From PC to AI Through Digital Twins - A glance into the Race for Technological Ideology

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Abstract. This paper examines the history of human industrial endeavours, along with key milestones in terms of industrial revolutions. Building upon these advances, Japan's Society 5.0 envisions a human-centric, super-smart society where digital innovation harmonises with social well-being. This progression reflects not only technological evolution but also a deepening integration of innovation with human value. This work discusses key directives put forward by different countries and associated plans of action for implementing these directives. It explores the European exclusive view of "Industry 4.0" and provides a brief overview of the intersection of two key technologies for "Industry 4.0", artificial intelligence and digital twins. It brings in the notion of "Society 5.0", "Super Smart Society" and discusses the evolution of Digital Twins and Artificial Intelligence.

1 Introduction

Xu et al. [1] stirred interest into an extensive and in-depth debate of the issues of human industrial development. They argue that the industrial revolution is driving fundamental transformations across social and economic spheres. While some of these changes represent desirable and logical developments, others do not.

In the context of Industry 4.0 and Industry 5.0, the former provides the technological foundation for the latter. Xu et al. also highlight the potential emergence of new "buzzwords" such as *Industry 4.0+*, *Industry 4.5*, or even *Industry 6.0* and *Industry 7.0,* which are already in use as this work is being written. These terms are primarily convenient keywords for academic exercise and boast for grant proposals yet contribute little to actual business or technological decision-making. Therefore, here is a call for a deeper and critical discussion of these concepts, which is the aim of this paper.

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2 Methodology

The methodology combines a structured literature review, case study analysis, and cross-industry comparison to ensure a comprehensive and evidence-based understanding of real-world implementations.
A qualitative research design was adopted to investigate how digital twins are deployed across industrial sectors, which is appropriate for emerging technologies where contextual, organisational, and technical factors play a significant role in adoption and performance.
The literature review and application data were obtained from academic databases. E.g. IEEE Xplore, Scopus, Web of Science, and ScienceDirect, using search terms including "digital twin," "cyber physical systems," "predictive maintenance," "industrial IoT," and "smart manufacturing."
To show some industrial applications, the search included white papers and reports from companies as Siemens, GE, Rolls Royce, Shell, AECOM, Skanska. An interesting case was a government and city planning of Singapore Smart Nation. It provided validated examples of applied digital twins in a real industrial environment. This covers manufacturing, energy, healthcare, logistics, aerospace, to urban infrastructure. The study included aspects like maintenance, performance, simulation, equipment and asset monitoring, healthcare and energy optimisation. The work used publicly available information, and there was no confidential data from companies.

3 Historical background

3.1 Industrial Revolutions

To contextualise the terms *Industry 4.0* and *Industry 5.0*, one should examine the sequence of industrial revolutions that preceded these notions. It is widely acknowledged that the industrial world has undergone at least three major industrial revolutions over the past two centuries [2], each introducing transformative innovations that brought a step-change in technological advancement and its impact on society as a whole, mainly in Europe and the USA (see Figure 1).

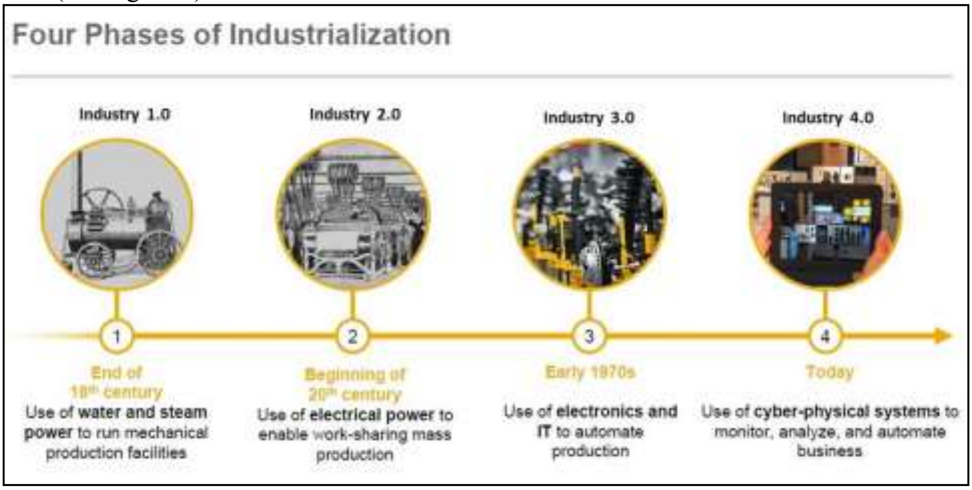

Fig. 1. Four Phases of Industrialisation [3].

The notion of "industrial revolution" is traced to the early nineteenth century in France, where scholars in the 1820s drew analogies between the British *révolution industrielle* and their own *révolution politique* [4]. The expression "Industrial Revolution" subsequently was broadened through the work of the British historian Arnold Toynbee in the 1880s. However, the conceptual foundation is more directly attributed to Friedrich Engels, whose analysis provided the definitional impression that most closely resembles contemporary usage. Since Engels's work "The Condition of the Working Class in England" (Die Lage der arbeitenden Klasse in England) was not translated into English until 1887, it was Karl Marx who effectively introduced this term to British scholars, including Toynbee. Marx and Engels deployed the expression primarily to underscore the acute social and economic hardships endured by the working classes during this period of industrial transformation [5].

In fact, current scholarly interpretations of "revolution" often invoke a more affirmative understanding of the term, framing it as a historical stage characterised by radical technological innovations or by the emergence of fundamentally new intellectual framework developments that bring paradigm shifts leading to cultural, economic, and social reconfigurations [6].

The First Industrial Revolution began in England in the mid-18th century and was driven by the introduction of steam power into industrial production. Mechanical power gradually replaced inefficient manual and slave labour in small-scale industries, leading to a significant rise in productivity. As a result, large numbers of people migrated from rural areas to rapidly growing urban centres [7].

The Second Industrial Revolution, generally dated from around 1870 to 1914 (the onset of World War I), was characterised by the development of inexpensive steel production and the widespread use of electricity and chemical technologies. The adoption of electrical energy in manufacturing enabled mass production, the introduction of assembly lines, and the automation of repetitive tasks [8]. This transformation accelerated after Thomas Edison's introduction of electric power systems in cities in 1882 [2]. Overall, electricity became, and remains, a fundamental driving force of industrial development.

The Third Industrial Revolution began shortly after the end of the Second World War and was defined by the rise of computerisation and microelectronics in manufacturing. Key developments during this period included the widespread use of programmable logic controllers (PLCs), the emergence of personal computers in the 1970s and 1980s, and the introduction of the Internet in the 1990s. This era, often referred to as the information or informatics revolution [2, 6], laid the groundwork for the transition to the Fourth Industrial Revolution [9].

In his 2017 book [6], Klaus Schwab, Founder and Executive Chairman of the World Economic Forum, argued that the world is entering a Fourth Industrial Revolution. He noted that this transformation began at the turn of the 21st century and builds upon the earlier digital revolution. According to Schwab, it is characterised by the widespread availability of mobile internet, increasingly powerful and affordable sensors, and rapid advances in artificial intelligence and machine learning.

The term "Fourth Industrial Revolution" was originally introduced in the 1980s by the American economist and political theorist Walt Whitman Rostow [10]. Rostow described this revolution as being driven by breakthrough technologies that are transitioning from invention to practical innovation. He identified four defining features: independence from any single country, a close link to fundamental scientific research, rapid adoption in industrialised nations, and transformative impact on core industries [11]. Over time, the concept became associated with the development and application of nanotechnology [12] and later gained widespread recognition at the Hannover Fair in 2011, where it was linked to the concept of "Industry 4.0" following Germany's "Industrie 4.0" industrial strategy.

3.2 Industry 4.0

Germany is widely regarded as a pioneer of the so-called Fourth Industrial Revolution, having prepared for this transformation well before it formally emerged. In 2011, the German government introduced the *High-Tech Strategy 2020 Action Plan*, within which *Industrie 4.0* was identified as a key strategic initiative. This approach placed strong emphasis on the manufacturing ecosystem, encouraging cooperation between large industrial corporations and small and medium-sized enterprises (SMEs) through the application of technologies such as the Internet of Things (IoT) and cyber-physical systems (CPSs). The overarching objective was to establish a foundational transformation linking research and development, manufacturing processes, and end users [13].

In 2014, the German standardisation bodies DIN and DKE published the *Standardisation Roadmap Industrie 4.0 – Version 1.0* [1], which aligned closely with the concept of the Industrial Internet proposed by General Electric (GE) [14]. One year later, the German government introduced an updated framework known as *Platform Industrie 4.0*. This revised strategy explicitly highlighted the importance of collaboration among industry, research institutes, and universities, supported by government coordination. Its stated goal was to establish new global manufacturing standards and enable so-called "ubiquitous mass customisation" by 2025 [13].

The United States represents another major actor in the adoption of Fourth Industrial Revolution strategies. In 2011, President Barack Obama launched the *Advanced Manufacturing Partnership (AMP)* at Carnegie Mellon University, aiming to bring together industry, academia, and the federal government to invest in emerging technologies that could strengthen manufacturing competitiveness and create high-quality jobs [15]. This initiative was later expanded into AMP 2.0. While similar to the German approach in its focus on manufacturing, the U.S. strategy placed greater emphasis on technologies such as artificial intelligence and cloud computing.

The American approach was strongly influenced by the Industrial Internet concept developed by General Electric. GE demonstrated the practical application of this concept by managing factory production systems and manufacturing processes through a cloud-based Platform-as-a-Service (PaaS) known as the *Predix Platform* [13]. In June 2013, GE formally introduced the idea of the Industrial Internet Revolution, emphasising the integration of industrial equipment, data, and advanced analytics to improve operational efficiency and service quality [14]. As stated by Jeffrey R. Immelt, former Chairman and CEO of GE, "*An open, global network will connect people, data and machines*" [16]. Subsequently, in 2014, the Industrial Internet Consortium (IIC) was established in the United States by AT&T, Cisco, GE, IBM, and Intel, with the goal of fostering industry-wide collaboration.

Other countries have interpreted and adapted the Industry 4.0 concept according to their own national priorities and economic conditions [17]. China and Japan, in particular, have developed strategies tailored to their domestic industrial structures. Japan introduced the *Japan Revitalization Strategy 2015*, leveraging its established leadership in industrial automation and robotics. The strategy emphasised the adoption of IoT, big data, artificial intelligence, and advanced robotics as core drivers of the Fourth Industrial Revolution [13].

China, meanwhile, launched several national initiatives in 2015 to promote smart manufacturing, most notably the *Made in China 2025* strategy. This program aimed to accelerate the adoption of intelligent manufacturing technologies by drawing on both the American Industrial Internet framework and the German *Industrie 4.0* model. Complementing this effort, the *Internet Plus* policy sought to enhance productivity by integrating traditional industries with Internet technologies and information systems. In 2024, China further announced an ambitious plan to become a global leader in science and technological innovation by 2035 [18].

Inspired by Germany's *Industrie 4.0* initiative, South Korea introduced the *Manufacturing Innovation 3.0* strategy in 2014 as part of its Fourth Industrial Revolution agenda [13]. Similarly, Singapore launched its own national strategy in 2016 through the Infocomm Development Authority (IDA). Unlike many other initiatives, Singapore's approach extended beyond manufacturing, aiming to build a nationwide "Smart Nation" through the deployment of sensors and real-time data infrastructure [13].

Figure 2 illustrates the global distribution of major technology initiatives, including *Industrie 4.0*, the Industrial Internet, and *Made in China 2025*. Although these programs differ in scope and implementation, they share a common foundation in digital transformation. As a result, digital transformation has increasingly become a central pillar of contemporary industrial policy worldwide [19].

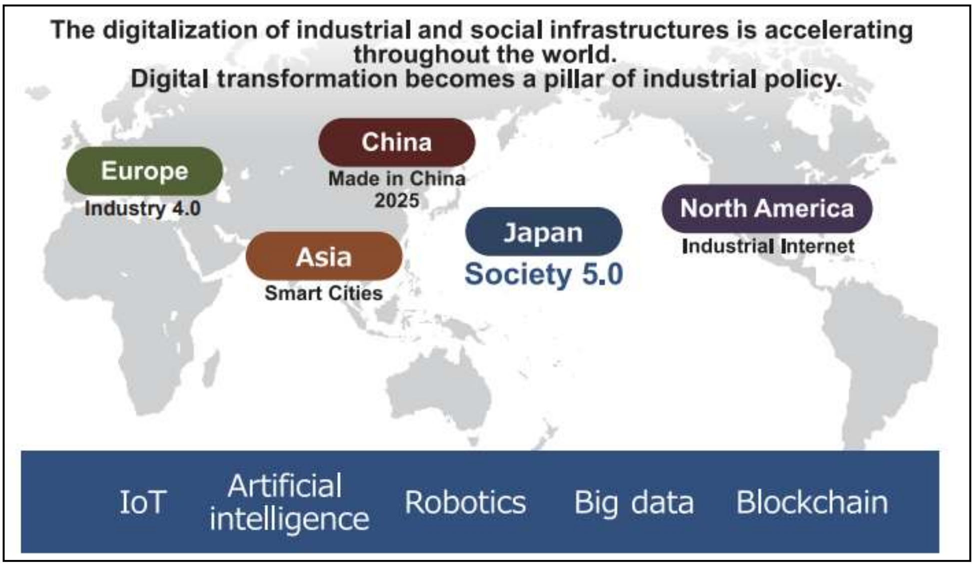

Fig. 2. Digital transformation from [19].

Thus, although each country, region, and even individual enterprise exhibits distinct national and organisational characteristics that shape manufacturing philosophies, problem-solving approaches, and strategic priorities for innovation, the overarching implementation concept that provides the framework for advanced technologies remains largely consistent across contexts [20]. When applied in practice, these converging ideas and technological approaches position manufacturing as a central and defining element of the forthcoming Fourth Industrial Revolution [21].

3.3 A New Human-centred Society or Society 5.0

The first contribution to clarifying the concept of human-centred society was made in 2016 by the Association of Japanese Industries (Keidanren) via the concept of "Society 5.0" as: "a society that seeks to balance economic development with solving socio-environmental problems, in which technologies are used not only for profit, but to improve the quality of life of every citizen." [22]. Although Society 5.0 originated in Japan, the developed frameworks and technology might no doubt contribute to resolving societal challenges worldwide [19]. The concept of Society 5.0 (see Figure 3) follows hunter-gatherer society (Society 1.0), agricultural society (Society 2.0), industrial society (Society 3.0), and information society (Society 4.0) in indicating the new society created by transformations led by scientific and technological innovation [23]. In this evolution, Society 5.0 is an information society built upon Society 4.0, aiming for a prosperous human-centred society. Society 5.0 aims to create a world where everyone can truly enjoy life, with technology and economic progress serving the common good rather than just benefiting a small group [19]. The concept of a human-centred society was first clearly articulated in 2016 by the Japan Business Federation (Keidanren) through the introduction of Society 5.0. Keidanren defined Society 5.0 as "a society that seeks to balance economic development with the resolution of socio-environmental challenges, in which technologies are applied not only for economic gain but also to enhance the quality of life of all citizens" [22]. Although the concept originated in Japan, the frameworks and technological approaches associated with Society 5.0 have the potential to contribute to addressing societal challenges on a global scale [19].

As illustrated in Figure 3, Society 5.0 represents the next stage in societal development, following hunter-gatherer society (Society 1.0), agricultural society (Society 2.0), industrial society (Society 3.0), and information society (Society 4.0). This classification highlights the emergence of a new form of society shaped by scientific and technological innovation [23]. Within this evolutionary framework, Society 5.0 builds upon the foundations of the information society while aiming to create a prosperous, human-centred social system. Its central objective is to ensure that technological advancement and economic growth serve the broader public interest, enabling all members of society to benefit and enjoy an improved quality of life, rather than concentrating advantages within a limited segment of the population [19].

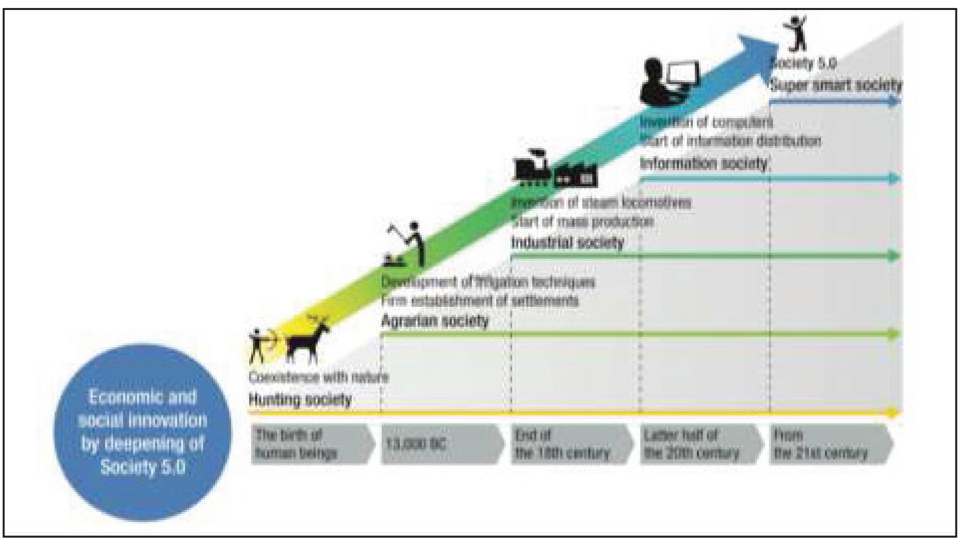

Fig. 3. Economic and social innovation by deepening of Society 5.0 from [19].

The concept of Society 5.0, also referred to as the "Super Smart Society," was introduced by the Council for Science, Technology and Innovation (CSTI) in Japan's Fifth Science and Technology Basic Plan (FY2016–FY2020) and formally approved by a Japanese Cabinet decision on January 22, 2016. The purpose of this concept was articulated as follows [24]: "Through an initiative that merges physical space (the real world) with cyberspace by fully leveraging information and communication technologies (ICT), an ideal vision of future society is proposed, a 'super-smart society' that brings prosperity to the people. The initiatives aimed at realising this vision are being further refined and actively promoted under the framework of 'Society 5.0.'"

In 2017, Japan's Prime Minister Shinzo Abe reinforced this perspective during his address at the CeBIT exhibition in Hannover, Germany, stating that "technology should be perceived by societies not as a threat, but as an aid" [25]. In other words, Society 5.0 emphasises the development and application of technology not in opposition to humans and nature, but as a means of serving societal needs and supporting sustainable coexistence with the natural environment [2].

3.4 Industry 5.0

The term *Industry 5.0* was first introduced in 2015 by Czech industrial entrepreneur Michael Rada in a LinkedIn publication entitled "INDUSTRY 5.0 - From Virtual to Physical" [26]. Before this, beginning in 2013, Rada had already implemented the Industrial Upcycling methodology across various companies, an approach focused on preventing waste generation at an industrial scale. Building on these experiences, he later proposed the concept of Industry 5.0, which he described as "the first industrial evolution ever led by humans" [27]. Central to Rada's perspective was the emphasis on people and the natural environment within industrial systems. He argued that industrial development must restore the central role of both human well-being and environmental responsibility, stating that "we need to return to the centrality of the environment and people in the industrial process" [22, 28].

In 2021, the European Commission formally adopted the Industry 5.0 approach with the publication of the document "Industry 5.0: Towards a Sustainable, Human-Centric, and Resilient European Industry" on 5 January 2021 [1, 29]. This framework emerged in response to perceived limitations of Industry 4.0 in meeting Europe's long-term objectives for 2030 [30]. In particular, the Commission highlighted concerns that the existing digital economy tends to follow a winner-takes-all model, contributing to technological monopolies and increasing economic inequality. From the European Commission's perspective, Industry 5.0 does not represent a purely technological progression beyond Industry 4.0. Rather, it reflects a reorientation of industrial transformation toward outcomes that benefit people, the planet, and overall societal well-being [31].

Although the European Commission referenced Rada's work and his original definition of Industry 5.0, its interpretation differs in emphasis. While Rada's concept focused strongly on the meaningfulness of work and human agency in industrial evolution [27], the Commission's framework places greater attention on technologies, digitalisation, and virtualisation as enabling mechanisms.

The concept of Industry 4.0 is traditionally structured around nine technological pillars [32]: big data and analytics, additive manufacturing and 3D printing, autonomous robots, simulation and digital twins, horizontal and vertical system integration, the Industrial Internet of Things (IIoT), cybersecurity, cloud computing, and augmented and virtual reality. In contrast, drawing inspiration from the Japanese concept of Society 5.0 [33], Industry 5.0 is founded on three core pillars [29]: human-centricity, sustainability, and resilience. Figure 4 illustrates the expansion and evolution of industrial technologies as the paradigm shifts from Industry 4.0 toward Industry 5.0 [33].

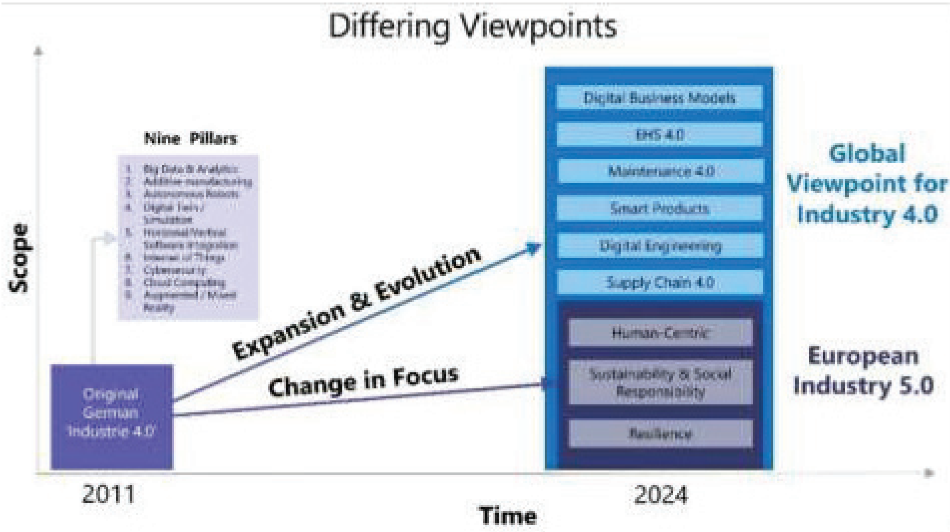

Fig. 4. The difference between a change in focus versus expansion and evolution by [33].

A human-centric approach places people's needs at the heart of the production process, focusing on how technology can support workers and enhance their capabilities [31]. This perspective emphasises the use of human potential within machine learning systems as well as close collaboration between humans and collaborative robots (cobots) [34].

Although sustainability has been defined in many ways, most interpretations converge to a common idea: natural resources must be used responsibly, with an emphasis on recyclability and reusability, so they remain available for future generations [35]. The concept of resilience, originally rooted in psychology and studies of robustness, has a long history in mechanics dating back to the nineteenth century. It gained broader recognition after being introduced to systems ecology by the US/Canadian ecologist Crawford Stanley Holling in his influential 1973 paper [36]. In an industrial context, resilience contributes to the robustness and continuity of production systems [31]. However, as pointed by the authors in [35], environmental protection and resource conservation become difficult to prioritise when basic human needs are unmet, raising important questions about the real-world implementation of sustainability and resilience principles.

In 2020, the European Commission identified six key pillars that define the transition from Industry 4.0 to Industry 5.0 [29]: (1) individualised human/machine interaction; (2) bio-inspired technologies and smart materials; (3) digital twins and simulation; (4) data transmission, storage, and analysis technologies; (5) artificial intelligence; and (6) technologies supporting energy efficiency, renewable energy, storage, and system autonomy. This study concentrates on two of these areas in particular: digital twins and artificial intelligence.

3.5 The Digital Twin Origins

The idea underlying the "digital twin" can be traced back to 1991, when computer scientist David Gelernter proposed this concept in his book "Mirror Worlds". He described such systems as "software models of some chunk of reality, some piece of the real world going on outside your window" [37]. The book envisioned detailed digital representations of real-world objects that continuously receive information from their physical counterparts and are updated in near real time to reflect changes in the physical environment [38,39].

In early 2002, Michael Grieves introduced a three-component model comprising a physical space, a virtual space, and a bidirectional information link between them. This model was proposed within the context of a Product Lifecycle Management (PLM) course at the University of Michigan [40]. Later that year, in October 2002, an unnamed model describing an "ideal" PLM framework was presented at a Society of Manufacturing Engineers (SME) conference in Troy, Michigan. This framework, referred to as the "Conceptual Ideal for PLM," formed a foundational element of Product Lifecycle Management theory [41].

By 2003, the notion of a virtual, digital counterpart to a physical product was formally introduced during the University of Michigan Executive Course on PLM and subsequently discussed in a 2005 journal publication under the name "Mirrored Spaces Model" [42]. This concept was later renamed the "Information Mirroring Model" in 2006 in the influential book Product Lifecycle Management: Driving the Next Generation of Lean Thinking [43]. In this work, the Digital Twin was also described metaphorically as a "virtual doppelganger" of the physical product [40].

The first explicit reference to the term "Digital Twin" appeared in NASA's draft technological roadmap in 2010, where it was also referred to as a "Virtual Digital Fleet Leader" [38]. In this roadmap, NASA defined a Digital Twin as "*an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and other information, to mirror the life of its flying twin*" [44].

The term "Digital Twin" was introduced by John Vickers, a technologist collaborator of Grieves, as a more concise and elegant alternative to the earlier terminology. The concept was subsequently instituted and popularised by Michael Grieves in his 2011 book "Virtually Perfect: Driving Innovation and Lean through Product Lifecycle Management" [45]. From that moment, the term gained widespread acceptance and gradually entered common usage within both academic and industrial communities [41].

Further formalization followed in a 2012 conference paper by Edward H. Glaessgen and David S. Stargel [46], who, similarly to NASA, defined the Digital Twin in the aerospace domain as "*an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*." Along similar lines, Hribernik et al. [47] introduced the concept of the "*Product Avatar*" in 2006 as a means of supporting a product-centric information architecture with bidirectional data flow. Over time, this concept has largely been superseded by the more comprehensive and widely adopted Digital Twin paradigm.

3.6 Digital Twin by Definition

Numerous definitions of the digital twin exist in both academia and industrial practice, largely reflecting the specific domains in which the concept is applied [48]. In 2014, Michael Grieves [49] published a white paper on manufacturing that further clarified the meaning of the Digital Twin. In this work, he identified three core elements of the model: the real space, the virtual space, and a bidirectional data connection linking the two. This data connection is commonly associated with the concept of the "Digital Thread," which was introduced by the United States Air Force (USAF) in 2013 [50].

In 2017, Grieves and Vickers [40] expanded the Digital Twin framework by defining it as a lifecycle-oriented information model. They described the Digital Twin as "*a set of virtual information constructs that fully describes a potential or actual physical manufactured product, from the micro-atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin*." Within this framework, three main types of Digital Twins were introduced: the Digital Twin Prototype (DTP), the Digital Twin Instance (DTI), and the Digital Twin Aggregate (DTA). These types correspond to four key phases of the product lifecycle that have been integral to the Digital Twin model since its inception [43]: creation, production (manufacturing), operation (support and sustainment), and disposal or decommissioning.

Each phase of Digital Twin development represents a specific state of the product across its lifecycle. The process begins with the creation phase, during which a Digital Twin Prototype is developed to fully describe the intended physical product. This virtual representation is essential for accurate modelling, simulation, and prototyping, allowing extensive testing and experimentation before physical production begins. Once the virtual product is finalised, the production phase commences, and a Digital Twin Instance is created. By the end of this phase, a bidirectional data link is established between the physical product and its virtual counterpart, enabling continuous data exchange.

During the operation and support phase, both the physical and virtual entities evolve together to reflect the product's current condition. At this stage, a Digital Twin Aggregate is formed by combining data from all system sources. The final phase involves product disposal or decommissioning, during which knowledge gained from the product's behaviour is preserved and used to inform future product generations [40].

Although Grieves' early work was primarily focused on establishing a new Product Lifecycle Management paradigm and did not initially label the concept explicitly as a Digital Twin, it has, however, provided the foundational framework for subsequent Digital Twin research and development [47]. Since the early 2010s, at least ten additional definitions have been proposed by both academia and industry [51]. For instance, building upon Grieves' original model, Tao et al. [52] extended the three-dimensional Digital Twin architecture to a five-dimensional framework for complex equipment by incorporating data and service components. In this model, Digital Twin data are positioned at the centre and supported by service layers. As illustrated in Figure 5, this approach has been applied across the entire lifecycle of complex equipment, including digital design, production, testing and validation, operation and maintenance, and service phases [53].

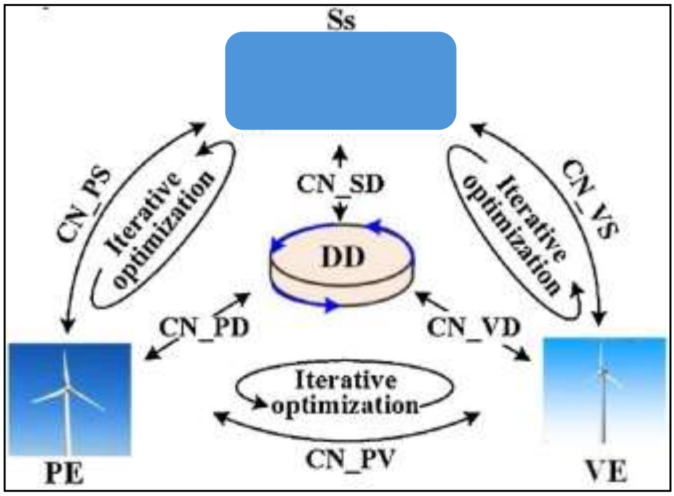

Fig. 5. Five-dimension DT model for complex equipment, where PE refers to the physical entity, VE is the virtual equipment, Ss stands for services for PE and VE, DD refers to DT data, and CN is the connection among PE, VE, Ss and DD [52].

3.7 Artificial Intelligence

The Age of Intelligent Machines started in the middle of 1950s with several high peaks of enthusiasm ("AI Summers") and low troughs of discouragement ("AI Winters") [54], see Figure 6.

Fig. 6. Timeline of the History of AI (1950-Present) (from reference [54]).

In 1950, the English mathematician Alan Mathison Turing published his historic paper "Computing Machinery and Intelligence" in the philosophy journal Mind [55]. He opened the paper with the now-famous question, "Can machines think?" and went on to propose a practical criterion for machine intelligence, originally called the "imitation game" and later known as the "Turing test." According to this test, a machine can be considered intelligent if it is able to imitate human behaviours convincingly enough to be indistinguishable from a human interlocutor. Around the same period, the American mathematician Claude Shannon, often referred to as the "Father of the Information Age", constructed a machine capable of learning [54]. His robotic mouse, Theseus [56], demonstrated one of the earliest examples of machine learning by navigating mazes using telephone relay switches.

The formal birth of artificial intelligence as a research field is commonly associated with the Dartmouth Summer Research Project on Artificial Intelligence, held in the summer of 1956 at Dartmouth College in Hanover, USA. The workshop was organized by John McCarthy, then a 28-year-old assistant professor of mathematics, with the aim of developing and clarifying ideas about "thinking machines" that had gained attention in the early 1950s

[57]. During the preparation for this event, McCarthy coined the term "artificial intelligence," deliberately choosing a neutral expression to avoid associations with automata theory and potential disagreements with Norbert Wiener, the founder of cybernetics [58]. McCarthy later defined artificial intelligence as "the science and engineering of making intelligent machines, especially intelligent computer programs" [59].

The term "artificial intelligence" first, appeared in a proposal submitted to the Rockefeller Foundation in August 1955 [60]. Titled "*A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*," the document stated that "*every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*." The proposal outlined ambitious goals, including enabling machines to use language, form abstractions and concepts, solve problems traditionally reserved for humans, and improve their own performance [61]. Although the initial funding request amounted to $13,500, the Rockefeller Foundation ultimately awarded $7,500 to the project's co-authors [62]: Marvin Minsky (Harvard University), Nathaniel Rochester (IBM Corporation), and Claude Shannon (Bell Telephone Laboratories). In later years, two of these pioneers were recognised with the A. M. Turing Award, presented annually by the Association for Computing Machinery (ACM): Marvin Minsky in 1969 and John McCarthy in 1971.

The most significant outcome of the Dartmouth Workshop was the establishment of artificial intelligence as a distinct scientific discipline, inspiring generations of researchers to pursue AI goals through diverse approaches. Despite substantial progress over the past five decades, the aspiration of achieving human-level artificial intelligence was not realised at Dartmouth. As noted by McCarthy in [60], new conceptual breakthroughs remain necessary. He argued that AI research had already begun to diverge, possibly even before 1956, into two main directions: approaches aimed at mimicking the human nervous system and engineering-based methods focused on solving practical problems faced by humans, animals, and machines striving to achieve objectives such as survival. These directions later evolved into what are now known as Machine Learning (ML) and Deep Learning (DL). To date, neither approach has succeeded in producing intelligence comparable to that of humans [60].

The term "machine learning" was introduced in 1959 by Arthur Samuel, a participant in the Dartmouth Conference, who defined it as the "field of study that gives computers the ability to learn without being explicitly programmed" [63]. The roots of deep learning can be traced even further back to 1943, when Warren McCulloch and Walter Pitts proposed the first artificial neural network model [64], inspired by the structure and functioning of biological neurons. While the engineering-oriented approach has achieved notable success in developing computer programs for specific, well-defined tasks, these systems still lack general intelligence and common sense reasoning abilities.

4 Digital Twins – from Inception to Adoption

4.1 The Twinning in a Digital Era

The concept of a digital twin can be seen as an electronic or virtual representation, a counterpart or "twin" of a real-world entity, which may be either physical or conceptual in nature [65]. In a broad sense, digital twins are not limited to tangible physical objects; they can also represent abstractions, including existing processes of various kinds.

The idea of "twinning" is not new, and historically, both the United States and the former Soviet Union employed multiple physical models of the same spacecraft within the aerospace industry to train crews and test different flight scenarios, [40]. In this traditional form of twinning, two or more replicas of a main entity existed independently, without any direct connection between them. From this perspective, twinning consisted of a primary object and its replica, operating separately. In contrast, Grieves' original and innovative contribution was not merely the notion of a "twin" as such, but rather the early idea, developed well before he collaborated with Vickers, of creating a digital representation of the manufacturing process itself.

Looking back at the origins of the digital twin concept, a well-known example of physical twinning can be found in NASA's practice of using duplicate spacecraft to simulate emergency situations. This approach was widely adopted at the time, and the Soviet Union followed a similar strategy, beginning with Yuri Gagarin's historic flight on April 12, 1961, and continuing through the construction of multiple copies of its own space shuttle, Buran. Developed in the late 1980s, Buran was the Soviet response to NASA's Space Shuttle program. Similarly, as noted by Grieves (2022), aircraft manufacturers were already using physical twins in the 1930s to replicate and investigate technical problems in aircraft systems. When issues arose in the automotive industry, it was also common practice to locate an identically configured vehicle to reproduce and analyse the problem. Despite these historical precedents, Grieves clearly distinguished his concept of a digital twin from NASA's earlier notion of physical twinning used for spacecraft modelling and simulation in the 1960s and 1970s (Grieves, 2022).

In the early twenty-first century, Michael Grieves and John Vickers introduced a fundamentally different approach: a digital, rather than physical, replica connected to its real-world counterpart through a bidirectional data link. The defining characteristic of their concept was that the twin had to be digital, a shift that profoundly transformed Product Lifecycle Management (PLM). In this framework, the digital twin does not merely mirror its physical counterpart but maintains continuous two-way communication, enabling real-time monitoring and updates of both entities. While Grieves primarily envisioned the digital twin as a core element of PLM, Vickers initially focused more on the physical counterpart. Nevertheless, the concise and increasingly popular term "Digital Twin," coined by Vickers, soon became dominant and was widely adopted, including within Grieves' own work.

As a result of this dual and somewhat divergent understanding of what constitutes a digital twin, the field today encompasses more than ten different definitions of the same term, along with an even greater number of claims regarding successful applications of the concept. To date, there is no universally accepted definition of a digital twin. Some interpretations focus exclusively on digital modelling components, while others emphasise the necessity of integrating both the digital representation and its corresponding physical entity. This lack of definitional clarity introduces conceptual ambiguity and may lead to inconsistencies in the development and implementation of digital twin technologies across different industrial domains [51,66].

Ultimately, a single term is used to describe digital twins, yet it carries multiple, sometimes conflicting, meanings. In principle, this allows almost any technology or combination of technologies to be labelled a digital twin without consequence. While such flexibility is not inherently negative, it becomes problematic when considering the conceptual rigour and "purity" of the technology. From this perspective, the absence of a clear and shared definition is more detrimental than beneficial to the long-term development of the digital twin paradigm.

4.2 Digital Twin in a software context

The overwhelming majority of works published to date in the field of digital twins focus on modelling and simulation. Clearly, both modelling and simulation have accompanied humans throughout human history. Moreover, prediction and analysis have already been successfully implemented in specialised software at an advanced level, so digital twins should provide the opportunity for cross-industry reusing accumulated knowledge, Interoperability [67].

Michael Grieves, in his 2016 work [68], defined the three types of digital twins, namely, Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and Digital Twin Aggregate (DTA). Later, in 2017, work [40] Grieves eliminated DTA from that classification. Meanwhile, both papers contended that a Digital Twin Environment is an integrated, multi-domain physics application space for operating on Digital Twins for a variety of purposes. Grieves defined these purposes as Predictive and Interrogative. Predictive – the Digital Twin would be used for predicting future behaviour and performance of the physical product. Interrogative - this would apply to DTI's as the realisation of the DTA, in the 2016 definition version [68], could be interrogated for the current and past histories. In other words, Digital Twin Instances and Aggregates exist within their Digital Twin Environment, mirroring the real product's environment through the three components: real space, virtual space, and a bidirectional linking mechanism between them [51].

Briefly consider the two definitions of the Digital Twin Environment. The first definition, given by Red Hat's EMEA Solutions in [69], states that DTE offer a logical environment in which software and potentially hardware components interact to simulate an entire system or subsystem, as opposed to an individual process, as allowed by a simulation. The second one describes DTE, as an environment, where the "virtual world" in which the DT exists. The practical use could be replicating the Physical Twin Environment (PTE) for different simulation scenarios. Without the Digital Twin Environment, what-if analyses are narrow, if not absent [70].

Sharma et al. [71] classified the software solutions for the digital twin implementation provided by companies like IBM, SAP and Siemens as follows: investing in DT technology, providing DT software as a service for clients, and using DT functionality for themselves. In turn, these providing DT software solutions can be categorised into three parts: infrastructure platforms, integration platforms, and specific task platforms.

Typical examples of infrastructure-based platforms include Microsoft Azure IoT, Amazon Web Services IoT Core, and Google. The key advantage of this type of platform is the client's access to a very powerful computing infrastructure, a highly scalable and reliable cloud, and various IT services such as security, analytics, data storage, and more.

The primary clients of the second type of solutions are large enterprises with significant legacy IT landscapes from previous generations. In this case, it is crucial to integrate a new solution into the current landscape without disrupting existing business practices. Therefore, the digital platform needs substantial integration capabilities in addition to its fundamental functionality.

Solutions of the third type are offered by companies with the relevant competencies and knowledge of the specific challenges of a particular industry. This category includes Siemens' MindSphere as a Service (PaaS) (transportation and healthcare), John Deere's MyJohnDeere (agriculture), ABB's ABB Ability (mechanical engineering and instrumentation), Schneider Electric's EcoStruxure Platform (energy and climate control), and several others.

Some well-known companies utilize so-called digital twin in their own businesses. Qi and Tao [72] collected the commercial software and platforms for the digital twins from the eight famous companies: GE Predix Platform, PTC ThingWorx, Siemens NX + Teamcenter / MindSphere, Oracle IoT Cloud Service, ANSYS TwinBuilder, Dassault Systèmes 3DEXPERIENCE Twin, SAP Digital Twin, Altair Digital Twin Platform. However, this work dates back to 2018, and the current state of these companies as well as their products, has changed. For instance, GE's industrial internet platform, Predix Platform, failed.

The authors agree with [71], that there is a gap between the ideal Digital Twin and its practical implementation. Even from the commercial software and platforms listed above, it is clear that there are many platforms. Giulianelli et al. [48] states the difficulties of creating a single technology or platform for everybody to use, especially in complex real-world contexts where legacy is the norm. As one of the reasons, they point to the presence of a diverse range of DT definitions existing in both academia and industry, influenced and enriched by the domain in which they are used. The second reason noted in [51, 67] - fragmentation and absence of standardisation in digital twins' software development result in isolated ecosystems that obstruct interoperability, complicate the integration of data and models, and create barriers to seamless communication among DTs, essential for optimising DT interoperability and compositionality across various manufacturing processes.

4.3 Combination of Digital Twins and Artificial Intelligence

Kreuzer et al. [73] conducted a systematic literature review examining the intersection of two key categories, artificial intelligence and digital twins, highlighted in the European Commission's document "Industry 5.0: Towards a Sustainable, Human-centric, and Resilient European Industry." Their analysis revealed that most of the reviewed studies lacked a feedback loop, even though bidirectional feedback is a fundamental characteristic of a Digital Twin according to the original concept proposed by Michael Grieves and John Vickers in the early twenty-first century.

As discussed in [73,74], many of the examined studies relied on traditional simulation models rather than true Digital Twins. Although these models often described real-time data connections between virtual and physical systems, they frequently depended on historical data to emulate data exchange between the digital and physical counterparts. While such approaches may function adequately for small datasets, they tend to produce inaccurate results when scaled or applied under different conditions. The authors in [74] further argue that, although simulation-based modelling has a legitimate role in certain applications, it should be distinguished conceptually and referred to using a different terminology. The primary limitation identified across most of the reviewed papers was the absence of a genuine, continuous connection between the virtual representation and the physical object.

Despite the extensive promotion of Digital Twin software solutions by major corporations such as IBM, SAP, and Siemens, academic research on the integration of machine learning within Digital Twin frameworks remains relatively scarce. Moreover, the extent to which these industrial platforms employ machine learning techniques is often unclear or insufficiently documented in the literature [71].

4.4 Transition from Industry 4.0 to 6.0

From a theoretical perspective, the conventional narrative of the Industrial Revolutions relies heavily on a Eurocentric and linear framework, which assumes that industrial, technological, and economic development follows a universal trajectory. As shown in Figure 2, only a small number of leading economies have been direct participants in these so-called revolutions. The numerical classification from Industry 1.0 to Industry 4.0, and the recent addition of Industry 5.0, reflects not an objective historical reality but a retrospective ordering imposed by dominant industrial powers. This raises a fundamental theoretical question: to what extent can such classifications meaningfully describe the development of emerging economies, whose industrial paths were shaped by local conditions, colonial histories, and geopolitical constraints?

The persistence of the linear model becomes particularly problematic when examining non-Western nations such as Taiwan, China, Korea, India, and post-Soviet states [75]. These countries could not replicate the accelerated industrial progression of Western powers due to structural and institutional limitations. The introduction of transitional concepts such as Industry 3.5 in Taiwan illustrates the conceptual contortions required to reconcile local realities with externally imposed industrial narratives (Chien, Hong and Guo, 2017). Industry 3.5, positioned between Industry 3.0 and Industry 4.0, highlights the theoretical tension between normative models of industrial evolution and the empirical realities of uneven development.

Similarly, alternative conceptualisations such as the Humanised Revolution or the Wise Anthropocentric Revolution [75,76] challenge the implicit technological determinism of conventional industrial discourse. These frameworks reposition the human subject and social well-being at the centre, signalling that historical accounts of industrial revolutions often privilege technological metrics over human outcomes. From this standpoint, Michael Rada's introduction of Industry 5.0 in 2015 and the Japanese vision of Society 5.0 serve less as straightforward industrial stages and more as normative projects attempting to redirect industrial discourse toward social objectives. The European Commission's later adoption and expansion of Industry 5.0 to include sustainability and resilience further demonstrates that these labels function as conceptual instruments for shaping policy, rather than empirically verifiable stages of industrial evolution.

The proliferation of terms such as Industry 6.0 and Industry 7.0 underscores the theoretical fragility of this model. Rather than reflecting identifiable structural shifts, these terms often appear to operate as rhetorical devices intended to signal modernity or global competitiveness. Their widespread use in publications from emerging economies such as India and China raises additional questions. Are these nations genuinely pioneering new industrial stages, or are they adopting fashionable terminology to assert parity with established industrial powers? The theoretical implication is clear: the language of industrial revolutions risks functioning more as ideology than as an analytic category.

A critical review of this discourse also highlights a temporal problem. Historically, labels such as the Industrial Revolution were applied only after profound transformations had already reshaped production, society, and economy. By contrast, contemporary terms like Industry 4.0 plus, Industry 4.5, or Industry 5.0 are frequently applied prospectively, to ongoing processes whose systemic impact remains untested. This anticipatory use of revolutionary terminology weakens the conceptual rigour of the framework and conflates incremental technological change with historical revolutions. For example, the widespread adoption of smartphones and other digital devices, while transformative in daily life, does not yet exhibit the systemic and structural properties that characterised the steam engine or mechanised production.

In conclusion, a theoretical critique of industrial revolution frameworks reveals several limitations. The dominant classifications are Eurocentric, linear, and technology-centric, often disregarding local historical trajectories and social outcomes. Transitional terms such as Industry 3.5 or normative constructs like Industry 5.0 reflect attempts to reconcile these limitations, yet they introduce additional conceptual ambiguity. The proliferation of Industry 6.0 and 7.0 illustrates the performative function of industrial labels in policy, marketing, and academic discourse, rather than serving as analytically precise categories. Without careful conceptual grounding, these terms risk obscuring rather than clarifying the dynamics of contemporary technological, social, and economic transformation.

5 Digital Twins in adoption

Digital twin technology has emerged as a transformative tool in industrial systems, enabling real-time monitoring, predictive analytics, and optimisation of physical assets through virtual replicas. The embedding of Internet of Things (IoT), artificial intelligence (AI), and modelling, digital twins can provide active monitoring for predictive maintenance, lifecycle management, and operational optimisation (Tao et al., 2018; Fuller et al., 2020). Below are some industrial applications of digital twins covering from manufacturing, aerospace, automotive, energy, infrastructure, and healthcare sectors, highlighting real-world implementations by leading global companies.

5.1 Digital Twins in Manufacturing

Large corporations in manufacturing seeking for increased gain from AI deploy digital twins for predictive maintenance, virtual commissioning, and production optimisation. Siemens integrates digital twin capabilities into its Product Lifecycle Management (PLM) and automation platforms, allowing manufacturers to simulate production lines before deployment. This approach reduces commissioning time and mitigates system integration risks (Tao et al., 2019). General Electric (GE Digital) uses digital twins for industrial turbines and rotating machinery. Their real-time monitoring and predictive analytics reduce unplanned downtime and extend equipment lifespan (Negri et al., 2017).

The aerospace engineering benefits largely from digital twins, which enable performance optimisation and service-based maintenance models. Rolls-Royce uses a wide rage of digital replicas of aircraft engines that are continuously updated with in-flight sensor data. This supports predictive maintenance and underpins outcome-based service contracts (Fuller et al., 2020).

In the energy sector, digital twins improve safety and operational efficiency. Shell applies digital twin to their offshore platforms for structural monitoring, production optimisation, and risk modelling. Several national energy grids employ grid-level digital twins to model load balancing, renewable integration, and infrastructure resilience, supporting decarbonisation strategies (Fuller et al., 2020).

In healthcare, digital twins support workflow optimisation and resource allocation. For example Philips has developed hospital digital twin systems to simulate patient flow and intensive care capacity, improving system resilience and operational decision-making (Fuller et al., 2020).

In built Environment, digital twin applications extend to urban-scale systems development, optimisation and sustainability. The Dassault Systèmes provides modelling platforms that enable city-scale digital twins for sustainability analysis, infrastructure management, and transport optimisation (Batty, 2018).

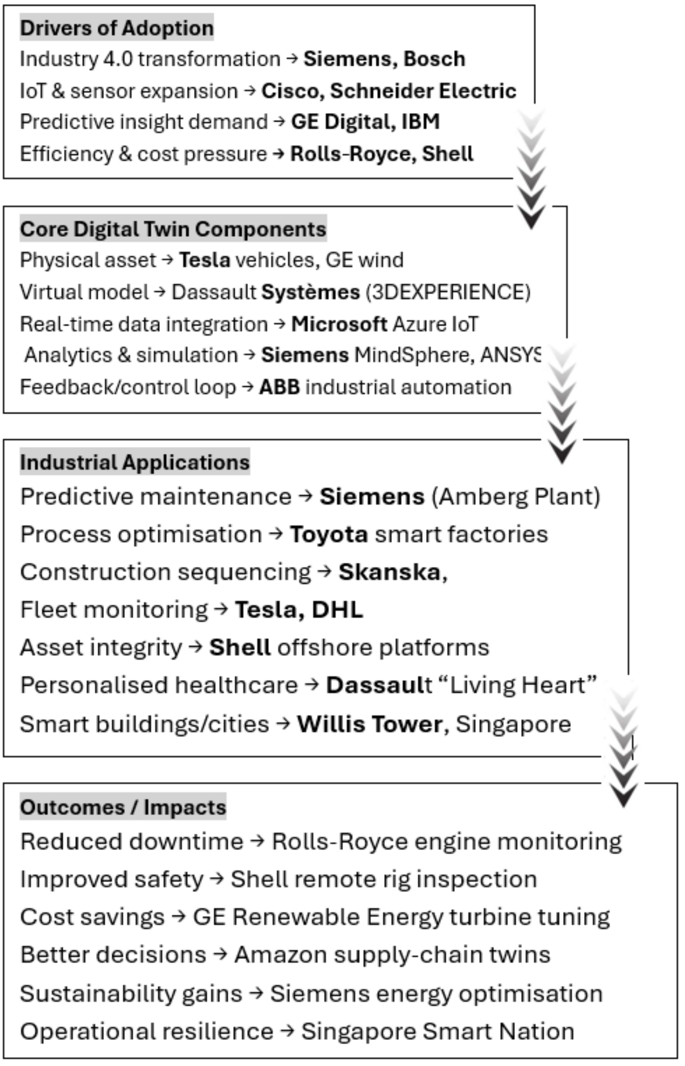

Fig.7. Example of adoption and deployment of digital twins in various industries.

Figure 7 shows samples of the drivers to adoption alongside some direct applications across the spectrum of industrial activities

Use-cases were undertaken throughout the available literature and white papers published by companies in various sectors. Table 1 shows a sample of the use-cases for manufacturing, energy, supply chain, cities, automotive sector and healthcare systems.

Table 1: Use cases of digital twin deployment in real world

Industry	Use-Case	Description	Real-World Example
Manufacturing	Predictive maintenance	Real-time sensor data integrated into virtual machine models to detect early signs of failure and optimise maintenance schedules.	Siemens uses digital twins in its Amberg Electronics Plant to reduce downtime and improve reliability.
Automotive & Logistics	Fleet-level monitoring	Vehicle-specific digital twins track engine health, battery status, and driving patterns to support predictive diagnostics and route optimization.	Tesla maintains a digital twin for every vehicle; DHL uses digital twins to optimize fleet routing.
Construction	Construction sequencing & clash detection	BIM-based digital twins simulate construction phases and detect spatial conflicts across structural and MEP systems.	Skanska and AECOM apply digital twins in large-scale infrastructure projects such as airports.
Energy	Wind turbine optimization	Virtual turbine models incorporate wind, stress, and performance data to optimize blade pitch and reduce mechanical fatigue.	GE Renewable Energy uses digital twins to increase turbine efficiency and reduce maintenance costs.
Aerospace	Engine health monitoring	Digital twins analyze real-time flight data (temperature, vibration, pressure) to support predictive maintenance.	Rolls-Royce uses digital twins in its “power-by-the-hour” service model; NASA pioneered early digital twin concepts.
Healthcare	Patient-specific organ simulation	Physiological and imaging data used to create organ-level twins for treatment planning and surgical simulation.	Dassault Systèmes’ “Living Heart” project; Philips uses digital twins to optimize hospital workflows.
Supply Chain	Disruption modelling & resilience planning	End-to-end supply chain twins simulate disruptions and evaluate mitigation strategies.	Amazon and DHL use digital twins to model logistics networks and optimize warehouse operations.
Smart Buildings & Cities	Energy optimization & urban management	Building-level and city-scale twins integrate HVAC, occupancy, traffic, and utility data for operational optimization.	Willis Tower uses a building twin for energy management; Singapore’s Smart Nation initiative uses a city-scale twin.
Oil & Gas	Asset integrity monitoring	Twins of pipelines and offshore platforms monitor corrosion, pressure, and structural integrity.	Shell uses digital twins for remote monitoring of offshore assets.

6 Conclusions

It is important to emphasise, as several authors have pointed out, that there is little credible evidence of successful industrial implementation of digital twin technology as a mature and functioning solution. In particular, Kreuzer et al. [73] reported that only one out of 149 reviewed publications at the intersection of artificial intelligence and digital twins met the core criteria of a genuine digital twin. This finding strongly suggests that the vast majority of existing studies describe conceptual models or academic prototypes rather than operational industrial systems. Despite frequent claims of success, the current body of literature provides limited proof that digital twins, as originally defined, have been realised in practice. This gap between theoretical development and practical deployment is especially striking given that digital twin technology is actively promoted at the highest policy levels, including by the European Commission.

The continued proliferation of digital twin definitions proposed by various academic and industrial organisations further reflects the absence of a shared conceptual foundation. Rather than indicating conceptual richness, this multiplicity of definitions points to ongoing ambiguity regarding the essential characteristics of a digital twin. The persistent search for a universal definition, as discussed in [67], may therefore be counterproductive. Instead, greater emphasis should be placed on addressing concrete industrial problems and supporting meaningful business decisions, as argued in [1]. Without such a shift in focus, the digital twin risks remaining a vague and fashionable label rather than a clearly defined technological paradigm. As stated in [1], careful reasoning and critical judgment are required, regardless of how the technology is named.

From a practical perspective, the implementation of digital twin technology cannot be reduced to a single, standalone solution. It necessarily depends on the coordinated integration of multiple technological domains, including big data analytics, artificial intelligence and machine learning, the Internet of Things, cyber-physical systems, edge computing, cloud platforms, and advanced communication technologies. Each of these components may be implemented using different architectures and tools [77], further complicating integration. This complexity makes the development of a universal digital twin solution highly unrealistic, particularly in industrial environments where heterogeneous and legacy systems are already deeply embedded [48]. Consequently, many so-called digital twin solutions appear to be fragmented assemblies of existing technologies rather than coherent and fully realised digital twins.

However, across industries, the integration of digital twins delivers benefits including predictive maintenance, reduced downtime, improved energy efficiency, and enhanced decision support. Core enabling technologies include sensor networks, cloud computing, artificial intelligence, and cyber-physical integration (Tao et al., 2018). The widespread industrial adoption of digital twin systems demonstrates their scalability and cross-sector applicability

Digital twin (DT) technology has evolved from static digital representations embedded within product lifecycle management systems to dynamic, data-driven cyber–physical architectures capable of predictive and prescriptive optimisation. This progression has been enabled by advances in Internet of Things (IoT) infrastructures, cloud computing, artificial intelligence, and real-time analytics, which collectively facilitate continuous data exchange between physical assets and their virtual counterparts.

Industrial implementation demonstrates that digital twins generate measurable operational and strategic value, particularly within capital-intensive sectors. Organisations such as Siemens, General Electric, and Rolls-Royce illustrate the application of digital twins in predictive maintenance, performance optimisation, and outcome-based service models.

These implementations confirm the potential of digital twins to reduce downtime, enhance asset longevity, and support business model innovation.

Despite these advancements, adoption remains uneven across industries. Key constraints include technological readiness disparities, high infrastructure and integration costs, data quality limitations, cybersecurity risks, and organisational resistance to digital transformation. Furthermore, conceptual ambiguity surrounding the definition of a "digital twin" complicates maturity assessment and standardisation efforts, as many deployed systems operate at the level of digital shadows rather than fully autonomous, bidirectional cyber–physical systems.

Digital twin technology represents a significant paradigm shift in industrial systems management. However, its sustained impact depends on clearer conceptual standardisation, improved interoperability, robust governance frameworks, ethical implications, and demonstrated economic feasibility across diverse sectors.

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