applied systematically, so the stages presented are repeated cyclically, leading to additional features (such as adjusting the obtained models based on continuous evaluations, retraining algorithms, etc.).

Going through all stages of IDA is associated with a large number of methodological issues, the scope and significance of which can vary significantly across different types of domain knowledge, including in the fields of economics and business. For our purposes, we will define the following main groups of issues: 1) problems related to constructing the feature space (complexity of the subject area, low level of understanding of the objects, completeness of their description, relationships between features, dependence on context, etc.); 2) data-related problems (complexity of diversity, suboptimal volume, rate of change, lack of understanding of data value, etc.); 3) problem formulation issues (lack of understanding of the context, interdisciplinarity, unclear understanding of the goals of solving the task, etc.); 4) problems related to obtaining empirical regularities (selection of the type of function, procedural and algorithmic issues, assessing the reliability of the obtained solution, etc.); 5) problems related to understanding and interpreting results (assessing results, lack of sufficient knowledge about the domain, etc.); 6) issues related to the practical application of results (transitioning from interpretation to implementation, understanding the limits of applicability of results, etc.).

Digital Infrastructure and Tools for IDA. As mentioned earlier, conducting IDA today is virtually inconceivable without the use of computer technology and specialized technologies. This requires examining the digital infrastructure used to prepare data for IDA and to deploy specialized software tools, which has effectively established a new approach to data-driven knowledge creation. IDA infrastructure includes specialized digital technologies, systems, and services that support data collection, transmission, storage, and provide computational power for their analytical processing. The range of elements in IDA infrastructure is quite extensive, with many being part of the fundamental data handling layer, meaning they are applicable beyond just IDA. Moreover, it is often challenging to draw a clear boundary between different categories of these technologies, systems, and services due to overlapping functionalities. IDA tools include computational software programs, specialized applications, and software libraries that automate operations such as preprocessing, preliminary calculations, and visualization, as well as direct data analysis, validation, and visualization of results. *Tbl. 2* presents the main types of elements in IDA digital infrastructure and tools.

The IDA infrastructure provides new opportunities for data operations and collaboration among specialists, and serves as the foundation for managing, automating processes (streams), and deploying analytical tools. As data volumes increase and IDA is performed in real-time, the significance of infrastructure as both a prerequisite for its execution and a factor in its effectiveness becomes increasingly critical.

Regarding IDA tools, they incorporate human-developed methods and algorithms that facilitate or replace routine computational tasks, as well as perform certain cognitive operations that were previously unique to humans. That is, the areas of computer applications are undergoing a sort of evolution: from basic calculations to network interactions, and now to a new stage focused on supporting human cognitive processes, which is just beginning.

At this stage, humans are still the only ones capable of formulating analysis tasks, choosing the most suitable processing methods, assessing the results, and interpreting them. Therefore, IDA tools, for the most part, cannot yet fully replace humans. In practice, a human-machine technology for data analysis is in use. With the expansion of IDA applications, there is a trend towards developing IDA tools not only for specialists (Data Scientists, Data Analysts) but also increasingly for professionals in various subject areas who have a better understanding of the task and its context but lack deep training in mathematics and computer science. Therefore, new digital tools expand the range of specialists who can utilize IDA, particularly when implemented as web-based systems and cloud services. These tools offer wider access and democratize the field, making it more widespread rather than

Table 2

Main types of elements in IDA digital infrastructure and tools

Infrastructure	Tools
– various types of Database Management Systems, including relational, graph, document-oriented, column-oriented, hybrid, key-value, etc., as well as specialized analytical warehouses and services (Apache Pinot, Apache Druid, Amazon Redshift, BigQuery, Snowflake, Greenplum, Apache Spark, Microsoft SQL Server and Microsoft Analysis Services); – cloud services, including specialized services for data processing (Amazon Web Services, Google Cloud Platform, Microsoft Azure); – systems for real-time data processing that provide infrastructure for data transmission, storage, and stream processing (Apache Flink, Apache Spark Streaming, Apache Kafka, Apache Kudu); – systems for managing data streams (Apache Airflow, Dataform, Alteryx Analytics); – specialized services for data analysis (Databricks, Azure Data Factory, Azure Machine Learning, Azure Databricks, Azure HDInsight, Amazon EMR, Google Cloud Dataproc); – service infrastructure for AI developers (Amazon SageMaker, Azure Machine Learning, MLflow, wandb.ai)	– special programming languages and computational environments (R, MATLAB, Julia, Scala, including libraries such as MLlib, Breeze, Smile), and Python (libraries such as Numpy, Pandas, Scikit-learn, Scipy, Xgboost, Matplotlib, Keras, Pytorch, Tensorflow, and Theano); – application software packages for working with spreadsheets (Microsoft Excel, Google Sheets); – software applications (SPSS, Minitab, Stata, Statgraphics, JMP) and environments/platforms for data analysis (Weka, Orange, RapidMiner, KNIME); – software for data and analysis result visualization (Microsoft Power BI, Tableau, QlickView, Qlik Sense, Amplitude, Google Looker Studio, Luxms BI, Redash, BeX Analyzer, SAP BusinessObjects, IBM Cognos Analytics). – web platforms with IDA tools (such as Tableau Online, ScienceHunter, Mode Analytics, Plotly Chart Studio), as well as online tools developed within comprehensive cloud systems (such as Amazon QuickSight, Amazon Athena, Amazon Redshift, Amazon SageMaker, Google Cloud Dataprep, Google Cloud AI Platform, Azure Synapse Analytics, Azure Machine Learning, and Azure Data Factory)

Source: compiled by the authors.

confined to a narrow group of experts. Additionally, it is important to highlight tools within the category of Large Language Model, such as ChatGPT. Advanced versions of these tools feature new computational data analysis functions, including those provided by plugins like Wolfram.

IDA results. In general, the application of IDA aligns with the universal scheme of cognition: from «living contemplation» (real experience) to abstraction, and then from abstraction to praxis. Indeed, «living contemplation» can be associated with data collection and the construction of OPT (or TS), obtaining abstraction with discovering EP or hypotheses and their validation, and applying these validated models corresponds to praxis. At the same time, it is essential to understand the results of IDA as outcomes of empirical knowledge, despite the numerous mathematical constructs involved.

Typically, the application of IDA results in: grouping of objects, a decision function, a model that distinguishes objects of different classes, etc., which essentially constitutes an inductive inference. All of these represent ER as generalizations, abstractions, relationships within the data, patterns, and trends in the studied domain knowledge. These patterns, transitioning from implicit to explicit, serve as preliminary generalizations of facts, descriptions of the overall structure, and initial understandings of the state of the domain knowledge, addressing questions such as «What?», «How?», «Who?», «What is happening?», and «What is the situation?»

The obtained empirical regularities allow us to identify what is important, replacing guesses with well-informed insights and providing a certain awareness and conviction, believability-weighted on data. Most often, this provides a retrospective view but allows for making informed assumptions whose reliability is higher than mere opinion. Moreover, with proper interpretation and justification, this can be considered empirical knowledge. This allows for determining subsequent actions, such as formulating hypotheses, creating methodologies, instructions, rules, making assessments, and forecasts. These EP can serve as a foundation for uncovering deeper insights. However, it only provides a preliminary level of cognition (understanding). This represents the limitation of IDA application from an epistemological perspective. Often, such empirical knowledge (assumptions) is sufficient for current practical activities in business to make operational management decisions («Data-to-Decision») that do not require a deep understanding of the essence of phenomena and processes or causal relationships. For example, this includes situational consumer segmentation in the market, targeted advertising, product price forecasting, and similar activities, which enable the realization of short-term economic gains. However, this is insufficient for developing strategic decisions in large companies, and even more so at the national economic level. Therefore, understanding the studied domain knowledge in economics, achieving a deep understanding of the nature of phenomena and processes, and obtaining reliable knowledge cannot rely solely on the acquired EP. It requires further establishment and justification of causal relationships to address questions such as: «Why?», «How does this happen?», and «Why does this happen in this way?» And this marks a transition from the empirical level of cognition to a deeper understanding, reaching a theoretical level where the ability to forecast and make long-term, more complex decisions is enhanced, embodying the «Data-to-Insight-to-Decision» approach. Such knowledge is essential for making strategic decisions in economics and business, as well as in scientific research, where empirical methods of cognition precede theoretical developments.

Thus, it is essential to properly understand and apply IDA, considering its inherent limitation – EP – and its role within the broader process of cognition. Automatic generation of these patterns (based on digital technologies) significantly aids in understanding reality, as provided by IDA. These empirical regularities serve as crucial supplementary material for formulating research hypotheses or abstractions, which are then validated to explain causal relationships. This is both the primary limitation of IDA in the process of cognition and the main opportunity it creates. Based on this, it can be concluded that IDA simplifies human cognitive activity, enabling the processing and analysis of large datasets, especially multidimensional ones. Given the essential role of humans in task formulation, interpretation, and implementation of results, the application of IDA requires collaboration between domain knowledge experts and IDA specialists (Data Scientists, Data Analysts), which can be quite challenging in terms of organization and communication. This is another reason for developing IDA tools specifically for domain knowledge experts who do not require advanced training in mathematics and computer science.

IDA is becoming an essential component of cognition, both in business and other practical activities, as well as in science. Summarizing various aspects of IDA's impact on cognition, it is important to note the following: 1) IDA offers fundamentally new and broader capabilities for processing empirical data and, consequently, for cognitive activities based on this data. In this regard, IDA both simulates and partially replaces human cognitive data processing; 2) IDA enhances human natural abilities in analysis, evaluation, hypothesis formulation, model creation, and ultimately, deeper understanding of phenomena. It also stimulates analytical, critical, abstract, and evaluative thinking in individuals; 3) IDA supports active human interaction with the world through data, enhancing intellectual work in describing objects using data, conducting measurements, and performing quantitative and qualitative assessments, among other activities; 4) IDA elevates the evidential method of cognition to a new level, incorporating both its advantages and limitations, and facilitates the emergence of new forms of cognitive activities (types of analytics); 5) IDA, with its extensive range of applications, promotes interdisciplinary research by integrating knowledge from mathematics, statistics, computational science, management, and various types of domain knowledge such as economics, sociology, and psychology. It can be said that the use of IDA promotes the development of a new cognitive framework and transforms human intellect. For instance, digital tools facilitate the automation of routine computational tasks, enabling a stronger focus on intellectual and analytical activities.

It is also important to mention a specific class of data mining models: neural networks. Their use in some cases yields satisfactory data processing results, but they often contribute little to understanding, as they do not bridge the gap between obtained EP and the explanation of causal relationships. Therefore, their level is limited to «primitive» recognition (classification). Replacing human oversight in the cognition process with artificial intelligence, at least for now, does not seem feasible.

The applications of IDA. The scope of practical applications for IDA, along with Big Data technologies, is rapidly expanding. De facto, it has become an integral part of research in economics and various scientific fields, and is widely used by businesses for managerial decision-making, operational intelligence, and process automation in areas such as marketing, logistics, finance, security, production, and management. *Tbl. 3* illustrates examples of how IDA solves business analytics tasks [3; 4; 10; 12; 13; 19–24].

The examples of tasks solved using IDA demonstrate both the broad range of its applications and its potential for use in various industries and for addressing diverse problems. In recent years, beyond e-commerce, the application of IDA has rapidly expanded in industrial and agricultural production management, logistics processes, various

Table 3

Examples of practical applications of IDA for key types of DM tasks

Typical DM tasks	Examples of practical applications
Clustering	Consumer grouping (social media users, service users, etc.), competing companies, territories (markets), company promotions, etc.; grouping products by seasonality, demand, and other characteristics for inventory optimization; creating catalogs; and assessing and selecting job candidates
Classification	Classification of consumers (users) by loyalty level, potential demand growth or decline; credit scoring; classification of fraudulent transactions, borrowers, agricultural lands, incoming documents (spam detection), etc.; identification of fake accounts; forecasting equipment failures; evaluating product quality and detecting defects
Regression Analysis	Forecasting macroeconomic indicators, asset values, prices and demand for goods (services), energy consumption, consumer behavior, etc.; evaluating factors influencing sales; optimizing production processes by assessing productivity and product quality factors; researching factors affecting environmental pollution levels
Association Rule Mining (Association Rules)	Analyzing consumer's shopping baskets to identify combinations of products frequently purchased together for recommendations and inventory optimization; discovering relationships between different topics or user behavior patterns in online services for content management and ad targeting; detecting suspicious transaction patterns during fraud detection; identifying failure relationships for managing maintenance processes
Anomaly Detection	Detecting fraud in financial transactions; identifying malfunctions and failures in production equipment; analyzing network traffic to detect network attacks or abnormal behavior; medical diagnostics to identify rare diseases
Time Series Analysis	Forecasting prices of goods (services) and demand (sales volume), identifying seasonal fluctuations for production planning, marketing strategies, and inventory management; predicting stock prices, currency exchange rates, energy consumption, traffic flows, internet traffic, user activity, etc., to enhance management effectiveness; justifying potential material and product needs to optimize supply chains; analyzing equipment performance for maintenance planning; monitoring healthcare services to identify trends

Source: compiled by the authors based on [3; 4; 10; 12; 13; 19–24].

service industries, and supply chains. This has integrated IDA into contemporary trends associated with Industry 4.0 and digital transformations, encompassing the intelligentization of web systems, equipment, and various devices. In this case, IDA is used in computer programs that manage systems, enabling them to collect and process data and apply the information to make decisions. A vivid example of digitization and intelligentization is healthcare, where IDA are used both for managing healthcare facilities and for diagnosing diseases, as well as for developing tools (technologies) for their treatment.

All of the above expands the scope and role of IDA in the economy. The ability to process big volumes of data is becoming one of the most significant challenges faced by most enterprises across any industry. Key prerequisites for this are the increasing number of specialists and the emergence of IDA digital technologies that facilitate data handling. At the same time, in practice, low effectiveness of IDA is often observed. In many cases, this is related to a misunderstanding of its purpose and inherent limitations, which leads to inflated expectations and irrelevant task formulations, ineffective management of IDA processes, and a low level of communication between IDA specialists and domain knowledge experts.

Data economy. Given the growing importance of data as a management factor and source of value, along with the expanding fields and applications of IDA, there is increasing discussion about the emergence of the data economy as a sector expanding within the context of digitization. Data economy can be understood in various ways, including: 1) an area where data accumulation and utilization processes take place, including specialized technologies, tools, services, and more; in other words, an entire industry is emerging that integrates various participants, with its level of organization continuously advancing; 2) activities focused on creating value through the collection and analytical processing of data, which requires viewing data as a resource for gaining knowledge, an economic factor, and an independent commodity. This gives rise to a new branch of the knowledge economy, aimed at studying the processes of generating, distributing, and utilizing data as a resource for gaining knowledge to create value, as well as assessing and enhancing the effectiveness of these activities.

The data economy encompasses a comprehensive system of markets, including technologies, IDA tools, specialists, data analysis services, ancillary services, data as a resource, and the outcomes of data processing. The data market, which is fundamental, is rapidly evolving due to the expanding application of digital technologies and acquiring new characteristics related to:

- the specificity of demand (from businesses, media, political parties, etc.) and supply (from Big Tech, Internet media, trading platforms, governments, universities, the public, etc.); data can be generated continuously or accumulated (prepared) gradually;
- the sectors and industries served, which shape market segmentation;
- the methods of data monetization, including the sale of access to data, «raw» data, structured datasets, and processed data results; as well as using data and the results of its processing to enhance products, management, and other areas;
- the mechanisms of market operation, based on specialized agreements, digital infrastructure, technologies, standards, services, and more;
- the localization, related to data generation and its value; some data may be of general interest from a knowledge perspective, valuable for global, national, or local markets, and for specific industry markets at various levels;
- institutional conditions, primarily shaped by national and international legislation concerning data protection and human rights, as well as within industry-specific markets (e. g., regulatory systems for financial services), which are related to security standards.

There is a broad range of current issues related to the operation and development of the data market, primarily concerning confidentiality, personal data protection, ethical use of data, data ownership policies, academic policies regarding the use of data accumulated in scientific research, and methods of data acquisition, such as through space technologies, among other aspects. Overall, national data markets remain quite fragmented due to significant differences in government regulatory systems, the particular value of data, and the specific ways in which different entities own and use data. In the coming years, the data market is expected to continue evolving, with increased institutionalization of many processes and relationships, especially at the international level. Professional communities, including those operating on digital platforms, and IT businesses advancing technical solutions for data exchange, are beginning to play a significant consolidating role in the data economy.

One of the most important challenges for the development of the data economy is understanding how value is derived from data and assessing its benefits. In the context of business, the ultimate outcomes of applying IDA results are: increased labor productivity; improved management quality; optimized business processes; reduced costs, and savings in resources and time; enhanced competitiveness of the enterprise; and increased efficiency of its economic activities. There may be specific cases where IDA contributes to the search for new ideas and the development of innovations, for example, by studying consumer behavior or comparing competing products, through the knowledge gained. Creating additional value from data makes it a standalone resource, enhancing economic effects from different points of view. IDA plays a direct role in revealing the value of data as a resource and increasing its level of monetization.

The usefulness of data is assessed based on the economic impact of its use, which significantly depends on the objectives of the data owner or the entity using it, as well as the methods of monetization. In many cases, especially in business, the effectiveness of using data is often correlated with the cost of acquiring it. In addition, the usefulness of data is often evaluated not only from an economic perspective but also by assessing social impacts, such as in the fields of healthcare or public safety.

The usefulness of data is not necessarily dependent on the labor invested in its collection and preparation. At the same time, there are cases where creating certain datasets requires extensive intellectual effort from highly skilled experts with specific knowledge and experience. However, even in these cases, the labor involved is not the primary source of data usefulness. It depends more on: *first*, the usefulness of the information contained within the data, which can vary significantly depending on the evaluation approach; at the same time, it is important to consider the subject, its problems, goals, and tasks, as well as the context of external conditions and the specific focus of the data processing results; *second*, the usefulness of EP and the knowledge gained from processing a specific dataset; at the same time, it is essential to consider the specific context in which knowledge is applied. For instance, in business, the emphasis is on assessing the commercial or economic effects derived from solving practical problems. In contrast, in science, the significance of knowledge is evaluated based on its role in advancing scientific discoveries or inventions, with only the potential economic impact considered.

In many cases, the usefulness of data depends on its volume, reflected in the number of objects and/or features, as well as its quality with respect to solving a specific task (a typical IDA problem) and the quality of dataset preparation, including accurate classification. Specialized tools are available for various IDA tasks that enable the preliminary assessment of data quality before main mathematical processing. For example, 3D visualization can aid in clustering and evaluating the informativeness of TS and their specific features (relevant tools are available on the ScienceHunter portal // https://www.sciencehunter.net). This approach significantly enhances the effectiveness of IDA, particularly when applied systematically. In general, IDA needs to develop approaches for assessing the usefulness and quality of data for solving specific tasks.

If the data is considered useful and accepted for processing, its «enrichment» happens progressively through preparation and phased transformation during IDA, evolving from «raw» data into a final, TS (*Tbl. 4*). This is important to understand, particularly from the perspective of data monetization, as it can take place at different stages of data processing depending on the circumstances.

CONCLUSIONS

At the current stage, countries are focusing their economic development on building a knowledge economy, which is centered on generating and utilizing new knowledge. One of the most important methods for obtaining new knowledge today is IDA (Intelligent

Table 4

Step-by-step «enrichment» of data to unlock its usefulness as it progresses through staged transformations during IDA

Data state	Level of usefulness
1. Unstructured data	Collected «raw» data require structuring and a preliminary analysis to determine their suitability for processing. The usefulness of data can only be estimated probabilistically, based on the understanding of the task and the perceived information that may be embedded in the data. At this stage, it is not possible to assess the quality of data for IDA
2. Structured data	Obtaining a structured dataset is the first level of its «enrichment» and requires some preparation, which can be partially automated. The dataset acquires a formalized structure and can be evaluated in terms of describing the domain knowledge (objects) for creating a feature description (OPT or TS) and subsequent processing, making such data more useful. However, the usefulness of the data can only be assessed superficially in terms of processing capabilities, as there is no evaluation of its quality for solving IDA tasks
3. Prepared OPT or TS	A feature description prepared by experts, and based on this, OPT (or TS) represents the next level of data «enrichment», as it is verified and ready for further processing; thus, the value of such data as a resource increases. The presence of OPT (or TS) allows for a preliminary assessment of its quality for solving specific IDA tasks, which serves as a key argument supporting its usefulness. A prepared dataset of verified data, especially when its high quality is confirmed, is a fundamental prerequisite for effective IDA, thus having greater value, provided the level of preparation (including expert input and verification) is taken into account
4. Identified ER	The empirical regularities identified as a result of IDA, considering the problem being solved, represent the practical usefulness of the data, as they are prerequisites for addressing specific issues or generating new knowledge. The usefulness of the results increases following a thorough validation of their relevance, which also confirms the quality of OPT (or TS). Generated EP can have independent commercial value for businesses due to their direct use or sale to interested parties. Naturally, the extent and nature of the economic impact from utilizing IDA results will vary depending on the field, whether business or science
5. Interpretation of the identified EP	Deriving the identified patterns into true knowledge, which ensures a deep understanding of processes, is primarily undertaken in science and, in some cases, in business. Well-grounded causal relationships offer the greatest usefulness (often alongside the data from which they are derived) because they provide the most extensive opportunities in the economy. At the same time, assessing the effects of applying the acquired knowledge is challenging due to its broad scope and diverse applications, including non-commercial ones. This assessment can be carried out when the acquired knowledge or solutions derived from it are directly monetized

Source: compiled by the authors.

Data Analysis), which aims to effectively analyze large, multidimensional datasets describing a specific domain knowledge to uncover previously hidden patterns. Using specialized IDA methods, several key tasks are addressed, including clustering, classification, regression analysis, dimensionality reduction, and association detection, among others. Modern IDA approaches are based on the application of specialized digital technologies, which can be divided into IDA infrastructure and tools. These technologies automate relevant operations at all stages and significantly enhance effectiveness. IDA application generally aligns with the universal scheme of cognition. At the same time, it is crucial to interpret IDA results correctly, acknowledging its inherent limitation: the generation of EP. On the other hand, the automatic generation of such patterns through digital technologies provides significant support in the process of cognition, as EP serves as supplementary material for further elucidating causal relationships. IDA is a highly versatile method for knowledge acquisition, leading to a rapid expansion in its practical applications, particularly in conjunction with Big Data technologies. Considering this, the data economy emerges, encompassing various sectors, processes, and activities related to the accumulation and utilization of data. The data economy is a system of markets with its own distinct characteristics and development challenges. One of the most critical issues is understanding how value is derived from data. To address this, it is necessary to consider the usefulness of the data, which is determined by the value of the information contained within it and the usefulness of the knowledge (EP) generated through IDA, as well as the outcomes (effects) of applying IDA results in practice. During IDA, data usefulness is progressively unlocked through the staged transformation from unstructured data to the generation and interpretation of empirical regularities. The propositions formulated in this article contribute to the contemporary scientific discourse on the application of IDA within the knowledge economy and provide general recommendations for advancing IDA in the following areas: digital infrastructure and IDA tools, legal conditions, data collaboration models, specialist training, enhancing data openness, and ensuring IDA accessibility. These areas are intended to be the focus of future research. ■

BIBLIOGRAPHY

1. Mounier P., Primbault S. D. Sustaining Knowledge and Governing its Infrastructure in the Digital Age: An Integrated View. *HAL open science*. 2023. P. 1–43. URL: https://hal.science/hal-04309735.
2. Wang X., White L., Chen X. Big Data Research for The Knowledge Economy: Past, Present, and Future. *Industrial Management & Data Systems*. 2015. Vol. 115. Art. 9. URL: http://www.emeraldinsight.com/doi/full/10.1108/IMDS-09-2015-0388.
3. Ahmed R., Shaheen S., Philbin S. P. The role of big data analytics and decision-making in achieving project success. *Journal of Engineering and Technology Management*. 2022. Vol. 65. Art. 101697. DOI: 10.1016/j.jengtecman.2022.101697
4. Krämer J., Whalley J., Batura O. The data economy and data-driven ecosystems: Regulation, frameworks and case studies. *Telecommunications Policy*. 2019. Vol. 43. No. 2. P. 113–115. DOI: 10.1016/j.telpol.2018.12.007
5. Caliari T., Chiarini T. Knowledge Production and Economic Development: Empirical Evidences. *Journal of the Knowledge Economy*. 2021. Vol. 12. Iss. 2. P. 1–22. DOI: 10.1007/s13132-016-0435-z
6. Choong K. K., Leung P. W. A Critical Review of the Precursors of the Knowledge Economy and Their Contemporary Research: Implications for the Computerized New Economy. *Journal of Knowledge Economy.* 2022. Vol. 13. Iss. 2. P. 1573–610. DOI: 10.1007/s13132-021-00734-9
7. North K., Maier R., Haas O. Value Creation in the Digitally Enabled Knowledge Economy. *Knowledge Management in Digital Change*. Cham: Springer, 2018. P. 1–29. DOI: 10.1007/978-3-319-73546-7_1
8. Shu X., Ye Y. Knowledge Discovery: Methods from data mining and machine learning. *Social Science Research*. 2023. Vol. 110. Art. 102817. DOI: 10.1016/j.ssresearch.2022.102817
9. Pohl M., Staegemann D. G., Turowski K. The Performance Benefit of Data Analytics Applications. *Procedia Computer Science*. 2022. Vol. 201. P. 679–683. DOI: 10.1016/j.procs.2022.03.090
10. Kim M., Lim C., Hsuan J. From technology enablers to circular economy: Data-driven understanding of the overview of servitization and product–service systems in Industry 4.0. *Computers in Industry*. 2023. Vol. 148. Art. 103908. DOI: 10.1016/j.compind.2023.103908
11. Cao L. Data science: A comprehensive overview. *ACM Computing Surveys*. 2017. Vol. 50. Iss. 3. Art. 43. DOI: http://dx.doi.org/10.1145/3076253
12. Sarker I. H. Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. *SN Computer Science*. 2021. Vol. 2. Art. 377. DOI: 10.1007/s42979-021-00765-8
13. Cao L. Data science: Challenges and directions. *Communications of the ACM*. 2017. Vol. 60. Iss. 8. P. 59–68. DOI: 10.1145/3015456
14. Aryal S. C. The Impact of a Digital Regime on Academic Knowledge Production. University West : School of Business, Economics, and IT, 2023. 132 p. URL: https://www.diva-portal.org/smash/get/diva2:1746631/FULLTEXT01.pdf

15. Kandel S., Paepcke A., Hellerstein J. M., Heer J. Enterprise Data Analysis and Visualization: An Interview Study. *IEEE Transactions on Visualization and Computer Graphics*. 2012. Vol. 18. No. 12. P. 2917–2926. DOI: 10.1109/TVCG.2012.219
16. Artificial Intelligence Trends for Data Analytics Using Machine Learning and Deep Learning Approaches / Eds.: K. G. Devi, M. Rath, N. Thi Dieu Linh. CRC Press, Taylor & Francis Group, LLC, 2020. 266 p.
17. Waters D. J. The emerging digital infrastructure for research in the humanities. *International Journal on Digital Libraries*. 2023. Vol. 24. P. 87–102. DOI: 10.1007/s00799-022-00332-3
18. Shannon C. E., Weaver W. The Mathematical Theory of Communication. The University of Illinois Press, 1964. 125 p.
19. Batko K., Ślęzak A. The use of Big Data Analytics in healthcare. *Journal of Big Data*. 2022. Vol. 9. Iss. 1. Art. 3. DOI: 10.1186/s40537-021-00553-4
20. Baum J., Laroque C., Oeser B., Skoogh A., Subramaniyan M. Applications of Big Data analytics and Related Technologies in Maintenance – Literature Based Research. *Machines*. 2018. Vol. 6. Iss. 4. Art. 54. DOI: 10.3390/machines6040054
21. Lehenchuk S., Zavalii T. Big Data in marketing analytics: opportunities and problems of use. *Problems of Theory and Methodology of Accounting, Control and Analysis*. 2023. Vol. 54. No. 1. P. 52–58. DOI: 10.26642/pbo-2023-1(54)-52-58
22. Pagano A. M., Liotine M. Technology in Supply Chain Management and Logistics: Current Practice and Future Applications. Elsevier, 2019. 208 p. DOI: 10.1016/C2017-0-04194-0
23. Semanjski I. C. Smart Urban Mobility: Transport Planning in the Age of Big Data and Digital Twins. Elsevier Science, 2023. 268 p. DOI: 10.1016/C2019-0-01443-4
24. Grimaldi D., Carrasco-Farré C. Implementing Data-Driven Strategies in Smart Cities: A Roadmap for Urban Transformation. Elsevier Science, 2021. 254 p. DOI: 10.1016/C2019-0-01442-2

REFERENCES

Ahmed, R., Shaheen, S., and Philbin, S. P. "The role of big data analytics and decision-making in achieving project success". *Journal of Engineering and Technology Management*, art. 101697, vol. 65 (2022). DOI: 10.1016/j.jengtecman.2022.101697

Artificial Intelligence Trends for Data Analytics Using Machine Learning and Deep Learning Approaches. CRC Press, Taylor & Francis Group, LLC, 2020.

Aryal, S. C. "The Impact of a Digital Regime on Academic Knowledge Production". University West : School of Business, Economics, and IT, 2023. https://www.diva-portal.org/smash/get/diva2:1746631/FULLTEXT01.pdf

Batko, K., and Slezak, A. "The use of Big Data Analytics in healthcare". *Journal of Big Data*, art. 3, vol. 9, no. 1 (2022). DOI: 10.1186/s40537-021-00553-4

Baum, J. "Applications of Big Data analytics and Related Technologies in Maintenance - Literature Based Research". *Machines*, art. 54, vol. 6, no. 4 (2018). DOI: 10.3390/machines6040054

Caliari, T., and Chiarini, T. "Knowledge Production and Economic Development: Empirical Evidences". *Journal of the Knowledge Economy*, vol. 12, no. 2 (2021): 1-22. DOI: 10.1007/s13132-016-0435-z

Cao, L. "Data science: A comprehensive overview". *ACM Computing Surveys*, art. 43, vol. 50, no. 3 (2017). DOI: http://dx.doi.org/10.1145/3076253

Cao, L. "Data science: Challenges and directions". *Communications of the ACM*, vol. 60, no. 8 (2017): 59-68. DOI: 10.1145/3015456

Choong, K. K., and Leung, P. W. "A Critical Review of the Precursors of the Knowledge Economy and Their Contemporary Research: Implications for the Computerized New Economy". *Journal of Knowledge Economy*, vol. 13, no. 2 (2022): 1573-610. DOI: 10.1007/s13132-021-00734-9

Grimaldi, D., and Carrasco-Farre, C. *Implementing Data-Driven Strategies in Smart Cities: A Roadmap for Urban Transformation*. Elsevier Science, 2021. DOI: 10.1016/C2019-0-01442-2

Kandel, S. et al. "Enterprise Data Analysis and Visualization: An Interview Study". *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, no. 12 (2012): 2917-2926. DOI: 10.1109/TVCG.2012.219

Kim, M., Lim, C., and Hsuan, J. "From technology enablers to circular economy: Data-driven understanding of the overview of servitization and product-service systems in Industry 4.0". *Computers in Industry*, art. 103908, vol. 148 (2023). DOI: 10.1016/j.compind.2023.103908

Kramer, J., Whalley, J., and Batura, O. "The data economy and data-driven ecosystems: Regulation, frameworks and case studies". *Telecommunications Policy*, vol. 43, no. 2 (2019): 113-115. DOI: 10.1016/j.telpol.2018.12.007

Lehenchuk, S., and Zavalii, T. "Big Data in marketing analytics: opportunities and problems of use". *Problems of Theory and Methodology of Accounting, Control and Analysis*, vol. 54, no. 1 (2023): 52-58. DOI: 10.26642/pbo-2023-1(54)-52-58

Mounier, P., and Primbault, S. D. "Sustaining Knowledge and Governing its Infrastructure in the Digital Age: An Integrated View". HAL open science. 2023. https://hal.science/hal-04309735

North, K., Maier, R., and Haas, O. "Value Creation in the Digitally Enabled Knowledge Economy". In *Knowledge Management in Digital Change*, 1-29. Cham: Springer, 2018. DOI: 10.1007/978-3-319-73546-7_1

Pagano, A. M., and Liotine, M. *Technology in Supply Chain Management and Logistics: Current Practice and Future Applications*. Elsevier, 2019.
DOI: 10.1016/C2017-0-04194-0

Pohl, M., Staegemann, D. G., and Turowski, K. "The Performance Benefit of Data Analytics Applications". *Procedia Computer Science*, vol. 201 (2022): 679-683.
DOI: 10.1016/j.procs.2022.03.090

Sarker, I. H. "Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective". *SN Computer Science*, art. 377, vol. 2 (2021).
DOI: 10.1007/s42979-021-00765-8

Semanjski, I. C. *Smart Urban Mobility: Transport Planning in the Age of Big Data and Digital Twins*. Elsevier Science, 2023.
DOI: 10.1016/C2019-0-01443-4

Shannon, C. E., and Weaver, W. *The Mathematical Theory of Communication*. The University of Illinois Press, 1964.

Shu, X., and Ye, Y. "Knowledge Discovery: Methods from data mining and machine learning". *Social Science Research*, art. 102817, vol. 110 (2023).
DOI: 10.1016/j.ssresearch.2022.102817

Wang, X., White, L., and Chen, X. "Big Data Research for The Knowledge Economy: Past, Present, and Future". Industrial Management & Data Systems. 2015. http://www.emeraldinsight.com/doi/full/10.1108/IMDS-09-2015-0388

Waters, D. J. "The emerging digital infrastructure for research in the humanities". *International Journal on Digital Libraries*, vol. 24 (2023): 87-102.
DOI: 10.1007/s00799-022-00332-3