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# DIGITAL TECHNOLOGIES IN THE ACCOUNTING INFORMATION SYSTEM SUPPORTING DECISION-MAKING PROCESSES

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**Purpose:** The aim of the article is to characterize the possibilities of improving the accounting information system supporting decision-making processes in the enterprise with the use of selected digital technologies with particular emphasis on artificial intelligence.
**Design/methodology/approach**: Basic research methods include critical analysis of literature. Simulation models of the stock market game using deep learning were also used. In addition, intensive computational experiments were carried out to analyze the quality of the solutions, which were determined by the proposed deep learning methods using artificial neural networks based on short-term memory (LSTM). The research presented in this article was verified by simulating the possibility of using deep learning.
**Findings:** The results exceeded the estimates described in the literature. The average error is estimated to be less than 3% when using the LSTM network. It should therefore be assumed that other deep learning paradigms will also be an effective tool in financial systems. The results of theoretical research and numerical experiments confirmed that the impact of selected digital technologies on the improvement of the accounting information system supporting decision-making processes is significant.
**Practical implications:** The results are the basis for formulating recommendations regarding the possibility of using the analyzed digital technologies in the accounting information system, supporting decision-making processes in the enterprise. They can also serve as an example of the digital transformation of the enterprise accounting information system.
**Social implications:** The obtained results indicate significant opportunities to improve the accounting information system supporting decision-making processes. This situation suggests the need to implement the latest achievements of digital technologies in the accounting information system for the effective collection and processing of a growing amount of data. A clear presentation, ongoing monitoring and precise prediction of future results are the basis for making effective decisions based on precise data analysis, and not based on intuition or experience of the decision maker.
**Originality/value:** The authenticity of the study results stems from the clear ideas for the effective use of digital technologies, in particular, deep learning with the use of artificial neural networks in the cloud to improve the accounting information system, especially in the field of estimating forecasted values.

**Keywords:** Accounting, Artificial Intelligence, Digital Technologies.

**Category of the paper:** research article.

# 1. Introduction

The main challenges in the post-pandemic realities of economic development are the digital revolution, energy transformation and climate change. As a consequence, the key factors influencing the changes in the approach to the accounting information system are sustainable social, ecological and technological development. Digital technologies play an increasingly important role in improving the accounting information system in terms of effective data processing and extracting business-useful information from them. This article is a synthetic analysis of the possibility of using selected digital technologies to improve the accounting information system in the conditions of growing information requirements and to adapt reporting to the needs of managers and individual stakeholder groups.

Digital transformation of business is a process that uses digital technologies in virtually every area of the company's operation, including accounting. Progressive digitization and growing information requirements increase the demand for an effective information and accounting system, enabling the acquisition of understandable economic and financial information in a relatively short time, on the basis of which the knowledge necessary to make effective decisions enabling the increase of the company's competitiveness is obtained. An effective information and accounting system that supports the decision-making processes of managers requires support from modern ICT systems for the collection and intelligent processing of a rapidly growing amount of data.

The factors affecting the extension of the scope of information required in corporate accounting is the global trend towards sustainable development of innovative circular economies based on knowledge and modern technologies. The circular economy means the use of innovative solutions in companies that reduce the consumption of natural resources and ensure environmental protection. On the other hand, the pursuit of sustainable development means integrated activities in the economic, social and environmental spheres. Sustainable development means that stakeholders expect not only accurate information about the type of company's operations and its financial results, but also about the research and development activities it undertakes, which are innovative, and at the same time take into account care for the natural environment and are characterized by social responsibility.

In the era of sustainable development of economies based on knowledge, innovation and modern technologies, it is necessary to prepare increasingly complex reports for internal recipients and to disclose more and more information in financial reporting to external recipients. In this context, it is of key importance to streamline the processes of collecting and intelligently processing the required data, as well as adapting reporting to the information needs of individual stakeholder groups. The effective use of modern digital technologies is a prospective direction for improving the accounting and reporting information system, in particular in the micro and small enterprises (MSE) sector in the countries of Central and

Eastern Europe, in the light of the ongoing system and economic changes. These technologies not only improve the process of data collection and storage, but above all create a huge space of various processing, analysis, reporting and transparent presentation of data in order to extract knowledge, which is a key resource in today's competitive conditions.

The aim of the article is to characterize the possibilities of improving the accounting information system using such breakthrough technologies as: Blockchain, Internet of Things, Big Data, Clod Computing and Artificial Intelligence. According to the Author, the effective use of the latest solutions based, in particular, on deep learning in the accounting information system, has great potential to improve decision-making processes in the company. Comprehensive and properly structured information is the basis for success, because up-to-date information allows you to achieve a competitive advantage and reduce economic and investment risk. There is a gap in the literature in this regard, because there are no clear ideas for the effective use of deep learning using artificial neural networks in the cloud to improve the accounting information system supporting decision-making processes in the enterprise.

The article discusses the possibilities of effective use of digital technologies to improve the accounting information system that supports decision-making processes in the enterprise. In particular, the issue of deep learning for forecasting in financial systems was described. Considerations on a specific case of a deep learning architecture based on artificial neural networks are also presented. Neural networks based on long-term memory were considered for estimating predicted values in relation to stock market investments. Finally, conclusions and planned future work are presented.

In the context of the above considerations, we should ask the following questions. How to effectively improve the accounting information system? How to use modern technologies, including artificial intelligence and cloud computing? How important is the use of deep learning and cloud computing to obtain business-useful information that facilitates making the right decisions? We may be able to answer some of the above questions at the end of this article.

The rest of this article is organized as follows. Part I presents an overview of the literature on the subject. Section II defines the role of the accounting information system in the decision-making process in the enterprise. Part III describes the importance of disruptive digital technologies to the accounting information system. Section IV presents the possibilities of improving the accounting information system using artificial intelligence and cloud computing. Section V describes deep learning for forecasting in financial systems. Considerations on a special case of deep learning architecture based on artificial neural networks (ANN) are also presented. The LSTM class recursive ANN has been validated for financial investments in the stock market in Section IV, which also considers long-term memory based neural networks for estimating predicted values. Finally, conclusions and planned future work are presented.

## 2. Related work

Accounting plays a very important information function both in the Shared Service Center (SSC) and in Business Process Outsourcing (BPO) of financial and accounting services (Martyniuk T., 2016). The essence of accounting is defined as an institutionalized information and control system adapted to the purposes of the broadly understood financial management of an economic entity, reflecting economic events and processes occurring in the enterprise, as well as in its relationship with the environment, included in the monetary measure for the purposes of supervision, control, planning and publishing (Kloock, 1997). The essence of accounting as an information system in the era of digitization of enterprises is interpreted as a system of continuous and systematic collection, measurement, processing and presentation of data (Gierusz, 2018). The increase in the functionality of the accounting system as an information system was influenced by the division into financial accounting, generating information in the form of financial statements for the environment, and management accounting, providing financial and non-financial information for internal recipients in the form of reports. Reliable interpretation and transparent presentation of data play a key role in the accounting information system, allowing for obtaining practical economic and financial information. An important qualitative feature of the accounting system as an international language of business and finance, increasing the usefulness of the generated information, is ensuring its comparability in the reporting of various entities (Gierusz, Martyniuk, 2017). An important premise for improving the accounting information system is the global trend towards the development of circular economies (European Commission Communication, 2.12.2015). The aforementioned trend increases the information requirements in the field of innovative solutions used in the company that reduce the consumption of natural resources and ensure environmental protection.

Sustainable development poses additional challenges to the accounting and reporting system, especially of the SME sector in the countries of Central and Eastern Europe (Martyniuk, 2021). They are related to growing information requirements regarding both financial and non-financial data. With regard to financial data, the most important is information on resource consumption, which allows for more accurate measurement and settlement of costs (Kotecha et al., 2022). Effective cost accounting principles should be applied in many areas, including in healthcare settings (Martyniuk et al., 2021). On the other hand, with regard to non-financial data, the extended scope of data expected by stakeholders mainly concerns the social and environmental responsibility of the conducted business activity (Martyniuk, Majerowska, 2017).

Digital technologies meet the challenges arising from the need to improve the accounting information system and adapt it to the information needs of individual stakeholder groups. In the era of digitization of the economy, it is particularly important to identify the opportunities created in the discussed area by digital technologies (Śledziewska, Włoch, 2020). In the literature on the subject, attempts are made to define the opportunities that modern digital technologies create for business (Gregor, Kaczorowska-Spychalska, 2020). Their impact on the increase in the competitiveness of enterprises no longer raises any doubts (Bartnik, 2016). The question is how to effectively use the potential of key technologies that intensify digital transformation to obtain clear information on the basis of which practical business knowledge necessary to make optimal management decisions (Olszak, 2007). This is because employees, especially managers, are expected to solve problems quickly and efficiently (Nazmiye, Mehmet, 2022).

Many solutions have already been developed in the field of creating and using electronic systems for processing company data and communicating information to recipients. These include domain-specific financial and accounting systems used in financial accounting to record events and prepare financial statements according to strictly defined rules. On the other hand, in the area of management accounting, spreadsheets and integrated ERP-class computer systems, based on a common database, mainly for consolidation and budget preparation, played a significant role in improving the information system. However, they were intended only for the collection and processing of historical data.

Computer programs for solving decision problems had much greater utility values, from the point of view of the possibility of generating forecasting information, used mainly for planning and reducing economic risk. Such programs additionally used methods from other fields and theories, such as game theory or operations research.

Another class of computer programs, based on ERP class systems, has already enabled the generation of information needed to improve process management and rationalize operational data. An exemplification of the improvement of process management in accounting is the automatic generation and sending of tax returns. Extending such systems with artificial intelligence modules would additionally enable automatic drawing of conclusions based on data and the creation of specialized business analysis. Programs to improve process management and rationalize operational data were developed under the name of Business Intelligence (BI) and were increasingly used in business at the turn of the 20th and 21st centuries (Olszak, 2012b).

In the following years, applications began to be created, which were to improve the management of achievements by viewing scorecards, generating reports and preparing specialized analyzes (CIMA, 2008). New solutions in the field of self-service systems also had an impact on the use of information collected as a result of the use of management accounting methods in the company. The new solutions had an impact on the use of information collected as a result of the use of management accounting methods in the company (Łada, Burnet-Wyrwa, 2015).

The ongoing digitization increases the demand for advanced, cognitive accounting information systems, including those using the most modern quantitative methods (Soszyńska-Budny, 2021) facilitating data analysis, as well as specialized software facilitating work in this area (Balicki, Balicka, Dryja, 2021). Advanced accounting information systems supporting decision-making processes in the enterprise should enable not only a clear presentation of the achieved results, but also the monitoring of current operations, updated on the basis of data flowing in real time, and, very importantly, the prediction of future outcomes.

How, then, against the background of the solutions used so far, can you improve the accounting information system and support the process of making optimal decisions, using the potential of breakthrough digital technologies, in particular the latest achievements of artificial intelligence? The author tries to answer this question in the following parts of the article, trying to at least partially fill the existing gap in the literature on the subject.

## 3. The role of the accounting information system in the decision-making process

An effective accounting information system is an increasingly popular term in the context of digitization of enterprises, as well as increasing their competitiveness and market value (Pioch, 2011). In short, this term can be defined as a type of systems that transform raw data into clear information, on the basis of which knowledge is built necessary to make the right decisions and consciously analyze activities in the enterprise. Initially this term was identified only with data analysis tools (Anandarajan, Srinivasan, 2004). Currently, effective information system is understood much more broadly, namely as an element connecting various components that make up the infrastructure supporting decision-making (Baaras, Kemper, 2008), providing decision-makers with comprehensive information, precise analyzes and reports (Negash, 2004). An effective information system is a kind of combination of tools, software and expert knowledge. The expected result of the effectiveness of such a system is the improvement of the company's results and the elimination of potential threats (Benbouzid, 2019).

The key technology for building an effective information system is a data warehouse (Inmon, Strauss, Neushloss, 2008; Sauter, 2008), that integrates data from various information systems for analytical purposes. Data warehouses store all possible information about the company, including transactions, settlements, processes and relationships. The more data the warehouse contains, the better results are obtained from data processing. The data warehouse is the basis for the effective use of various analytical tools, such as: data exploration and process exploration (Olszak, 2012a), but also more advanced, such as expert systems, neural networks (Balicka, 2020; Balicki, 2013) or genetic algorithms (Balicki et al., 2020). Advanced analytical tools are used for perform specialized analyzes using detailed "cross-sections" of data, allowing to verify hypotheses made on the basis of previously generated, standard reports and indicators.

Basic techniques for visualizing reports include scorecards and interactive dashboards. Presentation techniques are selected according to the individual needs of the user. The scorecard shows the company's progress based on current metrics and values against predefined goals. Scorecards are most often used to monitor the financial condition of a company (Figure 1).


**Figure 1.** Finance KPIs Using Scorecards.

Source: Saranya K. (2019). *Scorecards vs. Dashboards: Which Should Your Organization Use?*, https://www.boldbi.com/blog/scorecards-vs-dashboards-which-should-your-organization-use, 15.06.2022.

In turn, an interactive dashboard allows you to visualize a wide range of indicators in a clear picture form. The advantage of this presentation technique is the ability to monitor financial results in real time, which increases the effectiveness of decisions made. The interactive dashboard allows you to update reports on an ongoing basis based on real-time data. Continuously updated reports allow you to effectively monitor corporate finances, historical revenue data, company's critical financial metrics, and other important metrics (Figure 2). Interactive dashboard scenarios can be modified according to the user's information needs (Saranya, 2019). With the help of dashboards, you can acquire the knowledge necessary to optimize organizational processes in the company, financial optimization, increase sales and find the cause of poor sales of some products, as well as reduce costs and reduce business risk related to late payments by customers.


**Figure 2.** Monitoring of Financial Performance Using the Dashboard.

Source: Saranya K. (2019). Scorecards vs. Dashboards: Which Should Your Organization Use?, https://www.boldbi.com/blog/scorecards-vs-dashboards-which-should-your-organization-use, 15.06.2022.

The role of the accounting information system in the decision-making process in the enterprise is evidenced by the variety of solutions that enable the effective use of the potential of corporate data. There are many systems for data analysis and processing. Their classification is made mainly due to the purpose and purpose of the information obtained. Popular systems for data analysis include: OLAP, DSS and EIS. OLAP (Online Analytical Processing) enables data processing based on multidimensional analysis and multidimensional data structures. DSS (Decision Support Systems) is a system dedicated to supporting informed decisions based on precise data analyzes and reports. A specialized form of the DSS system is EIS (Executive Information Systems), which represents the systems of early informing of senior management, supporting the making of strategic decisions.

Depending on the purpose for which business information is sought, an appropriate division is made into analysis: predictive, prescriptive, diagnostic, descriptive and cognitive. Predictive analytics is about forecasting and modeling the future. Prescriptive analytics establish both possible scenarios and the consequences of potential decisions. Diagnostic analytics provides answers to questions about the causes of given events, based on historical data. Descriptive analytics processes historical data to describe specific past facts. On the other hand, the increasingly important cognitive analytics uses advanced technologies of artificial intelligence and machine learning to process large amounts of data in order to support managerial decisions, but also to enable autonomous decision-making by a dedicated accounting information system.

Making the right decisions leads the organization to success, and the use of appropriate analytical tools enables making decisions based on evidence (Szymczak, 2012). No unequivocal answers or indications of the only right solution were expected from the hitherto used accounting information systems. These systems only supported problem solving in key areas of finance, such as assessing the impact of the structure and cost of capital on the level of profitability of enterprises (Majerowska, Gostkowska-Drzewicka, 2021), however, they did not make decisions for the manager. On the basis of the economy transformation from analog, through digital to autonomous, cognitive information systems that use primarily artificial intelligence are becoming more and more popular (Czajkowski, Kuzior, 2019).

An effective accounting information system should be tailored to the needs of a given enterprise, constituting a dedicated solution that enables the use of the potential of company data. Therefore, the same schemes and algorithms are not used in individual enterprises (Lech, 2021). For this reason, the key role in creating dedicated solutions that enable the transformation of raw data into practical business knowledge is played by proper identification of both the type of data collected and processed, as well as the specification of information expected by decision makers. The expectations relate primarily to knowledge allowing to achieve a competitive advantage, as well as enabling the reduction of economic and investment risks. In order to support the decision-making process, new forms of management information with an extended range of data expected by business users, based on precise analyzes and appropriately visualized and interactive reports of advanced accounting information systems, are necessary.

## 4. The importance of breakthrough digital technologies

The most disruptive technologies (Figure 3), shaping the future of the digital economy and business, include: Artificial Intelligence (AI), Cloud Computing, as well as the Internet of Things (IoT), Big Data, Blockchain and Robotic Process Automation (RPA). The identification of the most breakthrough technologies, also referred to as technologies intensifying the digital transformation towards Industry 4.0 and Enterprises 4.0, was made on the basis of an assessment of global technology trends, carried out by major research centers and consulting and advisory companies, such as DELab UW (Śledziewska, Włoch, 2020), Gartner (Gartner, 2022), McKinsey (Manyika et al., 2013), Deloitte (Henke, Wilmott, 2018), and the Council on New Technologies of the World Economic Forum (World Economic Forum, 2018). An interesting approach not only identifying the most important new technologies, but also determining the phases of their maturation, was presented by the consulting company Gartner (Panetta, 2018).

Many companies try to apply modern technologies as soon as they are available on the market. It results from the belief that digital technologies are among the factors ensuring the achievement of a competitive advantage. Meanwhile, technologies by themselves do not guarantee anything, they only create certain opportunities. Effective ways of implementing and using them are important. The key to the survival and development of enterprises is to treat digital technologies as an integral part of the strategy and orientation in the new digital economy (Brzóska, Knop, Olko, 2017). It can be said that digital technologies constitute a kind of backbone, while the larger, up-to-date, reliable and precise knowledge obtained with them and its use in the process of reasoning and making optimal decisions is the basis of the digital economy based on knowledge, in which information and the ability to use it are becoming an increasingly important factor of production.

Technological solutions integrating cloud computing, mobile technologies and the Internet of Things contribute to the generation of large sets of various data (Big Data). Therefore, there arises the problem of skilful selection, evaluation and use of the collected information by managers operating in a large amount of data. It can be concluded that on the one hand, technologies improve the operation of enterprises, increasing efficiency, productivity, reliability, quality of manufactured goods, work safety and allowing to reduce operating costs. On the other hand, they generate an enormous amount of data (Figure 4).

Taking into account the fact that data is a strategic factor of production in the digital economy, it should be emphasized that the key issue is not the mere generation and collection of data, but their effective processing. In the smart business of the digital economy, the basis of success is skillful inference based on knowledge extracted in a relatively short time in the process of processing and analyzing many different sources and categories of data (Nguen et al., 2018). Intelligent reasoning, supported by technology, consists in comparing the acquired knowledge with the existing situation, which enables making optimal decisions and modeling future events related to the enterprise.

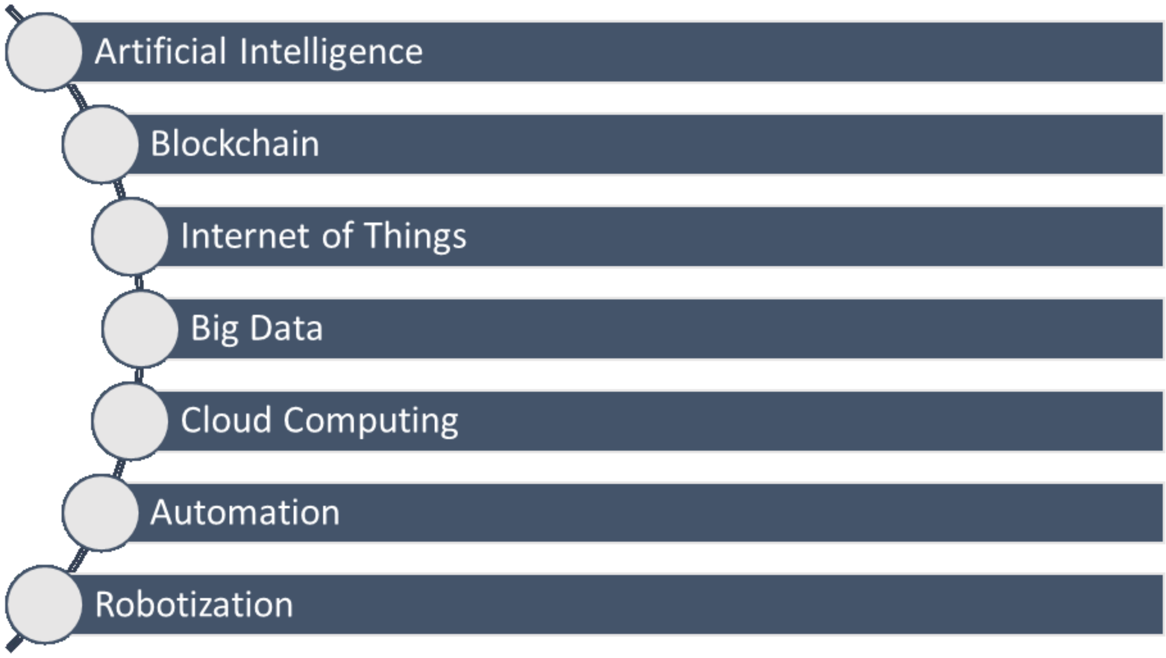


**Figure 3.** New efficient technologies for business.

Source: Own study based on: Rahman A. A., Hamid U.Z.A., Chin T.A. (2017), Emerging with Disruptive Effects, A Review, *PERINTIS eJournal, Vol. 7, No. 2*, p. 112.

Appropriate management of a rapidly growing amount of data requires skilful use of the knowledge and ideas of employees, supported by modern ICT technologies. Skilful acquisition and use of data increasingly determines the position and competitive advantage of enterprises. Collecting data mainly about the preferences of recipients allows you to optimize the offer, but also allows you to predict consumer behavior, using innovative methods of personalized internet marketing. The collected and properly used user data allowed companies such as Microsoft, Apple, Amazon and Alphabet to place in the top five corporations with the highest market value in 2021, created by the magazine "Fortune 500" and Financial Times Global 500". It is worth noting that the total revenues of the largest global companies from the above-mentioned list, driven by innovations introduced thanks to the effective use of digital technologies, account for over one third of the world's GDP. Thus, innovation creates market value and is the main driving force behind the development of enterprises.

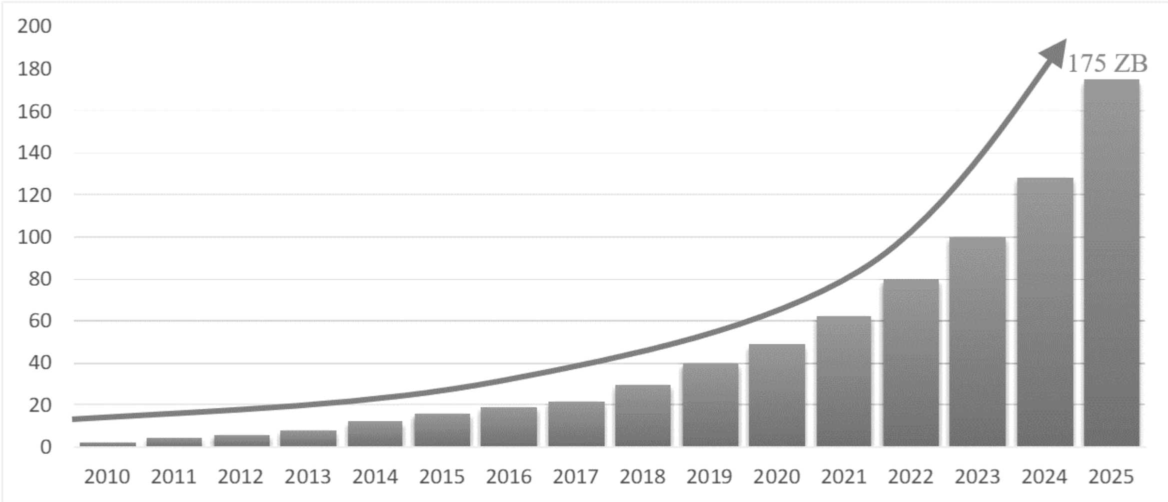


**Figure 4.** Annual data volume in the world in zettabytes (trillion gigabytes).

Source: Reisel D. (2018). *The Digitization in the World. From Edge to Core*, IDC White Paper, p. 6, http://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf, 07.07.2022.

Only enterprises with appropriate technological, organizational and economic potential have a chance to compete on a global scale (Malara, 2006). The basis of the victorious struggle for survival and development in global markets are innovation and knowledge, which are at the same time the most important drivers of digital, economic and social development (Antonowicz et al., 2021). A necessary condition for the development of a company in the post-pandemic global economy is the introduction of innovation, primarily in the IT dimension (Folwarski, 2021). However, these innovations should be perceived not only from the point of view of individual technologies and their infrastructure, but also from the perspective of previously unknown ways of their implications in practice.

Innovative solutions, enabling effective use of digital technologies and competitive advantage, are created on the basis of two types of technological innovations, namely: hardware innovations and software innovations. Hardware innovations mainly concern IT tools such as quantum computers and information transfer tools. A key criterion for the development of hardware innovations is the speed of data processing and transfer. Competition in the field of hardware innovation is referred to as the "arms race" in today's knowledge-based and modern technology economies.

Software innovations concern all kinds of information delivery and processing tools, such as big data analysis algorithms, classified as machine learning and deep learning tools within the wider area of artificial intelligence. Software innovations also include data processing implementation tools based on the joint use of IT services, such as cloud computing. In addition, software innovations include tools for reporting financial phenomena according to the concept of a distributed database, i.e. blockchain technology.

Generating and collecting data is mostly a technical problem. On the other hand, data processing and extracting knowledge from it, in addition to the necessary technical layer, is primarily an algorithmic, computational and intellectual problem (Tabesh, Mousavidin, Hasani, 2019). Making effective decisions based on the extracted knowledge in the realities of the digital economy depends mainly on the results of precise data analysis, and not on the intuition or experience of the decision maker (Provost, Fawcett, 2013).

Modern digital technologies used in business activities allow for obtaining and maintaining a competitive advantage on the market. If the competitive advantage obtained through the implementation of information technologies seems to be short-term, due to the benchmarking effect, attention should be paid to the resulting possibilities of converting information flowing from these systems into current, reliable and precise knowledge necessary for the proper management of the enterprise. It is the use of this knowledge gained with the use of appropriate IT systems, tailored to the individual needs of the company, that makes the obtained competitive advantage may be long-lasting.

The ongoing digitization processes in the developing economies based on knowledge and innovation mean that the possibilities of using digital technologies in enterprises of particular industries arouse more and more interest in global research. They are carried out mainly by significant research centers, as well as consulting and advisory companies. According to research carried out by experts from the Gartner group, as many as 87% of senior managers admit that digitization is a priority, and 79% of corporate strategists even say that digitization redefines their activities in a completely new way (Gartner, 2022).

Despite the fact that business representatives point out the need for digitization and optimization of processes in the era of dynamically developing digital technologies, Poland, according to the edition of the European Digital Economy and Society Index (DESI) for 2021, is ranked 24th in terms of digitization out of the 27 Member States of the European Union. Thus, the innovativeness of the Polish economy with the result of 41 is below the EU average of 50.7. The level of innovation is correlated with the degree of investment and the use of new technologies in business. Meanwhile, only 12% of Polish enterprises are characterized by a high degree of digitization, while the EU average is 18% (DESI, 2021).

Microsoft's Digital Futures Index (DFI) also indicates that the innovativeness of the Polish economy compared to innovation-driven countries is also 6% lower than the average in Central and Eastern Europe. The level of digitization of enterprises in Poland compared to the region is also lower by almost 10%. The DFI results also show that countries with higher levels of digital skills and more active use of various digital technologies and services score higher on the key quality of life indicators: productivity, earnings and innovation (Microsoft, 2022).

Micro and small enterprises (MSE) play a special role in the economy, both due to their impact on the development of entrepreneurship and their ability to quickly adapt to changing socio-economic conditions. Therefore, one of the key problems of the innovative economic development of the country is the creation of conditions conducive to the functioning of MSE in the realities of the digital economy based on knowledge and innovation (Jonek-Kowalska, Nawrocki, 2022). An innovative company is distinguished by intelligence, conducts research and development, systematically implements new scientific and technical solutions, represents a large share of new products in production and services, and constantly introduces something new to the market. So what are the main barriers in creating innovations in Poland against this background?

The main barriers to the development of innovation include, first of all, the lack of appropriate financial support in the form of reliefs for automation, including ICT systems and robotization, which would give small and medium-sized enterprises the opportunity to profitably invest in innovation. A 2018 study by the Keralla Research Institute shows that as many as 70% of small and medium-sized enterprises are not supported by any funds to finance their current operations. Therefore, it is emphasized that financial support should go hand in hand with advice on possible options for the development of innovative projects.

The barriers discussed also include overzealous bureaucracy and insufficient digitization of administration. The representation of women in the IT industry in Poland is also insufficient. Meanwhile, countries where women are involved in building a digital economy are leading the race for competitiveness as well as quality of life, according to the DESI economic and social index, included in the DFI (Microsoft, 2022).

The barrier is also not very modern universities and the shortage of specialists with appropriate digital competences (DESI, 2021; Kubik, 2016). Each year, Thomson Reuters publishes a ranking of the 100 most innovative universities in Europe. The list identifies and properly ranks educational institutions that conduct the most advanced scientific research, pride themselves on influencing innovations and patents, create new technologies and contribute to the development of the global economy. For the fourth year in a row, the highest place in the ranking is occupied by the Belgian university KU Leuven (No. 1). The German Erlangen Nuremberg (No. 2) came second, ahead of the British Imperial College London (No. 3) and the University of Cambridge (No. 4) and the Swiss EPFL (No. 5). Only one university from Poland and at the same time the only one from the countries of Eastern Europe to be included in the list of the 100 most innovative European universities is the Jagiellonian University, which took 90th position. According to the results of the ranking prepared in cooperation with Clarivate Analytics, in the top 100 most innovative educational institutions most of them come from Germany (23), followed by Great Britain (21), France (18), the Netherlands (9), Belgium (7), Spain (5) and Switzerland (5), Italy (4), Denmark (3), Norway (2) and 1 universities each from Austria, Ireland and Poland. Universities educate future employees. And it is them who determine how the potential of the available resources, both in the form of innovative tools and funds, will be used and will result in innovative implementations (Thomson Reuters IP Science, 2022).

The shortage of specialists significantly affects the uptake of digital technologies by enterprises, in particular MSE, which means that they cannot fully use the potential of the digital economy (Wolniak at al., 2022). According to the analyzes of the European Commission, up to 90% of professions will require new digital competences (DESI, 2021). The ranking of the most innovative companies in the world, created by the Boston Consulting Group (BCG), confirmed the thesis that "readiness to innovate" and the associated strong competitive position of companies mainly depend on access to intellectual capital with appropriate technological competences (BCG, 2022). Progressing digitization creates a demand for specialists primarily in the development of artificial intelligence, cloud services, software developers, as well as Big Data analytics (Marszycki, 2022) (Table 1).

**Table 1.**
*Trends which in the next 3-5 years will have an impact on the demand for specialists with new competences*

| No. | Trends | Influence |
|---|---|---|
| 1 | cybersecurity | 53% |
| 2 | artificial intelligence / machine learning | 45% |
| 3 | computing clouds / edge computing | 41% |
| 4 | 5G | 37% |
| 5 | virtual and augmented reality | 35% |
| 6 | personalization of the end user experience | 34% |
| 7 | industry 4.0 / economy 4.0 | 33% |
| 8 | big data / data science | 30% |
| 9 | quantum / bionic computers | 29% |
| 10 | internet of things and autonomous items | 26% |
| 11 | user experience design | 25% |
| 12 | autonomous transport | 22% |

Source: Own study, based on: BBKL IT 2nd edition, 2022 – employers survey.

It should be emphasized that in order to provide the appropriate infrastructure necessary to intensify the processes of digitization of enterprises in the conditions of sustainable development, green data centers are also necessary (IMARC Group Analysts, 2022). It is estimated that the demand for green centers will triple by 2027. It is estimated that this market will reach the value of USD 200.84 billion in 2027, while at the end of 2021 its value was estimated at USD 59.32 billion. Despite the fact that three-quarters of companies in Poland process data using their own server rooms, and their number is to increase by as much as 226% by 2025 compared to 2019, the progressing digitization of enterprise processes will require support from specialized data center services for several key reasons. These include, first of all, the growing demand for additional disk space, as well as computing power and devices that comprehensively support the proper operation of the ICT infrastructure. The server room security and service continuity aspects are also important. The above-mentioned reasons, combined with the growing prices of computer components and the costs of building company server rooms, translate into a growing demand for specialized data center services. Moreover, due to the energy transformation, which is to protect against rising energy costs and its possible lack, there is a growing interest in ecological solutions provided by green data center services.

They are characterized by high energy efficiency and use renewable energy sources in order not to emit greenhouse gases. The forecasted development of this sector in Poland will additionally result in an increased demand for highly specialized personnel.

The use of key technologies that intensify digital transformation makes it possible to adapt new solutions that increase the effectiveness of activities and improve their quality in every sphere of business activity (Wolniak, Gajdzik, 2022). Therefore, in the further part of the article, the author will present proposals for the use of selected digital technologies, with particular emphasis on artificial intelligence, to improve the accounting information system supporting decision-making processes in the company.

## 5. Opportunities to improve the accounting information system using cloud computing and artificial intelligence

Modern digital technologies provide many opportunities to improve the accounting information system, eliminating or significantly reducing many barriers to the current collection, processing, analysis, reporting and presentation of data. The impact of new technologies simply changes and improves the data management process. While the logic of the impact of the accounting information system on decision-making processes has not changed, the available tools have changed. In order to support the decision-making process, new forms of management information are necessary with an extended range of data expected by business users, based on precise analyzes and properly visualized and interactive reports of advanced accounting information systems.

### 5.1. Blockchain

Another technology that improves the functioning of the accounting information system is blockchain. The functionality of this technology is based on cryptographic algorithms with which each transaction is recorded. The main attribute of this technology is openness and transparency, while ensuring the security of transactions. The use of cryptography to save individual transactions significantly increases security against potential failures as well as hacker attacks. Ultimately, it may also significantly reduce the scope of inspections carried out by state authorities and large corporations.

Blockchain allows you to create a public, decentralized and distributed transaction register that can be used for a number of purposes (Klinger, 2017). The most popular applications are transactions made with cryptocurrencies, which are increasingly often acquired by small enterprises, next to large corporations. Despite the growing interest in altcoins, including as alternative sources of capital investment, the lack of appropriate legal regulations means that accounting specialists have a problem not so much of a technical nature as of accounting related to the use of cryptocurrencies. The problem is the lack of a developed method of correctly posting altcoin transactions in financial statements (Raiborn, Sivitanides, 2015).

This technology is also implemented for efficient project management (Kisielnicki, 2018). Blockchain is also a good solution for such transaction registers as, for example, open book accounting systems. The use of cryptographic algorithms allows you to share data from accounting books that are not disclosed in the company's external reporting due to trade secrets (Sobańska, 2013). The advantages of using blockchain technology in open book accounting systems include, above all, the aforementioned security of data registration and exchange, but also the speed of the system's operation and maintaining data consistency, all of which can be provided at a relatively low cost (Fanning, Centers, 2016).

In order to further improve corporate financial management, in the near term, we can expect to expand the use of blockchain technology to improve the exchange of financial data of the company with such financial service providers as banking institutions and fintech companies. There is a relatively long tradition of using the services provided by banks. On the other hand, the use of financial services provided by Fintech companies specializing in innovative technological solutions has a much shorter history (Hałasik-Kozajda, Olbryś, 2020). The growing demand for services offered by this type of enterprise results from striving to meet the needs of business units for innovative solutions that improve financial processes, especially in the field of banking (Folwarski, 2019).

### 5.2. Internet of Things (IoT)

The technology that greatly supports BI is Internet of Things (IoT), because it enables the integration of distributed data from various transaction systems, including Cloud Computing. IoT can be defined as a system consisting of objects with built-in sensors whose task is to detect, recognize and record specific signals from the environment. These signals may concern, for example, the occurrence of a specific event or exceeding a certain threshold value. A characteristic feature of the IoT system is that data is transferred between the things that compose it, also known as intelligent objects. Communication of intelligent objects and data exchange with other devices is possible thanks to a variety of network solutions, mainly wireless. It can be said that IoT, on the one hand, generates a large amount of data, thus being a rich source of information for analytical purposes, and on the other hand, it is a consumer of data that it obtains thanks to sensors and sensors embedded in intelligent objects (Kumar, Tiwari, Zymbler, 2019).

IoT can generate a large amount of information in accounting, e.g. on the implementation of specific processes in the company and its environment. The information of interest to the entrepreneur may be, in particular, customer preferences and the specificity of using the services or products offered. This technology provides much more data necessary for recording and reliable cost calculation, as well as identifying the factors that affect them. In addition, IoT enables better collaboration between buyers and suppliers in creating a new or improving an existing service or product, as well as determining the acceptable cost. Data exchange in IoT also allows for the active participation of the consumer in the prediction of costs and revenues, as well as cash flow. Thanks to a large amount of accurate data, it is also possible to detect new factors, which primarily determine the effectiveness of a given organization, which should contribute to precise planning and cost control, as well as to a fuller use of resources. In-depth control of individual objects of the IoT system also allows for a significant reduction or even elimination of potential failures and for making an accurate diagnosis as to the expected costs, revenues, cash flows and shaping of non-financial indicators.

### 5.3. Big Data

Big Data represents the specific structure of a large-volume, real-time stream of data, characterized by diversity, complexity and variability. The specificity of data with the Big Data structure does not allow for their management with the use of previously known tools. The characteristic structure of Big Data is the basis for the effective management of the rapidly growing amount of data (Beath et al., 2012). Data management, consisting in proper processing, interpretation and use in order to create valuable business knowledge (Willcocks, Whitley, 2009), it is the basis of action based on facts, not on intuition (Mayer-Schonberger, Cukier, 2013). The feature that distinguishes Big Data from traditional data processing is faster and easier collection of a large number of specific data, especially non-financial and unstructured data, such as video files or charts, characterized by a large number of information nodes. In addition, data can come from a variety of internal and external sources and stream in real time. Therefore, examining the correlation between individual data on the Big Data structure in order to obtain reliable conclusions and new knowledge in a relatively short time requires the use of innovative methods and technologies in Big Data analytics (Han, Kamber, Pei, 2016).

The starting point is to adapt the accounting information system to the use of Big Data structure data. The implementation of this technology in accounting enables a significant expansion of both the number and scope of available data. They can come from internal accounting data and from outside. The source of external data can be, among others, financial and non-financial institutions, state institutions, but also data from the Internet not indexed by most search engines (Deep Web Data), including, inter alia, social media (Balicka, 2018). Data collected in the accounting system can be used, for example, to record and calculate costs, but also to forecast costs, revenues, cash flows and a number of financial indicators. Large data sets in combination with advanced methods of artificial intelligence, such as machine and deep learning, as well as with advanced analytical methods and increased computing power, allow in accounting to precisely identify certain patterns in the formation of costs, revenues and cash flows, and also enable the capture of factors determining specific changes. The application of Big Data is also believed to influence the change of the cost structure, the way information is used and the knowledge creation process (Bhimani, Willcocks, 2014).

The implementation of Big Data in the accounting information system is the basis for generating not only better-quality reports, but also precise forecasts. It enables the discovery of new dependencies. It prompts a better understanding of the existing relationships between financial and non-financial information. It increases the perceptual possibilities in terms of the existing cause-effect relationships between the actions taken and the effects obtained. It also contributes to the improvement of performance measurement tools, including the popular Balanced Scorecard. It is also the basis for the development of new, flexible tools, such as interactive picture-based dashboards, enabling real-time monitoring of financial results, increasing the effectiveness of decisions made. An important support for decision-making processes thanks to the accounting information system is also the possibility of implementing automatic management systems, such as company liquidity management.

It should be noted that the pursuit of obtaining precise knowledge, enabling the optimization of decisions, with the participation of modern information technologies, will lead to further escalation of data. In order to tackle the data overload phenomenon, innovative advanced processing methods such as deep learning are already being used at data sources such as Internet of Things tools or local edge servers, that is, before the data goes to a dedicated database. This process is known as edge processing (Balicka, Balicki, Dryja, 2021). This process is known as edge computing (Balicka et al., 2019).

### 5.4. Cloud computing

Cloud computing is a technology that significantly supports the accounting information system (Balicka, 2019). Cloud computing is understood as a data processing model that is offered by external entities offering specific computing services, concentrated in one place on the Web (Post-Lee, Pakath, 2014). Access to the services is possible from anywhere using a computer with Internet access. These services are scalable due to the changing needs of the recipients. There are three main service models, which include: Infrastructure as a Service, Platform as a Service, Software as a Service (Kapeliński, 2014). Taking into account the ownership criterion of a specific data processing model and the specific nature of their implementation among recipients, the following types of computing clouds are distinguished: Public Cloud, Private Cloud, Community Cloud, Partner Cloud, Hybrid Cloud and Dedicated Cloud (Dziembek, 2016).

Using this technology in practice most often means transferring the provision of IT services to the servers of cloud service providers. What distinguishes cloud computing from the solutions offered so far related to IT outsourcing is the fact that users using this solution have dynamic and instant access to the resources necessary at a given moment using a remotely connected computer (Balicka, Balicki, Zakidalski, 2022). Storing data in the cloud of a specialized provider allows enterprises to reduce the costs associated with the maintenance of appropriate infrastructure, software and hosting (Balicka et al., 2014). Thus, the reliability and speed of calculations depends on the power of servers owned by the suppliers and the Internet bandwidth. IT systems operating in the cloud enable virtually immediate use of the necessary data processing services, increase flexibility and efficiency, and ensure effective data management in the future, thanks to the scalability of services in the cloud.

The key determinants of the development of cloud computing include the growing needs for data processing and storage along with the amount of data, as well as numerous technical solutions facilitating access to the Internet. It can be said that cloud computing has become a standard solution used by large corporations. According to Microsoft's strategic plans for the coming years, the most important thing for the company will be the expansion of the cloud. The corporate goal is to have 90% of all infrastructure in the public cloud. This strategy requires the construction of successive technological levels that will enable its effective implementation (Microsoft, 2021). Smaller enterprises are also increasingly interested in simple IT systems used to process information in the cloud. Interest in the cloud is to be expected to continue to increase, especially in EU Member States, as the Commission seeks to remove restrictions on the location of data as well as on their free flow within the EU. The Commission is also developing appropriate contractual clauses for the outsourcing of cloud storage services by financial institutions.

IT systems operating in the cloud allow you to keep accounting and generate analyzes based on documents sent in electronic form. The cloud is also a very good solution for interactive dashboards created with dedicated applications. These types of applications and services are largely cloud-based, thus facilitating the collection, management, processing, analysis and visualization of data from various sources, including IoT tools, in real time (Gartner, 2021). Microsoft's cloud solution is highly rated in this area (Enterium, 2022). There are also other cloud-based solutions of this type available on the market (Cloud solutions, 2022).

## 6. Machine Learning Models for the analysis of financial data

Forecasting in the accounting information system can be effectively supported by deep learning models, such as Convolutional Neural Networks or Long Short Term Memory Neural Networks (Mylonakis, Diacogiannis, 2010). This kind of financial forecasting requires cloud computing (Balicki, Balicka, Dryja, 2021). For example, some banking sector crises, also affecting corporate finances, can be anticipated by trained deep learning models (Balicka et al., 2013). This task is extremely difficult due to the small amount of data because about hundred banking crises have been observed in the last fifty years, only (Oet et al., 2011). The banking crisis in Poland in 2009 weakened the annual GDP by 14%. Because of EU funds, GDP returned in 2010 to the previous level of EUR 360 billion, and it reached EUR 574 billion in 2021 (Eurostat, 2022). Much more deep crises were in Italy and Spain that returned to the previous values of GDPs after five years (Eurostat, 2022). In Greece, GDP was reduced to level of 2003 year. The effects of the global banking crisis were very serious and long-lasting in the case of Greece because its value EUR 224 billion in 2010 fell to EUR 183 billion in 2021. In general, two-year period of slow decline of GDP precedes the banking crisis, and then it becomes an actual crisis with a significant decline in GDP (over ten percent) for the next two years. Finally, the next two years will be making up for the effects of the crisis and reaching the level preceding the banking crisis. Thus, effective models for predicting the occurrence of a global banking crisis can significantly contribute to mitigating the effects of related economic crises. For this reason, high hopes and expectations are associated with machine learning models as early warning systems of the banking crisis.

### 6.1. Deep learning models for prediction and classification

The crisis related to the Covid-19 pandemic can trigger a much more severe economic crisis, including financial and banking crisis. Compared with the same quarter of 2019, seasonally adjusted GDP decreased by 14.1% in the EU in the second quarter of 2020. Within the second quarter of 2020, GDP in the United States decreased by 9.5% compared with the previous quarter. In 2021, GDP of Poland increased by 7.1% due to the reference level in 2019. Spain (-3.2%), Portugal (-1.5%) and Italy (-1.2%) were the most affected by this crisis. On the other hand, Ireland's economy is developing the best, with a growth of 14.1% in 2021. In addition, Norway (11.3%), Lithuania (10.9%), Sweden (9.5%) and Denmark (8.3%) obtained the rapid growth of GDP. To discover the pandemic crisis some deep learning models can be developed, too.

Another area of development some deep learning models is the classification of the credibility of borrowers to shrink an amount of unpaid loans. Too liberal lending and high unemployment may lead to bank bankruptcy or to high social discontent in the case of probate inheritance law and restrictive debt collection. Avoiding innovation in financial systems, in particular, may lead to the uncontrolled development of a new currency system, as was the case with bitcoin, where the financial transaction approval process adds a new entry to the blockchain. Deep learning models can predict the course of Bitcoin, too (Frankel, Rose, 1996).

Bitcoin was applied in El Salvador, where Bitcoin Law granting the currency legal tender status went into effect. In October 2021, there were more Salvadorans (three million, 46% Salvadorans) with the Chivo bitcoin wallets than traditional bank accounts (29%). In January 2022, the International Monetary Fund urged El Salvador to cease using bitcoin as legal tender regarding its risk to the country's financial stability and consumer protection. The switch to bitcoin had made paying remittances more difficult for many Salvadorans, because the fees associated with the bitcoin transactions were several times as expensive as traditional remittances. Prior to the crash, several other countries had announced plans to adopt bitcoin as legal tender, but only the Central African Republic has done so (Roy, 2021).

The US economy is believed to be successful because of the aggressive absorption of high technology. It is worth noting that Asian manufacturers are also supporting their activities with artificial intelligence to develop products. In addition, several problems with climate modeling are solved by deep learning models. In addition, the US defense industry, which develops *dual-use* technologies, was called to make deep learning and IoT available to manufacturers, innovators and entrepreneurs. An interesting example of combining deep learning and parallel computing is the supercomputer IBM Watson that is helpful in making decisions, including medical diagnostics. It is equipped with artificial intelligence enables correct diagnostics in 90% of lung cancer cases (Balicki, Korłub, Tyszka, 2016). Nuance Communications Inc. uses Watson with speech recognition skills and medical knowledge in medical diagnostics. IBM is also exploring the use of Watson as a lawyer assistant (Shouwei, Mingliang, Jianmin, 2013).

French company ARIA Technologies performs calculations to predict flood risk for insurance companies by simulating extreme rainfalls. In addition, the impact of climate change on natural hazards is simulated. It is worth mentioning one more interesting project is IBM Blue Brain that try to simulate the human brain, one should reckon with modeling 100 billion neurons and 1 trillion neural connections (Balicki et al., 2015; Hanschel, Monnin, 2005).

Aldrich et al. show that GPUs estimated 200 times faster computing than CPUs when analyzing business cycles in markets (Aldrich E., 2011). Genetic programming is an alternative to classic stock exchange applications based on technical analysis, such as the CRISMA system, which determines a positive return on investment within 10 years with transaction costs of 2% (Chen, Kuoand, Hoi, 2006; Brabazon, Kampouridis, O'Neill, 2020). Frequently, program performance is compared with business strategies such as a *buy and hold* strategy (Schwaerzel, 2006) and more advanced autoregressive methods (Svangard et al., 2002).

Genetic programming may produce decision-making rules during dynamically changing conditions on the stock market. An investor may buy the company's stock and holds its assets for a relatively long period of time and sells when it makes a profit (Potvin, Soriano, Vall, 2004). In results, an algorithm provides buy and sell rules that can be triggered when certain conditions are met.

### 6.2. Long Short Term Memory neural networks for estimation of predicted values

Deep learning models are used in computer games based on behavioral models, which inspired similar applications in financial systems. Models are most often used in two areas: to simulate phenomena taking place on capital markets and to support decisions made on stock exchanges (Henley, Hand, 1996). It is assumed that the propensity to take risk depends on the personality of the investor. The capital market is modeled as a set of autonomous entities, each of which has the same goal (Atsalakis, Valavanis, 2013). The ability to model interactions between rival agents facilitates the simulation and analysis of occurring phenomena. The strategies of cooperation and negotiation of agents are also taken into account (Bosse, Siddiqui, Treur, 2010). On the other hand, simulating the market situation allows to predict trends and make recommendations for transactions (Balicki, 2013).

On the other hand, Long Short Term Memory (LSTM) artificial neural networks are the most efficient approach for stock market investments (Gately, 1999). LSTMs are learned based on historical data of time series that is available through technical analysis (Nazari, Alidadi, 2013). In the case of the anticipation of numerical values, we consider a regression problem, and in the case of symbolic values – the classification one. In the context of stock market prediction, we are dealing with a specific problem of predicting time series (Baesens et al., 2003). A training algorithm allows adjusting the synaptic weights in the model (Davis, Karim, 2008). Analyzing many training sets requires computing cloud.

The LSTM model remembers their states in memory cell. Data is passed through the cell information, and then is accepted or removed. The block of LSTM consists of a block input, three gates (input, forget, and output), a memory cell, and output activation function (Kumar, Haider, 2021). Past information is saved that was learned in previous steps (Figure 5). LSTM has two transfer states $c^t$ (cell state) and $h^t$ (hidden state). Among them, the transmitted $c^t$ changes very slowly, usually, the output $c^t$ is the $c^{t-1}$ passed from the previous state plus some values, while $h^t$ is often very different under different nodes. First, use the current input $x^t$ of LSTM and the $h^{t-1}$ passed from the previous state to concatenate and train to obtain four states (Aslam, Rasool, 2021).

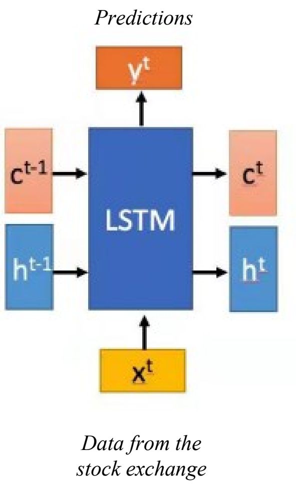


**Figure 5.** LSTM model to support stock market investments.

Source: Atsalakis G., Valavanis K. (2013). Surveying stock market forecasting techniques - Part I: Conventional methods in Computation Optimization in Economics and Finance Research Compendium, New York: Nova Science Publishers, p. 35.

An example of a prediction for the Warsaw Stock Exchange is based on a table with five columns: opening price, highest price on a given day, lowest price on a given day, closing price and trading volume. More advanced models can use information from social media about a sentiment of the considered organizations. Besides, the other input data can support decision making: average from the last $n$ days or Gini index.

For the selected organization, data of opening price are added to verify the prediction for one day and seven days ahead. Data of opening price before 30 days are added to train the model. 75% of the data is split as train data, and 25% is test data. Figure 6 shows how the dataset is split.

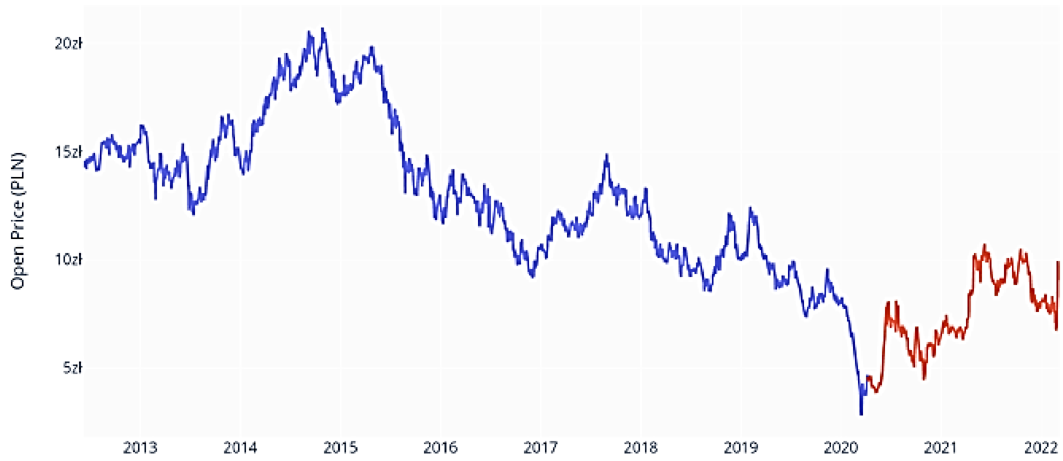


**Figure 6.** Division of PGE company data for supervised training (blue line) and testing (red line).
Source: Own study.

Figure 7 shows the simulated dependence of the achieved profit by the LSTM. The experiment was carried out in relation to PGE company stocks. Concurrently, two other predictions have been prepared by Support Vector Regression (SVR) (Awad, Khanna, 2015) and Convolutional Neural Networks (CNN) (Balicki, 2009). We can observe that prediction by LSTM (purple line) is very close to the actual values of PGE (blue line).


**Figure 7.** Prediction of PGE open price between July 2020 and January 2022.
Source: Own study.

Deep neural networks are also used to optimize the stock portfolio (Staniec, 2003). Tasks related to financial activities for which the support based on artificial neural networks was successfully applied include the analysis of the creditworthiness of bank customers (Yobas, Crook, Ross, 2000), risk analysis related to granting a mortgage loan (Zan et al., 2004), and building bid strategies. Besides, forecasting index values (German Credit Dataset, 2022) and directions of trends on the stock exchange can be determined. Some models predict risk classes of stock exchange financial instruments, detection of regularities in changes in the prices of financial instruments and forecasting of bankruptcies (Brown, 2011). Neural networks do not contain any assumptions about the modeled phenomenon. For this reason, they can identify local market disturbances or dependencies occurring for a short time in financial markets.

An alternative way of stock exchange investments is the implementation of virtual brokers to execute transactions on the market. Automated trading systems are used in high frequency trading (HFC). Currently, we can own shares for mille - or even microseconds. The selected models do not exhaust the enormous potential of using other methods of artificial intelligence in financial systems (Gierusz, Koleśnik, 2021). An important dilemma is how to develop machine learning models for an estimation of the informative value of the financial result in the light of the usefulness of the financial statements (Martyniuk, 2013).

## Remarks and conclusions

The results of theoretical research and numerical experiments confirmed that the impact of digital technologies on the accounting information system supporting decision-making processes is significant. Developing ideas for the implementation of solutions for the effective use of digital technologies, and then their implementation in cooperation with the business world is necessary to do not feel only the negative effects of automation and robotization. Then, it is possible to develop the emergence of new, creative jobs and, consequently, a higher position in the rankings regarding the level of digitization, as well as innovation and competitiveness.

The use of cloud computing, the Internet of Things and deep learning models creates a great opportunity to avoid deep crisis in the economy due to the negative effects in the banking systems, a pandemic lockdown or war perturbations. In particular, the models of deep neural networks implemented on cloud computing, predict the exchange rate, symptoms of corporate bankruptcy, and banking crises. Besides, we characterize issues related to deep learning for prediction in financial systems. Finally, a case study is studied for using Long Short Term Memory artificial neural networks for stock market investment.

Answering the questions we asked at the beginning of the article, it is worth emphasizing that the harmonious development of smart information technologies can be effectively supported by carefully investing significant funds in the development of modern technologies such as deep learning, Internet of Things and cloud computing. To support this hypothesis, many examples were presented or cited. It will also ensure the synergy effect resulting from the balanced interaction of key domain systems.

Also in the paper, we tried to answer the question, how to use modern technology, including machine learning, Internet of Things, and cloud computing. Complex deep learning models of the intelligent enterprise require a lot of computing power for training. Summing up, we can emphasize that we observe a very significant influence of deep learning and the Internet of Things on directions of development of integrated financial systems.

An interesting direction for further research is the development of the other deep learning models such as Convolutional Neural Networks for estimating the risk of the banking sector. Moreover, an important problem is the use of deep artificial neural networks for testing the credibility of potential borrowers.

The use of digital technologies accelerates the digital transformation towards Industry 4.0, in which the implementation of all processes, including accounting, is changing. As a consequence, the role of employees is also changing, including accounting specialists, mainly management ones, who are responsible for the quality of material information created for both internal and external financial reports. Business analysts are gaining more and more importance, while certain activities, such as accounting records, will be automated. The right choice, implementation and effective use of modern digital technologies in the accounting information system of Industry 4.0 requires the acquisition of new knowledge, competences and skills.

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