UDC 330.341.1
DOI: 10.15587/1729-4061.2025.326555

BREAKTHROUGH TECHNOLOGIES OF SOCIAL TRANSFORMATIONS: DEVISING AN IDENTIFICATION METHODOLOGY

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The object of this study is the breakthrough technologies of Industry 4.0, which are driving social transformations. Such a focus of research is due to the fact that under current conditions, all domains of society are undergoing transformation, the source of which is the accelerated development of equipment and technology. Innovation cycles generate inventions and open up new possibilities, but this is not always obvious to economic actors. The need arises to design a toolkit that would allow early identification of new trends in social transformations and form appropriate business models and economic policy directions for them.

This paper reports a methodological approach to identifying breakthrough technologies that drive the development of social transformations. It is based on the use of special indicators of bibliographic databases and information from social networks – platforms where the communication among researchers takes place. The specificity of the approach is the combination of bibliometric monitoring on a new, expanded database of sources with statistical analysis. The latter involved assessing the time series using the growth rate of publications and establishing a threshold value using the standard deviation method.

The prognostic capabilities of such an approach have been demonstrated on the example of identifying breakthrough technologies within Industry 4.0, which enabled the formation of a cluster of 7 technologies, which drive the deployment of a new technological paradigm. Focusing on these technologies could allow firms to improve business models and the state to concentrate resources on points of technological growth, thereby increasing the effectiveness of innovation policy

Keywords: digital transformation, Industry 4.0, breakthrough technologies, bibliographic databases of citation systems

Received 06.12.2024
Received in revised form 04.03.2025
Accepted 02.04.2025
Published 22.04.2025

How to Cite: *Pylypenko, H., Fedorova, N., Lytvynenko, N., Pylypenko, Y. (2025). Breakthrough technologies of social transformations: devising an identification methodology. Eastern-European Journal of Enterprise Technologies, 2 (13 (134)), 15–26. https://doi.org/10.15587/1729-4061.2025.326555*

1. Introduction

Under current conditions, the world is experiencing one of its greatest transformations, associated with a radical change in the economic, social, and political foundations of the functioning of society. These transformations have become a consequence of the rapid development of breakthrough technologies, which have determined the content and trajectory of the movement of human civilization. Such a force of change was characteristic only for the three previous industrial revolutions, which initially caused the transition from agrarian to industrial civilization and then established the foundations of the information society. At these stages, the source of progress was qualitative changes in technology and engineering, which opened access to new sources of energy, gave rise to new professions, put forward new requirements for the qualifications of workers, and transformed social institutions.

Currently, the fourth industrial revolution dominates, which is often called Industry 4.0 and is considered the last phase of digital growth in the production space. One of the developers of this concept noted that one of the challenges of today is how to understand and shape a new technological revolution, which involves nothing less than the transformation of humanity. It is at the beginning of a revolution that fundamentally changes the way we live, work, and relate to each other. In terms of its scale, scope, and complexity, the fourth industrial revolution is unlike anything that humanity has experienced before. It is necessary to fully understand the speed and scope of this new revolution [1].

In solving this problem, scientists have encountered new challenges: it turned out that without fully exhausting its potential, Industry 4.0 is gradually beginning to transition into the fifth industrial revolution. Within it, other technologies aimed at achieving harmony between man and technical systems are already coming to the fore [2]. As a result, there is a combination of real and virtual worlds, a change in the quality of human capital and, above all, its ability to realize the significance of changes and use them for innovative development [3]. Under the influence of new technologies, social institutions undergo transformation, becoming increasingly flexible and strengthening their adaptive capacity [4]. To a greater extent, this is characteristic of institutions of social coordination, which, through the interaction of the state and the market, determine the rules and norms for conducting innovative activities [5]. Technological changes change the social role of informal institutions, bringing social capital to the fore as a factor of innovative development [6].

Thus, the modern world is characterized by very rapid technological changes that transform society in a much shorter time period than it was before. At the same time, they do not give the economy the opportunity to fully exhaust the potential of its previous development but require rapid adaptation to changes and the creation of conditions for a new technological "breakthrough".

Under such conditions, the ability of economic entities to sense such changes in advance and take them into account in their activities becomes important. Therefore, we are arguing about devising such methodological approaches that would allow us to identify breakthrough technologies. Indeed, the lack of understanding of the level of novelty of technologies does not allow firms to develop such long-term strategies that would be flexible and make it possible to quickly adapt existing business models to changes. The state also becomes unable to identify the technological frontier in each specific period, and therefore, to determine growth points and concentrate its efforts on them in promoting innovative development. This issue is even more relevant because of the need to create such an institutional environment that would be flexible in the perception and regulation of technological changes. Therefore, the issue of forming approaches that would allow us to distinguish among the dominant technologies those that are breakthrough is important for both science and practice.

2. Literature review and problem statement

Modern researchers of the fourth industrial revolution tend to believe that its categorical definition is still in its formative stage and is a collective concept. It reflects various aspects of changes in the technological system of society with their subsequent transformation into all other domains of functioning and development of human civilization. Considering technological changes as the main feature of Industry 4.0, scientists, however, have not developed a single view of which new technologies are the basis of the new technical and technological paradigm. In the most detailed form, the issues of key technologies of the fourth industrial revolution were discussed at the 46th International Economic Forum in Davos (2016). It was noted there that Industry 4.0 is the process of introducing artificial intelligence into production, creating "smart factories" based on cyber-physical systems. Somewhat later, these issues were raised in a survey that was implemented in Germany in the project "Industrie 4.0 in a Global Context: Strategies for Cooperating with International Partners". Within its framework, 150 experts from six countries of the world recognized that Industry 4.0 is, first of all, the creation of networks and the introduction of digital technologies. Thus, the emergence of Industry 4.0 as a fundamentally new phenomenon of the 21st century was described through a list of technologies inherent to it.

Along with this, in a number of documents, the essence of Industry 4.0 is determined not on the basis of its key technologies but through the formation of fundamentally new business models. Thanks to the latter, firms ensure the vertical integration of "smart" machines, products and production resources into flexible production systems and their horizontal integration into inter-industry value networks. Thus, work [7] reveals the concept of Industry 4.0, which is based on the integration of digital technologies into production processes to create "smart" factories. The focus of the study is on increasing productivity, manufacturing flexibility, and building new business models through vertical and horizontal integration, which allows companies to adapt to market changes and create value networks. Although the paper mentions key elements of Industry 4.0, such as the Internet of Things, robotics, and big data analytics, the authors do not offer a methodology for assessing the maturity of these technologies or prioritizing their implementation. This reduces the practical usefulness of the study for companies looking for specific development strategies in the new environment.

Study [8] emphasizes the need for companies to adapt to rapid technological changes, such as the introduction of intelligent robots, autonomous drones, sensors, and 3D printing. From the authors' point of view, the main characteristics of Industry 4.0 include vertical integration of "smart" production systems, horizontal integration through new value chains, the implementation of engineering throughout the life cycle, and the implementation of exponentially growing technologies. At the same time, although the study provides valuable information about the challenges and opportunities of Industry 4.0, it focuses mainly on the Swiss market, which may limit its application to other regions.

New business models are more flexible, they make it possible to build long-term development strategies under conditions of risk and uncertainty. Therefore, among the studies on the impact of Industry 4.0, those that offer approaches to their formation are distinguished. Thus, in work [9], an algorithm for a strategy for optimizing the financial potential of machine-building enterprises to carry out digital transformations is proposed, taking into account the influence of risk-predicting factors. However, this algorithm is not unified and cannot be fully implemented in other sectors of the economy. These limitations are partially removed in [10], which presents a methodological approach to assessing the level of innovation and investment component of security of development of an industrial enterprise under different economic conditions. The model of pricing for scientific and technical developments of industrial enterprises reported in study [11] looks similar. It is a more flexible business model in the segment of pricing under conditions of variability and instability of the market environment. And although these two approaches take into account the features of all functional areas of activity of an industrial enterprise and their structural transformations, they have rather insignificant predictive capabilities to identify fundamentally new technological shifts.

There is also an opinion that Industry 4.0. is a complex paradigm that encompasses changes in the industrial sector. They are related to the integration of innovative information and communication technologies into the industry to promote the intelligent integration of products and processes along the value chain. For example, paper [12] examines how Industry 4.0, including the Internet of Things and cyber-physical systems, affects logistics. The study emphasizes the importance of transparency in supply chains and control over their integrity to ensure efficiency and effectiveness in the new digital environment. However, the study does not contain a structured analysis of the priority or interaction of these technologies, which reduces its practical significance.

Value chains in Industry 4.0 are becoming global and, as a result, are provoking shifts in the technological system of the world economy. These aspects are raised in [13], which shows the change in institutional conditions for the reproduction of economic relations and the realization of economic interests in countries around the world under the influence of new technologies. The importance of social and institutional conditions for technological development is also emphasized in [14]. This study shows the impact of Industry 4.0 technologies on the qualitative characteristics of human capital, which is a conductor of breakthrough technologies in social life.

The above interpretations of the components of Industry 4.0 are based on digital technologies but reflect a fairly wide range of their manifestations in various areas of the economy. The desire to solve the problem of terminological vagueness of the concept of the fourth industrial revolution prompted researchers to create classifications of its key technologies. This would make it possible to identify those technologies that have common and distinctive features in the entire variety of available technologies, to record the connections between them and to obtain deeper knowledge about the object of research. During the implementation of this task, scientists devised several ways of grouping Industry 4.0 technologies. First of all, this is a functional approach, in which technologies were combined depending on the role they play in industrial processes and business environments. In addition, integration, subject (domain-specific approach by areas of application), integrated (according to the criterion of function or area of application) and cluster approaches (according to the principle of technology connectivity) were formed. Moreover, often even within the framework of one approach, scientists do not agree on the belonging of technologies to one or another group.

For example, in [15], the technologies of the fourth industrial revolution are divided into two groups. The first is physical technologies related to production (Additive Manufacturing, Drones). The second is information and communication technologies (Big data and analytics, Blockchain, Cloud Computing). This classification of Industry 4.0 technologies is imperfect due to the fact that it distinguishes between what works together. Digitalization combines the physical and virtual worlds, due to which information technologies serve as the basis for the development of all other technological innovations. When using the classification proposed in the analyzed work, the scope of identification of breakthrough technologies is significantly narrowed. The latter are present in both production and information and communication systems. A similar limitation is also characteristic of study [16]. It analyzes five levels of integration, which are connection, communication, coordination, cooperation, and collaboration (5C). Each of these levels of integration was assigned to the corresponding technologies, which make it possible to outline the scope of technological innovations of the fourth industrial revolution. Using integration as a criterion for categorizing technologies and focusing on finding their compatibility, the scope of identifying breakthrough technologies turned out to be narrowed. The list of technologies reported in [16] did not include those that define the modern contours of Industry 4.0. In particular, these are such breakthrough technologies as Robotics, Digital twins, and Additive Manufacturing. Therefore, the cited study has certain limitations related to the ability to identify a wider range of technologies.

Paper [17] identifies Industry 4.0 technologies according to three types of integration: vertical, horizontal, and end-to-end design. This includes automated design and manufacturing, integrated engineering systems, digital automation with sensors, flexible production lines, manufacturing execution systems (MES), and dispatching and data acquisition. This list leaves out the cluster of technologies that are directly at the heart of the digitalization process and are characterized by the greatest transformative power.

There is also an approach according to which scientists analyze how the integration of different levels of technologies, such as IoT, CPS, big data, can change production processes. They also pay attention to the different levels of technology integration that are key to the successful implementation of Industry 4.0 [18]. The focus of the cited study was to identify technologies that, according to experts, have already been implemented in the countries selected for the study. These were Germany, the UK, the USA, China, Japan, and South Korea. The researchers did not pay attention to technologies that have not undergone diffusion but are present at the stage of "creation" of the innovation cycle and determine the future contours of Industry 4.0. Another limitation of the study is the small sample of countries for which respondents were surveyed.

Those studies demonstrate the lack of an established understanding of the essence of Industry 4.0 and the set of breakthrough technologies inherent in it. This is due to the choice of different classification criteria (functionality, scope, integration, connections between technologies) and the desire to represent the technologies belonging to them as breakthrough. The latter are radical technological innovations, and therefore, can be present in each of the created groupings. The identified problem complicates the identification of breakthrough technologies, since the imperfection of classifications leads to a blurring of the boundaries between different types of technologies, their prospects and real transformational potential. As a way to solve this problem, it was proposed to create special ratings of breakthrough technologies along with classifications. The most popular among them are the lists of the McKinsey Global Institute and the MIT Technology Review, the Massachusetts Institute of Technology. Both of these ratings identify breakthrough technologies based on expert assessments that reflect qualitative changes in the domains of functioning of society. However, they demonstrate a different set of technologies that are considered breakthrough. Thus, according to the

McKinsey Global Institute, these include 12 technological innovations: Mobile Internet, Automation of knowledge work, The Internet of Things, Cloud technology, Advanced robotics, Autonomous and near-autonomous vehicles, Next-generation genomics, Energy storage, 3D printing, Advanced materials, Advanced oil and gas exploration and recovery, Renewable energy [19]. MIT Technology Review includes 10 technologies as breakthrough: Ultra-efficient solar power, Super grids, Prenatal DNA, Baxter, Big data Additive manufacturing, Smart watches, Temporary social media, Memory implants, Deep learning [20]. These two ratings demonstrate quite different sets of technologies that are breakthrough. This discrepancy is explained by different procedures for forming samples for expert analysis, and therefore, the approaches used in the rating cannot serve as a universal tool for identifying breakthrough technologies.

Along with this, methodologies have also become widespread, according to which the identification of breakthrough technologies is carried out using bibliometric data analysis. With this approach, the basis for ranking is either the number of citations or keywords that the authors of publications use to describe the technologies that form Industry 4.0.

Thus, in [21], the popularity of technologies related to Industry 4.0 is determined based on the number of their mentions in publications indexed in 2014–22 by the scientometric database Scopus. The criterion for forming this technology rating was exact matches in the titles, abstracts, and keywords of articles. Based on a study of the dynamics of these indicators, the cited work devised a rating of 11 technologies of Industry 4.0. The highest citations were recorded for the following technologies: Internet of Things (5405), cyber-physical systems (2876), cloud technologies (2253), simulation (2245), and big data analytics (1193). The main limitation of the study is the choice of only Scopus database to collect relevant publications, which significantly narrowed the scope of dissemination of breakthrough technologies. As is known, the scientometric database Scopus indexes the vast majority of articles in the humanities, rather than technical or natural sciences. In addition, the study focused mainly on the manufacturing sector, with little attention paid to the service economy. Finally, the review emphasizes that the main focus of previous studies was on developed countries, with little attention to developing countries.

In [22], data from the analysis of 620 publications from eight information sources (CiteSeerX, ACM, AISeL, EBSCOhost, Emerald Insight, Taylor Francis, Science Direct and Google Academic) are presented and 11 key technologies of Industry 4.0 are highlighted. Among them are the Internet of Things (110 citations), cyber-physical systems (81), integrated enterprise management system and business analytics (55), cloud systems (53), smart factory (45). However, although the list of sources was much wider than in [21], it did not take into account such powerful databases as Scopus, Web of Science, etc. In addition, only articles written in English were subject to consideration, and any publications in other languages were excluded.

In study [23], not only an analysis of keywords in publications related to Industry 4.0 was conducted but also 16 breakthrough technologies were identified. At the first stage of the study, they were combined into three clusters according to the principle of connectivity: (smart factory (C_1), simulation and modeling (C_2), and digitalization and virtualization (C_3)). The second stage of the study allowed the authors to construct a conceptual matrix indicating the statistical results of the studied scientific and practical publications and to identify 17 main concepts/technologies, combined into the three aforementioned clusters. Thus, in work [23], qualitative content analysis for categorically oriented interpretation of the text and frequency analysis for its statistical interpretation were combined in order to obtain the benefits of both methods. This study, like the previous one [22], did not take into account publications from Scopus, Web of Science. Its information base was Google Scholar, ScienceDirect, Emerald, Wiley Online Library, EBSCO Host and Ingentaconnect, as well as practical publications based on Google Open Search.

441 academic sources were sampled for study [24], in which the most mentioned technologies were grouped into nine sections. These include big data, artificial intelligence, cloud computing, IoT and IoE, digital twins, industrial robotics, augmented (AR) and virtual reality (VR), additive manufacturing and cybersecurity technologies. The developed taxonomy demonstrates three phases of subjectivity during its development and use by stakeholders. The full involvement of the human factor in the development of the taxonomy implied that the taxonomic classification and conceptualization of needs and technologies, as well as the manual attribution of each bibliographic source were carried out at the discretion of the authors. Therefore, it is understandable that there were difficulties in refining the taxonomy, especially with regard to industrial needs. In addition, the taxonomy was not linked to other already existing ontologies to achieve compatibility of knowledge areas that are not considered in the study but are still related to Industry 4.0.

In [25], four Industry 4.0 technologies were selected based on a similar technology, which had the greatest relevance and the widest range of mentions. They were grouped into four groups: cyber-physical systems, Internet of Things/services, smart data, and smart factory. Next, it was analyzed how often these technologies were associated with the characteristics of Industry 4.0 and the contribution of each of them to its development was shown. As a result of the study, it turned out that only “smart factory” technologies are inherent in all seven characteristics of Industry 4.0: virtualization, interoperability, autonomization, real-time availability, flexibility, service orientation, energy efficiency. The results had scientific value but were obtained on a structured literature review consisting of twelve main articles on the topic of the study. Therefore, they need to be verified on a wider sample of scientific publications.

Our review of the literature [7–25] does not solve the problem of defining its breakthrough technologies. Moreover, there are significant differences in the opinions of scientists not only regarding the composition of the technological core of Industry 4.0 but even regarding the names of the same technologies. These difficulties are explained in work [26] by the specificity of the historical stage, where the formation and development of a fundamentally new scientific paradigm occurs, which generates the corresponding technologies and technological matrices. And this requires time and research efforts so that revolutionary changes in scientific thinking and the organization of economic activity on a new technological basis lead to corresponding changes. The latter are implemented in the system of initial categories, ideas, provisions, assumptions, and principles of scientific thinking, which make it possible to give a consistent explanation of the phenomena under study, build theories and methods on the basis of which research is implemented. This explanation links the difficulties of identifying breakthrough technologies with a short period of time, within which the theoretical and methodological apparatus for research in the relevant field has not yet had time to form. However, it cannot be considered exhaustive since there are other reasons that give rise to theoretical and methodological problems in researching Industry 4.0. In particular, this may concern the very techniques of identifying technologies as breakthrough, as well as information sources that outline the scope of their search.

Information about the emergence of new knowledge comes to society through communication between researchers at conferences, symposia, and through the publication of scientific results in articles. In this way, scientists acquaint the world community with their discoveries. New knowledge is a public good and only thanks to its free circulation, in fact, does science evolve. Therefore, the easiest way to learn about new discoveries is to analyze scientific papers.

To obtain it, scientists constantly monitor published articles but use different approaches to understand the level of novelty reported in them. Publications that consider ways to obtain information about the emergence of breakthrough technologies and that are analyzed in this section of the paper are based on bibliographic monitoring. However, in those publications, breakthrough technologies are recorded at each specific point in time by counting the number of citations of selected papers. Another way is to establish the number of publications on the relevant issues by keywords. Such a static approach makes it possible to record the emergence of certain technologies but does not make it possible to see the actual dynamics of changes. This limitation affects the ability of economic entities to understand the trajectories of technological development, to anticipate structural shifts, and to respond to them by changing their strategic behavior.

On the other hand, the increase in citations is not always a reliable indicator of the emergence of new technological knowledge, but rather a reflection of the growing attention of the scientific community to a previously made discovery. For example, the origins of Edge Computing technology can be traced back to the 1990s but publications on this topic were not distinguished by a high level of citations, although their number was growing. In the early 2000s, the topic of Edge Computing gradually attracted the attention of scientists, and more and more papers appeared aimed at finding a combination of cloud and edge computing. However, this trend remains unnoticed given the number of citations. In particular, one of the fundamental works on this issue [27], published in 2004, collected the largest number of citations only in the period from 2020 to 2023. During this time, Akamai company was able to radically change the way data is managed around the world and become a leader in Industry 4.0. Thus, the problem arises of improving the source base of bibliographic monitoring, as well as choosing a more effective tool for identifying breakthrough technologies within the dominant technological paradigms.

3. The aim and objectives of the study

The aim of our study is to identify breakthrough technologies of Industry 4.0 that initiate social transformations. This will make it possible to establish guidelines for innovative business strategies and points of technological growth when implementing the state's economic policy.

To achieve the goal, the following tasks were solved:

– to identify the dynamics of publications on the issues of the technologies of the fourth industrial revolution;

– to identify breakthrough technologies of Industry 4.0 based on the accelerated growth model.

4. Research methodology

The object of our study is the breakthrough technologies of Industry 4.0, which cause social transformations.

When determining the technique for identifying breakthrough technologies of Industry 4.0, the following hypothesis was put forward. If a sample for bibliographic monitoring is formed based on a combination of Web of Science and Academia.edu, then it is possible to identify breakthrough technologies at the initial stage of the emergence of new knowledge. Based on the assumption that the dynamics of publications over the years can reflect changes of a revolutionary nature, an accelerated growth model was chosen to obtain the result. All other techniques for identifying breakthrough technologies were not addressed, which can be considered a simplification when conducting our study.

The starting thesis when forming the technique on the basis of which the identification of breakthrough technologies of Industry 4.0 is carried out is the understanding of the latter as radical innovations. They give impetus to the birth of a fundamentally new technological cycle, are prerequisites for the transition to new methods of production and consumption. On their basis, products and communications change, knowledge and skills of employees are transformed, and therefore, the previous technological paradigm is radically destroyed and replaced by a new one. The identification of technologies that are harbingers of social transformations should be based on data that make it possible to register the starting point from where the impetus for the deployment of a new innovation cycle actually begins. Such information is obtained on the basis of the analysis of patent statistics, data on researchers' awards, as well as the study of those scientific publications on the specified issues that are indexed in significant international scientometric databases. Since each source of information has its advantages and disadvantages, the source database is selected depending on the specific research goals.

Patent statistics, as well as information on awarding awards, become available to the general public much later than the first publications about inventions and the prospects for their transformation into innovations. Therefore, special indicators of bibliographic databases of citation systems are most suitable for the purposes of such research. However, when working with such indicators, scientists do not always obtain relevant results. The reasons for this are limitations related to the quality of the sample of papers on which the research is conducted. The specificity of each individual scientometric database often narrows the search field, which leaves out a number of important publications. Therefore, scientometric databases should be selected based on the thematic focus and breadth of indicators.

Web of Science emphasizes the impact and interdisciplinarity of research. Its indexes, such as Science Citation Index

Expanded (SCIE), Social Sciences Citation Index (SSCI), and Arts & Humanities Citation Index (AHCI), have a high reputation. For many researchers and institutions, Web of Science is the basis for conducting scientometric research and assessing citations due to more accurate classification and quality control of data. This database focuses on high-impact papers, publications from global research centers and influential international journals, and, most importantly, on the widest range of disciplines. For comparison: while the percentage of publications in Scopus is dominated by the humanities, in Web of Science – by the basic, natural, and social sciences. This aspect is necessary for technology research. Along with the scientometric database Web of Science, it is worth using the social network Academia.edu to obtain data. It is a platform for exchanging scientific works and serves as a platform for researchers to communicate, as well as tracking publication activity in selected fields. This network has millions of registered users from all over the world who actively publish papers, preprints, presentations, dissertations, and other materials. Academia.edu presents the work of researchers from different countries and institutions, which contributes to the formation of a more complete picture of current scientific topics. It covers a much wider range of interdisciplinary research than other resources. And, most importantly, it appears much faster in new scientific areas than Scopus or Web of Science.

Focusing on data from Web of Science and Academia.edu makes it possible to significantly improve the quality of the sample for identifying breakthrough technologies. It provides a comprehensive approach to the analysis of publications on the research topic since these platforms have different approaches to working with scientific information, complementing each other. In this way, it is possible to optimally combine accuracy and scientific quality with accessibility, breadth of coverage and convenience. This is especially useful for conducting in-depth literature review and research on new and niche topics, as well as assessing the quality of works through scientometric and informal metrics. For these reasons, Web of Science and Academia.edu were chosen as the source base for bibliographic monitoring.

Overcoming stativity in identifying breakthrough technologies was achieved by using quantitative monitoring of technologies through the dynamics of publications in the field of science about modern technological development. The latter is considered a more accurate indicator of scientific achievements since each published paper reports a separate new result. The empirical basis of the study was formed by searching for articles relevant to this thematic focus, presented during 2014–2023 in the international scientometric database Web of Science and the social network Academia.edu. The choice of these scientometric databases is an improvement of the procedure for forming a data sample, with which the vast majority of researchers work under current conditions.

Another characteristic that distinguishes the chosen technique for identifying breakthrough technologies among existing ones is the use of analysis of the dynamics of bibliometric indicators by year. This makes it possible to use the accelerated growth model to obtain the result. The assessment of the data set was carried out on the basis of calculating indicators that characterize the trends of dynamics, namely growth rates, average growth rates for each technology, and their subsequent comparison with each other. To determine the accelerated growth rate, a minimum growth threshold value was established. With this approach, only those technologies that overcame the specified barrier were considered breakthrough technologies. Data processing was carried out using Exele software (Microsoft, US).

5. Results of applying the methodological approach to identifying breakthrough technologies

5. 1. Identifying the dynamics of publications on the issues of the fourth industrial revolution technologies using graphical analysis

The verification of the predictive capabilities of the outlined approach is carried out on the basis of information on the technologies of the fourth industrial revolution. The most common among bibliographic indicators is the total number of publications on a particular issue. Therefore, it is considered necessary to base the process of identifying breakthrough technologies precisely on this indicator. Its application in the field of technologies of the fourth industrial revolution made it possible to determine the technological core of modern social transformations. It turned out that among the 43 existing technologies of Industry 4.0, the largest number of works considered Virtual Reality, Renewable energy, 3D modeling, Big Data, and the Internet of Things (Table 1).

The graphical representation of the data in Table 1 makes it possible to verify the presence of a stable dependence, which is manifested either in a quantitative increase or in a decrease in publications in 2014–2023 in the complete absence of cyclical fluctuations (Fig. 1).

According to the graphical models shown in Fig. 1, there is a decrease in the number of publications on such technologies as Wireless Technologies, Clean Tech, Integrated sensing and communication (ISAC), Hidden Markov models, Mobile devices, Radio Frequency Identification (RFID), Crowdsourcing, the sharing economy, Flexible production system (FMS), and cluster concept, Network solar photovoltaic stations, Machine to Machine. Such a downward trend may mean a weakening of both scientific and commercial interest in these technologies. It is most likely due to the fact that at the moment these technologies have reached certain technical or technological limits that cannot or are not advisable to cross. This does not exclude the possibility of "new breakthroughs" in the future in the field of further development and application of these technologies, however, in modern realities they cannot be considered so advanced as to be included in the possible list of breakthrough technologies.

The opposite trend – an increase in the number of papers – is observed for such technologies as Virtual Reality, Renewable energy, Internet of Things, 3D modeling, Artificial Intelligence, Smart Manufacturing, Advanced (Smart) Materials, Nanotechnology, Automation, Additive Manufacturing, Network solar photovoltaic stations, Drones, Cybersecurity, Blockchain, 5G Network. Exponential growth in the number of publications indicates increased interest of researchers in a certain technology and therefore can serve as an indicator of its breakthrough nature. Preliminary identification of breakthrough technologies based on graphical analysis should be supplemented with accelerated growth models, which requires the use of statistical methods.

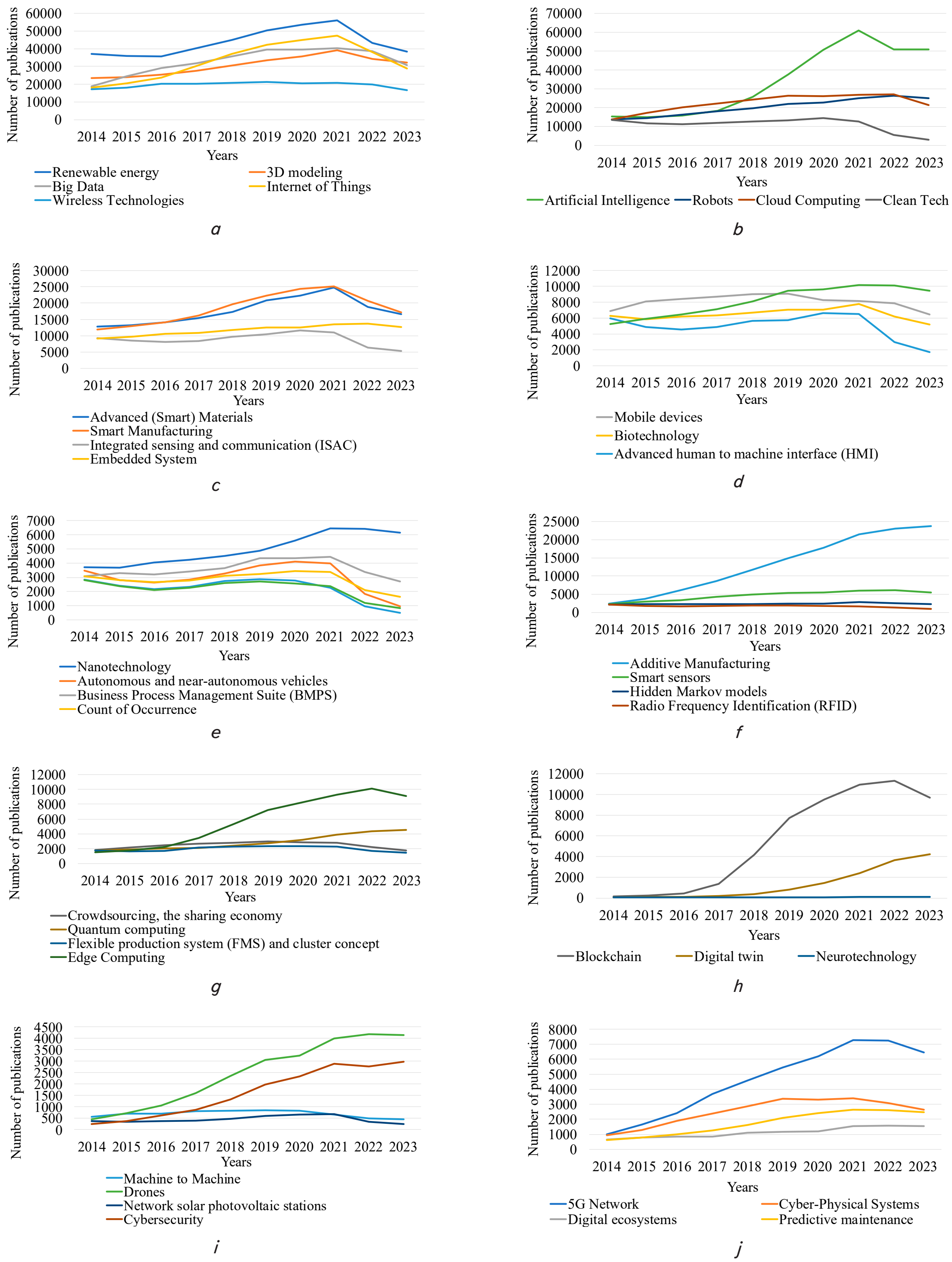

Fig. 1. Dynamics of publications on Industry 4.0 technologies, 2014—2023: *a* — Renewable energy, 3D modeling, Big Data, Internet of Things, Wireless Technologies; *b* — Artificial Intelligence, Robots, Cloud Computing, Clean Tech; *c* — Advanced (Smart) Materials, Smart Manufacturing, Integrated sensing and communication (ISAC), Embedded System; *d* — Mobile devices, Biotechnology, Advanced human to machine interface (HMI), Automation; *e* — Nanotechnology, Autonomous and near-autonomous vehicles, Business Process Management Suite (BMPS), Count of Occurrence, Wireline high-performance networks, Vertical and horizontal (V&H) system integrations; *f* — Additive Manufacturing, Smart sensors, Hidden Markov models, Radio Frequency Identification (RFID); *g* — Crowdsourcing, the sharing economy, Quantum computing, Flexible production system (FMS) and cluster concept, Edge Computing; *h* — 5G Network, Cyber-Physical Systems, Digital ecosystems, Predictive maintenance; *i* — Machine to Machine, Drones, Network solar photovoltaic stations, Cybersecurity; *j* — Blockchain, Digital twin, Neurotechnology

Table 1

Combined search results from the scientometric databases Academia and Web of Science

No.	Technologies	Number of publications by year									
		2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	Virtual Reality	104,715	107,322	116,683	125,495	135,752	148,522	152,902	163,502	162,770	153,174
2	Renewable energy	36,923	35,929	35,583	40,351	45,033	50,213	53,716	56,052	43,360	38,422
3	3D modeling	23430	23,909	25,261	27,496	30,473	33,573	35,586	39,114	34,443	32,150
4	Big Data	18,914	24,397	29,112	31,977	35,738	39,585	39,353	40,196	38,727	30,695
5	Internet of Things	17,994	20,455	23,800	30,101	36,971	42,156	44,992	47,268	38,115	28,997
6	Wireless Technologies	17,278	18,053	20,096	202,96	20,659	21,215	20,319	20,732	19,977	16,654
7	Artificial Intelligence	15,213	14,891	15,766	18,286	25,669	37,539	50,634	60,791	50,779	50,809
8	Robots	13,733	14,384	16,243	18,000	19,482	22,022	22,716	24,976	26,258	24,904
9	Cloud Computing	13,594	17,187	20,203	22,194	24,313	26,199	26,026	26,671	27,009	21,423
10	Clean Tech	13,527	11,660	11,043	11,989	12,768	13,321	14,499	12,813	5,570	2,963
11	Advanced (Smart) Materials	12,805	13,272	14,176	15,520	17,390	20,940	22,371	24,774	18,786	16,653
12	Smart Manufacturing	11,959	12,924	14,174	16,209	19,670	22,401	24,397	25,052	20,741	17,253
13	Integrated sensing and communication (ISAC)	9,321	8,519	8,173	8,502	9,685	10,485	11,701	11,050	6,388	5,300
14	Embedded System	9,187	9,766	10,677	10,849	11,726	12,543	12,477	13,560	13,693	12,661
15	Mobile devices	6,885	8,071	8,384	8,688	9,024	9,073	8,268	8,146	7,826	6,444
16	Biotechnology	6,283	5,823	6,188	6,307	6,695	7,093	7,086	7,777	6,221	5,153
17	Advanced human to machine interface (HMI)	5,999	4,895	4,573	4,853	5,687	5,754	6,627	6,533	2,991	1,712
18	Automation	5,227	5,886	6,444	7,146	8,109	9,427	9,626	10,190	10,088	9,405
19	Nanotechnology	3,694	3,674	4,033	4,260	4,525	4,898	5,589	6,464	6,431	6,152
20	Autonomous and near-autonomous vehicles	3,484	2,788	2,635	2,843	3,272	3,843	4,117	3,962	1,826	939
21	Business Process Management Suite (BMPS)	3,083	3,300	3,218	3,388	3,651	4,334	4,335	4,437	3,381	2,707
22	Count of Occurrence	3,080	2,799	2,655	2,773	3,095	3,245	3,455	3,363	2,100	1,638
23	Wireline high-performance networks	2,848	2,400	2,155	2,335	2,722	2,884	2,768	2,267	956	470
24	Vertical and horizontal (V&H) system integrations	2,808	2,354	2,097	2,275	2,584	2,697	2,559	2,370	1,182	803
25	Additive Manufacturing	2,485	3,781	6,099	8,645	11,711	14,844	17,807	21,597	23,154	23,768
26	Smart sensors	2,270	2,979	3,345	4,278	5,010	5,366	5,465	5,989	6,158	5,464
27	Hidden Markov models	2,121	2,269	2,267	2,272	2,260	2,415	2,417	2,898	2,616	2,348
28	Radio Frequency Identification (RFID)	2,117	1,796	1,698	1,745	1,867	1,897	1,719	1,687	1,314	964
29	Crowdsourcing, the sharing economy	1,852	2,135	2,467	2,670	2,808	2,984	2,897	2,833	2,235	1,755
30	Quantum computing	1,768	1,914	2,004	2,094	2,432	2,771	3,212	3,924	4,351	4,550
31	Flexible production system (FMS) and cluster concept	1,749	1,661	1,733	2,163	2,296	2,349	2,383	2,287	1,685	1,464
32	Edge Computing	1,553	1,766	2,250	3,420	5,299	7,234	8,280	9,300	10,133	9,079
33	5G Network	994	1,650	2,403	3,694	4,579	5,455	6,200	7,286	7,256	6,456
34	Cyber-Physical Systems	950	1,288	1,902	2,374	2,850	3,360	3,304	3,406	3,089	2,624
35	Digital ecosystems	665	777	859	831	1,108	1,175	1,182	1,545	1,567	1,553
36	Predictive maintenance	633	782	996	1,274	1,617	2,083	2,412	2,639	2,590	2,481
37	Machine to Machine	559	715	713	803	835	861	822	656	500	466
38	Drones	447	726	1,068	1,599	2,351	3,071	3,244	4,002	4,185	4,139
39	Network solar photovoltaic stations	377	358	368	387	484	600	658	678	361	258
40	Cybersecurity	253	383	615	876	1,324	1,980	2,327	2,898	2,771	2,983
41	Blockchain	155	240	439	1,380	4,155	7,717	9,511	10,947	11,339	9,711
42	Digital twin	72	89	92	175	388	824	1,452	2,377	3,645	4,197
43	Neurotechnology	35	46	42	58	66	61	73	115	77	115

5. 2. Identification of Industry 4.0 breakthroughs based on the accelerated growth model

Before conducting this stage of our study, it is worth paying attention to the obvious fact that all plots in Fig. 1 show a turning point in 2021. After it, a sharp decrease in the number of publications in almost all technologies is observed. This phenomenon can be explained by the fact that in 2020, during the global COVID-19 pandemic, most countries introduced a quarantine regime. The forced isolation of scientists did not provide many opportunities for creative search and self-realization and therefore prompted them to concentrate mainly on desk-based research. This affected the increase in the number of papers in 2020 and 2021. This situation is not typical for scientific activity, and therefore somewhat distorts the modeling results. Thus, to improve the predictive qualities of the accelerated growth model, it is necessary to perform exponential smoothing of the time series of the number of papers for each technology in the time interval 2014–2023.

Time series smoothing is performed using the exponential smoothing method. Smoothing is performed using the following formula:

$$\begin{cases} S_1 = y_0, \\ S_t = ay_t + (1-a)S_{t-1}, \end{cases} \quad (1)$$

where y_t – observations of the initial time series;

S_t – observations of the smoothed time series;

a – smoothing parameter, and $0<a<1$.

The parameter a is set at 0.8 since the studied time series do not have seasonal and cyclical fluctuations in the studied period.

The results of exponential smoothing of the data array of indicators of the number of papers are given in Table 2. Smoothing was performed in Excel using the "Exponential smoothing" function.

Having calculated the growth rates and average growth rates of the number of scientific papers for each technology for both the basic and smoothed datasets, the results were obtained, which are given in Table 3.

To identify breakthrough technologies, a minimum threshold value for the growth rate of the number of scientific papers in the studied data set was established. As such, the standard deviation from the average growth rate of the number of scientific papers for the entire sample was used (the average growth rate of the number of scientific papers for all technologies). Breakthrough technologies are radical in nature but are characterized by different levels of revolutionary impact. That is why it is important to determine different threshold values for identifying this level. For this purpose, a hypothesis is introduced regarding the threshold value for the growth rate of the number of papers:

1. A technology is breakthrough if:

$$G_i \geq \overline{x} + \sigma. \quad (2)$$

2. The breakthrough technology with the greatest destructive potential is if:

$$G_i \geq \overline{x} + 2\sigma, \quad (3)$$

where G_i is the average growth rate of the number of papers for the i-th technology;

$\overline{x}$ is the average growth rate of the number of scientific papers for the entire sample (technologies);

σ is the standard deviation of the average growth rate of the number of scientific papers for the entire sample (technologies).

Table 2

Exponential smoothing for time series of the number of papers for each technology in the interval 2014–2023

No.	Technologies	2015	2016	2017	2018	2019	2020	2021	2022	2023
1	Virtual Reality	104,715	105,236.4	107,525.7	111,119.6	116,046.1	122,541.2	128,613.4	135,591.1	141,026.9
2	Renewable energy	36,923	36,724.2	36,495.96	37,266.97	38,820.17	41,098.74	43,622.19	46,108.15	45,558.52
3	3D modeling	23,430	23,525.8	23,872.84	24,597.47	25,772.58	27,332.66	28,983.33	31,009.46	31,696.17
4	Big Data	18,914	20,010.6	21,830.88	23,860.1	26,235.68	28,905.55	30,995.04	32,835.23	34,013.58
5	Internet of Things	17,994	18,486.2	19,548.96	21,659.37	24,721.69	28,208.56	31,565.24	34,705.8	35,387.64
6	Artificial Intelligence	15,213	15,148.6	15,272.08	15,874.86	17,833.69	21,774.75	27,546.6	34,195.48	37,512.19
7	Robots	13,733	13,863.2	14,339.16	15,071.33	15,953.46	17,167.17	18,276.94	19,616.75	20,945
8	Cloud Computing	13,594	14,312.6	15,490.68	16,831.34	18,327.68	19,901.94	21,126.75	22,235.6	23,190.28
9	Advanced (Smart) Materials	12,805	12,898.4	13,153.92	13,627.14	14,379.71	15,691.77	17,027.61	18,576.89	18,618.71
10	Smart Manufacturing	1,1959	12,152	12,556.4	13,286.92	14,563.54	16,131.03	17,784.22	19,237.78	19,538.42
11	Embedded System	9,187	9,302.8	9,577.64	9,831.912	10,210.73	10,677.18	11,037.15	11,541.72	11,971.97
12	Mobile devices	6,885	7,122.2	7,374.56	7,637.248	7,914.598	8,146.279	8,170.623	8,165.698	8,097.759
13	Biotechnology	6,283	6,191	6,190.4	6,213.72	6,309.976	6,466.581	6,590.465	6,827.772	6,706.417
14	Advanced human to machine interface (HMI)	5,999	5,778.2	5,537.16	5,400.328	5,457.662	5,516.93	5,738.944	5,897.755	5,316.404
15	Automation	5,227	5,358.8	5,575.84	5,889.872	6,333.698	6,952.358	7,487.086	8,027.669	8,439.735
16	Nanotechnology	3,694	3,690	3,758.6	3,858.88	3,992.104	4,173.283	4,456.427	4,857.941	5,172.553
17	Autonomous and near-autonomous vehicles	3,484	3,344.8	3,202.84	3,130.872	3,159.098	3,295.878	3,460.102	3,560.482	3,213.586
18	Business Process Management Suite (BMPS)	3,083	3,126.4	3,144.72	3193.376	3,284.901	3,494.721	3,662.777	3,817.621	3,730.297
19	Count of Occurrence	3,080	3,023.8	2,950.04	2,914.632	2,950.706	3,009.564	3,098.652	3,151.521	2,941.217
20	Wireline high-performance networks	2,848	2,758.4	2,637.72	2,577.176	2,606.141	2,661.713	2,682.97	2,599.776	2,271.021
21	Vertical and horizontal (V&H) system integrations	2,808	2,717.2	2,593.16	2,529.528	2,540.422	2,571.738	2,569.19	2,529.352	2,259.882
22	Additive Manufacturing	2,485	2,744.2	3,415.16	4,461.128	5,911.102	7,697.682	9,719.546	12,095.04	14,306.83
23	Smart sensors	2,270	2,411.8	2,598.44	2,934.352	3,349.482	3,752.785	4,095.228	4,473.983	4,810.786
24	Quantum computing	1,768	1,797.2	1,838.56	1,889.648	1,998.118	2,152.695	2,364.556	2,676.445	3,011.356
25	Edge Computing	1,553	1,595.6	1,726.48	2,065.184	2,711.947	3,616.358	4,549.086	5,499.269	6,426.015
26	5G Network	994	1,125.2	1,380.76	1,843.408	2,390.526	3,003.421	3,642.737	4,371.39	4,948.312
27	Cyber-Physical Systems	950	1,017.6	1,194.48	1,430.384	1,714.307	2,043.446	2,295.557	2,517.645	2,631.916
28	Digital ecosystems	665	687.4	721.72	743.576	816.4608	888.1686	946.9349	1,066.548	1,166.638
29	Predictive maintenance	633	662.8	729.44	838.352	994.0816	1,211.865	1,451.892	1,689.314	1,869.451
30	Drones	447	502.8	615.84	812.472	1,120.178	1,510.342	1,857.074	2,286.059	2,665.847
31	Cybersecurity	253	279	346.2	452.16	626.528	897.2224	1,183.178	1,526.142	1,775.114
32	Blockchain	155	172	225.4	456.32	1,196.056	2,500.245	3,902.396	5,311.317	6,516.853
33	Digital twin	72	75.4	78.72	97.976	155.9808	289.5846	522.0677	893.0542	1,443.443

Table 3

Average growth rates of the number of scientific papers by base sample and smoothed time series

No.	Technologies	Average growth rate (based)	Average growth rate (exponential)
1	Virtual Reality	0.04431	0.03805
2	Renewable energy	0.01127	0.02705
3	3D modeling	0.03873	0.03874
4	Big Data	0.06427	0.07635
5	Internet of Things	0.06872	0.08917
6	Artificial Intelligence	0.16099	0.1239
7	Robots	0.06981	0.05439
8	Cloud Computing	0.05949	0.06919
9	Advanced (Smart) Materials	0.03828	0.04849
10	Smart Manufacturing	0.04989	0.06389
11	Embedded System	0.03766	0.0337
12	Mobile devices	–0.0031	0.02065
13	Biotechnology	–0.0162	0.00834
14	Advanced human to machine interface (HMI)	–0.093	–0.0141
15	Automation	0.0699	0.06194
16	Nanotechnology	0.06026	0.04335
17	Autonomous and near-autonomous vehicles	–0.0935	–0.0089
18	Business Process Management Suite (BMPS)	–0.0056	0.02443
19	Count of Occurrence	–0.0546	–0.0053
20	Wireline high-performance networks	–0.1398	–0.0269
21	Vertical and horizontal (V&H) system integrations	–0.1059	–0.0261
22	Additive Manufacturing	0.29836	0.24653
23	Smart sensors	0.10957	0.09875
24	Quantum computing	0.1123	0.06969
25	Edge Computing	0.23324	0.19845
26	5G Network	0.25354	0.22403
27	Cyber-Physical Systems	0.13675	0.13731
28	Digital ecosystems	0.10595	0.07326
29	Predictive maintenance	0.17078	0.14625
30	Drones	0.2993	0.25284
31	Cybersecurity	0.3338	0.27989
32	Blockchain	0.74054	0.66312
33	Digital twin	0.62188	0.48927

The average growth rate of the number of scientific papers for the entire sample is calculated as the simple arithmetic mean of the average growth rates of the number of scientific papers by technology (Table 3).

The results of calculating the threshold values of the growth rate of the number of papers for identifying breakthrough technologies for both the basic data set and the smoothed data set are given in Table 4.

As follows from Table 4, the threshold value of the growth rate of the number of papers of breakthrough technologies for the base sample is 30 %, for the sample with smoothed time series – 25 %, for breakthrough technologies with the greatest disruptive potential – 48 % and 40 %, respectively.

The calculated threshold values were applied to the values of the average growth rates for each technology, which are given in Table 3. According to the results of the classification, we have established:

1. Breakthrough technologies are Cybersecurity (33 %), Additive Manufacturing (30 %), Drones (30 %), 5G Network (25 %), and Edge Computing (23 %).
2. Blockchain (74 %) and Digital twin (62 %) technologies have the greatest disruptive potential.
3. Technologies with significant growth are Predictive maintenance (17 %), Artificial Intelligence (16 %), Cyber-Physical Systems (14 %), Quantum computing (11 %).

Table 4

Estimated threshold data

No.	Indicator	Basic sampling	Sampling with smoothed time series
1	Average Growth Rate of the number of scientific publications for the entire sample (technologies), $\overline{x}$	0.111451	0.10969
2	Standard deviation from the average growth rate of the number of scientific publications by sample (technologies), σ	0.185026	0.144761
3	Publication growth rate threshold for disruptive technologies	0.296477	0.254451
4	Publication growth rate threshold for disruptive technologies with the greatest disruptive potential	0.481503	0.399212

6. Discussion of results based on identifying the breakthrough technologies of Industry 4.0

The resulting list of breakthrough technologies differs from those reported in studies [20, 21, 23, 24]. Among the technologies that were considered breakthrough in the analyzed articles, the following remained: Artificial Intelligence, Cyber-Physical Systems compared to [21, 23], Digital twin and Cybersecurity [20, 21, 24], as well as Additive Manufacturing. Instead, such fast-growing technologies as Drones, 5G Network, Predictive maintenance, Edge Computing, and Quantum computing came to the fore. Along with this, this study managed to identify breakthrough technologies that have the greatest disruptive potential, namely Blockchain and Digital twin. Technologies characterized by significant growth potential include Predictive maintenance, Artificial Intelligence, Cyber-Physical Systems, Quantum computing.

It turned out that it is precisely the technologies that were singled out in this study that underlie the current innovative breakthrough of the most successful high-tech businesses. These include Vodafone and Samsung, which have made an incredible leap in the application of 5G Network technology. This includes manufacturers such as Kale Group and Baykar Technologies, which are leaders in the development of Drones technology and its use for military purposes. This includes the RepRap by A. Bowyer project, two Chinese construction companies WinSun and HuaShang Tengda Industry and Trade, which are leaders in the development of Additive Manufacturing. Edge Computing technology, presented by Akamai, is actively used and improved by a number of high-tech companies and, above all, Microsoft. An interesting fact is that these companies implement corporate foresight, conducting technological scouting on an ongoing basis.

The following made it possible to identify breakthrough technologies that meet modern realities. First, their identification was carried out on the basis of an analysis of the dynamics of papers in the field of science of technological development, and not by observing the number of citations or papers. This made it possible to more accurately determine the points of emergence and diffusion of new technological knowledge. Second, it was based on the use of an expanded range of special indicators of bibliographic databases of citation systems, as well as information from social networks – platforms on which researchers communicate. Unlike similar studies [20, 24, 25], our study used data from Web of Science and Academia.edu, which significantly improved the quality of the sample for identifying breakthrough technologies. On the one hand, this is due to the different approaches that these platforms use in working with scientific information, which thus complement each other. On the other hand, it is in Web of Science that papers in the exact and natural sciences are more widely represented, which is important for technology research.

As a result, a stable, non-cyclical trend of multidirectional changes in the number of papers for 43 Industry 4.0 technologies was recorded in 2014–2023 (Table 1, Fig. 1). In order to improve the predictive qualities of the accelerated growth model, exponential smoothing of the time series of the number of papers for each technology in a given time interval was carried out (Table 2). By comparing the average growth rates of the number of papers for each technology (Table 3) with the threshold value of the growth rate of the number of studies (Table 4) for both the base array and the smoothed one, seven breakthrough technologies were identified.

The results reported in our paper reveal only one of the possible ways to identify breakthrough technologies. Under modern conditions, companies are increasingly paying attention to the need to search for external data for innovative activities, trying to improve the methodology for applying bibliographic analysis [28]. Often, such a search requires greater attention to new search spaces and informal sources that make it possible to detect breakthrough technologies at an early stage of their emergence and dissemination. In this regard, the experience of Tesla, which, thanks to social network analytics, was able to introduce an improved technology for regulatory control of autonomous driving [29], is illustrative.

The limitations of our study are the difficulty of applying the presented technique for identifying breakthrough technologies to a wider range of information sources, especially those that are informal in nature. Although Academia.edu is a social network, the object of interaction is still scientific papers, which cannot be said about Facebook, Instagram, or the X network. The answer to this research gap may be further improvement of the methodology of bibliographic monitoring and the search for more effective tools for early detection of new trends in the field of technology. It is especially important to extend their application to areas in which scientific and technical information is still unstructured and invisible at present.

7. Conclusions

1. An exponential growth in the number of scientific papers has been found. This is evidence of the growing interest of scientists in a certain technology and therefore can serve as an indicator of its breakthrough nature. In this way, it was established that the largest number of papers accounts for five technologies out of forty-three inherent in Industry 4.0. These technologies are Virtual Reality, Renewable energy, 3D modeling, Big Data, and Internet of Things.

2. Identification of breakthrough technologies of Industry 4.0 based on the accelerated growth model made it possible to form a cluster of 7 technologies that give impetus to the deployment of a new technological paradigm. Such technologies include Blockchain, Digital twin, Cybersecurity, Additive Manufacturing, Drones, 5G Network, Edge Computing. Along with this, Predictive maintenance, Artificial Intelligence, Cyber-Physical Systems, and Quantum computing turned out to be technologies whose breakthrough nature requires more in-depth research to confirm. Researchers should pay special attention to Virtual Reality technology, which is rapidly gaining popularity in scientific papers and can be considered breakthrough. Taking into account the accelerated deployment of these technologies will allow economic entities to increase their adaptive capacity, and the state to concentrate resources on important areas of technological growth and increase the effectiveness of innovation policy.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Funding

The study was conducted without financial support.

Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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