UDC 330.46(075.8)
JEL Classification: M21, O14, O32
DOI: 10.15587/2706-5448.2024.301423

Yaroslava Yakovenko,
Roman Shaptala

STUDY OF DIGITAL TWINS AS THE DRIVING FORCE OF DIGITAL TRANSFORMATION AND ACHIEVING THE GOALS OF SUSTAINABLE DEVELOPMENT

The object of research is the use of Digital Twin (DT) technology in the manufacturing sector and its impact on sustainability. The scientific problem addressed is the identification and quantification of the potential advantages and challenges associated with the adoption of DTs at operational, tactical, and strategic levels, particularly in the context of sustainable development. The paper investigates how DTs can redefine the measurement of sustainable development and diversify implementation within manufacturing infrastructure. The study concludes that DTs are a sophisticated technology that enables manufacturers to create precise virtual replicas of physical products or processes. This helps in optimizing resource utilization, reducing energy consumption, and minimizing waste, thereby promoting sustainability.

Main DT clusters and common uses highlighted by the authors demonstrate huge impact on energy efficiency, waste management, sustainable design, logistics emissions reduction, water conservation, and stakeholder engagement. It is proved that DTs simulate and analyze complex systems, enabling the evaluation and improvement of sustainability levels. The paper presents promising practical examples of DT's use, such as optimizing warehouse management in Ukraine, automating robots for increased efficiency, and aiding in the post-war reconstruction of cities with a focus on environmental friendliness and accessible infrastructure.

The research specifically focuses on the top five tech giants and their use of DTs to drive sustainability. Additionally, the findings project substantial market growth potential for DTs in multiple sectors, emphasizing the urgent need for industries to integrate DTs into their sustainability strategies.

Keywords: *digitization, digital twins, digital transformation, sustainable development, digital economy.*

Received date: 06.03.2024
Accepted date: 29.04.2024
Published date: 30.04.2024

How to cite
Yakovenko, Y., Shaptala, R. (2024). Study of digital twins as the driving force of digital transformation and achieving the goals of sustainable development. Technology Audit and Production Reserves, 2 (4 (76)), 11–20. doi: https://doi.org/10.15587/2706-5448.2024.301423

1. Introduction

In recent years, sustainability has become a critical principle in the manufacturing sector. With stakeholders placing a growing emphasis on sustainability, the industry is proactively adopting technological innovations to meet these expectations. Among these innovations, the use of digital twins is revolutionizing sustainability. By creating a virtual replica of an entire manufacturing process, digital twins enable manufacturers to optimize their processes and reduce their environmental footprint.

Digital Twin (DT) stands as a potent technology that aids in optimizing and enhancing our physical world by offering a more profound understanding of how things operate and how they can be improved. Emerging tools and methodologies associated with digital twins are proving to be transformative in various domains, including product lifecycle management, architectural design, aircraft engine and wind turbine modeling, smart city simulations, and enhancements in healthcare across hospitals and the human body. Presently, 30 to 50 percent of large industrial companies are adopting digital twins to enhance their organizational outcomes [1]. The leading providers in this space are Microsoft, General Electric, Oracle, Siemens, Dassault Systems, Cisco, and IBM. Numerous instances of production digital twins have often overlooked sustainability as a consequential benefit. The newfound operational efficiency not only enhances productivity but also results in decreased energy consumption and waste, ultimately contributing to a reduced environmental footprint.

Beyond enhancing existing products and systems, digital twins contribute to smart vehicle systems/the design of smart cities, and elevate medical training. As technology progresses, digital twins are becoming an indispensable tool for simulating the physical world within a digital framework, providing a deeper understanding of how physical objects behave under diverse conditions as well as driving sustainability by integrating real-world physical systems with digital representations. They enable the modeling and analysis of complex systems, allowing for the evaluation and improvement of sustainability levels [2]. Authors of [3] discus the integration of digital twin technology with GIS and VR to improve environmental sustainability and mentions that digital twins offer a richer capability to model and analyze real-world systems, which can contribute to sustainability efforts [3]. However, it does not explicitly discuss the role of digital twins in driving sustainability. Authors of [4–6] pay attention to the fact that by leveraging the Internet of Things, digital twins enable the automatic collection of product lifecycle data, enhancing the accuracy of product design and supporting low-carbon design. Furthermore, digital twins can contribute to sustainability transitions by coupling with sustainable innovations, leading to radical twin innovations that open new pathways for sustainability [7]. Overall, digital twins provide a powerful tool for monitoring, optimizing, and driving sustainability in various domains.

In such a way through the strategic use of technology, data, and innovative solutions, there is the opportunity to shape a more sustainable future. Expanding the concept to a comprehensive product DT implies that, to fully harness the benefits of this approach, businesses should extend digital representation beyond products to encompass associated processes and services. However, the identification of potential advantages and challenges in applying this innovative approach to sustainability at operational, tactical, and strategic levels remains an important question. Additionally, understanding the rate of return on investment for leaders in the DT sector and assessing the prospects of implementing digital twins in Ukraine's post-war reconstruction are also relevant problems.

The aim of this research is to explore the substantial impact DT can have on redefining the measurement of sustainable development and identify the diversity in implementing DT within manufacturing infrastructure. This will make it possible to assess how profitable investments in research and development of tech giants are from the point of view of ensuring sustainable development.

2. Materials and Methods

In the course of researching and composing this article, the authors conducted a comprehensive review of recent scientific literature. Additionally, relevant information was gleaned from the websites of various organizations and supplemented by data procured from Statista, a leading global business intelligence platform. The study used statistical analysis to evaluate the impact of big tech company's raw data for determination of sustainability. Finally, the article delves into the historical context and contemporary understanding of the research question.

3. Results and Discussion

A digital twin is, simply put, a sophisticated technology used by manufacturers to create a precise virtual replica of a physical product or process [8]. From an engineering standpoint, the creation of models is a longstanding concept, exemplified by tools such as Computer-Aided Engineering. The functionalities of digital twins initially emerged as a preferred tool in the engineer's toolkit due to their ability to streamline the design process and eliminate the need for extensive prototype testing. Since its inception in the early 2000s, this concept has found applications in various sectors such as manufacturing, construction, urban planning, healthcare, and more. However, the concept is often misunderstood as applications of AI or a tool for supply chain management. What distinguishes digital twin technology is its AI/ML intelligence engine, which operates on a digital replica of real-world assets and processes. This digital model is designed to simulate the behavior of the physical system, providing an accurate representation of its performance in real-world scenarios. This involves the integration of extensive datasets from various systems, all powered by cloud technology. By creating a digital twin, manufacturers can use the data generated by the virtual model to identify inefficiencies, optimize resource utilization, and enhance overall performance. Digital twin technology is poised to facilitate the emergence of the next generation of prescriptive and immersive control towers. The associated use cases are expected to undergo continuous evolution, encompassing both tactical and strategic domains [9].

In other words, digital twins can be used to explore various scenarios, such as changes to the manufacturing process or product design. By simulating these scenarios in the virtual model, manufacturers can make data-driven decisions to improve efficiency, reduce costs, and enhance product quality. The adoption of DT in manufacturing holds substantial implications for sustainability. For instance, manufacturers can employ digital twins to detect and eliminate waste in the manufacturing process. Additionally, they can optimize energy consumption by simulating various scenarios and determining the most efficient resource utilization [10]. Through the utilization of this technology, manufacturers can improve resource efficiency, decrease energy consumption, and diminish waste, crucial elements in fostering sustainable manufacturing practices. In addition, digital twins can be used to monitor the physical system and predict potential failures or issues before they occur. This proactive approach to maintenance can help reduce downtime and improve overall reliability.

Wireless communication technology has revolutionized data transfer, making it faster, more efficient, and more convenient. The latest technological development in the computing world is the Metaverse, which promises to usher in a new era of computing. One of the standout tools for the manufacturing industry committed to achieving sustainability goals in the Metaverse advancements is the concept of digital twins. This tool is not new in general, but it is particularly revolutionary for manufacturing [11].

Subsequently, the Metaverse constitutes a virtual realm where users can engage with one another and interact with digital entities within a three-dimensional environment. This innovation holds the promise of revolutionizing traditional face-to-face interactions by transitioning them into virtual realms, thereby enhancing learning methodologies and pushing technological boundaries. Positioned as the user-friendly interface driving the decentralized Web 3.0 ecosystem, the Metaverse relies on decentralized networks and applications constructed on blockchain technology (Fig. 1). The integration of machine learning and artificial intelligence (AI) is essential to cultivate more intelligent and adaptive ecosystems.

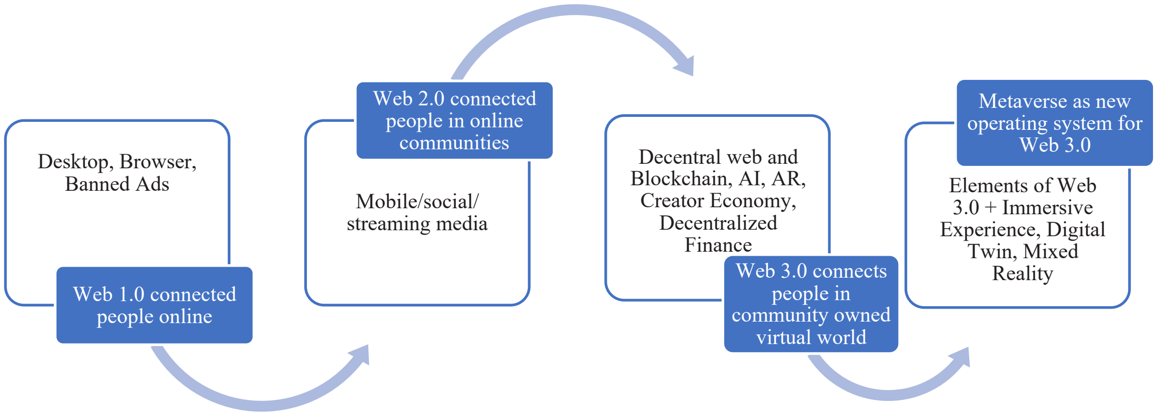

Fig. 1. The convergence of Web3, Metaverse and Digital Twins

One could also say that the Metaverse's technological progression centers on three fundamental pillars: the Internet of Everything (analogous to the Internet of Things, IoT), DT and AI. The transformative potential of the Metaverse in the realm of information technologies is immense, with far-reaching implications. It is poised to reshape our interactions with one another, digital entities, and the surrounding environment. Moreover, it stands to revolutionize our approaches to learning, work, and leisure activities. While still in its early stages, the Metaverse is a technology that warrants close observation as it undergoes development and evolution. Consequently, by assimilating data and replicating processes, a digital twin can precisely anticipate potential outcomes and issues in the actual product or system.

Fundamentally, adoption of digital twins as a potent tool is gaining momentum, offering access to a diverse array of items such as products, equipment, factories, buildings, cities, and more. This is why significant growth rates for this market are predicted (Fig. 2).

In 2021, the worldwide digital twin industry reached a valuation of 6.5 billion USD, with a projected growth to 125.7 billion USD by 2030. The anticipated compound annual growth rate (CAGR) from 2022 to 2030 is estimated at 39.48 percent [13]. The automotive and manufacturing sectors held the most significant market share by industry, and this dominance is anticipated to continue expanding through 2025 (Fig. 3).

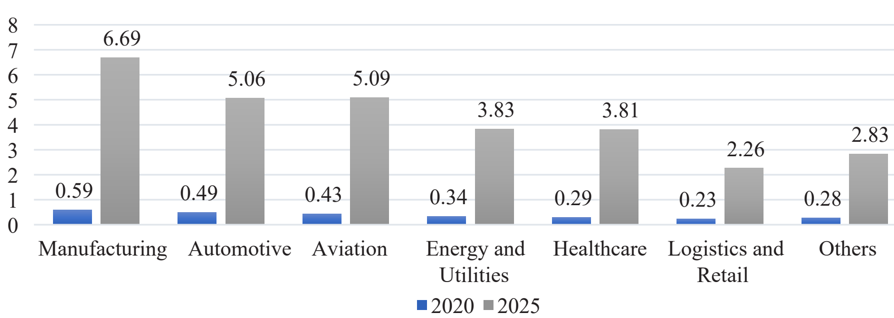

Fig. 2. Digital twins market size by industry in billion USD [12]

In the Metaverse, the incorporation of real-time technology holds the key to unlocking thrilling possibilities, reshaping the Metaverse experience and elevating it to unprecedented levels. As a result, one can think of the digital twin as a simulation. Digital models are not new issues to explore as far as there have been models in CAD, games or animation for years, and many things can be simulated. The main and the biggest difference is that the digital twin is simulating how value is created. Based on purpose, standard digital models can be classified into functional or analytical. The digital twin model incorporates real-world data from both its sensors as well as its external systems.

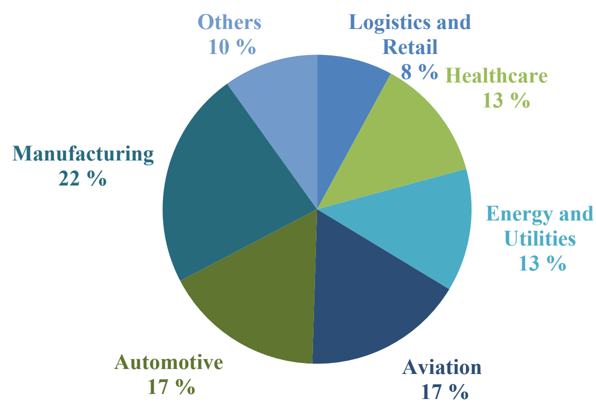

Fig. 3. Digital twins market share in 2025 by industry [12]

Like any statistical model, it initiates with a statistical sampling of cause and effect, gradually improving its accuracy over time. The digital twin's application component delineates the product's operation, encompassing its functionality, usability, and utility. Furthermore, it establishes both a human interface and a data interface, managing the orchestration of data flows to and from the model. Crucially, it actively utilizes the model to bring forth its value.

Most significantly, when translated into mathematical expressions, the physical product takes on a software-like nature. Similar to software, it can interact with other software through APIs.

Models exist in two primary forms: statistical models, incorporated by linking to statistical libraries, and learning models, commonly known as machine learning. The latter involves training models in the background, collecting cause-and-effect IoT data, and employing them in

ISSN 2664-9969

real-time – implemented using machine learning libraries integrated into the application [14].

The digital twins as digital models serve two main purposes. Initially, they operate in an offline mode, providing analytics. In this scenario, they contribute to model creation, defining the parameters for a specific type of statistical or machine learning model. Afterwards, they integrate into runtime, residing within an application. These models are executed, a process sometimes referred to as inference. This execution generates value, and, as previously mentioned, models are dynamic, consistently undergoing a cycle: building the model, running the model, improving the model, running the model, improving the model, running the model – continuously evolving.

The application is developed, compiled, and run on a computing infrastructure, encompassing the cloud technologies as well as mobile and desktop platforms. It establishes connections with external systems via APIs, in order to link external system libraries to the application. At the core of virtualization lies the digital twin, essentially encapsulating the process of transforming the physical into the digital when undergoing digital transformation.

In essence, the digital twin serves as a simulation of all the data coursing through the intelligent products or operational systems. Delving deeper into this definition reveals that building a digital replica of a physical entity can markedly enhance one or more of the following processes: design, simulation, planning, construction, operation, maintenance, optimization, and disposal. Regardless of the phase, it remains fundamentally a data-driven model. Data is instrumental in making essential decisions during both design and construction phases, where factors like environmental and historical data guide design choices. Iterative virtual simulations under diverse conditions inform decisions related to construction materials, weather considerations, disaster preparedness, specific mechanical components, and indoor environmental factors such as humidity and heat. Robust data, especially in large volumes, contributes to the development of higher-performing end products [15].

While the digital twin concept presents substantial advantages in the design and construction phases, its significant focus lies in the operational and maintenance aspects of a physical object. Essentially, a digital twin serves as a data-driven representation of its real-world counterpart. Real-time data from sensors placed on the physical object, be it a complex machine on an assembly line, a wind turbine, mineral extraction machinery, a building, a city, healthcare devices, or even a human, continuously feeds into the digital twin. This extends beyond, encompassing a broad spectrum of objects and scenarios.

IoT Analytics looked at 100 digital twin case studies and classified each project by enhancing operations and maintenance efficiency [16]. It was found out that after construction digital twins offer continuous real-time monitoring and predictive analytics.

Main clusters of digital twin activity being matched with most common uses and lifecycle phases are represented by Fig. 4 (the three scopes approach has not yet been demonstrated here).

As for lifecycle phases, it should be noted that during the design phase, it becomes feasible to virtually conceive a solution and accurately simulate its functionality before any physical implementation occurs. Subsequently, the solution can be simulated under various real-world scenarios, making the digital twin an invaluable asset in streamlining the procurement process. Notably, in the build phase, sensors are affixed to the physical object to collect and transmit data back to its virtual counterpart. With a sufficient number of sensors, the virtual twin provides comprehensive data about the state of the physical twin. Throughout operations, copious amounts of data are collected and relayed back to the digital twin via a digital thread – an analogous concept to a data pipeline facilitating analytics of diverse states and stages. Empowered by AI, the digital twin can identify and even predict maintenance issues before they manifest, evolving into a data-informed model of a physical system. This feature significantly reduces costs, as proactive maintenance is generally more economical than repairing a malfunction after it occurs. Ultimately, the continuous real-time influx of data aids in optimization by enhancing the system's performance, allowing for automatic adjustments or triggering manual intervention.

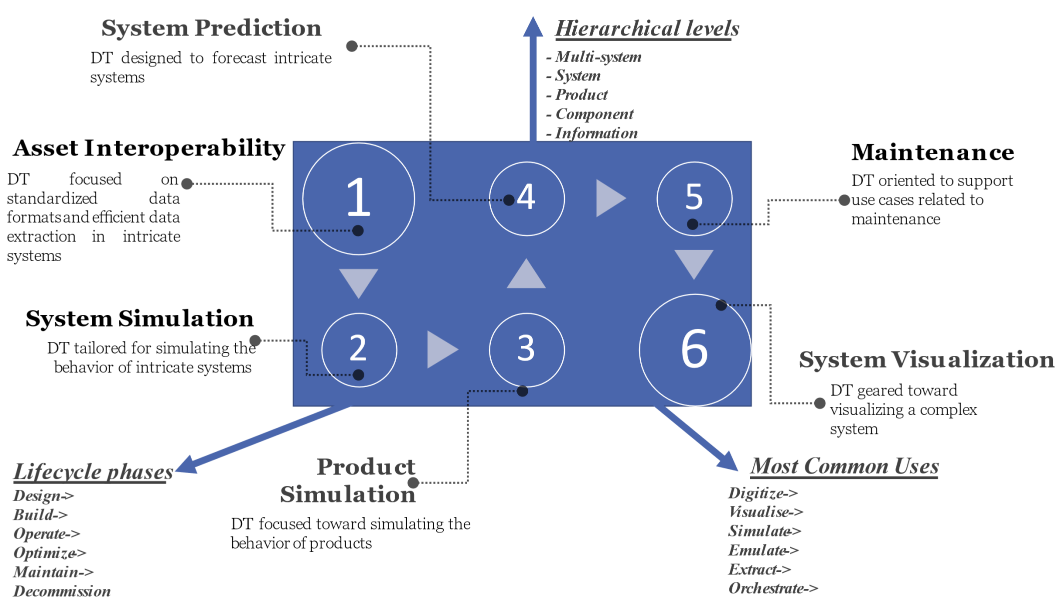

Fig. 4. Main clusters of digital twin activity matched with most common uses and lifecycle phases [16]

It is crucial to clarify that the «build phase» encompasses both the construction of products and systems, as well as the systems responsible for manufacturing those products. Digital twins are increasingly playing a pivotal role in both these domains. Sophisticated digital twins have the capability to generate specifications for the manufacturing process, encompassing details about the production line, metrics to be captured during construction, and testing procedures for both components and the final product. Utilizing AI, a digital twin can engage in predictive maintenance at any stage of the production line, allowing for the anticipation and resolution of potential issues before they escalate [17]. This proactive approach is always preferable. The insights gained from digital twins are immensely valuable to various stakeholders within an organization. Moreover, depending on established relationships, digital twins of manufacturing processes or their data can be shared with external entities such as providers, maintenance companies, regulators, and even buyers. This opens avenues for collaboration, fostering improvements across the entire supply chain.

One should also note a remarkable benefit during the operational, optimizing and maintenance phases of product lifecycle management. Like the build or manufacturing phase, virtual and dynamic DT phases exist to mirror real physical objects. In operations, these specific types of digital twins are known as an emulation twin, or the more popular term, supervisory twin.

A supervisory twin supports three core operational processes: supervisory, diagnostic and control, and predictive. The supervisory capability means that the digital twin is accurately replicating and illustrating the behavior of the physical object. The diagnostic and control capabilities enable analysis of performance in real time. Insights gleaned from analysis can help improve physical asset and process performance, reduce risk and better manage costs.

With real time data being fed to the supervisory digital twin, this data can in turn be fed to analytical systems. Coupled with digital twins in the build phase, diagnostic and control capabilities can be integrated into systems that support asset performance management (APM). APM synchronizes information from a variety of sources in product lifecycle management in order to provide a comprehensive view of production and asset performance. These operational and maintenance capabilities are creating game-changing opportunities across many domains in the economy.

Finally, the predictive capability of a digital twin helps discover new opportunities beyond improving performance. Predictive simulation software that works in conjunction with a supervisory digital twin can be used to run future scenarios. These can be used to inform decisions without any of the risk or cost of making changes to the physical counterpart. Positive outcomes from predictive capabilities can be used for investment decisions, for both processes and systems.

Furthermore, the incorporation of digital twins can play a role in advancing the circular economy. Through the generation of a digital counterpart for a product, manufacturers can oversee its performance across its entire lifecycle, spanning from the design stage to decommission. DT are advanced tools that are used to support decision-making processes in three different scopes: operational, tactical, and strategic. These tools are designed to provide businesses with a detailed and comprehensive view of sustainable development, enabling them to make better, more informed decisions (Fig. 5).

Let's look at each of the three scopes, giving examples from industries, and later summarize the role of digital twins in ensuring sustainable development. So, *at the operational scope*, digital twins use sophisticated algorithms to automate and optimize decision-making processes. This means that businesses can make quicker and more accurate decisions than if they were doing everything manually. Moreover, by creating a virtual replica of their physical processes or equipment, companies can simulate and optimize their energy consumption patterns, leading to significant reductions in greenhouse gas emissions. A recent report by EY highlights that digital twin can reduce the carbon footprint of an existing building by up to 50 percent, while also achieving cost savings of up to 35 percent [18].

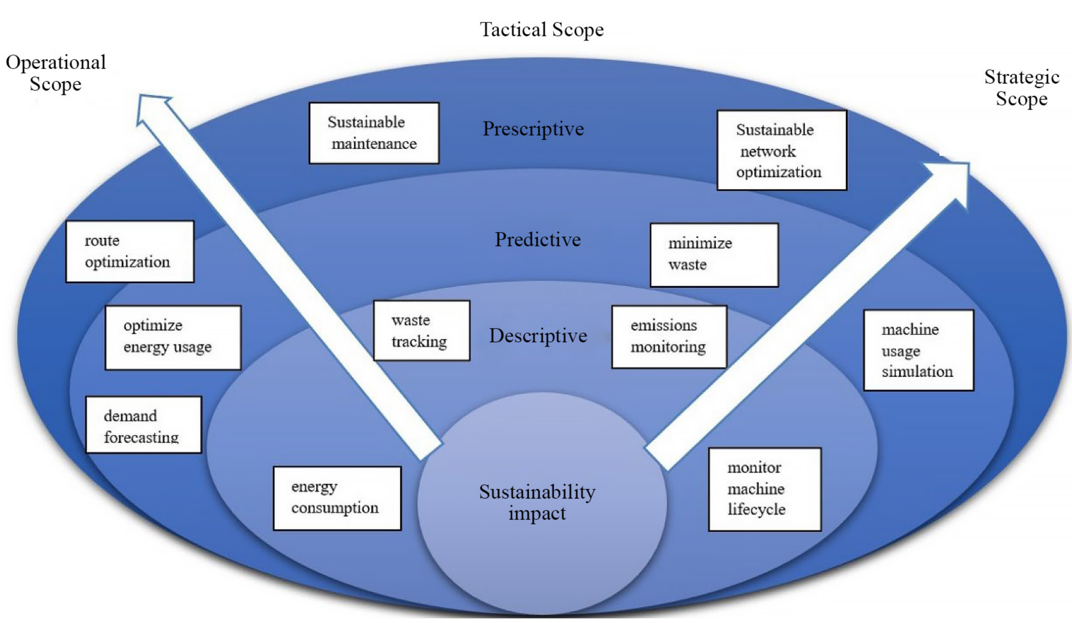

Fig. 5. A three scopes approach to the sustainable impact made by DT

With the help of DT, companies can not only achieve their sustainability goals but also optimize their operations to meet the demands of a changing market. DT can help businesses in several areas, including [19]:

1) *manufacturing*: a global manufacturing company can use a digital twin to anticipate or quickly adjust its manufacturing plan; this can help to reduce downtime and minimize the impact of supply chain disruptions;

2) *retail*: a global retail company can use a DT to determine the best way to liquidate certain products against the highest margin. They can also use this tool to optimize their supply chain and improve inventory management;

3) *distribution*: the local distribution team can use a DT to adjust their route to market based on warehouse constraints. This can help to minimize delivery times and improve customer satisfaction.

At the tactical scope, DT provide businesses with the ability to make quick decisions that improve the performance of their supply chain. For example, a global retailer can use DT to reallocate inventory between warehouses based on actual and forecast demand. They can also determine new target stock levels based on changes in market behavior. This can help optimize their inventory management and reduce the risk of stockouts.

On the strategic scope, DTs enable businesses to test different strategies and identify the best course of action. Some examples include:

1) a FMCG company can use DT to achieve the highest savings by opening a new distribution center. This can help reduce transportation costs and improve supply chain efficiency;

2) a car manufacturer can assess the potential impact of supply disruptions and develop contingency plans to minimize the risk of disruptions in the future;

3) an industrial products manufacturer can change their source base to lower CO_2 emissions or change their product/mix allocation to meet sustainability targets. This can help to reduce their environmental impact and improve their reputation and the level of sustainability.

In summary, Digital Twins are powerful tools that can help to improve sustainability in the following ways:

– *Energy Efficiency*: As the demand for sustainable energy continues to grow, efficient design and implementation of new infrastructure is critical. So, digital twins provide an optimal platform for simulating the planning, construction, and operation of complex systems such as offshore wind farms, grid connections, gigafactories, and hydrogen plants. This virtual environment enables companies to identify and rectify any issues before actual implementation, reducing time-to-market and improving efficiency and sustainability;

– *Waste Management*: DTs are revolutionary virtual models that offer a unique way to surpass the current industrial paradigm based on extraction, production, consumption, and disposal. By using digital twins, companies can simulate the entire lifecycle of a product, from the extraction of raw materials to its disposal. This allows them to optimize the design, production, and distribution processes, reducing waste and pollution throughout the product's life cycle. Ultimately, this circular economy model aims to extend the life of products and materials by integrating them into a recycling loop, which in turn contributes to the regeneration of natural systems;

– *Sustainable Design*: Digital Twins are a cutting-edge technology that enables live monitoring of the carbon footprint across the complete supply chain. It also calculates the carbon footprint of the product's design and development life cycles. This technology provides complete transparency throughout the product's lifecycle, from design to delivery;

– *Logistics Emissions Reduction*: DT play a pivotal role in optimizing logistics and distribution processes, thereby reducing carbon emissions associated with logistics. Visualization tools empower logistics system operators to visually monitor the placement of pallets in the warehouse and track traffic;

– *Water Conservation*: this is where DT can identify areas of water wastage and detect leaks. This information can help manufacturers to make informed decisions and implement the most efficient water conservation strategies. They can also help manufacturers to test different water conservation strategies in a virtual environment before implementing them in the real world;

– *Stakeholder Engagement*: the transition to sustainable energy involves various participants, such as energy providers, policymakers, technology providers, and consumers. Digital Twins simplify the communication of sustainability measures to stakeholders by providing visual and quantifiable representations of strategies related to sustainability.

Undoubtedly, big tech and gaming players will expand their competencies across DT. Nevertheless, the digital realm is primarily controlled by a select few entities: Google, Amazon, Meta, Apple, and Microsoft. Originally identified by the acronym GAFAM, they are now referred to as GAMAM or GAMMA, constituting the top five tech giants that reign as the most significant internet corporations globally.

Amazon already presented AWS IoT TwinMaker; Google – Supply Chain Twin and Pulse; Microsoft – Azure Digital Twins; Tencent – Tencent Cloud; Epic Games – Unreal Engine. Through AI and Digital Twins, spending on Research and Development has skyrocketed across industries: Microsoft expanded partnership with OpenAI, launched Azure Digital Twins, reported 2,500 Azure OpenAI customers, and expects to drive cloud growth; Amazon is now investing in generative AI and LLMs, launched AWS IoT TwinMaker and will use AI to drive advertising business growth.

An algorithm for enterprises that requires them to maintain a high rate of growth over time, in order to be classified as «gazelle companies» was proposed [20]. These companies have significant rates of profitability and rapid development, making them successful even in changing business conditions. However, driving business growth is complicated without following the sustainability-oriented strategy. The data that define the elements of sustainable development, collectively serving as markers of sustainability, are presented in Table 1.

In the next stage of the research, it is possible to use the Principal Component Method developed by Harold Hotelling, a statistician and econometrician who introduced the concept of principal components in statistical analysis [23]. This method simplifies the interpretation of information and enables us to compare multidimensional research objects. Hotelling's modifications have been designed to enhance the effectiveness of the principal component method under specific conditions or for solving particular problems.

Table 1

Big tech company's raw data for determination of sustainability (based on [21, 22])

Indicator	Company			Year	Indicator	Company		
	Amazon	Microsoft	Alphabet (Google (brand))			Amazon	Microsoft	Alphabet (Google (brand))
Market Capitalization (T of USD)	1.570 0.857 1.691 1.634 0.920	2.794 1.787 2.522 1.681 1.200	1.756 1.145 1.917 1.185 0.921	2023 2022 2021 2020 2019	Gross Profit (mln of USD)	269.640 225.152 197.478 152.757 114.986	146.052 135.620 115.856 96.937 82.933	179.470 156.633 146.698 97.795 89.961
Revenue (mln of USD)	554.02 513.98 469.82 386.06 280.52	211.915 198.270 168.088 143.015 125.843	313.948 282.836 257.637 182.527 161.857	2023 2022 2021 2020 2019	Operating Income (mln of USD)	28.380 12.248 24.879 22.899 14.541	88.523 83.383 69.916 52.959 42.959	93.223 74.842 78.714 41.224 34.231
Brand Value (bln of USD)	299.28 401.82 683.852 135.4 97.0	191.570 611.460 410.271 162.900 125.300	281.380 766.780 457.998 207.500 167.700	2023 2022 2021 2020 2019	Shares Outstanding (mln of Shares)	10.413 10.189 10.296 10.198 10.080	7.472 7.540 7.608 7.683 7.753	13.633 14.046 14.462 14.665 14.902
R&D Expenses (mln of USD)	79.670 73.213 56.052 42.740 35.931	27.195 24.512 20.716 19.269 16.876	43.288 39.500 31.562 27.573 26.018	2023 2022 2021 2020 2019	Number of Em-ployees	1541000 1541000 1608000 1298000 798000	221000 221000 181000 163000 144000	190234 190234 156500 135301 118899
ROE, %	12.32 -1.98 27.98 27.07 21.07	38.32 39.32 48.39 42.19 42.89	25.24 23.54 31.56 19.03 17.79	2023 2022 2021 2020 2019	ESG Risk Rating	30.6 31.0 30.9 31.7 24.0	15.2 15.0 15.1 14.8 14.7	24.1 24.5 24.3 24.8 22.1
ROA, %	4.25 -0.63 8.98 7.88 5.84	19.25 18.82 21.60 17.22 15.95	17.62 16.71 22.21 13.76 13.19	2023 2022 2021 2020 2019	Total Carbon Foot-print (in mln metric tons CO_2)	71.27 71.54 60.64 51.17 44.4	14.1 13.8 11.4 11.1 12.0	10.2 11.7 13.5 14.0 4.9
ROI, %	11.59 6.28 15.13 20.98 18.61	38.53 38.04 39.97 33.37 29.17	28.30 27.77 30.83 18.67 17.36	2023 2022 2021 2020 2019	–			

The method essentially involves transforming a multivariable dataset into a smaller set of uncorrelated variables, referred to as principal components. These components are ranked based on their contribution to the variance observed in the original data. This allows to reduce the amount of raw data, determine the relationships between them, quantify and rank them. The process of identifying principal components entails a series of mathematical calculations that aim to uncover the underlying factors driving the patterns observed in the data. The first principal component captures the maximum variability in the data, while each subsequent component explains a diminishing amount of variance. By selecting the most significant components, researchers and analysts can effectively reduce the complexity of the data and concentrate on the most critical factors driving the observed patterns.

Indicators used by enterprises can be divided into the following groups:

1) y_1 – Benchmarking Indicators (Market Capitalization, Revenue, Brand Value, Research and Development Expenses);

2) y_2 – Return on Investment (ROE, ROA, ROI);

3) y_3 – profit indicators (Gross Profit, Operating Income, Shares Outstanding);

4) y_4 – Environmental, Social, and Governance (ESG) (Number of Employees, ESG Risk Rating, Total Carbon Footprint).

The traditional calculation of principal components involves transitioning from the original observation matrix X to the correlation matrix S between the original features, and then calculating eigenvalues.

The observations collected at the beginning meet all the necessary requirements. They are homogenous in quality and quantity and are of sufficient volume (according to the Burch method, a sample for five years is required). The mathematical processing of data was done using the GRETL package [24] while applying the principal components method.

To get a score per sustainable development feature group, let's perform multiple isolated PCA runs. Every run it is possible to determine the principal component that explains the most variance, and loadings to show original feature contributions towards this component. First principal component results per group are shown in Table 2, where «PC1» columns indicate principal component values and «TV1» – the ratios of total variation explained by the component.

To gain insight into which features contribute most to the first principal components, it is possible to show loadings in Table 3.

ISSN 2664-9969

Table 2

First Principal Components per indicator group

Company	Benchmarking Indicators		Return on Investment		Profit Indicators		ESG	
	PC1	TV1	PC1	TV1	PC1	TV1	PC1	TV1
Amazon	2.4420	0.6105	2.8136	0.9379	2.4328	0.8109	2.5819	0.8608
Microsoft	2.8685	0.7171	2.0383	0.6794	2.9890	0.9963	2.4867	0.8289
Alphabet	2.7178	0.6794	2.8910	0.9637	2.8861	0.9620	2.2721	0.7574

Table 3

Original feature loadings

Indicator Group	Original Feature	Amazon	Microsoft	Alphabet
Benchmarking Indicators	Market Capitalization	0.253	0.484	0.405
	Revenue	0.621	0.583	0.603
	Brand Value	0.479	0.324	0.398
	Research and Development Expenses	0.567	0.567	0.561
Return on Investment	ROE	0.592	0.308	0.584
	ROA	0.581	0.699	0.581
	ROI	0.558	0.645	0.566
Profit Indicators	Gross Profit	0.547	–0.578	–0.587
	Operating Income	0.539	–0.577	–0.578
	Shares Outstanding	0.641	0.577	0.568
ESG	Number of Employees	0.612	0.621	0.447
	ESG Risk Rating	0.565	0.553	0.652
	Total Carbon footprint	0.553	0.556	0.612

The differences in loadings between companies suggest varied strategic focuses and operational characteristics. For instance, Amazon's positive loadings in Gross Profit and Operating Income could reflect a strong operational efficiency, whereas the negative loadings for Microsoft and Alphabet in these areas might indicate different strategic priorities or industry dynamics. Other principal components might capture different aspects of company performance and characteristics, but based on explained variance values they were considered negligible for this investigation.

Alphabet's efforts in reducing their carbon footprint, promoting diversity and inclusion programs, ethical AI development, and transparency in privacy practices contributed to their high indicator values [21]. On the other hand, Microsoft and Amazon have taken different approaches to sustainability. Microsoft has set a goal of becoming carbon negative by 2030 and has developed a comprehensive sustainability plan, focusing on renewable energy and responsible business practices [25].

Amazon, while making sustainability pledges, has faced criticism for its environmental impact due to its vast logistics operations. Nevertheless, the company has set ambitious targets, such as becoming net-zero carbon by 2040 and investing in renewable energy projects.

Overall, the sustainability rating serves as a valuable tool for investors, stakeholders, and consumers to assess a company's commitment to sustainability and responsible business practices.

Some companies find investing in sustainable development and Research and Development of DT or implementing a digital twin too challenging, or like something that should be tackled after upgrading an ERP system. While these may be valid concerns, companies not as big as Microsoft, Amazon or Alphabet (Google) can 'start small' and use the digital twin as a catalyst to accelerate complementary initiatives and revolutionize sustainability.

Practical Relevance. Digital Twin technology can be used to develop prescriptive and immersive control towers that offer strategic and tactical decision-making capabilities. Three-scope approach outlines the most common areas digital twin clients find useful to focus on, each of which can provide a meaningful impact on resource optimization to support more sustainable outcomes. DT is not limited to monitoring and analysis; it can also be used to make targeted sustainability improvements. By integrating sustainability as a parameter in optimization equations, organizations can influence decisions across various use cases. For example, waste tracking can be used to identify areas for improvement, leading to reductions in waste and cost savings.

Practical Meaning: The study of DTs holds immense practical significance across various sectors, as mentioned in the study, including enabling better understanding and management of environmental resources and ecosystems, enabling personalized medicine, and the need to optimize operations, enhance productivity, and minimize resource consumption. The research findings can provide valuable insights for policymakers crafting initiatives to bolster digital transformation and advance Sustainable Development Goals (SDGs). Moreover, the study's discoveries can serve as a roadmap for further research and development (R&D) endeavors in the DT arena.

Limitations of the Study: The effectiveness of digital twins hinges heavily on the quality and accessibility of data.

Besides, the practical implementation of DTs may require significant technological infrastructure and expertise. Furthermore, developing and maintaining digital twins can be costly. However, as mentioned earlier, the use of DTs can help reduce transportation costs and improve supply chain efficiency.

Influence of Martial Law Conditions: In Ukraine, digital twins are increasingly used to replicate warehouse facilities and optimize their management. These facilities are often targeted by a country-aggressor, so the use of digital twins allows for quick updates and reorientation according to wartime if needed, optimizing their operations and enhancing their resilience. The technology is also being used to automate robots in warehouses, leading to increased efficiency and productivity. The digital twins enable the robots to work in a coordinated manner, ensuring that they make optimal use of their surroundings while minimizing energy consumption. This results in faster and more accurate order fulfillment, improved inventory management, and reduced operational costs. Furthermore, digital twins can be used to boost the green energy of Ukraine in the future. In addition, digital twins can be used for the post-war reconstruction of destroyed cities to satisfy the needs of locals in terms of environmental friendliness, comfort, prospects for development, and accessible infrastructure for people with disabilities.

Prospects for Further Research: The potential of DT technology is vast, and organizations that fully leverage it can establish resilience against macro-environmental pressures and foster sustainable growth for the future. Investigating the broader social and economic implications of digital twins, one can encompass aspects like job displacement, equitable access to technology, and ethical considerations. By judiciously managing their resources, organizations can achieve better outcomes over the long term and make a positive impact on the environment. Already playing an important role in industrial companies and what we know as Industry 5.0, DT is beginning to play a role in modeling entire cities for urban planning and more, in the healthcare space including hospitals and the human body, in the automotive sector, and even in financial services. In the years ahead, this is a subject that is poised to grow substantially.

4. Conclusions

The research findings indicate that DTs are not just a technological innovation, but a vital tool for achieving environmental, economic, and social sustainability. The results obtained from the study are useful for further practical implementation and illustrate how DTs provide a framework for understanding complex systems and their interactions with sustainability goals. Based on the analysis of raw data from big tech companies, the most common areas where digital twin clients could be useful to focus on for sustainability were identified. By enabling the creation of precise virtual models, DTs help optimize resource usage, energy consumption, and waste production, all of which are critical in the pursuit of sustainable manufacturing practices and broader sustainable development goals.

The study's qualitative results highlight the strategic value of DTs in decision-making processes at all levels of operation and outline a three-scope approach that can be applied to identify key areas where DT implementation can offer the most impactful contributions to resource optimization and sustainability goals. This approach can be customized to specific industry needs, as the utility of DTs goes beyond simple monitoring and analysis. By integrating sustainability parameters into optimization algorithms within the DT environment, organizations can proactively steer decision-making towards more eco-friendly practices across diverse applications. Furthermore, for academic researchers, the study opens new avenues for exploring the potential of DTs in various other sectors beyond manufacturing.

Quantitatively, the research presents a clear picture of the positive correlation between DT adoption and sustainability performance metrics. The data collected and analyzed throughout the study reveal that the adoption of DT technology is a promising solution.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

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

References

1. *Digital twins: The key to smart product development* (2023). McKinsey Insights. Available at: https://www.mckinsey.com/industries/industrials-and-electronics/our-insights/digital-twins-the-key-to-smart-product-development
2. Abdoune, F., Ragazzini, L., Nouiri, M., Negri, E., Cardin, O. (2023). Toward Digital twin for sustainable manufacturing: A data-driven approach for energy consumption behavior model generation. *Computers in Industry, 150,* 103949. doi: https://doi.org/10.1016/j.compind.2023.103949
3. Wang, C., Miller, D., Gimona, A., Nijnik, M., Jiang, Y. (2023). *An integration of digital twin technology, GIS and VR for the service of environmental sustainability*. doi: https://doi.org/10.5194/egusphere-egu23-5626
4. He, B., Mao, H. (2023). Digital Twin-Driven Product Sustainable Design for Low Carbon Footprint. *Journal of Computing and Information Science in Engineering, 23 (6)*. doi: https://doi.org/10.1115/1.4062427
5. Mäkitie, T., Hanson, J., Damman, S., Wardeberg, M. (2023). Digital innovation's contribution to sustainability transitions. *Technology in Society, 73,* 102255. doi: https://doi.org/10.1016/j.techsoc.2023.102255
6. Kasych, A., Yakovenko, Y., Tarasenko, I. (2019). Optimization of Business Processes with the use of Industrial Digitalization. *2019 IEEE International Conference on Modern Electrical and Energy Systems (MEES),* 222–225. doi: https://doi.org/10.1109/mees.2019.8896531
7. Yakovenko, Y., Shaptala, R. (2023). Intelligent process automation, robotic process automation and artificial intelligence for business processes transformation. *Globalisation Processes in the World Economy: Problems, Trends, Prospects.* Riga: Baltija Publishing, 496–521. doi: https://doi.org/10.30525/978-9934-26-378-1-20

ISSN 2664-9969

8. Saracco, R. (2019). Digital Twins: Bridging Physical Space and Cyberspace. *Computer, 52 (12),* 58–64. doi: https://doi.org/10.1109/mc.2019.2942803
9. Hüsener, D., Schluse, M., Kaufmann, D., Roßmann, J. (2022). The Digital Twin as a Mediator for the Digitalization and Conservation of Expert Knowledge. *Annals of Scientific Society for Assembly, Handling and Industrial Robotics 2021*, 241–251. doi: https://doi.org/10.1007/978-3-030-74032-0_20
10. Vohra, M. (2022). Overview of Digital Twin. *Digital Twin Technology*, 1–18. doi: https://doi.org/10.1002/9781119842316.ch1
11. Kaarlela, T., Pitkäaho, T., Pieskä, S., Padrão, P., Bobadilla, L., Tikanmäki, M. et al. (2023). Towards Metaverse: Utilizing Extended Reality and Digital Twins to Control Robotic Systems. *Actuators, 12 (6),* 219. doi: https://doi.org/10.3390/act12060219
12. Vailshery, L. S. (2023). *Digital twin – statistics & facts.* Statista. Available at: https://www.statista.com/topics/9847/digital-twin/#topFacts
13. *Digital Twin Market Size, Share, Competitive Landscape and Trend Analysis Report by Type (System Digital Twin, Product Digital Twin, Process Digital Twin), by Industry: Global Opportunity Analysis and Industry Forecast, 2021–2030*. Available at: https://www.alliedmarketresearch.com/digital-twin-market-A17185
14. Rojek, I., Mikołajewski, D., Dostatni, E. (2020). Digital Twins in Product Lifecycle for Sustainability in Manufacturing and Maintenance. *Applied Sciences, 11 (1),* 31. doi: https://doi.org/10.3390/app11010031
15. Elias, D., Ziegenbein, D., Mundhenk, P., Hamann, A., Rowe, A. (2023). The Cyber-Physical Metaverse – Where Digital Twins and Humans Come Together. *2023 Design, Automation & Test in Europe Conference & Exhibition (DATE)*. doi: https://doi.org/10.23919/date56975.2023.10137285
16. Hasan, M. (2023). *Digital twin market: Analyzing growth and emerging trends.* IoT Analytics. Available at: https://iot-analytics.com/digital-twin-market-analyzing-growth-emerging-trends/
17. Mourtzis, D. (2023). Digital twin inception in the Era of industrial metaverse. *Frontiers in Manufacturing Technology, 3.* doi: https://doi.org/10.3389/fmtec.2023.1155735
18. *How digital twin technology is transforming supply chains* (2020). EY Report. Available at: https://www.ey.com/en_ae/consulting/how-digital-twin-technology-is-transforming-supply-chains
19. Wright, L., Davidson, S. (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences, 7 (1)*. doi: https://doi.org/10.1186/s40323-020-00147-4
20. Birch, D., Medoff, J.; Solomon, L. C., Levenson, A. R. (Eds.) (1994). *Labour Markets, Employment Policy and Job Creation.* Westviews Boulder, Co, 159–168.
21. *The Premier Research Platform for Long Term Investors.* (2024). Macrotrends. Available at: https://www.macrotrends.net/
22. Kilroy, A. (2023). *A Guide to Understanding ESG Ratings.* Available at: https://finance.yahoo.com/news/guide-understanding-esg-ratings-151501443.html
23. Henrekson, M., Johansson, D. (2009). Gazelles as job creators: a survey and interpretation of the evidence. *Small Business Economics, 35 (2),* 227–244. doi: https://doi.org/10.1007/s11187-009-9172-z
24. Baiocchi, G., Distaso, W. (2003). GRETL: Econometric software for the GNU generation. *Journal of Applied Econometrics, 18 (1),* 105–110. doi: https://doi.org/10.1002/jae.704
25. *What is digital-twin technology?* (2023) McKinsey. Available at: https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-digital-twin-technology#/

✉***Yaroslava Yakovenko,*** *PhD, Associate Professor, Department of Economics, Kremenchuk Mykhailo Ostrohradskyi National University, Kremenchuk, Ukraine, e-mail: yaroslavayakovenko@gmail.com, ORCID: https://orcid.org/0000-0001-5042-2701*

Roman Shaptala, *PhD, Department of System Design, National Technical University of Ukraine «Igor Sikorsky Kyiv Polytechnic Institute», Kyiv, Ukraine, ORCID: https://orcid.org/0000-0002-4367-5775*

✉*Corresponding author*