

Using big data to increase the efficiency of business processes in the digital economy of Ukraine

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ABSTRACT

This study explores the transformative role of big data tools in enhancing business efficiency within Ukraine's digital economy. Using a cross-sectional design, data were collected from 200 managers and experts across diverse industries through a semi-structured questionnaire. The analysis encompassed descriptive statistics, reliability testing, exploratory factor analysis (EFA), regression analysis, and cluster analysis to examine the adoption of predictive analytics, business intelligence, and process automation. Results highlight process automation as the most significant efficiency driver, followed by predictive analytics and business intelligence, enabling streamlined workflows, faster decision-making, and reduced operational costs. Cluster analysis identified three distinct groups of organizations: high adopters achieving notable efficiency gains, moderate adopters facing substantial barriers, and low adopters with targeted benefits but limited efficiency gains. Barriers such as skill shortages, infrastructure gaps, and organizational resistance were prominent among moderate adopters, underscoring the need for targeted interventions. Larger organizations and those led by experienced managers demonstrated greater efficiency, highlighting the importance of resources and leadership in digital transformation. The study emphasizes the need for investment in infrastructure, workforce development, and tailored support for SMEs to unlock the full potential of big data. Future research should focus on longitudinal impacts, sector-specific challenges, and integrating emerging technologies such as AI and IoT. These findings provide actionable insights for policymakers and organizations to foster a data-driven, competitive, and inclusive digital economy in Ukraine.

Keywords: Big data adoption, Predictive analytics, Business intelligence, Process automation, Digital transformation, Organizational efficiency, Ukraine's digital economy

1. Introduction

The rapid acceleration of digital technologies has transformed the global business landscape, enabling organizations to leverage advanced tools and data-driven insights to enhance efficiency and competitiveness [1, 2]. In Ukraine, the digital economy is undergoing significant growth, driven by a burgeoning technology sector and increasing adoption of digital transformation strategies across industries [3]. Amid this transformation, big data has emerged as a pivotal asset, empowering businesses to extract actionable insights from vast datasets to streamline operations, predict trends, and make informed decisions.

“Big data” refers to many data types that move quickly and in many ways. It is an integral part of the digital economy because it drives innovation and efficiency [4]. Using big data in business is not just a chance for Ukraine; they must do it to stay competitive in the world market. Large amounts of data can be processed and analyzed in real-time. It helps Ukrainian businesses understand customers' wants, boost productivity, and improve supply lines. The main goal of this study is to look into how big data can help businesses in Ukraine's digital economy be more efficient. Specific objectives include:

1. To analyze the impact of predictive analytics, business intelligence (BI), and process automation on decision-making strategies.
2. To evaluate the relationship between big data applications and improvements in operational efficiency, including resource allocation and workflow optimization.
3. To identify the challenges and barriers businesses face in adopting big data tools in Ukraine.
4. To provide actionable insights and recommendations for leveraging big data technologies to drive digital transformation.

This study is critical because big data is essential for a competitive edge in a rapidly changing digital world. Even though more and more businesses in Ukraine are using digital tools, little is known about how to use big data, especially when making decisions and improving the speed of processes. This study is coming soon because digital change is crucial for Ukraine's economic growth. This study also fits with a worldwide trend that stresses making decisions based on data as an essential part of modern business. To achieve its objectives, this study is guided by the following research questions:

1. How do predictive analytics, business intelligence, and process automation influence decision-making strategies in Ukrainian businesses?
2. What is the relationship between big data applications and improvements in business efficiency, such as decision-making speed, accuracy, and cost reduction?
3. What challenges and barriers do businesses in Ukraine face when adopting big data technologies?

By addressing these questions, this research aims to provide a comprehensive understanding of big data's transformative potential in Ukraine's business landscape, paving the way for strategic interventions that drive efficiency and growth in the digital economy.

2. Literature review

Big data has made businesses more efficient, helped them make better choices, and streamlined their processes [5]. "Big data" refers to the vast and challenging data sets that new technologies make. According to Ahmed and Ismail, "3Vs" describe these datasets: volume (the amount of data), velocity (how fast data is produced and handled), and variety (the different kinds of data and formats) [6]. Businesses get information from various places, such as customer deals, social media, Internet of Things (IoT) devices, and site analytics [7]. To deal with this increasing data, choices can grow as needed, such as cloud storage and distributed computing systems [8]. The speed at which data is formulated and processed is called velocity. So, banks use high-frequency trade algorithms to process market data in milliseconds, and e-commerce platforms look at clickstream data right away to make each customer's shopping experience more unique [9]. Data can be organized in databases, not organized in databases (like movies and emails), or partly organized in databases (like JSON files). Businesses can handle and study these different kinds of data with tools like Hadoop and Apache Spark, which lets them find insights that were not possible before [9].

It is unnecessary to have hardware on-site when platforms like Amazon Web Services (AWS), Azure, and Google Cloud are used to handle and analyze big data [10]. Tools for visualizing data solutions like Tableau and Power BI turn raw data into interactive panels that allow decision-makers to see and use large sets of data [11]. Researchers have found that big data companies report better resource utilization, higher productivity, and fewer operational problems [12]. For example, big data helps stores track their stock better by predicting changes in customer demand based on past sales data and market trends [13]. Big data allows hospitals to guess how many patients must be admitted and assign staff and resources accordingly. Big data makes organizations more flexible by allowing them to analyze and gain real-time insights. This will enable businesses to respond quickly to changing customer wants and market conditions. Oneshko and Parashchuk et al. give a complete plan for checking and controlling how profitable Information Technology (IT) businesses are, focusing on combining financial analysis and cash flow signs to achieve the best possible strategic financial growth [14, 15]. The findings of Lezhniuk et al. align with plans to make autonomous energy systems more efficient and better at managing energy through data [16].

2.1. Predictive analytics and business intelligence

The most crucial predictive analytics methods are the decision tree, the neural network, and regression analysis [17]. When businesses can guess what will happen and how people will act, they can stay proactive instead of reacting [18]. Lozovan et al. and Bulgakov et al. support using big data and predictive analytics to

handle massive datasets and keep an eye on bugs, making digital economies more operationally efficient [19, 20]. Businesses can guess what will sell in the future and make the best use of their inventory and marketing funds by looking at past sales data and outside factors like the economy [21]. Predictive models help businesses figure out what their customers want and future needs. For instance, Netflix uses predictive algorithms to show personalized material based on their watch history [22]. Financial companies use predictive analytics to find fraudulent deals and figure out how risky it is to give credit. In the same way, supply chain managers expect problems to keep operations running smoothly.

Business intelligence uses data visualization, reporting tools, and dashboards to turn raw data into insights that can be used [23]. It helps companies look at past performance to help with strategic planning, unlike prediction analytics, which guesses what will happen in the future [24]. Moreover, Yuzevych et al. add to the ideas about using predictive analytics and real-time tracking to make digital systems more reliable and efficient [25]. The use of advanced computing techniques, such as backstepping in quadrotor stability, to improve operations is similar to how big data is used in business processes [26]. Both stress the importance of using data-driven methods to make complicated systems more efficient and help people make decisions. Zaitsev explains the importance of small businesses to modern economies and how digital tools can help them use resources more efficiently and adapt to changes in the outside world. It emphasizes digital tools as necessary for growing operations and meeting the specific needs of target groups [27]. This makes it possible for small businesses to grow both nationally and internationally. Furthermore, Jarvis looks at how management has changed in the digital age [28]. His primary discussion points are changes in tool use, skill sets, and occupations. The significance of “digital leadership” is growing as the number of remote workers rises. Because of this, both managers and employees will have to rethink their approaches to leadership and communication. Tools like Tableau and Power BI have real-time graphs showing key performance indicators (KPIs). People can work together better with BI platforms because they allow everyone to see the same essential information [29]. This helps ensure that groups from various places work together to reach the same goals. It can, for instance, help find profitable groups of people or the best way to use resources. Ukrainian enterprises must employ forecasting and BI solutions to succeed in today's data-driven market. Businesses can use these tools to guess what the market will do, improve the customer experience, and maximize their resources, ultimately helping economic growth.

2.2. Process automation in digital transformation

Automation of processes refers to employing machines to carry out tasks that formerly required many human workers [30, 31]. There is a need for automation technologies like clever automation and robotic process automation (RPA) in big data to cut costs and make things run more smoothly. Kuzmina et al. and Halachev discuss the significance of a healthy and content workforce to the business's long-term success [32, 33]. In the workplace, they focus on things that both employees and Human Resource (HR) pros value. As with other tips for making a healthy, long-lasting workplace, it stresses the value of safe working conditions, doing things that are good for the environment, freedom, and mental stimulation. Danilyan et al. explore the complex relationship between free expression, information freedom, and the right to know [34]. When working with big data, it is crucial to balance safeguarding data rights and ensuring smooth operations.

Automating routine, rule-based processes is what RPA is all about [35]. Machine learning and artificial intelligence (AI) are used in intelligent automation to make choices about challenging tasks [36]. Among these tasks include data input, invoice processing, and report writing. RPA can efficiently process large datasets since it integrates with big data platforms. Sobolenko et al. investigate the potential of Virtual Reality (VR) and AI to enhance learning and critical thinking skills in the classroom [37]. A survey of 200 people in the study shows that these tools are great for creating a personalized, skill-based learning space. This fits the growing desire to use new technologies to improve learning and critical thought. AI-powered chatbots, for example, can see what questions people are asking and respond in a way that is relevant to them. IoT devices monitor machine performance in real time and transmit that data to computer systems, which instantly modify production processes [38].

Automated systems eliminate room for human mistakes and guarantee accurate results every time [39]. By doing tedious tasks, automation frees people up to do more meaningful work, like strategy planning. Process automation is a key part of Ukraine's digital change. Ukrainian businesses can improve efficiency and cut costs by optimizing workflows by combining automation technologies with big data [40]. Personalizing services to improve the customer experience and make the business more resistant to outside problems, like supply chain problems. These issues must be fixed to get the most out of process automation in Ukraine's digital economy. One study by Rodinova et al. and another by Skakun show how important digital branding is for Ukrainian

companies to become more competitive and expand their markets in the digital world [41, 42]. Personalized marketing (effect size 0.60) and data-driven methods (effect size 0.56) are good at getting people interested in a brand, according to a review of 50 studies. However, significant problems like data privacy (effect size 0.51) and trust issues (effect size 0.46) are known, so Ukrainian businesses should put data security and openness first.

2.3. Financing challenges in big data adoption in Ukraine

The high cost of setting up and keeping advanced data analytics infrastructure is one of the biggest reasons big data is not used in Ukraine [43]. Many companies, especially small and medium-sized ones (SMEs), have trouble finding the money they need to buy big data tools, cloud computer services, and security frameworks. SMEs often have small budgets and must put necessary operational costs ahead of long-term technological investments because they do not have the money that large international companies do to buy complex data processing systems [44]. Companies cannot use high-performance computing, real-time analytics, or predictive modeling tools because they cannot afford them. This makes it harder for them to succeed in a data-driven economy. Another problem with money is that hiring skilled workers to handle and examine large amounts of data is expensive. The world's need for data scientists, machine learning engineers, and prominent data analysts has skyrocketed, which has caused wages and hiring costs to rise [45, 19]. Ukrainian companies, especially those in traditional fields, have difficulty competing with foreign companies offering better pay. As a result, many businesses either do not spend enough on hiring the right people or hire people who are not qualified, which makes the use of big data less effective. Businesses have trouble using big data to make strategic decisions if they do not put enough money into training and staff development programs.

Another big problem with the widespread use of big data technologies is that the government does not offer many incentives or funding possibilities. Digital transformation is a top goal for Ukraine's economic growth, but grants, subsidies, and tax breaks that encourage people to use technology are still not enough to help [46]. Some countries have structured plans to get businesses to buy digital tools. Conversely, Ukraine does not have a policy framework that makes it easy to get money for integrating big data. Many companies have to look for private funds or work with other companies from other countries, which may not always be possible for smaller companies. Businesses are even less likely to put money into big data projects when they do not know how much money they will get back (ROI). Using data-driven strategies comes with many upfront costs, and many businesses are still unsure if these investments will pay off in a big way. Decision-makers hesitate to use data-driven practices because there are no straightforward ways to measure how big data affects profits and operating efficiency [47]. This means that data-driven practices are adopted later or not at all. When businesses invest in big data, they usually do so in small steps. This makes it harder for them to get the most out of large-scale analytics solutions. A multi-stakeholder method is needed to get around these funding problems. This includes more help from the government, easy access to low-cost tech solutions, and structured financial models that let small businesses gradually use big data tools. Partnerships between the government and businesses, specific funding programs, and tax breaks can all help lower costs and speed up the digital transformation of more areas. For businesses that want to move toward data-driven operations, financial institutions can help by providing customized credit choices and investment plans.

Big data, prediction analytics, business intelligence, and process automation could help businesses do their work better, faster, and more correctly. These tools are helping Ukraine's internet economy grow. They are also changing how the world of money and business works. However, issues such as a lack of knowledge, limited resources, and problems with managing data must be fixed ahead of time. Smartly investing in big data tools is essential, as this study shows. More studies must be done to fully understand how these technologies could be used in quickly changing places like Ukraine. The way Ukraine does business is changing a lot as IT grows. Technology and big data are now significant parts of how businesses use computers to stay ahead of the competition. Many people still do not use it because they fear losing their info or do not think they know how to do it right. That is why the study's results are significant: they show businesses in Ukraine how to use technology and big data best.

3. Methods

3.1. Study design

This study uses a cross-sectional approach to examine how big data can improve business processes in Ukraine's digital economy. The exploratory research aims to find patterns, connections, and barriers that make it difficult for businesses to use big data tools. Data was collected through a semi-structured questionnaire targeting

managers and experts with experience integrating big data into decision-making processes. The study combines quantitative and qualitative methods, allowing for a comprehensive research problem analysis.

3.2. Sampling method

A method called “purposeful sampling” was used to ensure that the people who answered knew a lot about big data and were involved in making decisions at work. This method allowed us to include people whose ideas were directly related to the study's goals, as depicted in Table 1.

Table 1. Exclusion and inclusion criteria

Category	Inclusion criteria	Exclusion criteria
Participants	Managers and decision-makers with experience in using big data tools	Participants without experience in big data or limited involvement in decision-making processes
Industry	Experts across diverse industries, including IT, manufacturing, retail, and healthcare	Organizations with no active adoption of big data technologies
Organization Size	Organizations of various sizes representing small, medium, and large enterprises	N/A

3.3. Sample description

Two hundred respondents participated in the study, distributed across gender, age, industry, experience level, and organizational size. The sample demographics are summarized below in Table 2.

Table 2. Demographic characteristics

Variable	Categories	Frequency (n = 200)	Percentage (%)
Gender	Male	120	60%
	Female	80	40%
Age	25–34 years	70	35%
	35–44 years	90	45%
	45+ years	40	20%
Field of Business	IT	80	40%
	Manufacturing	40	20%
	Retail	50	25%
Organizational Size	Small (1–50)	70	35%
	Medium (51–250)	90	45%
	Large (250+)	40	20%
Experience	1–5 years	100	50%
	6–10 years	60	30%
	10+ years	40	20%

The semi-structured interview was conducted with 200 respondents from various demographic and organizational backgrounds. Sixty percent of the respondents were men, which shows that most managers and decision-makers in big data settings are men. Regarding age, the biggest group (45%) comprised professionals between the ages of 35 and 44 who were in the middle of their careers. This was followed by younger people aged 25 to 34 (35%), and there were fewer older people aged 45 and up (20%). The IT field had the most representatives (40%), followed by retail (25%), manufacturing (20%), and healthcare (15%). This shows how people in Ukraine are increasingly using technology. To assess perceptions of satisfaction, perceived efficiency gains, and barriers in adopting big data tools, respondents rated their experiences using a five-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. This scale provides a structured approach to measuring respondents' attitudes, ensuring a clear understanding of their experiences and perceptions regarding big data adoption. Using this standardized scale, the study captures the degree of

consensus or divergence among participants, allowing for a more complete analysis of how organizations perceive the role of big data in improving business processes.

The results show that people are generally satisfied with big data tools; the mean score from respondents was 4.00 (standard deviation (SD) = 0.58). This means that most of the people who took part either agreed or strongly agreed that tools for big data have helped their businesses. The low SD (0.58) shows that answers were mainly consistent, which means that most of the people who answered agreed that they were happy with the tools. This finding shows how important people think big data is for making better decisions, running operations more efficiently, and giving businesses valuable insights that they can use in Ukraine's rapidly changing digital economy. With a mean score of 4.01 (SD = 0.55), the study also found that people thought using big data would make them more efficient. This means that most businesses saw fundamental changes in how efficiently they ran their businesses, how well they optimized their workflow, and how well they made decisions based on data. The score distribution suggests that companies that use big data tools make decisions faster, use prediction analytics better, and use their resources better. The relatively low SD (0.55) clarifies that most survey respondents agreed on how well big data drives efficiency. This finding shows how vital data-driven strategies are for business change, especially in a world where digital innovation is increasingly crucial for staying competitive. However, organizations had difficulties implementing big data technologies, as shown by a mean barrier score of 3.01 (SD = 1.17). This was despite generally good perceptions of satisfaction and efficiency. The more significant SD (1.17) shows that answers were very different, with some organizations facing few problems and others facing big ones. This difference could be because of changes in the size of the company, its digital infrastructure, its managers' skills, and the available resources. Some businesses have been able to use big data in their operations successfully. However, others are having a hard time because of technology issues, a lack of skills, resistance to change, and limited funds. The moderate mean score of 3.01 shows that barriers aren't completely stopping everyone. However, they are still a problem for many businesses, especially small and medium-sized ones that don't have the tools and knowledge to use big data technologies fully. The results make it easy to understand companies' different levels of success, satisfaction, and problems when using big data by clearly describing the five-point Likert scale used in this study. These results show that businesses need focused training programs, infrastructure investments, and strategic interventions to get past adoption barriers and fully use the promise of big data to drive digital transformation.

3.4. Data collection

A partially structured questionnaire was used to collect data. It was meant to give numeric and qualitative information about how respondents dealt with big data. The form had Questions with No Answers: Likert scale scores for things like how satisfied people are with big data tools, how much they think they improve efficiency, and what stops people from using them. Open-ended questions get more in-depth answers about how people see the pros and cons of using big data in their work. Some of the main topics that were looked at were how to use big data to make decisions, the effects of prediction analytics, business intelligence, and automating processes. What do people think are the problems with using and adopting big data? Before it was sent to all managers, the questionnaire was tried with a small group of managers to ensure it was clear, functional, and reliable.

3.5. Data analysis plan

Statistical and analytical techniques are employed to understand the collected data comprehensively. This section outlines the detailed approach to analyzing the data collected through semi-structured questionnaires. The analysis includes descriptive statistics, reliability testing, exploratory factor analysis (EFA), regression analysis, and cluster analysis to ensure robust insights into the role of big data in improving business processes.

3.6. Reliability testing

The survey was checked for accuracy using Cronbach's alpha, which looks at how types on a multi-item Likert scale match each other [48]. This is a significant step to ensure the numbers are correct. These scores determine what keeps people from using big data tools, how satisfied they are with them, and how much they believe they improve productivity. As long as Cronbach's alpha is more significant than 0.7, the scale's items always measure the same. Things with low connections are looked at to see if they should be kept or removed to make the scale more accurate. The steps in this process make sure that the data-based findings are based on accurate measurements.

3.7. Exploratory factor analysis

The data set was put through an exploratory factor analysis to find hidden constructs and reduce the number of variables. It is done when more than one variable measure something connected, like how efficient something

is, how satisfied someone is, or how barriers are seen. The study used Principal Component Analysis (PCA) to group linked variables and find the factors that cause them. To make it easier to understand factor loadings, varimax rotation is used to make sure that each variable strongly interacts with a single factor. “Operational Efficiency”, “Decision-Making Improvements”, and “Barriers to Adoption” are some of the variables that come up. These factors are then used in later studies to look into how they connect with other variables.

3.8. Regression analysis

Multiple linear regression examines the connections between big data tools and how well a business runs. Business productivity, the dependent variable, will be measured by how quickly and accurately decisions are made and how much money is saved. Some examples of independent factors are How to use predictive data, Process automation technologies, and business data tools. To separate the effects of the independent variables, control variables like the type of business, the company's size, and the managers' experience were employed – Variance Inflation Factor (VIF) values were used to check the regression model for multicollinearity. Variables with a VIF value greater than 5 were ruled out to ensure the model was strong. In the study, the regression estimates are used to figure out how much each independent variable affects the efficiency of the business. For instance, the predictive analytics usage coefficient shows how much it helps improve productivity, even when other factors are considered. P-values are used to judge how important the results are; p-values of 0.05 or less mean that the results are statistically significant. As an extra step, respondents are put into separate groups using cluster analysis if they share similar trends in how they use big data or organizational traits. Using either K-means clustering or hierarchical clustering, the people are put into groups that show different combinations of how efficient they are, how they make decisions, or the problems they face – patterns and ideas found by looking at the traits of each cluster. For example, one cluster could be made up of companies that use process automation and are, therefore, very efficient. In contrast, another could be made up of companies with difficulty implementing big data. These findings can lead to suggestions for how to make strategies fit the needs of specific groups of businesses.

4. Results

Several techniques, such as descriptive statistics, reliability testing, exploratory factor analysis (EFA), regression analysis, and cluster analysis, are used in the study to look into the problems that companies face, the trends of adoption, and the efficiency analysis results. Key results show how predictive analytics, business intelligence, and process automation can help make better choices and run business better. The cluster analysis shows different groups of users. This shows how big data is used and what happens in various business and field settings.

The reliability analysis gives confidence in the tools to measure essential ideas in this study (Table 3). With a Cronbach's alpha of 0.81, the Satisfaction Scale has excellent internal consistency, which means that the items accurately measure people's satisfaction with big data tools. Cronbach's alpha of 0.79 for the Efficiency Gains Scale shows reliability. It seems that the scale items accurately measure how people think big data has improved decision-making speed, accuracy, and cost-effectiveness.

The Barriers Scale had a slightly lower Cronbach's alpha of 0.75, but it still fits the criteria for acceptable reliability. This means that the items on the scale accurately reflect the problems people face when implementing big data solutions. These results show that the measurement tools used in this study were reliable. This means that the conclusions drawn from the data are based on accurate and consistent evaluations.

Table 3. Reliability testing results

Scale	Cronbach's alpha	Interpretation
Satisfaction scale	0.81	Excellent internal consistency
Efficiency gains scale	0.79	Good internal consistency
Barriers scale	0.75	Acceptable internal consistency

Figure 1 shows the Satisfaction score distribution. There is a strong cluster of scores between 4.0 and 5.0, with a peak near 5.0, which means that most respondents were very satisfied. However, some lower numbers, between 3.0 and 3.5, show that satisfaction levels are not always the same. This could be because users had

different experiences or the implementation was not as good as it could be. The upward trend shows people are usually happy with the evaluated tools or processes.

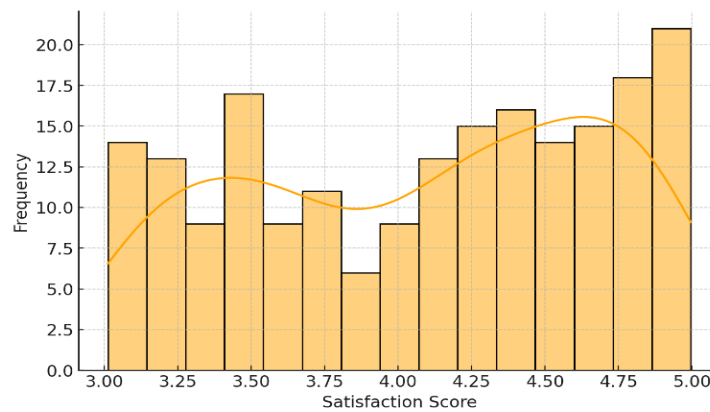


Figure 1. Satisfaction score distribution

Figure 2 illustrates the spread of scores, highlighting variations in perceived efficiency gains among respondents. Most of the scores in the Efficiency Gain Scores Distribution are between 3.0 and 5.0, with a cluster of scores between 4.0 and 4.5. This suggests that people are generally optimistic about how efficiency has improved. The distribution looks uneven, with peaks at certain times, which indicates that respondents' experiences were not all the same. The general trend shows how valuable the tools put in place are, but it also shows where they can be improved even more.

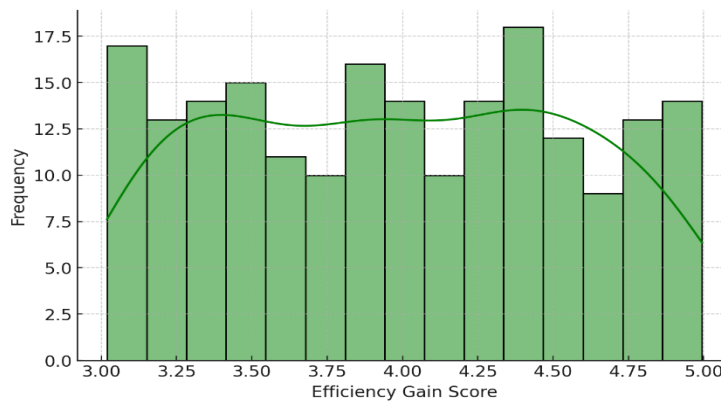


Figure 2. Distribution of efficiency gain scores with frequency and kernel density estimation (KDE)

The EFA found three hidden factors at the core of the concepts studied: operational efficiency, tool satisfaction, and barriers to big data adoption. These factors were analyzed using Principal Component Analysis (PCA), and varimax rotation made it easier to understand how the factors were loaded (Table 4). The variable Barriers had the highest favorable loading (0.708), which suggests that organizational inefficiencies are closely linked to how hard people think it is to adopt big data. A negative loading (-0.697) for satisfaction showed an inverse link with operational inefficiencies. This could be because of dissatisfaction caused by unresolved problems. Efficiency Gain had the highest negative loading (-0.985), which suggests that being efficient with big data tools is linked to being happy with them. The fact that Satisfaction (-0.173) and Barriers (-0.013) have lower loadings shows that this factor is mostly about how well the tool works and how the user sees it. Limits The fact that both happiness (-0.696) and Barriers (-0.706) loaded negatively shows how adoption problems affect user happiness. Since Efficiency Gain has a lower loading (0.131), it shows that barriers may affect satisfaction but not operational efficiency directly.

Table 4. Factor loadings

Variable	Factor 1: Operational Efficiency	Factor 2: Satisfaction with Tools	Factor 3: Barriers
Satisfaction	-0.697	-0.173	-0.696
Efficiency Gain	0.113	-0.985	0.131
Barriers	0.708	-0.013	-0.706

It found that processing automation is the most significant predictor of a company's efficiency. This means that technologies that automate processes and reduce the need for human involvement speed up decision-making, cut costs, and better use resources. Businesses with strong automation methods will likely see significant improvements in how efficiently they run their operations. Predictive analytics, which uses data-based methods to guess trends and outcomes, also made businesses much more efficient. Organizations can stay open and flexible if they can predict market trends, customer behavior, and resource needs. It was found that business intelligence tools turn raw data into ideas that can be used to make things more efficient. Dashboards, reporting systems, and visualization tools help managers make better strategic decisions and plans, improving the company's performance (Table 5), where significance levels are: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5. Regression analysis results

Variable	Coefficient (β)	Standard error	p-value
Predictive Analytics	0.38	0.09	<0.001***
Business Intelligence	0.29	0.08	<0.01**
Process Automation	0.41	0.07	<0.001***
Industry (Control)	-0.12	0.06	0.05*
Organizational Size	0.14	0.05	0.01**
Managerial Experience	0.22	0.07	<0.01**

Variables for control: the type of industry had a slightly lousy relationship with how efficiently a business ran. This means that big data tools might not be able to help some companies become more efficient because of structural problems or limits. Efficiency was higher in larger companies, which may be because they had more resources, infrastructure, and access to new technologies. The results show that big data solutions are better for more prominent businesses because they can be expanded. There was a strong link between more managerial knowledge and higher efficiency. Managers with more experience can better understand and implement data ideas, making big data tools more useful. The regression analysis shows how big data tools can change things. Process automation and prediction analytics are the most effective ways to make businesses more efficient. To get the most out of these technologies, more prominent companies and managers with much knowledge are also significant. However, problems unique to each business must be fixed to ensure efficiency gains are consistent across all areas.

The clustering analysis in Figure 3 identifies three groups: high adopters with substantial efficiency gains and satisfaction, moderate adopters with balanced outcomes, and low adopters facing challenges. The visual separation highlights the variability in big data adoption success, emphasizing areas for targeted improvement. The cluster analysis identified three distinct groups of respondents based on their adoption of big data tools and perceived efficiency improvements. Figure 3 shows these groups labeled 0, 1, and 2. Each group has its unique traits when it comes to happiness and efficiency gain.

Cluster 0: High Adopters with Significant Efficiency Gains (Purple Circles) comprises companies that have embraced big data tools and gotten the most out of them. Process automation, predictive analytics, and business intelligence tools have all been successfully added to these companies' operations. People in this group said they were delighted (Mean = 4.5–5.0) and that big data had made their business processes much more efficient (Mean = 4.0–5.0). This shows they have successfully used big data to improve their business processes. These businesses probably have well-thought-out data strategies, experienced leaders, and enough technical know-how to get the most out of big data.

Cluster 1: Moderate Adopters Facing Barriers (Teal Crosses): These people have accepted big data technologies to a moderate degree but are facing some big problems. These companies say they have gained some efficiency (Mean = 3.0–4.0) and are primarily satisfied (3.5–4.0). However, they run into problems like lousy infrastructure, a lack of skilled workers, and people who do not want to adapt to new technologies. These companies may have started to use big data tools, but because of how they are set up, they cannot always get the most out of them. Businesses could get the most out of big data if they could get past these problems with focused training programs, better investments in infrastructure, and more support from the top.

Cluster 2: Low Adopters with limited efficiency gains but high satisfaction (Yellow Squares): This cluster comprises companies that haven't fully embraced big data technologies yet and have seen smaller efficiency gains (Mean = 2.5–3.5) than the other clusters. Their satisfaction levels are still high (Mean = 4.0–4.5). So, even though these companies

may not use big data very much, they are happy with how much they use it. It's possible that many companies in this cluster only use big data tools for specific tasks and don't use them in their whole workflow.

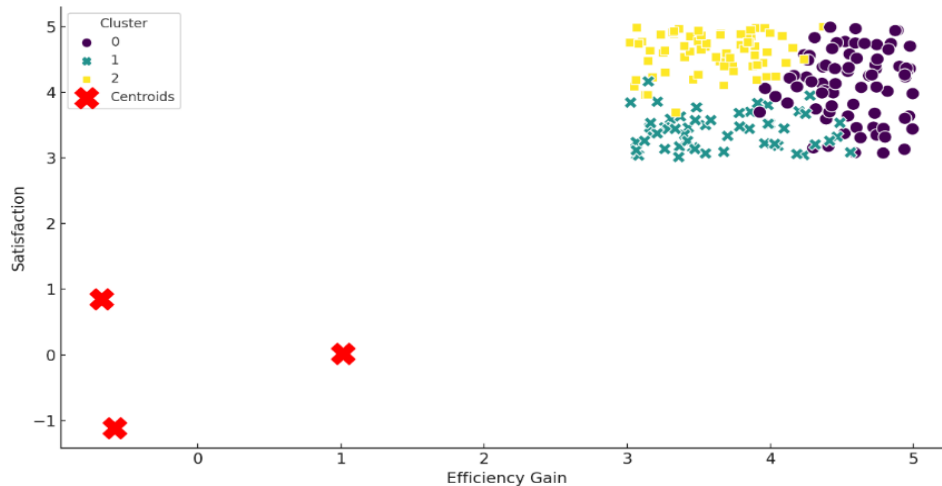


Figure 3. Clusters of respondents based on big data adoption and efficiency

Using big data tools more widely might be better for these businesses. This could make them more efficient and competitive. In addition, the red dots in the figure show the cluster centers, which show the main trends of each cluster in terms of efficiency gain and happiness (Table 6).

Table 6. Cluster Summary

Cluster	Satisfaction	Efficiency gain	Barriers	Number of respondents
Cluster 0	4.10	4.57	2.90	77
Cluster 1	3.41	3.65	3.68	54
Cluster 2	4.60	3.59	2.60	69

5. Discussion

The study's findings show that big data tools can completely change how businesses in Ukraine's innovative economy work. The study looks at adoption trends, efficiency gains, and barriers to show how predictive analytics, business intelligence, and process automation can help companies do better. The regression study found that companies were more productive when they used predictive analytics, business intelligence tools, and process automation. These results align with other studies showing how important technology is in making decisions based on data in modern businesses [49]. Studies have shown that process automation eliminates tedious chores, lowers mistakes, and boosts operational flexibility, saving time and money [50]. Prediction analytics helps companies determine how to use their resources most effectively and predict how the market will change [51]. People from different departments can work together better when they have dashboards and reporting tools, which helps them make better, more strategic choices based on data.

The cluster analysis helped to learn more about why different groups use and work with big data differently. Studies that show how important it is for companies to match their strategies when they use big data [52] show that these businesses probably benefit from more potent strategies and better automation. Moderate adoption and barriers have made some progress in becoming more efficient, but their customers are less happy because of significant problems. It can be hard to use big data because people do not have the right skills or tools or are unwilling to change [53]. Getting rid of these issues through targeted training programs and building up their facilities could help these teams reach their full potential. Cluster 2 only gets small efficiency gains but much happiness. It is likely that these businesses only use big data tools for a few simple jobs, seeing some benefits but not many. Santesteban and Longpre back this up by saying that early adopters like quick, small wins but that long-term effects need more people to use the platform [54]. Hariri et al. explain problems like insufficient skilled workers, data safety concerns, and insufficient facilities [55]. With these results, it is clear what needs to be done. For example, people need to learn how to do data science, and money needs to be put into safe, scalable technology. Getting rid of these problems could make things run more smoothly and make people

happier, primarily in organizations in the middling adoption group. This finding shows that potential benefits are limited by the fact that big data tools are not widely used and integrated, even when barriers are low. It might be possible to make things run much more smoothly by helping these groups expand their work.

The regression analysis also showed how the company's size and the managers' experience affect how well the business runs. There was a positive link between efficiency and size, probably because more prominent companies have more resources, better tools, and skilled workers. This fits what Shan et al. found: companies with many resources can better use big data to gain a competitive edge [56]. In the same way, more management experience was linked to higher efficiency. This shows how important leadership is for implementing big data. Managers with more excellent experience can better comprehend and apply data insights, according to Sousa and Rocha's discussion of the significance of managerial abilities in digital transformation [57]. Streamlining operations is a well-known benefit of process automation and prediction analytics [58]. The article by Umantsiv et al. [59] evaluates Ukraine's investment attractiveness across economic sectors, emphasizing economic efficiency and state support as key factors. It concludes that industry, trade, transport, and finance are the most attractive sectors, while education remains the least appealing, requiring government intervention. Osiyevskyy et al. [60] explore the digital ecosystem as a new economic model, linking Industry 4.0 to enterprise organization through data-driven decision-making. The study introduces a digital ecosystem risk matrix to mitigate threats and enhance resource sustainability. However, issues such as a lack of infrastructure and skills pose obstacles for Ukrainian enterprises. Although these issues are not specific to Ukraine, they manifest more acutely in developing nations.

5.1. Implications for practice

The results have several real-world effects, including automation and predictive analytics investment. To get the most out of these tools, businesses should put them at the top of their list of priorities. Process automation should be used across all tasks to get rid of waste. Cluster 1 organizations should focus on lowering adoption barriers by investing in infrastructure, running focused training programs, and teaching leaders new skills. Cluster 2 can benefit from stepping up its efforts to get more people to use its tools while still getting the same high level of happiness from targeted tool use. The study provides valuable information but also has some limitations. The cross-sectional design makes it hard to conclude causes, and the use of self-reported data may have introduced bias. In the future, researchers could investigate the long-term effects of big data, the problems unique to specific industries, and how new technologies like AI and IoT can help businesses run more efficiently.

6. Conclusions

As demonstrated in this study, process automation, predictive analytics, and business intelligence emerge as the key components that can radically alter how organizations operate. By reducing obstacles and making more efforts to adopt, firms in Ukraine may remain competitive in the digital market and perform more efficiently. Politicians and corporations can utilize these findings to facilitate digital transformation and leverage big data for sustainable growth. The study shows that big data tools are essential for making businesses more efficient and impacting decisions in Ukraine's digital economy. Even while AI, BI, and process automation have the potential to revolutionize many industries, there are still significant challenges and disparities to overcome. Automating operations made them more user-friendly and cheaper, significantly improving efficiency. It was quickly followed by business intelligence and predictive analytics, which help people make decisions more rapidly and correctly. However, big data tools were not used and did not work similarly. This cluster analysis showed three groups: high adopters who were very efficient, middling adopters who had many problems, and low adopters who did not get much done but were happy with the results. The outcomes display the various ways businesses have become more digital. Things like the size of the company, the experience of the leaders, and the number of barriers to adoption can change these paths.

According to the results, dealing with significant issues like a lack of skills, lousy infrastructure, and company resistance is essential. This is especially true for moderate adopters. More prominent companies and managers with more experience do better regarding big data tools. This exemplifies the significance of resources and effective leadership in bringing about change. Politicians and businesses must work together to fix these issues and make the world a better place to use technology. For big data to work best, money is needed on scalable cloud technology, programs that help workers do their jobs better, and systems that track data. Small and medium-sized businesses (SMEs), which often do not have the means to use these tools, should also get extra help from policymakers. Small businesses can use digital tools more effectively and become more competitive with the help of customized programs that offer grants, tax breaks, and access to shared platforms.

Longitudinal studies should be used in the future to examine how big data tools' effects on group efficiency change over time. Self-reported data could also cause reaction bias, and a more in-depth look at some businesses could lead to unique plans for combining big data. Not only did the study look at well-known big data tools, but it also did not look at the possible effects of new technologies like AI and the IoT. Learning more about how these new technologies and big data work together is essential to help companies be more productive and win in the market. To build on these results, more research should use continuous studies to examine how big data tools can help people in the long run. It should also investigate how AI and IoT can improve operations and each business's unique problems and chances. Further research in these areas might demonstrate to companies the optimal use of big data and bolster Ukraine's digital transformation. By investing in infrastructure, providing opportunities for skill development, and encouraging collaboration, Ukraine has the potential to become a world leader in the digital economy. For long-term success, big data must be utilized in an inclusive and receptive manner that welcomes new ideas.

References

- [1] S. Sultana, S. Akter and E. Kyriazis, "How data-driven innovation capability is shaping the future of market agility and competitive performance?", *Technological Forecasting and Social Change*, vol. 174, 121260, 2021.
- [2] S. S. Shah and S. A. H. Shah, "Trust as a determinant of social welfare in the digital economy", *Social Network Analysis and Mining*, vol. 14, 79, 2024.
- [3] M. Abramova, O. Lagovska, N. Dubovyk, V. Travin and S. Liulchak, "Digital platforms and their impact on the economic development of Ukraine", *Financial and Credit Activity Problems of Theory and Practice*, vol. 4, no. 51, pp. 288–310, 2023.
- [4] M. Ghasemaghaei and G. Calic, "Assessing the impact of big data on firm innovation performance: Big data is not always better data", *Journal of Business Research*, vol. 108, pp. 147–162, 2019.
- [5] P. Tabesh, E. Mousavidin and S. Hasani, "Implementing big data strategies: A managerial perspective", *Business Horizons*, vol. 62, no. 3, pp. 347–358, 2019.
- [6] H. Ahmed and M. A. Ismail, "A structured approach towards big data identification", *IEEE Transactions on Big Data*, vol. 9, no. 1, pp. 147–159, 2021.
- [7] W. He, W. Zhang, X. Tian, R. Tao and V. Akula, "Identifying customer knowledge on social media through data analytics", *Journal of Enterprise Information Management*, vol. 32, no. 1, pp. 152–169, 2018.
- [8] A. K. Sandhu, "Big data with cloud computing: Discussions and challenges", *Big Data Mining and Analytics*, vol. 5, no. 1, pp. 32–40, 2022.
- [9] G. Heinemann, "Business model of online trade", *The New Online Trade: Business Models, Business Systems and Benchmarks in E-Commerce*, pp. 65–177, 2023.
- [10] P. Mathur, "Cloud computing infrastructure, platforms, and software for scientific research", *High Performance Computing in Biomimetics: Modeling, Architecture and Applications*, pp. 89–127, 2024.
- [11] K. Padmavathi, C. Deepa and P. Prabhakaran, *Internet of things (IoT) and big data*, Auerbach Publications eBooks, 2020.
- [12] S. Yu. Maksimov, V. Makarenko, S. Tkachenko and O. S. Panchenko, "Influence of temperature and Long-Term operation on metal durability of pipelines of hydrotechnical structures", *Key Engineering Materials*, vol. 952, pp. 25–33, 2023.
- [13] T. Boone, R. Ganeshan, A. Jain and N. R. Sanders, "Forecasting sales in the supply chain: Consumer analytics in the big data era", *International Journal of Forecasting*, vol. 35, no. 1, pp. 170–180, 2018.
- [14] S. Oneshko, "Assessing the Profitability of IT Companies: International Financial Reporting Standards", *Review of Economics and Finance*, vol. 21, pp. 1361-1369, 2023.
- [15] L. Parashchuk, Y. Shelekh, M. Sabat and L. Odosii, "Electromechanical System of Control and Determination of Strength of Concrete by Non-Destructive Method", in *IEEE 4th KhPI Week on Advanced Technology (KhPIWeek)*, pp. 1–4, 2023.
- [16] P. Lezhniuk, O. Kozachuk, N. Komenda and Y. Malogulko, "Electrical power and energy balance in the local electrical system by using reconciliation of the generation and consumption schedules", *Przegląd elektrotechniczny*, vol. 9, pp. 57–63, 2023.
- [17] J. S. Kushwah, A. Kumar, S. Patel, R. Soni, A. Gawande and S. Gupta, "Comparative study of regressor and classifier with decision tree using modern tools", *Materials Today Proceedings*, vol. 56, pp. 3571–3576, 2021.
- [18] L. Holbeche, "Designing sustainably agile and resilient organizations", *Systems Research and Behavioral Science*, vol. 36, no. 5, pp. 668–677, 2019.

- [19] V. Lozovan, R. Skrynkovskyy, V. Yuzevych, M. Yasynskiy and G. Pawlowski, “Forming the toolset for development of a system to control quality of operation of underground pipelines by oil and gas enterprises with the use of neural networks”, *Eastern-European Journal of Enterprise Technologies*, vol. 2, no. 5, pp. 41–48, 2019.
- [20] V. Bulgakov, S. Pascuzzi, S. Ivanovs, V. Nadykto and J. Nowak, “Kinematic discrepancy between driving wheels evaluated for a modular traction device”, *Biosystems Engineering*, vol. 196, pp. 88–96, 2020.
- [21] Y. M. Omar, M. Minoufekr and P. Plapper, “Business analytics in manufacturing: Current trends, challenges and pathway to market leadership”, *Operations Research Perspectives*, vol. 6, 100127, 2019.
- [22] E. L. I. Albores, “Consumption prediction on Netflix: Audience tracking analysis based on the recommendation algorithm in times of pandemic”, *Predictive Technology in social media*, pp. 52–74, 2022.
- [23] C. T. Gonçalves, M. J. A. Gonçalves and M. I. Campante, “Developing integrated performance dashboards visualisations using Power BI as a platform”, *Information*, vol. 14, no. 11, 614, 2023.
- [24] S. Popereshnyak, S. Grinenko, O. Grinenko, O. Kovalenko and T. Radivilova, “Methods for Assessing the Maturity Levels of Software Ecosystems”, *CybHyg*, pp. 251–261, 2019.
- [25] V. Yuzevych, R. Skrynkovskyy and B. Koman, “Intelligent Analysis of Data Systems for Defects in Underground Gas Pipeline”, in *IEEE Second International Conference on Data Stream Mining & Processing (DSMP)*, pp. 134–138, 2018.
- [26] D. Kucherov, A. Kozub, O. Sushchenko and R. Skrynkovskyy, “Stabilizing the spatial position of a quadrotor by the backstepping procedure”, *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 2, pp. 1188–1199, 2021.
- [27] S. Zaitsev, “Using Digital Tools to Increase the Competitiveness of Small Businesses (Experience of Full-Service Bakeries)”, *Futurity of Social Sciences*, vol. 1, no. 4, pp. 75–90, 2023.
- [28] M. Järvis, “Leadership in the Era of Sustainable Development: Challenges and Opportunities for Modern Managers”, *Law, Business and Sustainability Herald*, vol. 3, no. 4, pp. 4–20, 2023.
- [29] Y. Niu, L. Ying, J. Yang, M. Bao and C. B. Sivaparthipan, “Organizational business intelligence and decision making using big data analytics”, *Information Processing & Management*, vol. 58, no. 6, 102725, 2021.
- [30] D. Acemoglu and P. Restrepo, “Automation and new tasks: How technology displaces and reinstates labor”, *Journal of Economic Perspectives*, vol. 33 no. 2, pp. 3–30, 2019.
- [31] S. S. Shah and Z. Asghar, “Dynamics of social influence on consumption choices: A social network representation”, *Heliyon*, vol. 9, no. 6, e17146, 2023.
- [32] J. Kuzmina, D. Atstāja, G. Dambe, Y. Kichuk and V. Bykhovchenko, “Well-being in the work environment as foundation to achieve sustainable development goal”, in *International Conference on Sustainable, Circular Management and Environmental Engineering*, vol. 255, 01023, 2021.
- [33] P. Halachev, “Web application with Python and security of the information system”, *Security & Future*, vol. 4, no. 3, pp. 103–106, 2020.
- [34] O. G. Danilyan, A. P. Dzeban, Y. Y. Kalinovsky, E. A. Kalnytskyi and S. B. Zhdanenko, “Personal information rights and freedoms within the modern society”, *Informatologia*, vol. 51, no. 1–2, pp. 24–33, 2018.
- [35] R. Syed, S. Suriadi, M. Adams, W. Bandara, S. J. J. Leemans, C. Ouyang, A. H. M. ter Hofstede, I. van de Weerd, M. T. Wynn and H. A. Reijers, “Robotic Process Automation: Contemporary themes and challenges”, *Computers in Industry*, vol. 115, 103162, 2019.
- [36] A. K. Tyagi and P. Chahal, “Artificial intelligence and machine learning algorithms”, *Advances in computer and electrical engineering book series*, pp. 188–219, 2019.
- [37] L. Sobolenko, A. Davydiuk, V. Kornieva, I. Lopatynska and O. Bazyl, “Optimisation of Learning and Development of Cognitive Skills through the Use of Integrated Technologies of Virtual Reality and Artificial Intelligence among Students”, *E-Learning Innovations Journal*, vol. 2, no. 2, pp. 102–118, 2024.
- [38] S. Munirathinam, “Industry 4.0: Industrial Internet of Things (IIOT)”, *Advances in computers*, vol. 117, no. 1, pp. 129–164, 2019.
- [39] B. Shneiderman, “Bridging the gap between ethics and practice”, *ACM Transactions on Interactive Intelligent Systems*, vol. 10, no. 4, pp. 1–31, 2020.
- [40] A. Kasych, Y. Yakovenko and I. Tarasenko, “Optimization of Business Processes with the use of Industrial Digitalization”, in *IEEE International Conference on Modern Electrical and Energy Systems (MEES)*, pp. 522–525, 2019.
- [41] N. Rodinova, N. Pylypchuk, S. Domashenko, I. Havrylyuk and A. Androsovyeh, “Ukrainian economy in the era of digital branding: Risks and opportunities”, *Futurity Economics&Law*, vol. 4, no. 4, pp. 4–24, 2024.
- [42] I. Skakun, “Values and Ideals in Modern Philosophy: A Bibliometric Study”, *Futurity Philosophy*, vol. 2, no. 4, pp. 75–86, 2023.

- [43] S. Fedushko, T. Ustyianovych and M. Gregus, “Real-Time High-Load infrastructure transaction status output prediction using operational intelligence and big data technologies”, *Electronics*, vol. 9, no. 4, 668, 2020.
- [44] O. Dobrovolska, “Management of innovative development of agriculture in the digital era”, in *26th Conference on Communities in New Media. Inclusive Digital: Forming Community in an Open Way Self-Determined Participation in the Digital Transformation*, 197913, pp. 110–125, 2023.
- [45] R. Elshawi, S. Sakr, D. Talia and P. Trunfio, “Big data systems Meet Machine learning challenges: Towards Big data science as a service”, *Big Data Research*, vol. 14, pp. 1–11, 2018.
- [46] I. Britchenko, I. Svydruk, Y. Pidlypnyi and O. P. Krupskiy, “Lessons to Be Learned from Ukraine’s Positioning in International Rankings: The Need for Institutional Support and Financial Support for Economic Creativity”, *Problemy Zarządzania Management Issues*, vol. 2020, no. 4, pp. 125–146, 2021.
- [47] E. Yadegaridehkordi, M. Hourmand, M. Nilashi, L. Shuib, A. Ahani and O. Ibrahim, “Influence of big data adoption on manufacturing companies’ performance: An integrated DEMATEL-ANFIS approach”, *Technological Forecasting and Social Change*, vol. 137, pp. 199–210, 2018.
- [48] M. S. Castro, B. Bahli, J. J. Ferreira and R. Figueiredo, “Comparing single-item and multi-item trust scales: insights for assessing trust in project leaders”, *Behavioral Sciences*, vol. 13, no. 9, 786, 2023.
- [49] U. Awan, S. Shamim, Z. Khan, N. U. Zia, S. M. Shariq and M. N. Khan, “Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance”, *Technological Forecasting and Social Change*, vol. 168, 120766, 2021.
- [50] N. Yadav and S. P. Panda, “A Path Forward for Automation in Robotic Process Automation Projects: Potential Process selection Strategies”, in *International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)*, pp. 801–805, 2022.
- [51] S. Gupta, V. A. Drave, Y. K. Dwivedi, A. M. Baabdullah and E. Ismagilova, “Achieving superior organizational performance via big data predictive analytics: A dynamic capability view”, *Industrial Marketing Management*, vol. 90, pp. 581–592, 2019.
- [52] S. Gupta, T. Justy, S. Kamboj, A. Kumar and E. Kristoffersen, “Big data and firm marketing performance: Findings from knowledge-based view”, *Technological Forecasting and Social Change*, vol. 171, 120986, 2021.
- [53] I. B. Pugna, A. Duțescu and O. G. Stănilă, “Corporate Attitudes towards Big Data and Its Impact on Performance Management: A Qualitative Study”, *Sustainability*, vol. 11, no. 3, 684, 2019.
- [54] C. Santesteban and S. Longpre, “How big data confers market power to big tech: Leveraging the perspective of data science”, *The Antitrust Bulletin*, vol. 65, no. 3, pp. 459–485, 2020.
- [55] R. H. Hariri, E. M. Fredericks and K. M. Bowers, “Uncertainty in big data analytics: survey, opportunities, and challenges”, *Journal of Big Data*, vol. 6, no. 1, pp. 1–16, 2019.
- [56] S. Shan, Y. Luo, Y. Zhou and Y. Wei, “Big data analysis adaptation and enterprises’ competitive advantages: the perspective of dynamic capability and resource-based theories”, *Technology Analysis and Strategic Management*, vol. 31, no. 4, pp. 406–420, 2018.
- [57] M. J. Sousa and Á. Rocha, “Skills for disruptive digital business”, *Journal of Business Research*, vol. 94, pp. 257–263, 2018.
- [58] K. K. H. Ng, C. H. Chen, C. K. M. Lee, J. Jiao, and Z.-X. Yang, “A systematic literature review on intelligent automation: Aligning concepts from theory, practice, and future perspectives”, *Advanced Engineering Informatics*, vol. 47, 101246, 2021.
- [59] Y. Umantsiv, I. Cherlenjak, V. Prikhodko, Y. Sonko, and M. Shtan, “Integrated evaluation of investment attractiveness in the context of economic sectors: Ukraine as a case study”, *Investment Management and Financial Innovations*, vol. 18, no. 2, pp. 118–129, 2021.
- [60] O. Osiyevskyy, Y. Umantsiv, and Y. Biliavska, “Digital ecosystem: A mechanism of economic organization of enterprises of the future”, *Rutgers Business Review*, vol. 8, no. 2, pp. 175–194, 2023.