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IoT and Industry 4.0 technologies in the digital manufacturing transformation

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"Success hits different when nobody believed in you"

So here I will take the chance to show my heartfelt appreciation and express my gratitude to those who stood by my side during my PhD journey and believed in me.

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Chapter 1: Introduction

The evolution of information technologies and their integration into the digital ecosystems of the industry's entire value chain contributed to the fourth industrial revolution, called "Industry 4.0". By adopting CPS cyber-physical systems, Industry 4.0 will lead to intelligent production, with products, machines, networks, and systems that will communicate and cooperate independently with each other throughout the entire production process with minimal human intervention.

Industry 4.0 is a concept of smart integration of processes that enable the transformation of traditional industries into more customized and smart ones by providing fully integrated products and services, which will lead to more digitalized processes and intelligent factories.

Therefore, the main objective of Industry 4.0 is to favor the intelligent networking of products and processes along the value chain, thus allowing organizational processes to be used more efficiently in the creation of goods and services to improve the benefits for customers. Offering them new products and services. In this way, advances in digital technologies will be made possible, such as artificial intelligence, cyber-physical systems, the Internet of Things, which, combined with nano and biotechnologies and materials sciences, will allow the actualization of paradigms Industry 4.0.

The focus of IoT is the ability to connect devices, gather real-time data, and provide value-added information through the help of artificial intelligence technologies. The next step is selling these collated data and providing more services instead of physical products. This strategy is known as the servitization of processes. The application of servitization can provide financial benefits to the manufacturing companies and competitive advantages to make them stand among the other competitors in the market.

Moreover, IoT and data aggregation and analytics play an important role in achieving these financial and strategic benefits. This can be done through embedded IoT sensors and actuators, which are used to aggregate real-time data throughout the lifecycle of the products. For businesses considering servitization, this means they will be able to get more data about their products in real-time, improving the health maintenance of such products.

The fourth industrial revolution and servitization are established along with the idea of smart factories, where people, machines, and resources communicate effectively using the Internet of things, Cyber-Physical Systems, Digital Twins, and other key technologies. Therefore, the vision of industry 4.0 can be simplified in the following:

- Connecting the virtual world with the physical objects in a better way in order to facilitate the exchange of information in real-time by combining the Internet of things, Internet of Service, and Internet of Data.

- Using effective cyber-physical systems to integrate intelligent sensors, computers, networks and manufacturing systems and processes.

- Delivering products/services according to individual customer requirements.

- Operations are more easily operated and coordinated across the system.

- Assessing the situation of IoT and CPS and their application with respect to manufacturing and operations research.

- Understanding the relative importance of cyber-physical systems in production and manufacturing and their relationship with other operational research and key technologies

(Internet of Things, Artificial Intelligence, Machine Learning, Big Data, and Digital Twin).

1.1 IOT and DT potentialities

IoT is a fundamental technological component in Industry 4.0 projects to make machines and production lines intelligent through the integration of IoT sensors, actuators, and Edge computing components for real-time processing and, therefore, the start of automatic processes and alarms. The operational data, selected and synthesized by the Edge systems, are made available for further processing, such as to feed dashboards for factory control, feed external machine learning and AI systems useful for predictive maintenance and optimize production: the availability of information and the ability to control allow more reliable forecasts, benefits in terms of flexibility and energy balance, and reductions in waste.

The technologies provided by the IoT, when integrated into protocol architectures, can concretely give life to the vision of the Internet of Things, being able to communicate with the nodes of the Internet. Indeed, Internet-based services (IoS) offer great growth potential for both providers and users of IT services. Technically, a service is an envelope of functionality available in enterprise software systems or through other services or combinations.

These services have a potential impact not only in product portfolios but also in optimizing the operation of industrial plants through new knowledge platforms and the virtualization of ICT infrastructures, with adequate consideration of the resulting IT security problems.

Digital twin “DT” potentialities, for the successful implementation of digital production, an indispensable and powerful tool is a real-time simulation is when a computer runs at the same speed as the physical system, so the simulation model must be fed with real-time data that can be achieved using the Internet of Things. Compared to conventional simulation, simulation in real-time, online, can therefore analyze user and system behavior in milliseconds, allowing the user to develop and produce "virtually" a prototype for the product or service.

The new simulation modelling paradigm based on the concept of Digital Twin (DT) is very high fidelity. It plays an important role for Industry 4.0. It extends simulation to all product lifecycle stages, combining real data with simulation models to improve productivity and maintenance performance based on realistic data. Therefore, the new vision of the digital twin is to integrate artificial intelligence techniques with advanced data analytics to support the end-users through their decision-making process. In addition, this digital presentation of data allows an innovative approach to the development, realization and maintenance of a product:

- Predicting or anticipating problems in production
- By improving product development
- Reducing the costs of prototyping and testing

Therefore, the main motivations that encourage the industrial sector to implement Digital Twins technology are the benefits of such advanced technology. Continuous improvement along with the product lifecycle phases, monitoring the physical system for the sake of preventing problems, simulating the physical system and tracking the system performance in real-time (Lu et al., 2020) and resolving several problems originating from insufficient information are small samples of advantages that comes out the Digital Twins technology.

Moreover, the integration between the Product Lifecycle Management system and the Manufacturing Operation Management system has a direct and positive effect on the realization of Digital Manufacturing. This kind of integration between these two systems has been presented in the book of "Advances in Production Systems. Towards Smart Production Management Systems" (Demartini M. et al., 2019). This paper is listed below in the appendix section of this thesis.

1.2 Cyber Physical Systems CPS

The vision of Industry 4.0 is to develop intelligent factories where cyber-physical systems (CPS) can integrate and monitor physical processes by creating a virtual copy of the physical world to assist the end-users in improving their decisions. In this way, intelligent data is collected and processed throughout the product lifecycle. This leads to the optimization of intelligent and flexible supply chains and distribution models and the efficient and optimized use of machines and equipment. In this way, companies can make faster and smarter decisions, responding quickly to customer requests and minimizing costs.

Cyber-physical systems (CPS) are engineered physical systems that depend on the integration of computational algorithms and physical components, whose system operations can therefore be monitored, coordinated, controlled, and integrated by a computer and communication system. A cyber-physical system comprises an embedded system (hardware and software) and a set of networked agents, including sensors, actuators, control processing units, and network access devices. Although embedded systems have been used since the advent of the microprocessor in the 1970s, their use until recently was intended for specific tasks such as controlling individual devices, machines, and processes.

However, in reality, CPSs can interact with their environment and other dynamically determined cooperative tasks, including collective self-adaptability.

CPS are enabling technologies whose potential is strictly connected to how people will be able to interact with engineered systems. These systems will unite the virtual and physical worlds and allow a networked world where intelligent objects communicate and interact. These technologies thus promise to revolutionize human interactions with the physical world in much the same way the Internet has transformed human interaction with information.

Therefore, CPS uses knowledge and information shared by processes to independently control logistics and production systems. They can be considered the bridge connecting the Internet of Things (IoT) with higher-level services, which were previously described as the Internet of services (IoS).

Through these technologies, traditional processes such as; production, monitoring and control processes are becoming digital and smart. This digitalization allows real-time control of performance which enables early detection of a failure or malfunction in those smart processes, eliminating the need for an inspection at the end of the process (Zheng et al., 2018).

The interconnection and interoperability of CPS entities within the workshop, combined with methods for data analysis and machine learning derived from knowledge, provide intelligent support for making decisions. These represent a paradigm break. Compared to existing business and market models, revolutionary new applications, service providers and value chains are made possible thanks to such systems. Furthermore, the new generations of CPS will influence the formation of future intelligent and connected environments. This will affect several challenges that will need to be addressed through the creation of a sustainable governance model of industry 4.0, including ensuring control, reliability, networking, privacy, safety, security, security, transparency, and interpretability.

Smart Warehouses

The smart warehouse is an example of implementing CPS in smart manufacturing because flexibility, efficiency and storage costs are the main challenges in designing a suitable warehouse system for manufacturing companies (Basile F. et al., 2015) (Sadowski A. et al., 2021). An inefficient warehouse layout can negatively affect the business and leads to an increase in operation and storage costs, and of course, decrease the efficiency of the enterprise (Lin H. 7 Ma Y., 2021, Choy KL et al., Salaheen F. et al., 2014), While the right management strategy for warehouses can minimize the costs and increase the productivity and efficiency (Jemelka et al. 2016). The correct and rational management of the warehouse contributes to maintaining an adequate state of health of the company. The right balance between incoming and outgoing goods guarantees customer satisfaction, the absence of excessive unsold inventories with capital immobilization and the containment of management costs and product handling times.

An efficient warehouse protects the company from unpredictable events, which can cause production blocks and customer dissatisfaction in certain industrial situations. In other situations, the efficiency of the warehouse allows us to overcome the fluctuations in demand due to seasonal changes, trend changes, or fashion needs.

Therefore, automated warehouses play a key role in such systems and are currently governed using hierarchical and centralized control architectures, with conventional programming and automation techniques.

Advances in computing and communication resources have given birth to a new generation of high-performance, low-power electronic components. This has led to new possibilities that enable better integration of devices and systems, focusing on platform independence and real-time solutions requirements. Thanks to these systems, the times required to search for a product, prepare it, and place it times are reduced. In addition to that, the likelihood of making errors in order preparation is reduced, resulting in better customer service.

Therefore, assigning incoming items to different storage locations inside the warehouse (considering the warehouse's capacity and structure, its process for storage and retrieval, and other factors) is an important aspect to be considered. It enables effectively managing the warehouse, improving its performance and reducing operational costs. In literature, there are three types of assignment policies for locating the final products in the storage, including dedicated, randomized, and class-based. The dedicated assignment policy is the easiest policy among these three types to store products. However, it requires a high storage space. The randomized policy doesn't require high storage space, but it is hard and time-consuming to find the locations of the stored products.

Speaking about the class-based policy, it is a combination of the other two policies, and it has been considered as a tradeoff between these two where products are divided into classes, then the dedicated policy is used to determine the area of each class and the randomized policy is used to assign the locations randomly inside each class (Zhang G. et al., 2021)

Several researchers in the literature discussed the effectiveness of implementing a class-based storage policy with the aim of reducing the costs, increasing customer satisfaction, and the efficiency of the systems (Peterson C. at. al., 2004). And ABC analysis is one of the most commonly employed inventory classification techniques (Yu M., 2011). However, no articles describe how to implement the class-based storage strategy when there is a fluctuation in the demands of the individual products.

The class-based policy is based on the Pareto diagram principle (ABC Classification), which divides into three classes of analysis (A, B and C, from the most relevant to the least relevant). It presents the 80/20 law, which can be summarized by stating that "most of the effects are due to a small number of causes". The wording 80/20 means that 80% of the effects are due solely to 20% of the causes (Yu M., 2011). For example, class A consists of a limited number of items that contribute most to the stock. Therefore, they must be managed more carefully since they are responsible for a large share of the stocks. Class B is in an intermediate position and has less impact on inventory. Class C represents a large number of articles that have a low incidence. Consequently, they are articles with low criticality, to which less attention is paid in the analysis phase.

Caron et al. (2000) showed that there are three main rectangular layouts for warehouses in the literature. The first one is divided into two sections with a cross aisle located parallel to the I/O point located in the middle of the front-end of the warehouse. The second layout contains one section instead of two. The cross-aisle is located perpendicular to the I/O point instead of parallel. The third layout is the same as the second layout. However, the I/O point is in the corner of the front end by analyzing the different layouts about the travelling distance. Sooksakson & Kachitvichyanukul, (2009) found that warehouse layouts with the I/O point in the middle usually give the lower expected travel distance. Moreover, the travel distance is minimized when the warehouse is operated with the class-based storage strategy. The class-based assignment method stores high shipping frequency products near the central aisle and I/O point (Chuang et al., 2014).

Choy KL et al. in 2013 discussed the effect of the fluctuations in the seasonal demand in the fashion industry. They showed that by integrating the class-based storage assignment policy and association rule mining, the order picking efficiency was improved because of the reduction in the travel distance.

The growth of IoT (Internet of Things) sensor and data analytics technology provide new opportunities for designing proper warehouse management systems that detect and reorganize around real-time constraints, which mitigates the impact of day-to-day warehouse operational issues. Past warehouse research literature has largely focused on strategies for optimizing warehouse processes, such as optimizing the picking paths and the storage of products. However, nowadays, research started to concentrate more on realizing a smart "living" warehouse that can communicate with its environment and analyses the changes in real-time through the implementation of Internet of Things (IoT) sensors and data analytic to respond faster to real-time events (Binos T. et al., 2019).

Therefore, advances in IoT and CPS technologies help optimize the real-time performance of warehouse processes through the ability to detect fluctuations in demand driven by changes in customer behavior (Binos T. et al., 2019).

Implementing industrial IoT (through embedded devices such as RFID or wireless sensor networks) in warehouses provides the ideal platform to facilitate its management and perfectly support the fluctuations in demand and labor costs. (Reaidy P. et al., 2014). This implementation provides self-organization behavior and interconnection networks between all warehouse entities to find the optimal solution to the resource allocation problems due to the fluctuations in demand. In other words, smart warehouses must have a dynamic real-time smart storage system, where components interact with each other and with the environment in real-time, to optimize the execution of processes inside the warehouse through the implementation of internet of things technologies (IoT) and cyber-physical systems (CPS) technologies. It reflects the need to reconfigure the allocation of products within a warehouse subject to dynamic external stresses or market demands that may change over time for each individual product.

Cyber-physical systems (CPS) derive from these integrations of computation and physical processes. Embedded computers and networks monitor and control physical processes with feedback loops that affect calculations and vice versa.

The general paradigm underlying the new cyber-physical systems is constituted by the set of intelligent, distributed, autonomous, proactive, fault-tolerant and reusable units, which operate as a set of cooperating entities. These entities can work proactively, initiate collaborative actions and interact dynamically with each other, thanks to the internet of things (IoT) technology, to improve performance.

This system, where the physical structure and the software are tightly integrated, comprises a network of devices. Each of them has been equipped with computational and control capabilities, acquiring data from the environment in which it is located, processing information and building a digital representation of the behavior of the monitored phenomena.

The system uses sensors to acquire environmental data and software to understand and evaluate the information.

The individual devices that will form the nodes of the network must have communication capabilities, for example, wireless, so that they can communicate and allow the entire system to exploit local data. The availability of more data from different nodes helps in building a more accurate system.

A cyber-physical system, as already mentioned, is made up of distributed devices that communicate with each other. This concept in recent years has been called the Internet of

Things, which is considered an extension of the network concept. Each device can communicate with the others and make the information collected available to the population. A name or address distinguishes each device through the implementation of radio frequency identification “RFID” technology. It relates to the environment through its sensors to process and find the meaning of the information it acquires and communicate with other devices through common communication technologies.

The Internet of Things should not be considered as the general case of cyber-physical systems. It should be considered as a tool that they use to implement the physical network with all its components and manage its communications.

These technologies help in maintaining the warehouse processes constantly under control in order to detect events that introduce change and to be able to react to them by self-adapting to new environmental conditions. Therefore, the system must be aware of itself. That is, it must be able to monitor its resources, its state and its behavior. Its behaviors and decisions made are strictly influenced by the context in which it operates.

After monitoring and comparing the values, if the measures are different from the expected behavior, this means that the model is no longer valid for the environmental conditions due to a change that has affected it. Therefore, the system must replace the model with a new one and perform future analysis based on this new model..

Therefore, warehouses need identification systems that are able to process information and flows and that are supportive for:

- Promptly identify each product and where it is positioned.
- Uniquely identify a corridor, shelf, level or shelf within the warehouse.

- Be in control of activities in real-time, with the recording and reporting of any flow or information
- Keep track of different locations of the same product.

And this can be done through the right implementation of cyber-physical systems and the internet of things, as mentioned above

1.3 IOT and CPS potentialities

The manufacturing paradigm is rapidly shifting from mass production to custom manufacturing through reconfigurable automation technology. In this sense, the abilities of calculation, communication, control, autonomy, and sociality are obtained by combining microprocessors and artificial intelligence (AI) with products, services, and machines. This ability makes them smarter and facilitates the manufacture of different products, consequently decreasing production costs.

AI is spreading, allowing machines to perform cognitive functions similar to human ones. In this sense, intelligence intersects with autonomy and adaptability through the ability of AI to learn from a dynamic environment. Enhanced by advanced technologies and techniques such as' machine learning, big data and cloud computing algorithms, AI can identify complex patterns in large data sets and outperform human performance in some cognitive functions.

AI is mostly intangible in its manifestations. On the contrary, robotics operates at the intersection of mechanical engineering, electrical engineering, and computer science. In an "autonomous machine", AI can be characterized as intelligence or cognitive functions, while robotics refers to motor functions; Popular examples of the convergence of artificial intelligence and robotics are self-driving cars or humanoid robots. Robots equipped with ultra-sensitive sensors can perceive lights, sounds, smells, and temperatures, which man, by his nature, cannot grasp. It allows realizing an even deeper concept of the internet of things, the internet of skills (IoA).

However, it is important to mention that robots and advanced automation technologies have been mainly used to speed up operations. At the same time, artificial intelligence must be able to automate processes and machinery to respond to unfamiliar or unexpected situations. Such intelligent decisions benefit efficiency and productivity and change existing business models into new smart ones.

Among the potential of AI, it is possible to highlight the ability to counter and prevent fraud, as machine learning is used to identify criminal and fraudulent behavior and ensure compliance in innovative ways. Therefore, AI would be effective against cyber attacks and identity theft, using AI to defend against hackers and as a proactive and just-in-time response to hacking attempts. Moreover, AI has a significant impact on transport, with the introduction of route mapping based on traffic data and autonomous driving capabilities.

To date, however, autonomous machines that combine advanced AI and robotics techniques still struggle to reproduce many basic non-cognitive motor functions, difficulties also amplified by existing political challenges that raise political and ethical questions, for example in relation to its potential effects on the future of work and skills development, or its implications for supervision and transparency, accountability for example.

In this research, an example about implementing artificial intelligence and machine learning algorithms is being applied to the human-machine relation in manufacturing safety, discussed in chapter 3.

1.4 The existing gaps in creating such systems

One of the big challenges that companies face is maintaining and enhancing the market share of companies in the further step. It depends on how well they can identify the customers' requirements and upgrade the current products or develop new products accordingly. Overcoming this challenge entails a huge amount of information and data from the client's order to the product delivery. The big objective of most companies working in digitalization is to digitalize the information lifecycle process. Digital Twin assists companies in achieving this goal in different phases.

Moreover, rethinking the role of the human operator in a general ergonomic framework is a major challenge to undertake within the 4th industrial revolution, in a renewed approach involving new technologies and methodologies. Indeed, in the current industrial practice, ergonomics is still frequently approached with standard worksheets filled by experts and processed with statistical tools rather than real-time quantitative measurements. In such regard, the enabling technologies of industry 4.0 offer an unprecedented occasion for improving the health and safety conditions of the workplace through real-time data gathering and analytics. The recent advances in sensing technologies demonstrate the possibility of developing miniaturized devices capable of measuring the workers' exposure to physical (e.g. vibrations) and cognitive (e.g. fatigue) hazards, their wellbeing status (e.g. the presence of stress markers in biological fluids), as well as the health and safety conditions of the workplace (e.g. wrong postures or the presence of dangerous substances). In addition, operators in smart factories are becoming part of an interconnected environment that enables them to exchange information with a centralized system that is capable of warning them about any actual risk exposure.

Chapter 2: Research objectives & Methodology

Therefore, the main scope and objective of this research is to allow organizational processes and companies to benefit form the value added information that can be achieved through the right implementation of advanced technologies such as IoT, DT, CPS, and artificial intelligence which can provide financial benefits to the manufacturing companies and competitive advantages to make them stand among the other competitors in the market. The effectiveness of such technologies can not only improve the financial benefits of the companies, but the workers' safety and health through the real time monitoring of the work environment. Here in this research the main aim is to present the right frameworks that can be used in the literature through companies and researchers to allow them to implement these technologies correctly in the boundaries of their businesses. In addition to that, machine learning and artificial intelligence algorithms will be provided in this research to facilitate the implementation and the real time monitoring of the workers' activities to increase their health and safety in smart industry context.

Regarding the methodologies that were applied in this research, are both theoretical (literature review) and then experimental (application in a case study).

Literature review has been carried out to develop the research and deepen the knowledge in the field of IoT, CPS, DT and Artificial Intelligence, and then interviews with experts have been conducted to validate the contents, since DT is a quite new technology, so there are different points of view about certain concepts of this technology. Therefore, the purpose of this research is achievable through the personal experience of experts (Whittemore et al., 2001).

Moreover, industrial applications of IoT, DT & Artificial Intelligence in industrial study cases have been presented in this research. Further details about these methodologies will be discussed in the following chapter (Chapter 3).

Chapter 3: Results & Discussion

3.1 Literature review

This section represents an in-depth investigation of the literature in order to understand better the relation between cyber-physical systems, the related enabling technologies, and the operations research applications in order to be able to identify the new research areas in which the researchers need to focus and study more.

Therefore, a number of articles were collected and analysed from two different databases; Scopus and ISI Web of Science. However, one of these two databases – Scopus - was considered the most appropriate database for this research.

Methods of data collection

The analysis was done within a fixed time range (2008-2018) to understand the research trend in the last ten years.

The steps of the analysis were as follows:

- Searching for papers' titles, abstracts, and keywords: "cyber-physical system, cyber-physical manufacturing system, cyber-physical production system, operations research, CPS, big data, digital twin Internet of things, artificial intelligence, machine learning" and their different combinations, in both Scopus and ISI Web of Science datasets.
- Choosing the most suitable dataset and keywords for my research by comparing the results of Scopus and ISI Web of Science.

- The comparison results showed that Scopus is more intense than ISI Web of Science; hence, it covers more articles (Figure 1).

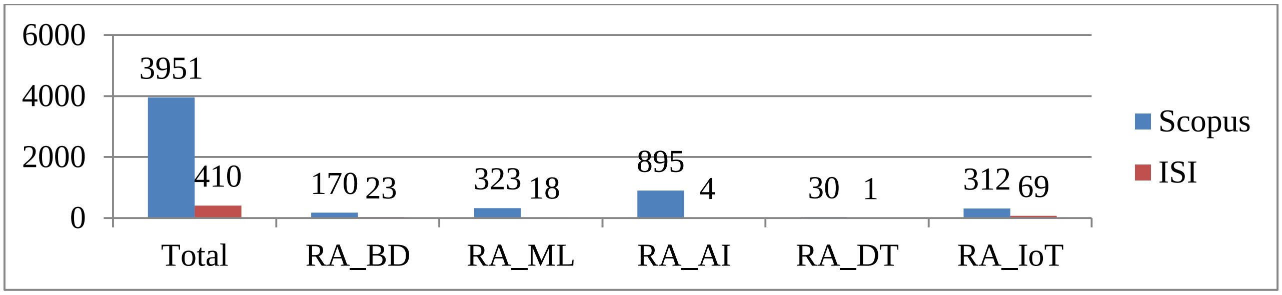


Figure 1: Comparison results between Scopus and ISI Web of Science

- Using Scopus dataset, I've Searched for the following keywords in the papers' titles, abstracts, and keywords: "CPS OR CPMS OR CPPS OR cyber-physical system OR cyber-physical manufacturing system OR cyber-physical production system", and "OR Operations research". Then the results were filtered and became limited to "English" articles that were published in "Journals" only in the field of "Engineering, and Computer Science" ,in the window frame from 2008-2018
- The filtered results showed a list of 3951 articles which needs to be filtered more to get the most important articles out of this list that need to be analyzed in a more detailed way. As mentioned before, works included in the search was limited in time "2008-2018", and restricted to the following two categories: "Engineering and Computer Science". Moreover, the document type was limited to "Article," which are in "English" and published in "Journals" only.

- To understand how many articles out of this big set have studied the following Industry 4.0 key technologies: big data BD, Internet of things IoT, digital twin DT, machine learning ML, and artificial intelligence AI, another search was applied to this list, using the following keywords: (big data OR BD), (Digital twin OR DT), (internet of things OR IoT OR IIoT), (machine learning OR ML), (Artificial intelligence OR AI).

After searching for the number of articles related to each key technology, the percentage was calculated (compared with the first database of 3951 articles) and their trends to have a clearer idea of the most studied research areas in the last ten years. See Table 1.

Table 1: Percentage of Published Articles for each Technology

Research Specific Area 1		No. of Articles	% of Articles
BD	"big data" OR "BD"	170	4.3%
ML	"machine learning" OR "ML"	323	8.2%
AI	"artificial intelligence" OR "AI"	895	22.7%
DT	"digital twin" OR "DT"	30	0.8%
IoT	"internet of things" OR "IoT" OR "IIoT"	312	7.9%

- Therefore, based on these research results, machine learning was mentioned in the last ten years of literature, followed by “machine learning” and “internet of things” topics. After that comes the “big data” topic, and at the end comes the “digital twin,” which hasn’t received much importance from the researchers yet.
- After doing so, an analysis of the distribution of articles over the years, and the distribution over countries, was carried out for the full list of articles, and then for each subset list for each key technology to reflex their time trend, in order to understand whether there is an increment, decrement, a stable or unstable trend in research over the ten years.

Quantitative data analysis and results

1. **For the full list**

The distribution of articles over the years (Figure 2) shows an increase in the number of published articles (No. of Articles) regarding this topic over the years, which shows an increasing interest to study this topic by the researchers.

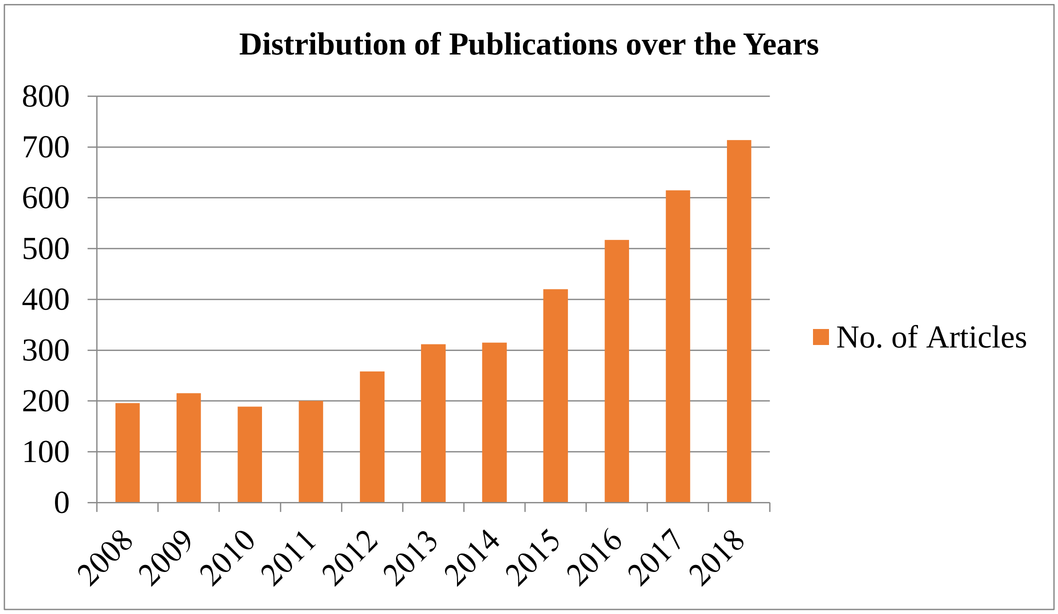


Figure 2: Distribution of Publications over the Years

The distribution of articles over the countries (Figure 3), focusing on the top 10 countries in this field- shows that the USA and China are conducting most of the research in this area, with 906 and 866 articles (out of 3951), respectively. While Italy is in the last place. However, Germany and France are in third and seventh place respectively.

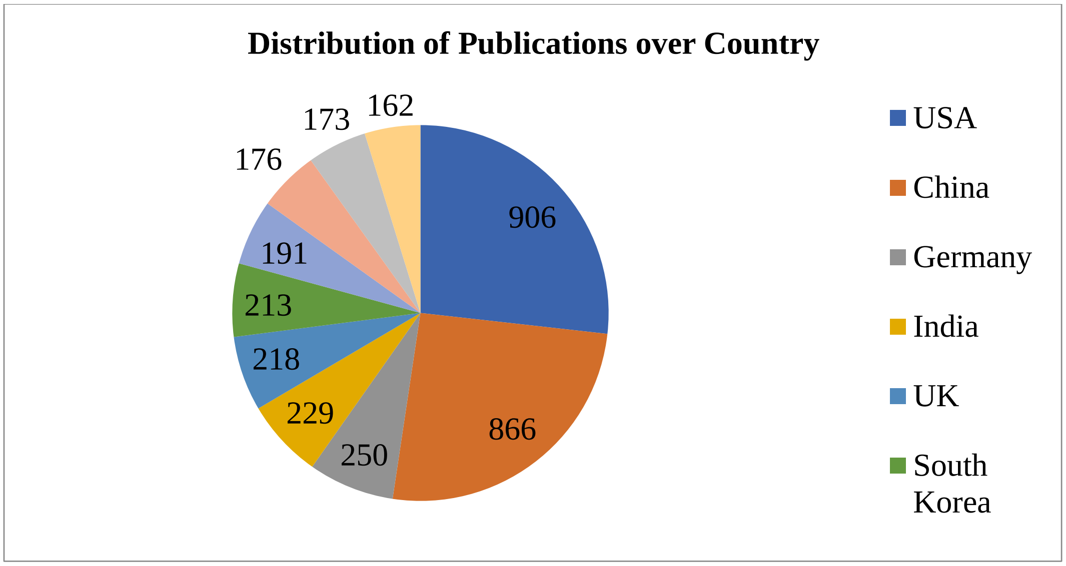


Figure 3: Distribution of Articles over the Countries

2. **For the "Artificial Intelligence" subset data list**

The distribution of AI articles over the years (Figure 4) shows an obvious increment in the number of published articles in the last four years, "since 2015", especially in the last year, "2018".

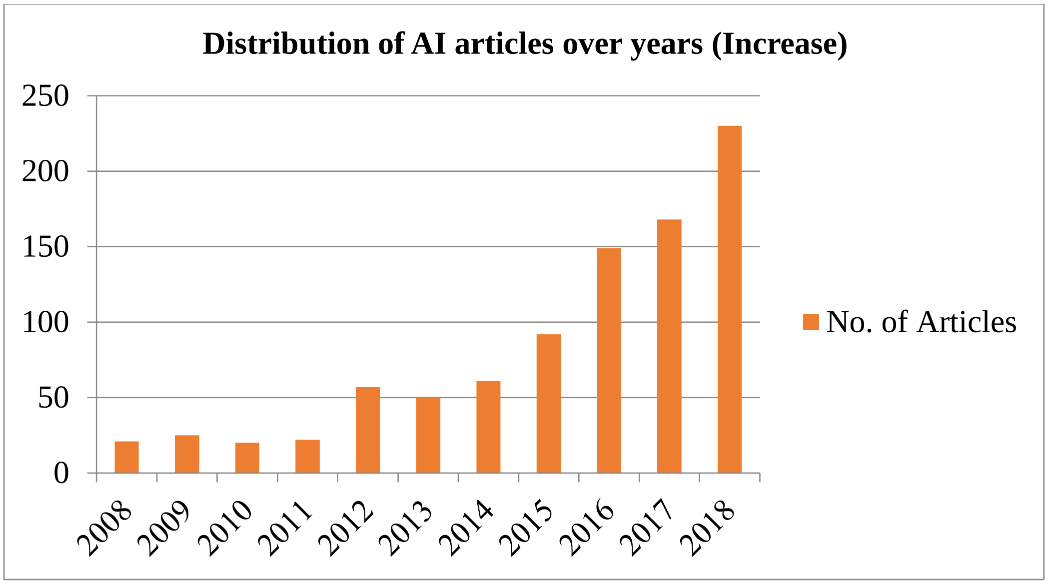


Figure 4: Distribution of AI articles over the years

The distribution of AI articles over the countries (Figure 5) -focusing on the top 10 countries in this field- shows that the USA and China are still conducting most of the research in this area. At the same time, Italy comes in seventh place in this case, but still after Germany “the third place”, and France “the fourth place”.

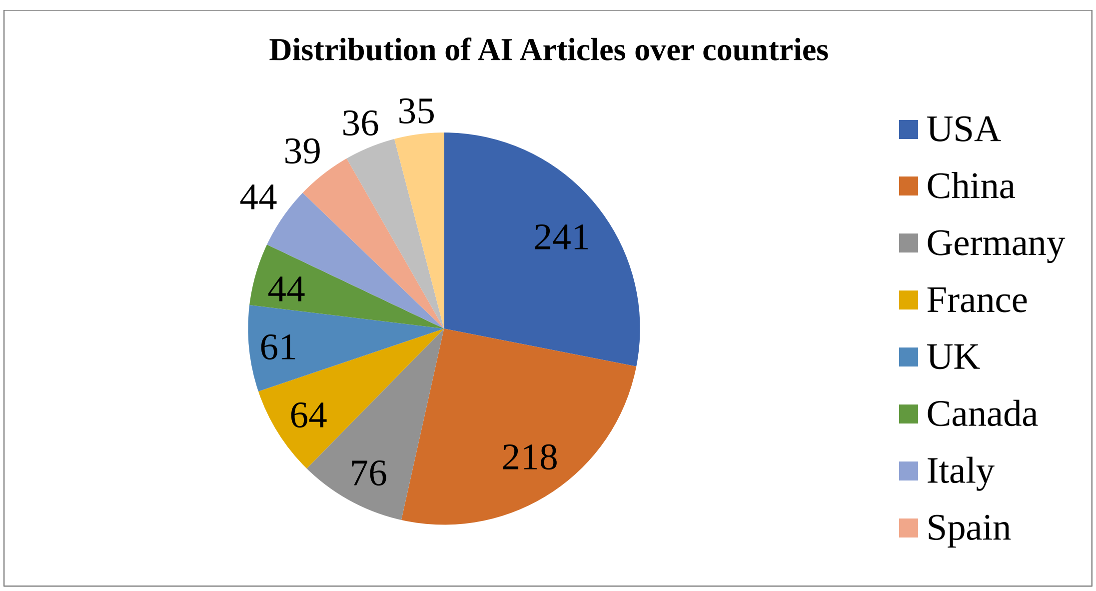


Figure 5: Distribution of AI articles over the countries

3. **For the "Machine Learning" subset data list**

The distribution of ML articles over the years (Figure 6) shows a stable increase in the number of published articles over the ten years, especially in the last two years, "2017 and 2018".

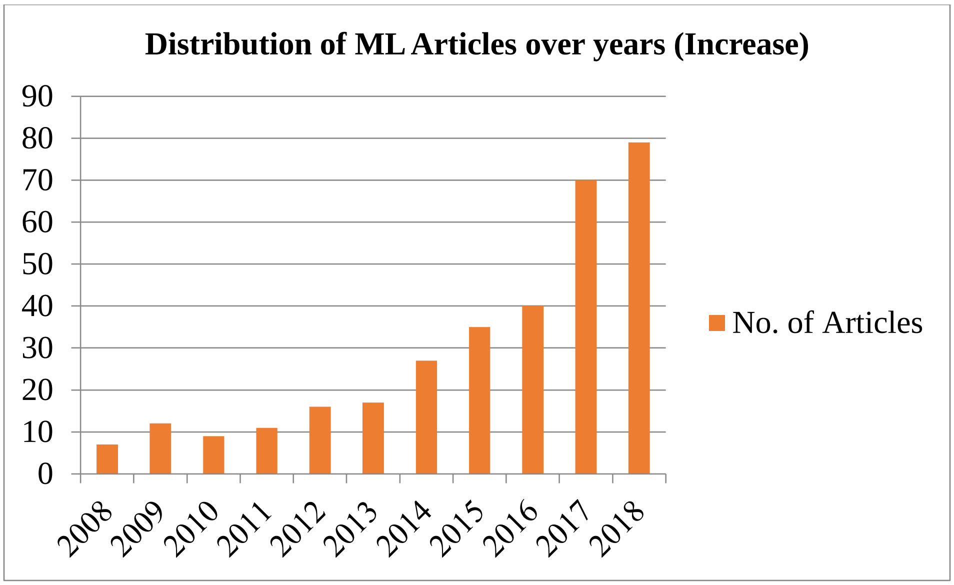


Figure 6: Distribution of ML articles over the years

The distribution of ML articles over the countries (Figure 7) focusing on the top 10 countries in this field shows that USA and China are still conducting most of the research in this area, Germany and France in the third and fourth place respectively, while no presence for Italy in this field. Even though USA and China are in the first two posts, China (with 62 articles) is not studying the ML field as much as the USA (with 116 articles).

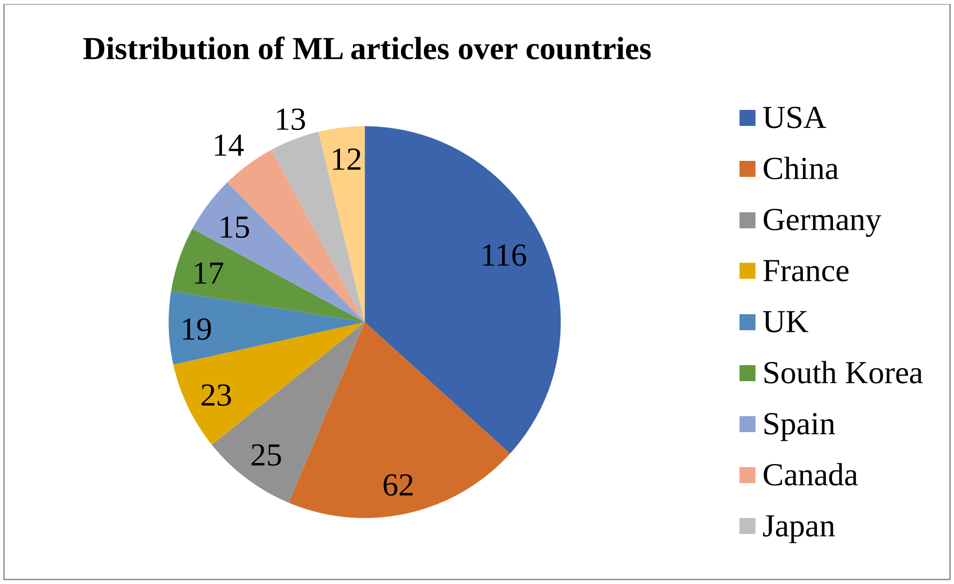


Figure 7: Distribution of ML articles over the countries

4. **For the "Internet of Things" subset data list**

The distribution of IoT articles over the years (Figure 8) shows that IoT started to appear in 2012 with a few focuses. Since 2015 an obvious increase in this area of research was noticed and with a high increment peak in the last year, "2018", reflecting that IoT is becoming one of the most important trends in the literature.

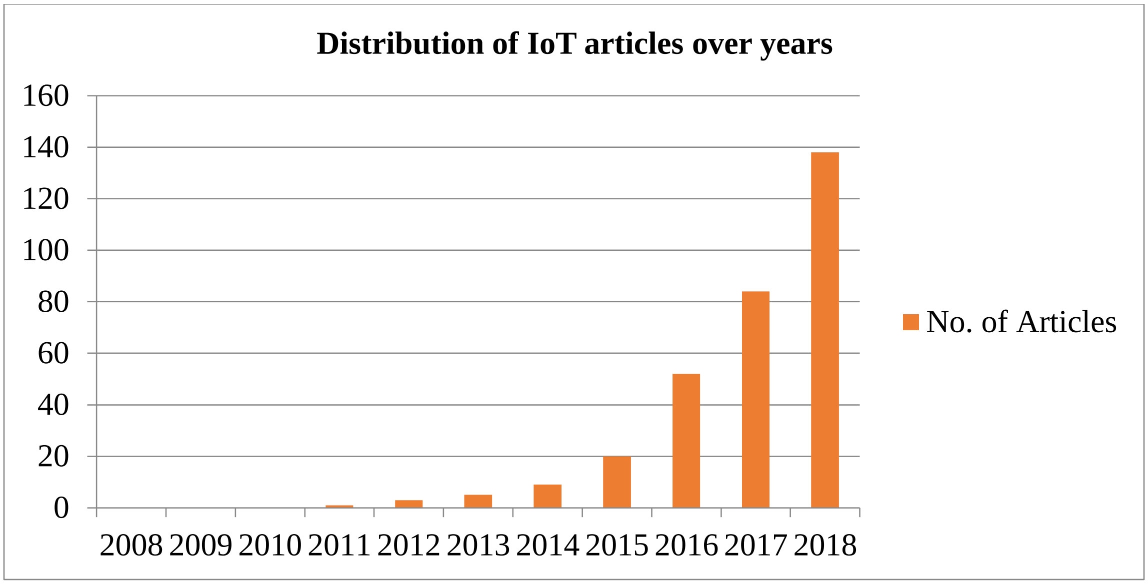


Figure 8: Distribution of IoT articles over the years

The distribution of IoT articles over the countries (Figure 9) focusing on the top 10 countries in this field shows that the USA and China are still conducting most research in this area. Italy is moving up in this list to set on sixth place. Regarding Germany and France, Germany has third place in this list. In contrast, France has no presence among the top ten countries in the IoT research field.

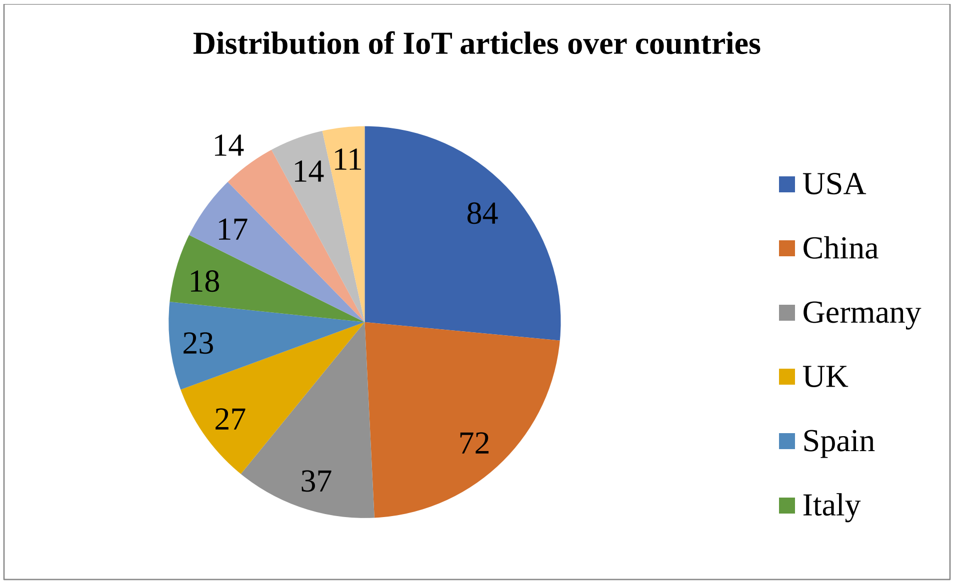


Figure 9: Distribution of IoT articles over the countries

5. For the "Big Data" subset data list

The distribution of articles over the years (Figure 10) shows that it almost had no presence from 2008 to the end of 2014. However, since 2015, the research results showed a high increment in the number of published articles with a noteworthy peak in the last year, "2018".

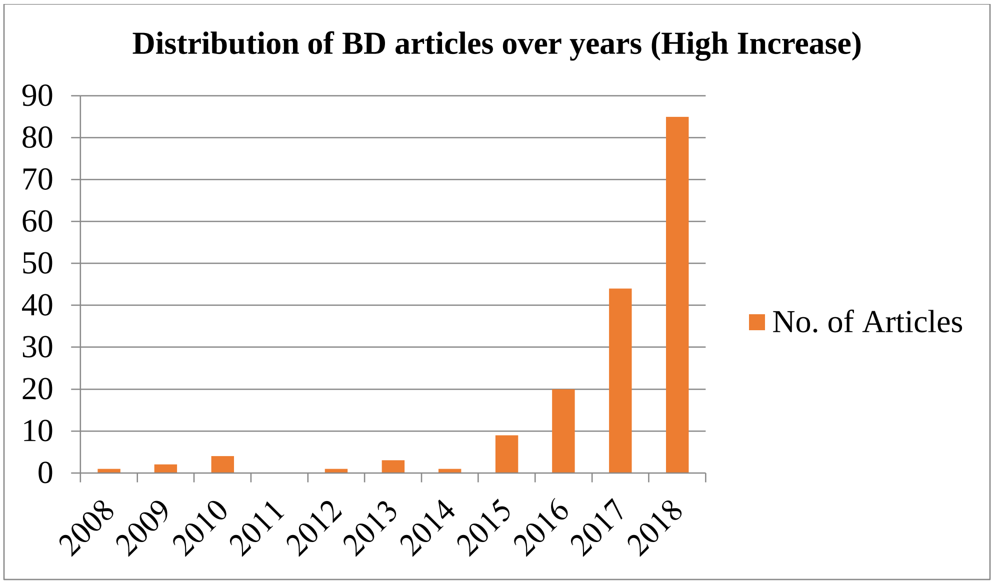


Figure 10: Distribution of BD articles over the years

The distribution of articles over the countries (Figure 11) -with a focus on the top 10 countries in this field- shows that USA and China are still conducting most of the research in this area, Germany in the third place, while Italy comes on the sixth place and this time above France which comes on the ninth place.

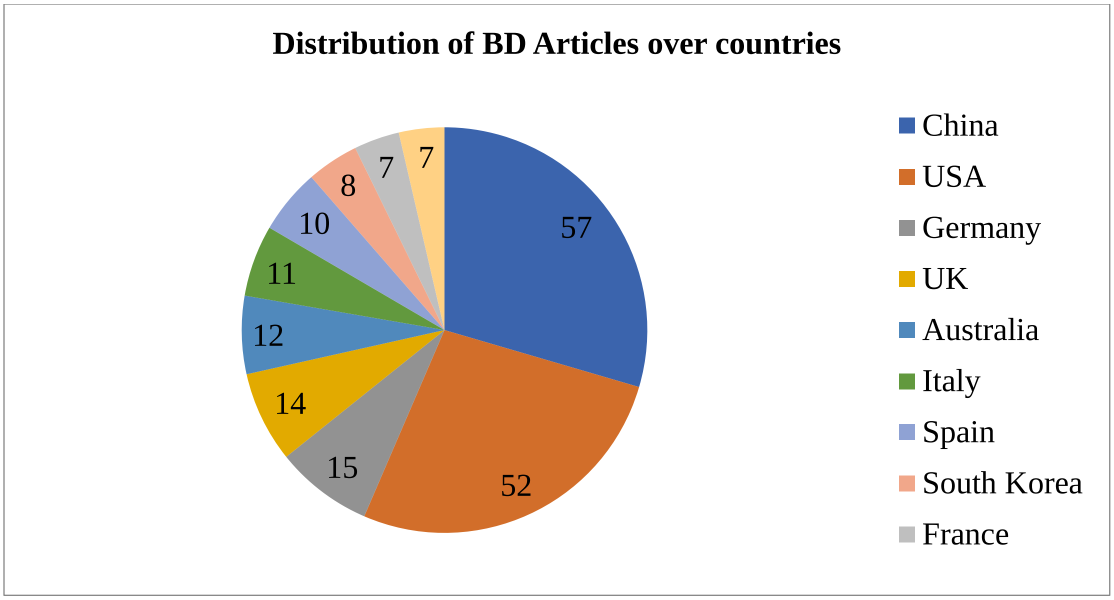


Figure 11: Distribution of BD articles over the countries

6. For the “Digital Twin” subset data list

The distribution of articles over the years (Figure 12) shows that it almost had no presence from 2008 to the end of 2012. However, since 2013, the research results showed an unstable increment in the number of published articles with a noteworthy peak in the last year, “2018”.

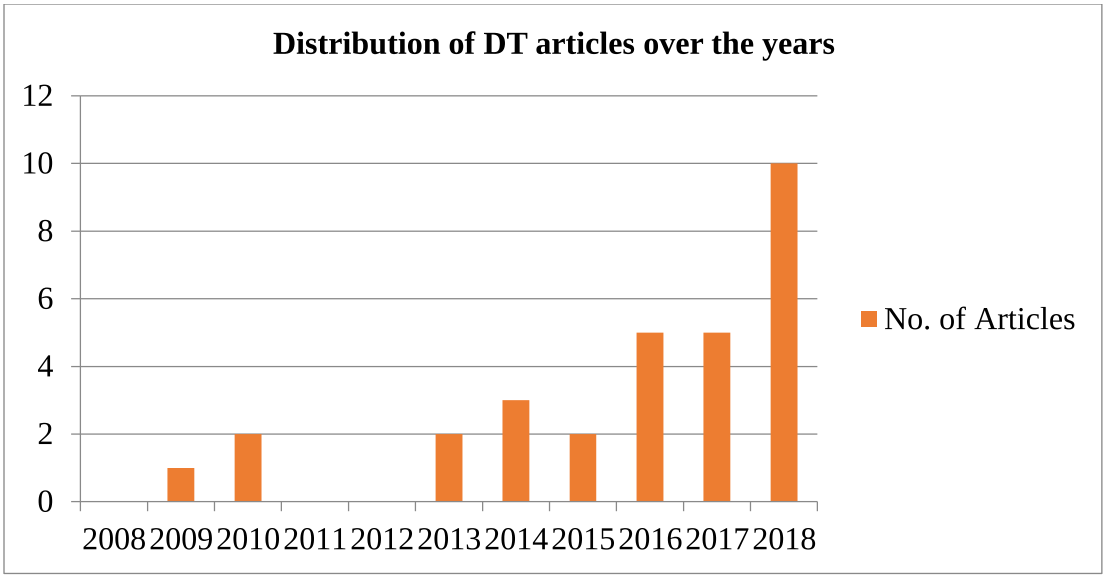


Figure 12: Distribution of DT articles over the years

The distribution of articles over the countries (Figure 13) - with a focus on the top 10 countries in this field- shows that USA and China are still conducting most of the research in this area, Germany in the fourth place, with no presence for Italy among the top ten countries in this field.

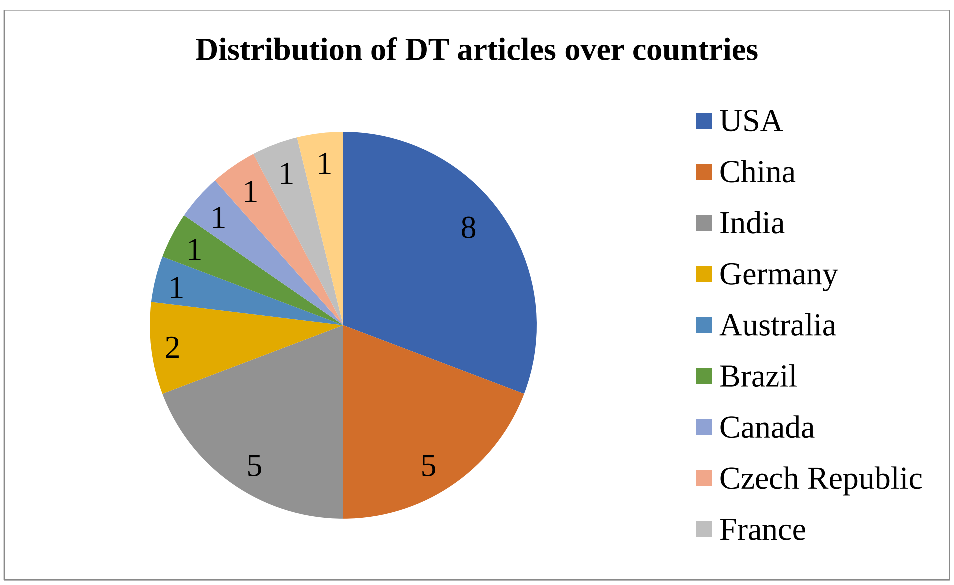


Figure 13: Distribution of DT articles over the countries

After the first research results, another research criteria were done, but this time without the use of “Operations research” in the keywords, and instead, using only “CPS OR CPMS OR CPPS OR cyber-physical system OR cyber-physical manufacturing system OR cyber-physical production system” to search for papers’ titles, abstracts, and keywords. And then, searching within this list for the other key technologies using the following keywords: (big data OR BD), (Digital twin OR DT), (internet of things OR IoT OR IIoT), (machine learning OR ML), (Artificial intelligence OR AI).

Doing this has helped us to understand the real relations between CPS and the other key technologies. Revealing this fact whether this relation depends on some operational research techniques or not. Of course, this time, an analysis regarding the distribution of the articles over the years and the countries have been done for the full list of articles and each of the subset list of each technology.

The following results were presented, the number of articles that were resulted from the search analysis without “Operational Research” as one of the main keywords (Table 2) is higher than the number of articles that were resulted from the search with “Operational Research” as one of the main keywords (Table 3). This means that applying cyber-physical systems CPS with some operational research techniques is still a new area of research that is continuously growing and needs more focus from the researchers. .

Table 2: Number of search results on Scopus without using Operations Research as one of the keywords

keywords1	Total	Filtered
"CPS" OR "CPPS" OR "CPMS" OR "Cyber Physical System" OR "Cyber Physical Manufacturing System" OR "Cyber Physical Production System"	31316	12032

Table 3: Number of search results on Scopus with Operations Research as one of the keywords

keywords1	keywords2	Total	Filtered
"CPS" OR "CPPS" OR "CPMS" OR "Cyber Physical System" OR "Cyber Physical Manufacturing System" OR "Cyber Physical Production System"	"OR" OR "Operations Research"	49631	3951

Regarding the subset lists of each technology (Table 4), again, doing the research without mentioning “operational research” in the keywords shows an increase in the number of articles, especially in IoT, DT, and BD, since the increment was significantly high. However, in the case of ML and AI, the increment wasn’t as high as the previous technologies (IoT, DT, BD). These results show that the presence or absence of operational research in the keywords doesn’t have an effect on ML and AI, which means that these two technologies are highly dependent on and related to operational research techniques, and the research in these two areas is always carried out with some operational research techniques

These results show that using some operational research techniques with the implementation of AI and ML is not a new area of research. However, it is a well-investigated and studied area. While in the case of the other three technologies (IoT, DT, BD), the combination of implementing these technologies with some operational research techniques is still a new area of research that needs more focus by researchers.

Table 4: Comparing search results for each technology subset

	Number of Articles with OR	**% of articles with OR**	**Number of articles Without OR**	**% of articles Without OR**
Total	***3951***		***12032***	
BD	170	4,30%	542	4,5%
ML	323	8,18%	802	6,7%
AI	895	22,65%	2269	18,9%
DT	30	0,76%	89	0,7%

IoT	312	7,90%	907	7,5%

Moreover, these results show that the percentage of articles in the case of machine learning and artificial intelligence is higher with the presence of operational research techniques. This says that ML & AI are related to OR techniques.

To understand the relation between ML and AI, an analysis for the ML list of 323 articles, and the AI list of 895 articles, has been done. The analysis resulted in an overlap between these two lists of articles with a percentage of 55.7% of similarity. This means that we are looking almost at the same list of articles, and whenever is mentioned ML, there is AI as well.

After that, I tried to search for the main AI techniques by exploring google and reading some related articles to figure out which of them are the most used and common ones. Then see how many times these AI techniques were mentioned in the ML list of articles to get a clear idea about the most used ones (Table 5).

Table 5: Number of articles who focus on AI techniquies

AI Techniques & Tools	No. of Articles
Case-based reasoning	3
Rule-based systems	2
Artificial neural networks ANN	42
Fuzzy models	2
Genetic algorithms	31
Multi-agent systems	12
Swarm intelligence	6
Reinforcement learning	19
pattern recognition	54
fuzzy logic	7

Table 5shows that Pattern Recognition, Artificial Neural Networks, and Genetic Algorithms are the most used artificial intelligence techniques in this research area.

Analyzing the literature of CPS and OR techniques:

Here comes the step of analyzing a group of articles by exploring their abstracts and reading them to extract valuable information for my research that might help me develop and evolve my research methodology and provide beneficial knowledge and outcomes for my industrial partners. Therefore, the framework that I have followed in order to aggregate that value-added information was by constructing an excel sheet with the information that valuable for me and then looking for this information in the list of articles that I have found from searching for the following keywords on Scopus, “cyber-physical systems” AND “operational research techniques”. After filtering the results and making them limited to “English” articles that were published in “Journals” only in the field of “Engineering, and Computer Science”, in the window frame from 2008-2018, a list of 80 articles was the result (Table 6).

Table 6: Research results on Scopus

<table>
<tr><th>Entity</th><th>Description</th><th>No. of Articles</th></tr>
<tr><td>keyword1</td><td>cyber-physical systems</td><td rowspan="2">239</td></tr>
<tr><td>keyword2</td><td>operations research'</td></tr>
<tr><td>Categories filter</td><td>computer science OR engineering</td><td>224</td></tr>
<tr><td>Document type</td><td>Article</td><td rowspan="3">80</td></tr>
<tr><td>source type</td><td>Journals</td></tr>
<tr><td>language</td><td>English</td></tr>
</table>

Qualitative data analysis and results:

Speaking about these 80 articles, *the distribution of articles over the years* (Figure 14) shows an increase in the number of published articles regarding the implementation of CPS and OR techniques over the years, which shows an increasing interest to study this topic by the researchers.

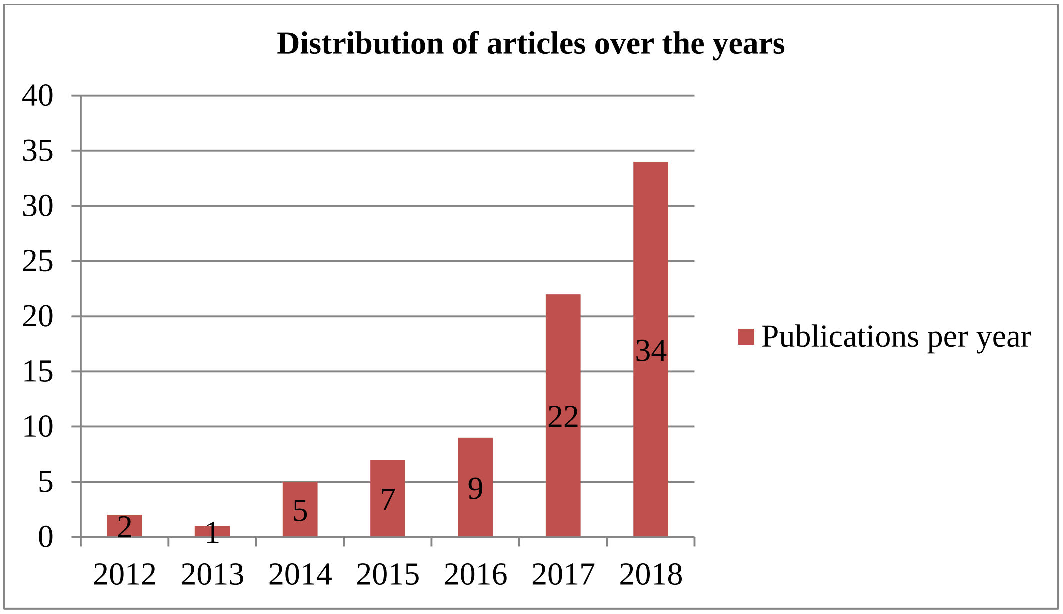


Figure 14: Distribution of articles over the years

The distribution of articles over the countries (Figure 15) focusing on the top 10 countries in this field- shows that Germany is conducting most of the research in this area, while the USA, China, and Italy come in the third, fourth, and seventh place respectively.

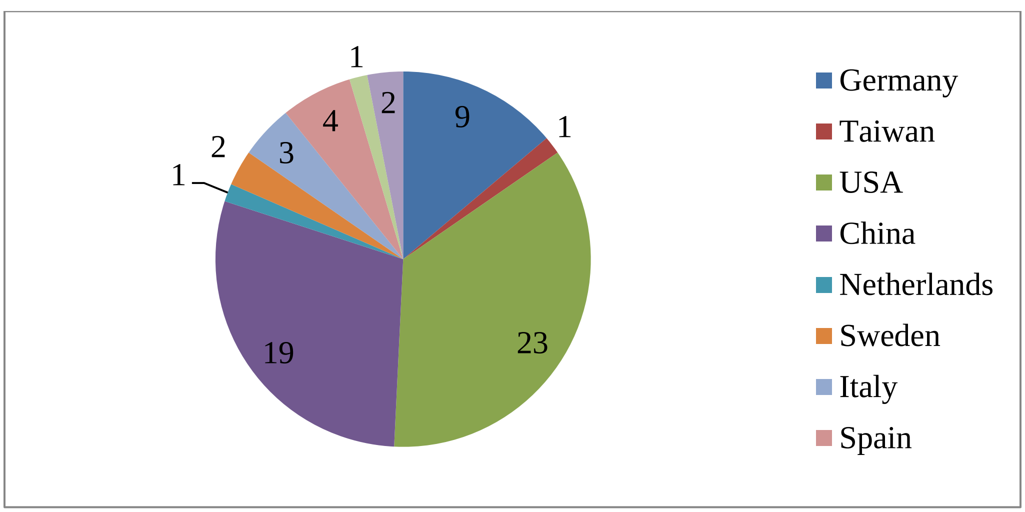


Figure 15: Distribution of articles over the countries

By analyzing those 80 articles, eight articles were defined as the most related ones for my research. After that, they were analyzed to extract valuable information from them.

The information which I was searching for in each article was:

- The most commonly used research methodology, “qualitative or quantitative.”
- The reason for implementing these technologies is “the aspects that required improvements.”

That information was collected in an excel sheet to ease the analysis process and to be able to extract and go back to them at any time.

After collecting these 80 articles and analyzing them, another group of articles was extracted out of these 80 articles based on OMT’s requirements, needs and interests (OMT is an industrial partner company of this research, more details about this company can be found below in Chapter 3)

Therefore, a list of 8 “interesting” articles that are related to the interest of OMT was extracted and analyzed to understand the following:

1. The area of improvement that was achieved after implementing these technologies.
2. The method used to achieve each article's outcome was “whether it’s qualitative or quantitative.”

This analysis has helped divide these eight articles into four categories, generating the research assumptions and formulating the research questions.

In the table below (Table 7), you can find the four groups of categories with the number of articles within each one:

Table 7: Four main categories in the literature

Main categories	Number of articles in each category
Human and CPS in failure predecting and problem solving	2
Collecting and minimizing the tardiness in real-time data to improve decision making	4
Security and safety of the manufacturing environment	1
Connecting design and manufacturing processes by establishing a cyber pgysical environment for digital product design and manufacturing	1

Assumptions, hypothesis, and research questions

After investigating and reading so many articles related to this topic, the following four assumptions were formulated:

1. Money growth and value-added outcomes of the service-oriented process lead to new businesses
2. A clear shift from product-centric processes toward digital service-oriented ones
3. The digital transformation can be achieved by integrating and developing IoT, CPS, with other physical devices.
4. Operational research technologies are used to support the data intelligence development

And from these assumptions, the following four hypotheses were introduced:

1. The increasing interest of the marine sector in servitization
2. Engines and related systems (subsystems) will benefit from integrating IoT, CPS, and OR techniques.
3. Cyber security issues will increase in importance
4. The success of servitization depends highly on data understanding.

According to the eight articles list and the group of four categories, the following research questions relationship were formulated:

High-level question (BM level):

HOW IoT enhanced CPS and PSS can add value to Digital OMT “BM.”

First level questions (Product level):

RQ1.1: HOW RTD (IoT) can be used by CPS applied to the injector

RQ1.2; WHAT is the effect of RTD (IoT) Tardiness to feed CPS

RQ1.3: WHO are those decision-makers that will use these RTD either on process or data

Second level questions (Manufacturing process level):

RQ2.1: HOW to improve the product manufacturing process by using operational collected data?

3.2 Digital Twin implementation and data collection process

As discussed above, one of the main four categories that need more focus by the literature is the digital connection between manufacturing processes (category number four in Table 7). To do so, the right implementation of advanced technologies is required. Digital Twin is one of the most important technologies that can integrate processes and bi-directional communications between the manufacturing companies' entities.

Digital Twin technology, like other technology, has its lifecycle that involves four phases, including the creative phase, productive phase, support phase, and disposal phase (Grieves & Vickers, 2017)

The creative phase is where there is a huge amount of work to be done. The creative phase is the fundamental stage of using Digital Twin, which has many details that need to be carefully considered.

The productive phase is about constructing physical systems with the specific configurations resulting from the previous phase. The main goal of this step is to allow and optimize the communication of the information between the virtual world and the physical one.

In the support phase, there are several analyses about the behavioral concepts of the system that were defined in the creative phase. The connections between the real and the virtual system are maintained. Here, it is important to consider possible changes to optimize the actual situation or eliminate the unpredicted undesirable behaviors that were not identified in the creative phase (Miller et al.,2018).

The disposal phase is considered because information about a product is of huge value for the business, even after the product is retired from the market. Next-generation products could have similar problems, and companies can save costs and time by taking care of this information.

Digital Twin can be classified into two types: Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). Digital Twin works in a Digital Twin Environment (DTE) (Grieves & Vickers 2017).

DTP considers the prototypical physical artifact. It considers all the information needed to reproduce the product in the physical world after defining the prototype in the virtual one. So here, the information flow ideally goes from the virtual model to the physical model. The goal of this type is to improve efficiency in terms of time and cost.

DTI means the digital representation of a physical product. This process needs continuous connections throughout the entire lifecycle to optimize the virtual model over time. Here the information flow has the opposite direction of DTP because, in this case, it goes from the physical to the digital model.

DTE is a multi-domain application used for managing the Digital Twin for different purposes. Predictive purpose means the possibility to do forecasting about future scenarios and the performance of the physical product. Here we can analyze the predictive purpose in the two types of Digital Twin described before. Prediction about DTP might be the analyses of product tolerances to ensure that the as-designed product met the proposed requirements in the physical one. While predictions in DTI consider the historical processes of product components and performance, providing a range of possible future states. The interrogative purpose is used basically on DTI. The use of interrogative purposes is related to the prediction of future states. For example, the aggregate of actual failures could provide probabilities for predictive uses (Grieves & Vickers 2017).

As the traditional method of designing a new prototype, DTP wants to verify and validate the PD result and eliminate the PU output. In addition to this, DTP provides the capability of identifying UU scenarios that might create problems for the system.

The creative phase has great significance because it is the first stage where validation and verification must first occur to ensure that every decision will positively affect the investment and maximize it. Moreover, data is collected and analyzed in this phase to obtain the needed information to define improvements and develop all possible solutions. Therefore, the Digital twin in the creative phase allows simulations, real-time analyses in the operations and manufacturing process, predictions about problems or possible future scenarios, and more other applications that create several benefits for the organization (Lu et al., 2020). Due to the undeniable importance of this phase and the lack of studies and research on this area (Jones D. et al., 2020), the main concentration of the current study has been dedicated to developing a comprehensive framework for implementing digital twins in the creative phase.

Moreover, a detailed analysis of the importance of the creative stage of a digital twin will be taking place. The big share of this section can be attributed to data as the fuel of the digital twin. Fuel quality and distribution have a direct effect on the final performance of the system. To ensure the mentioned characteristics, all aspects of how data should be collected, analyzed, and managed and in what situations should be used have been scrutinized under the following headings.

Creative stage of Digital Twin

The creative (or design) phase in Digital Twins sets its foundation based on the creation of the digital model (Tharma et al., 2018). Digital models could be about something that exists in the real world, as a process, or about something that doesn't exist yet in the real world, as a product prototype. The latter might be based on data and information that comes from previous experience or different physical models with similar characteristics. In this stage, the main goal is the digital creation that can allow analyses and virtual verification, which gives its user the possibility of identifying defections, behaviors, and structures of the digital prototype (Tao et al., 2018).

The creation of the Digital Twin starts with a new pipeline of manufacturing data. Integrating historical data about operations, performance, and system interaction support Digital Twin (RajratnaKharat et al., 2018). This data gives the industrial owners a special opportunity to simulate the system and its processes and evaluate how well they will perform in the physical world under various what-if scenarios. In this regard, having no high cost in the prototype is the notable point that stimulates companies to utilize this opportunity. The concept of feedback to design is compatible with this situation, representing solutions based on historical design systems used in the past (Erikstad, 2017).

In the way of exerting Digital Twin on the position that the physical system has an external presence, various technologies have been developed that assist the simulation process. One of the popular technologies is the Internet of Things “IoT.” IoT is the concept of connecting different objects to the internet, and it has accelerated the movement from connecting devices to the Internet to collecting and analyzing data by using sensors to extract data throughout the lifecycle of the product, to create value and knowledge from the huge amount of the collected data, such as the knowledge of the product performance and conditions (Marco C. et al. 2004), and this has enabled the transformation in several industries to move toward selling these collected value-added data to get more revenue and higher margins instead of selling their final product; Bianchi N. at al. 2009 & Tonelli F.et al. 2009)

The related sensors and devices are positioned and in charge to exploit data from products and processes. RFID is one of the most used sensors in IoT. The RFID implementation is relatively cheap. It improves the communication quality between the physical and digital models and the practicability of sensing systems (He et al., 2018).

One fascinating detail in the creative phase of Digital Twin is following the design-driven approach, which compensates for the inefficiency of the traditional design approaches. By identifying the system's behaviours, Digital Twin forms the digital prototypes that align with the requirements of the considered business. The goal of this procedure is to improve decision-making by way of generating information. Meaningful information comes from data, and data come from the physical model through sensors and devices. Regarding the undeniable importance of data quality, placing sensors responsible for collecting data optimally in the right position has great sensitivity. Fortunately, the simulation capability of the digital model could govern them toward the luminous direction.

The role of Digital Twin in the product design process is also outstanding. Designing a product can be divided into three stages: conceptual design, detailed design, and virtual verification (Tao, Cheng, et al., 2018). The conceptual design phase is where the designers identify the characteristics, as aesthetic and main functions of the final product. Here designers must consider several data types like customer satisfaction, investment plans, product sales, etc. In this situation, Digital Twin can help by considering all these data and establishing more efficient and transparent communications like communication between clients and designers to get feedback and identify problems. The detailed design phase focuses on completing the product design prototype considering appearance, functions, configuration, parameters, and tests. Digital Twin is helpful for the simulation of this prototype in a faster and cheaper way. The virtual verification is conducted based on the pointing out of performances and defects using Digital Twin.

Xu et al. analyzed how Digital Twin can assist the fault diagnosis using deep transfer learning (DTL), which allows the extraction of knowledge from one or more sources for using it in another target domain. The Digital Twin creation process starts with creating a virtual system that obtains data and insights from the physical system simulation. This is the intelligent development phase. As always in statistical scenarios, high-quality input data are needed to obtain high-quality output; when the virtual entities achieve a satisfactory level, the second phase is the construction of the physical entity. Meanwhile, DTL is used to create a diagnosis model using the knowledge of the previous phase. The problem of insufficient training data for high-quality diagnosis is addressed here by the DTL solution. Therefore, DTL improves the diagnosis quality in the first stages. It could also be used to establish new working conditions in the future (Xu et al., 2019).

Data acquisition for Digital Twin

The role of data in today's digitized systems is more prominent than ever. Data plays the role of fuel for the system and causes it to run and survive. Since fuel quality plays a significant role in system performance, data quality will also affect system performance and output. As a result, the process of data acquisition needs to be considered carefully.

Systems have their own data sources. Most of the time, the structure of data coming out of these sources is not the same. In addition to sources that generate and store data, other important sources are valuable but difficult to store, like human experiences and personal behaviors. Collecting all these data types to create digital representation (Singh et al., 2018) and better simulations of the physical system in different scenarios is necessary (Coronado et al., 2018).

For better implementation of digital representation, information acquisition should not be confined to only data originating from machines. It should encompass a comprehensive perspective of the process through a multi-modal data acquisition (Uhlemann et al., (2017).

Data acquisition could be conducted by two main approaches, including sensor-based tracking and machine vision. Sensor-based tracking approach provides information about the position and the moves of employees, products, and devices around the organization. At the same time, machine vision is used to identify products in certain processes. This implementation enables the use of a single sensor or tag for each product. The machine vision approach could be employed in certain conditions, for example, when the number of the product is high, or the process characteristics are not compatible with sensor-based tracking. From the economic point of view, the cost of a sensor-based tracking approach is proportional to the number of devices that have to be tracked. In contrast, machine vision has different steps considering the number of devices. However, generally, its cost is fixed and depends on quantity (Uhlemann et al., (2017).

The challenge of data storage is an issue that needs to be addressed in addition to data collection. Companies can decide to store data in-house or use a cloud-based system. The latter scenario is well described by Alam & El Saddik They analyzed the cloud-based system for the scalability of storage, computation, and cross-domain communication capabilities (Alam & El Saddik, 2017). In this case, every physical system has a digital twin hosted in the cloud. They also argued about a one-to-one connection between physical and digital systems. The changes in the real world are updated through sensors in the virtual one. Their study has a unique ID for an object and a relation ID for every communication.

Hofmann and Branding described four different data sources that are used for simulation in Digital Twin. These sources include an existing system that contains daily useful information, a historical database that includes data from the past, external sources from the surrounding environment and real-time data from sensors technologies (Hofmann & Branding, 2019).

While the abundance of data (big data) improves the simulation quality in digital models, their analysis will face greater challenges. The three main challenges that need to be managed in this direction are volume storage, velocity, and variety. To conquer them, three brilliant responses or scenarios for questions, including how to reduce the stored set of data, speed up data collection and real-time analysis, and combine multiple data sources, respectively, are required (Wärmefjord et al., 2017).

The data collection could be established on two platforms. One is concerned with the prediction service, and the other is related to production management and control service. Enterprise information systems, big data-based prediction and analyses systems, Digital Twin technology-based prediction and analyses systems are all requirements for setting up these platforms (Zhuang et al., 2018).

Data Management for Digital Twin

Data collection will have no added value without the right implementation. Therefore, the data management process needs to be taken into account meticulously.

After the data collection, all these resources need to be implemented efficiently in the digital system to have a continuous data flow. Nowadays, software technologies make Digital Twin data implementation more feasible and affordable (Zhou et al., 2019). The key to giving power to Digital Twin simulation is a complete data model that includes the features of the Cyber-Physical System (CPS) (Negri et al., 2017). In order to establish data flow, the Centralized Support Infrastructure is needed. It supports the semantic metadata model, the simulation framework, and the communication layer. Data acquisition and data evaluation are characterized by location independence. This is helpful to contrast the low level of knowledge about industry 4.0 and Digital Twin. In fact, companies do not need employees to be inside the company to do their job. Technologies help the remote-working (Uhlemann et al., (2017).

Besides collecting, storing, and transmitting data, it is important to clarify what purpose these data will apply. The purpose has a direct effect on the type of data. For example, suppose the purpose is about maintenance. In that case, Digital Twin needs available historical knowledge, and it needs to be close to the process (Cattaneo & Macchi, 2019).

Digital Twins' performance is not limited to its entities. However, the people who put these components together and manage them also significantly impact the final performance. The bottom level of Digital Twin implementation is composed of people, engineers, and scientists who have both software development skills and engineering skills to implement these technologies. West & Blackburn support the idea that an engineer with deep engineering knowledge about the physical system and basic software development skills can do a better job than a professional software developer with a limited understanding of the engineering part of the system that has to be modelled (West & Blackburn, 2017). A comprehensive understanding of the process allows the data to be transformed into meaningful information and insights and implemented properly. Effective information management across the built environment provides overall improvement (Zdravkovic & Stirna 2019) and several benefits. The most important of these benefits are better decision-making and financial savings.

One factor that affects the correct use of data in the digital model is aligning the upstream data (from the physical to the digital system) with the requirements of the downstream (from the digital to the physical system) process operation. This wide view will lead to effective data management (Gohari et al., 2019). Blockchain is one of the best creative solutions for managing the data flow of digital currency, Bitcoin, which can trace information through the entire lifecycle and protect the security of the artifacts through hashes (Nakamoto, 2019). A comprehensive assessment of whether the concept of Blockchain could be implemented in Digital Twins is provided by Heber & Groll (Heber & Groll, 2017).

Continuous improvement of Digital Twin depends on rectifying the deviation between the simulated signal and the measured signal using data management, which will eventually upgrade Twin's digital system. There are two main phases in order to have an updated Digital Twin, including local data processing and global data processing. The first is used for simple feedback as data cleaning, data storing in a private database, and the data used to make local decisions. The second is used from the shop floor-level management. It includes the transmission of clean data in public databases and data exploitation to extract information and knowledge (Ding et al., 2019).

Data management gives assistance to the built-in data flow to improve the actual situation of the physical and digital systems. To achieve these expectations, several aspects of data flow need to be adjusted properly according to the strategy behind data management. Data synchronization between different resources, low latency data transfer to the cloud, data security and privacy, reliability in data transfer, low energy consumption in data transfer, and interconnectivity between different smart objects are all entities associated with data flow that need to undergo special kind of regulation (Ding et al., 2019), (Lee et al., 2020).

Digital Twin-driven product design

Product design through utilizing Digital Twin requires ascertaining some entities. At the initial step, the main ideas behind the considered product should be determined. Following this, the related criteria need to be structured into the Digital Twin vision. To set up the virtual model, the main resources which represent the physical part into a virtual one should be identified. Product data coming out of tests, prototypes, and similar components from the past should be organized to support the digital model (Wärmefjord et al., 2017).

The design phase of Digital Twins has been supported by two pillars, including design, theory, and methodology (DTM) as well as the data lifecycle management (DLM).

The Digital Twin in this phase considers existing DTMs to optimize and customize them for the specific product. DTMs are also helpful to identify conflicts and contacts through the different design phases. DLM exploits data that comes from the physical model. It improves data quality through cleaning and mining processes. The Digital Twin-Driven Product Design (DTPD) is an engine that enables the use of a huge quantity of data transformed by the DLM into beneficial information to be used to make decisions aligned with the DTM (Tao, Sui et al. 2019).

An interesting design approach is the FBS framework. FBS stands for function (F), behavior (B), and structure (S). Function means “what the object is for”, the behavior means “what it does”, and the structure means “what the object is”. It aims to integrate the knowledge of the design agent to have a dynamic and open vision of the system. The design phase of a Digital Twin needs to consider the connections between these aspects to have a logical and rational system view.

Geri & Kannengisser well described the FBS framework as a process for designing. The process includes eight steps (need, analysis of the problem, statement of the problem, conceptual design, selected schemes, the embodiment of schemes, detailing, and finally working drawings) based on the information flow between different entities that contain sets of information. These sets include expected behavior, behavior derived from the structure, function, and design description. In the phase of designing the external world, expected world, and interpreted world, three domains are constantly interacting with each other. These domains are constructed based on the interpreting process, which creates the interpreted world based on the external world, a focusing process that allows the designer to create actions based on the interpreted world to reach the goals of the expected world, the action process that is the result of these connections and it is responsible for changing the external world in order to achieve the predefined objective (Gero & Kannengiesser, 2004).

To deeply define the design of a final product or process, it's important to consider the concept of Virtual Commissioning (VC). This is the verification and validation of the virtual model against the real one (Ayani et al., 2018). VC can be done during the development of the physical system, and it's helpful to define the real commissioning.

3.2.1 Methodology

In this research, an interview with fourteen experts in the Digital Twin area was organized. The Mayring Content Analysis approach was applied to their response to extract meaningful information. The interviews' goal is strictly related to the research question about

"How the digital twin implementation framework in the creative phase should be?". The purpose of this research is achievable through the personal experience of experts (Whittemore et al., 2001).

The qualitative content analysis using the Mayring inductive category development approach has been adopted for this research to analyze the interviews because the classical quantitative content analysis can not provide clear answers of how the categories were defined and developed (Mayring, 2000). However, the qualitative approach proves its capability in content analysis and the interpretation of data and the development of categories that are highly similar to the original content/material. One of the procedures developed by the qualitative content analysis is the inductive category development, which is based on a group of reductive processes to the original text to develop and extract the final categories (Mayring, 2000).

The inductive approach was used to create a general framework from specific cases. The presentation of new information in a real scenario gives the possibility to easily link new knowledge with existing cognitive structure (Thomas, 2006). The reason behind adopting an inductive approach is that Digital Twin is a quite new technology, so there are different points of view about certain concepts of this technology. Using a deductive approach (from a general theory to a specific case) was not feasible because it is not compatible with the purpose of the research to design a general framework for creating a Digital Twin. The inductive approach needed analyses about Digital Twin technology state of the art. It was a fundamental step to have a wider view of this topic and be more specific about the inductive research (Thomas, 2006).

Moreover, the qualitative content analysis based on the Mayring approach is used to do step-by-step systematic text analysis and interpret texts within any kind of recorded communication, such as interviews, by dividing the text into content analytical units, in order to be able to develop the appropriate categories (Mayring, 2000).

The questionnaire was strictly designed based on a research gap in the creation phase of Digital twins. The answer to how a Digital Twin Implementation Framework in the first stages of the Digital Twin creation should be "considering data collection process" is the foundation of the proposed framework. And, it has been designed according to the hypotheses and reflections emerging during the literature review analysis. To eliminate redundancy and make the answer more efficient, only three questions have been presented for the interview. These questions are as follows:

1. There are two main scenarios for the creation of a Digital Twin. The first is when we have a physical system, and the second is when we do not. What is the difference in the framework for Digital Twin data collection between these two scenarios?
2. Data is the fuel of Digital Twin. Therefore, data collection systems need to be implemented in order to enable an efficient data flow. How do companies choose the right systems for Digital Twin data collection? Which are the main systems? (e.g., sensor-based system, machine vision system).
3. One of the main challenges in Digital Twin data collection is the diversity of data that come from the physical world (e.g., structure, size, frequency, noise). How can different types of data be implemented into a single Digital Twin system? (e.g., lake databases).

After defining interview questions, fourteen interviews were conducted with an average duration of 26 minutes. These interviews were recorded and stored to undergo analysis. The software application used for the interview was Skype which provides the opportunity to have high-quality video and audio interviews (Janghorban et al., 2014).

The next step after recording their responses is the analysis, that is, extracting the meaningful insights and directions) which was structured following the qualitative content analysis based Mayring inductive approach, and the main steps taken for this approach are as the following:

1. Definition of the material, which is the interview text in our case
2. Determination of the units of analysis
3. Paraphrasing of content-bearing text passages.

   3.1 Determining the envisaged level of abstraction, generalization of paraphrases below this level of abstraction.

   3.2 First reduction through selection, erasure of semantically identical paraphrases.

   3.3 Second reduction through binding, construction, integration of paraphrases on the envisaged level of abstraction.

4. Generalization and collection of the new statements as a category system.
5. Re-testing of the new statements as a category system.

Therefore, the development of the categories was a step-by-step Systematic qualitative text analysis process that was done during the text interpretation using an inductive approach (Mayring approach).

Speaking in more detail, identifying the right Digital Twin experts was one of the main challenges. This is a critical step for the quality of qualitative research. The choice of the right interviewers was a step-by-step process. The research of these people was done using the network of researchers that came out of the theoretical background academic papers. A message was created that well described who the researcher is, what the researcher is doing and the purpose of this research. This message was sent to the e-mail addresses of the network that came out from the theoretical background research. These contacts were available online or directly on the research papers. Social media as LinkedIn and Twitter were used for discovering other experts and digital twin researchers. This research is composed of fourteen qualitative interviews. Each one was anticipated by a phone call to understand if the respondent had the requirements needed for the interview questions. It was a crucial step to ensure the quality of the answers.

After recording the interviews, the first action was to transcribe the fourteen interviews into a text paragraph. The interview transcription was initially divided into three questions. The researcher transcribed the clean read or smooth verbatim transcription method description in the Mayring approach (Mayring, 2000). This transcription considers all the respondents' words, but all the utterances were left out. The choice of this transcription rules system was based on the research question requirements. All the possible information from the experts can be useful for improvements and the creation of the framework.

After the choice of the transcription method, the next step was the analysis of the text content. The analyses started with the division of the whole text of each interview into segments called units. The division analysis of the text was made in three levels. The first was the coding unit representing the minimum portion of text that can fall in one category. The second was the context unit representing the largest portion of text that can fall in one category. The third one was the recording unit that determines the text portions confronted with other categories. This classification was done with an inductive method for the first round of reduction of the entire text. This means that the different units were defined along the content analysis process.

The original text was reduced into paraphrases, then these paraphrases were generalized, and in the end, the generalizations were classified into categories. The coding unit was around 40 words because there were cases where the text was so clear and valuable that it had to be highlighted as a category.

The context unit was the answer to a question that is composed of approximately around 180 words for the shortest answers (e.g., answers for question number three). This choice was based on the fact that some interviewees had a clear vision of Digital Twin. They summarized a meaningful and linear message related to a specific question. Therefore, some answers didn't need something more to be added, and they formed a category. Having a context unit bigger than these means that the level of detail would have been too general, and it would not have been in line with the research question.

The recording unit was the same as the context unit for the same reason; some answers were so clear and logical that they could be confronted with one system of categories. It never happened that a shorter piece of text could be confronted with another system of categories.

The reduction process was done two times. This is because the amount of information was huge, and the first reduction was not enough for creating balanced categories. The second reduction had as first text the output of the previous reduction that means the first category. The latter was reduced into paraphrases, then generalized, and finally, the generalization fell into five categories. These five categories will be the pillars of the framework. The repetition of content data analyses ensures the quality of the final results. In fact, this process has led to the categories that will be addressed in the next section

3.2.2 Results & Discussion

The results of the qualitative analyses and Mayring approach are classified into five categories with the title of Digital Twin definition and classifications, Digital Twin framework, Data collection process, Data diversity problem, and Scenario 1 "DT based on existed physical object" and Scenario 2 " no physical object" analyses aligning with the research question which inquires how a Digital Twin Implementation Framework in the first stages of the Digital Twin creation should be "considering data collection process". All these categories have to take into account the aspects through the creation phase of Digital Twin. The level of details between these categories in some cases is different. What emerged from the interviews was that it is important to have a wide awareness of the process (low level of details) and more precise analyses about specific parts of Digital Twin critical.

All the following considerations are based on the information that emerged from the 14 interviews of Digital Twin experts. Based on the answers collected from these interviews, we defined four main ideas and concepts that any framework for the Digital Twin implementation at the creation phase needs to be cover. These concepts are purpose-driven, agile, step-by-step, trade-offs through the framework, and feedback loop. More details about each of these concepts are discussed in the following section.

3.2.2.1 Digital Twin Framework

As mentioned above, this section defines the answer to the research question of this research. It contains the four important concepts that emerged from the qualitative interviews that a framework for the Digital Twin needs to be able to cover.

Purpose-Driven Approach

The main concept that almost all interviewees have underlined was about the purpose of Digital Twins. It means that all the decisions that are taken during all phases of the framework must be consistent with the overall purpose of the Digital Twin. At this point, the question is "how a company should set the purpose of the Digital Twin?" and also "is Digital Twin the right investment/solution for the considered business?". Referring to insight obtained through analysis, companies should start from market needs. Once companies identify the market needs they want to satisfy, it is critically important to consider the possible Digital Twin directions based on the digital capabilities required for those specific market needs. This means that companies need to consider the market needs and the digital system needs for the data collection process to be able to collect the required and right data related to their previously defined purpose.

Agile and step-by-step approach

Digital Twin creation is a long process and time-consuming. What emerged from the interviews was that having an agile approach is the right way to create Digital Twin. This is because an agile approach is continuously prepared for changes in order to improve the actual situation (Agarwal et al., 2006). Another concept that came out from the interviews is the step-by-step method. The benefit of this method is that it allows for meaningful digital representation. All the interviewees believe that everything starts from a raw representation of the ideal physical system. This representation can be created digitally using simulation software and different data sources. Consider that in order to ensure a decent quality level of the first representation, having awareness and knowledge of the physical system is required.

Trade-offs through the framework

The Digital Twin framework provides various possible scenarios. In some cases, there is not always a right or a wrong decision. A common approach that interviewees noted in this situation are trade-offs. The pros and cons of each option completely depend on the companies' priorities which could be attributed to three main entities, including data storage system (cloud storage system vs on-premise storage system), sensors (value received vs costs), and data collection system (machine vision system vs sensor-based system).

Some interviewed considered these data analyses as out of the company domain. What the company must do is understand the purpose of the Digital Twin and the data needed. Then the technical parts should be developed by external partners. This is a really key part of the interviews' results because it gives a certain level of detail to the framework. It shows that there is not a technology problem for the companies. However, there is a value and purpose-defining problem in the process of the implementation of the digital twin. Therefore, companies need to focus more on their purpose of extracting the value-added data instead of thinking and investing in the technical solutions to extract and analyze this data because technical solutions can be achieved easily by external partners nowadays.

Feedback loop

Feedback is the ability to continuously extract and feed data from and to the system in a closed-loop in order to be able to improve the digital representation.

Continued improvement in digital representation occurs by relying on feedback loops. The procedure of feedback loop is that in the first step, Digital Twin data workflow is simulated, in the second step, the deviation between physical and digital system is calculated, and in the last step, according to deviation, a new possible variable is proposed, and again all these steps are repeated.

Two important points were noted by interviewees which should be considered in the feedback loop. The first point is related to deviation, which emphasizes that a deviation should be considered only if it could affect the purpose of the Digital Twin. If the predefined purpose is achieved, it means that the received value from the digital twin is at the highest level, so it does not matter if there is a deviation between the physical and the digital system. As interviewees claimed, physical and digital changes are two main reasons that cause the deviation between the systems. Therefore, it is important to search the problem through physical and digital systems to identify the problem. The second point for improving the feedback loop was about including variables related to the purpose. This means that the level of details for the data analysis can be increased or decreased based on the defined purpose by the companies. In other words, if the digital twin needs to be used only to simulate the object's prototype (in the pre-design phase of the object's lifecycle), this needs a basic data analysis. While, if the purpose of the digital twin is to do a bi-directional aggregation of the data in real-time and to mirror the performance in real-time, in this case, this means that the level of details for the data analysis increases during the Digital Twin lifecycle in order to have more sophisticated analyses related to the purpose.

Framework for the creation of a Digital Twin

Now, after carrying this research and getting the results discussed above, it is important to have a structured theoretical framework for the implementation of the digital twin in the creative phase. The proposed framework is discussed in further detail in this section.

The goal of this theoretical framework (Figure 16) is the creation of the Digital Twin, and it includes all the concepts that emerged from interviews

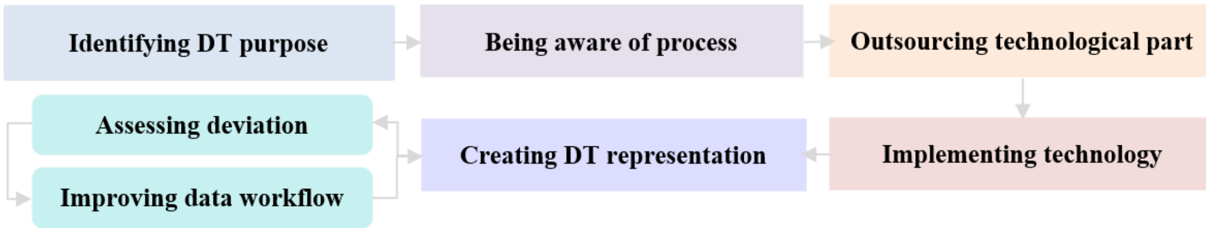


Figure 16: The framework for creation of Digital Twin

As it is shown in Figure 17 below, the cornerstone of the proposed framework for the creation phase of Digital Twins is the purpose. It affects all subsequent components and needs to identify precisely. The purpose could be identified from different points of view. Identifying market needs, creating new business assets, and solving problems throughout processes are dimensions that could be defined. Digital Twin implementation requires a huge workforce to be implemented through processes. To organize all components and interactions among various entities properly, the identified purpose needs to be analyzed from two aspects, time horizon (long, medium, short) and decision level (Strategic, tactical, operational) with the continuous check about the correctness of the purpose.

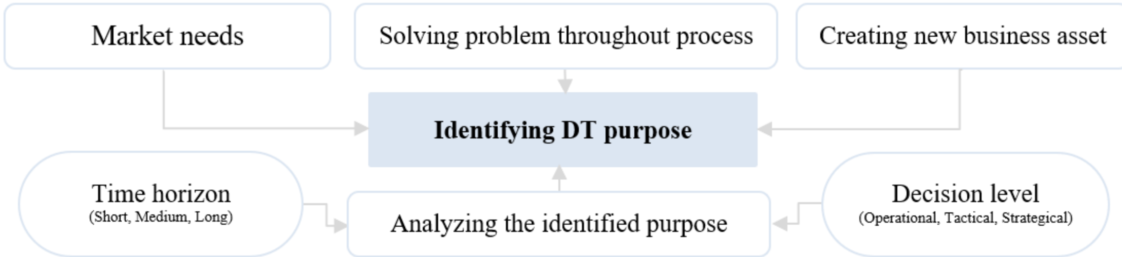


Figure 17: Identifying digital twin purpose as the first step in the creation phase of Digital Twin

It is important to be aware of the process you want to reproduce digitally to achieve the purpose. According to Figure 18, achieving this awareness depends on two prerequisites: acquiring knowledge about process workflow and analyzing the required data. The latter one should undergo the minimum viable concept to hierarchically classify the importance of the data that the system could reproduce. An obtained minimum viable dataset includes the required data that enables a first raw digital representation. In this phase, the company starts considering hypotheses about the structure of the digital system. The agile approach and a step-by-step vision enter this field to evaluate different variables that are needed for digital representation. Three different data sources, including human knowledge, IT systems, and sensors, support this phase.

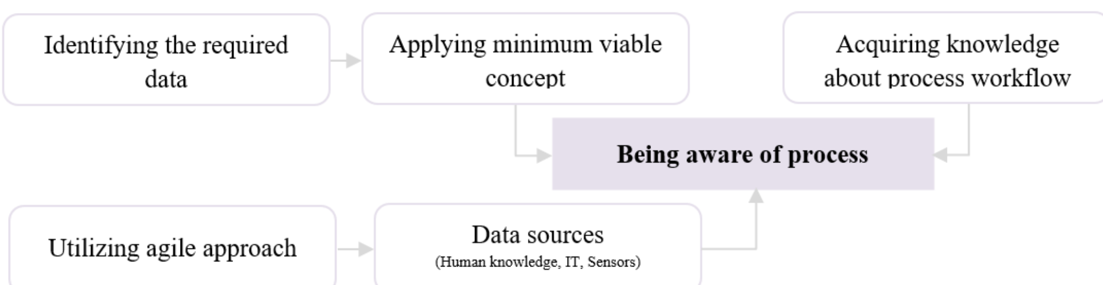


Figure 18: Being aware of the process as the second step in creation phase of Digital Twins

The company's role in implementing the digital twin is based on the purpose identification, the implementation of the technologies through the processes and the continuous improvement of Digital Twin. Therefore, the company that wants to create Digital Twin has to leave the technological aspects to external partners that can offer the right solutions for the case needs. Technological part requires time and cost. So if the companies outsource this part, they will have more opportunities to focus on the rest part of DT. According to Figure 19, all the technical aspects such as how to collect data, store data and transmit data are developed by the technology partners.

The external partners provide the company with solutions regarding data collection methods, data storage methods, software and platforms for data management. The platforms enable the transmission of the data. It is important to consider the compatibility of the new software with the previous ones.

According to interviewees ‘responses, there are two main challenges for a technology partner in this phase. One problem is with data diversity, and the other is with cyber security. For the former challenge, the interviewees underlined that it would be better to look for a solution from the beginning to prevent it from happening. A common solution is creating the standardization of data structure and communication layers to enable the link of different data. Nowadays, various kinds of software and technological solutions have facilitated the process of harnessing data diversity (Biesinger et al., 2018). The cyber security problem is a real challenge that requires a lot of attention from the company. The warning point in this situation is that all kinds of processes and knowledge are digitized, and there is the possibility that they get hacked. So technology partners are responsible to offer an appropriate cyber-security solution for companies which ensure the Digital Twin implementation will not endanger their systems.

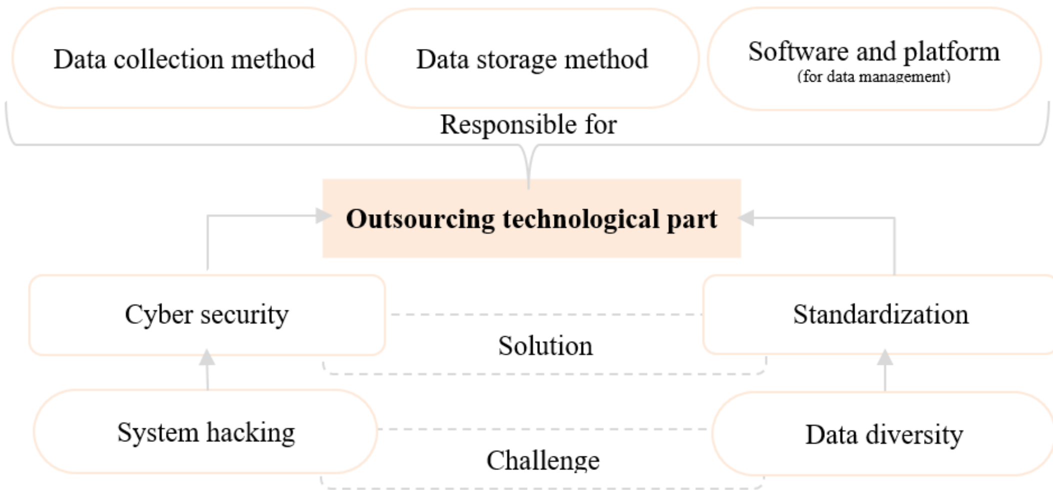


Figure 19: Identifying technology partners as the third step of creation phase of Digital Twin

When the partners were identified, and the technological solutions were selected, the process could move forward, and technology solutions could be implemented. According to Figure 20, there are three main operations that the company has to dedicate more concentration to organize them in the perfect way. The first one is related to choosing the right type and right place for sensors which are the foundation of data collection. The second one is associated with establishing the proper way, which ensures the expected quality level for transmitting data and the right time requirements. Last but not least is concerned with training workers who need to learn about how they should work with the new technology. Without training, interaction with the system will be confusing for them and taking incorrect action could put the system into trouble.

Interviewees emphasized that there are pivotal principles that must be followed in technology implementation. Data in the Digital Twin system is a kind of fuel, and data loss is an inevitable problem in this regard. So it is better to employ the standards through the system from the beginning to avoid any problems. Digital Twin systems could take the advantage of a step-by-step approach and establish a balance between the overview of the system and operational actions to make a standardized, connected, and integrated process from the beginning of the implementation till the end.

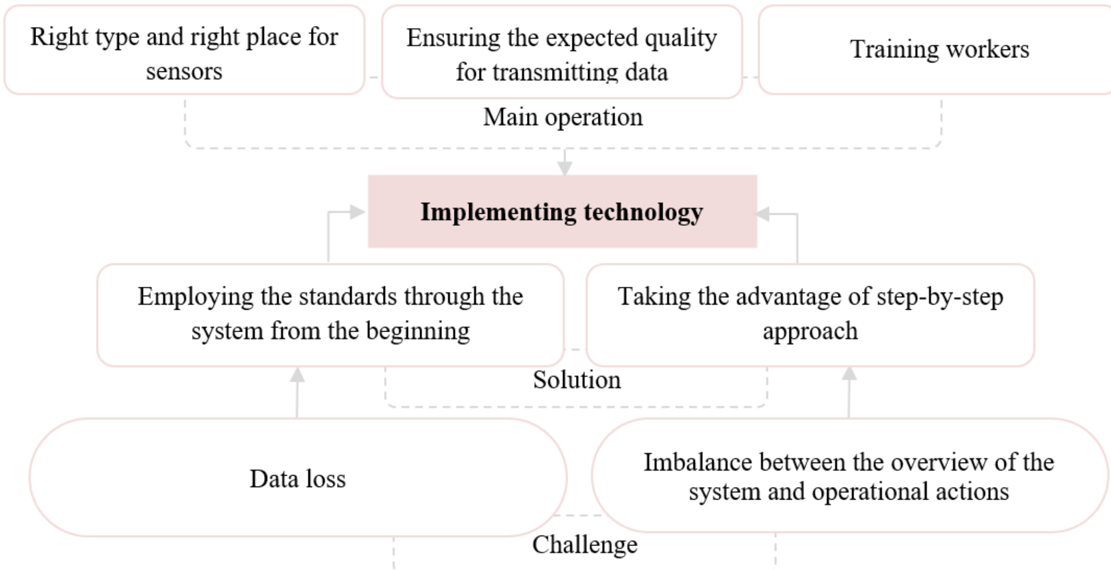


Figure 20: Technology implementation as the fourth step of creation phase of Digital Twin

The next step, according to Figure 21, is the Digital Twin representation. At this stage, we have the entire infrastructure for collecting, storing and managing the data. Therefore, the company can start with the first raw representation of the Digital Twin. This interpretation will reveal what is going on in the system. In order to realize the realistic interpretation of a system, by relying on human knowledge, the helpful data must be selected and interpreted. From the interviews emerged that in some cases having the right level of detail is not easy, and in complex systems could be useful to divide the overall system into smaller ones. This approach enables a more precise result where the output of the small systems generates the overall Digital Twin. The selection of the right data is important for the digital representation and the continuous improvement in the feedback loop. The use of human knowledge enables us to exploit the data and obtain an efficient digital representation. In fact, the training of the employees about using software and the new technologies is an activity of the previous phase.

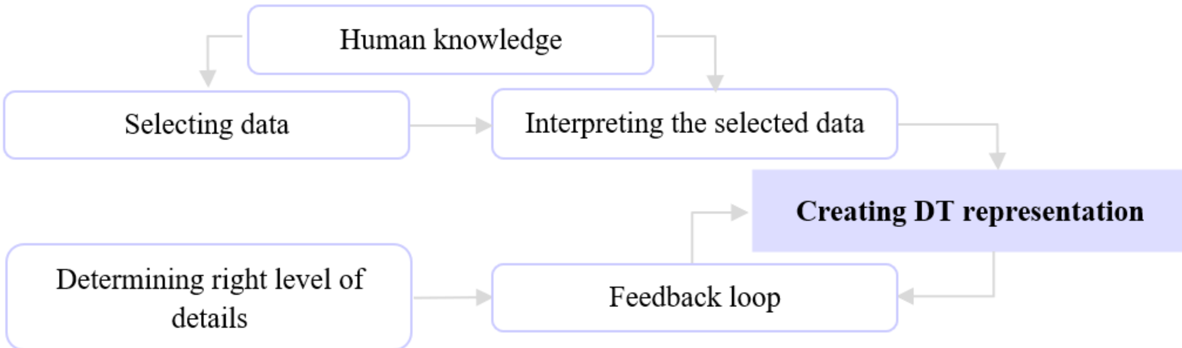


Figure 21: Digital twin representation as the fifth step of creation phase of Digital Twin

Figure 22 indicates the feedback loop as the prime part of Digital Twin. This loop is extremely important because the continuous improvement of Digital Twin is directed by it. In the first stages of the Digital Twin creation, the first representations are raw and not precise. Using this loop, the company can identify the deviation between the measured value and the expected value. Here the company analyses where the problem is. After these analyses, the companies can modify and improve their physical products' performance based on the real-time presentation of the collected data.

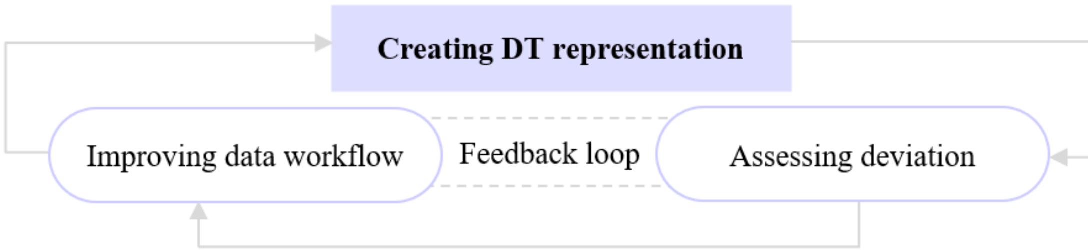


Figure 22: Feedback loop as a prime part of creation phase of Digital Twin

The use of visual and design software, as CAD, is important in order to have an overview about how the system works and which data the company needs in order to achieve the purpose.

This digital twin research has been published in an international journal, "Processes," as an article under the name of "to Set Up the Pillars of Digital Twins Technology in Our Business: Entities, Challenge and Solutions" (Abusohyon I. et al., 2021). This paper is listed below in the appendix section of this thesis.

3.3 Industrial applications of IoT, DT & Artificial Intelligence

3.3.1 OMT & IOT Framework Formulation for Smart Monitoring System

During the research, external collaboration with ABODATA and OMT was done. The former exists at Genoa and aims at providing support Research and Development services for software systems by taking advantage of the substantial growth opportunities present in emerging vertical markets generated by the world of Internet of Things (IoT), while the last exists at Turin and aims at developing tailored solutions using the new technologies to help their customers optimize their diesel, gas and dual-fuel engines in the marine market for highest performance and lowest life-cycle costs. This collaboration was intended to help both companies implement the Internet of Things and other technologies and techniques to help them achieve their aims and goals.

Starting from Industry 4.0 and its key technologies and understanding the needs and requirements of ABODATA and OMT, the work focused more on analyzing the literature and studying the projects in which ABODATA is going to implement IoT technologies to identify obtainable advantages (particularly one concerning marine engines and fuel injectors).

Their main interest was implementing IoT technologies and cyber-physical systems “CPSs” as a whole system of digital twins (device, engine, ship). After conducting the research, it turned out that OMT is more interested in digitalizing their product “injector”. In the future, they will start thinking about the concept of Factory 4.0 to be able to digitalize the whole business and manufacturing processes.

Therefore, this research took the path toward realizing the full potential of implementing PSS, IoT and CPS with some operational research to be able to fulfill OMT requirements of digitalization.

To do so and to test and validate results from the literature review analysis done in chapter 1, a 10-step approach for the development of IoT-based product design for servitization was proposed accordingly by detailing the previously identified five areas represented in Table 7 and the results of the analysis of the articles found in the literature. Figure 23 shows the ten main blocks in this approach.

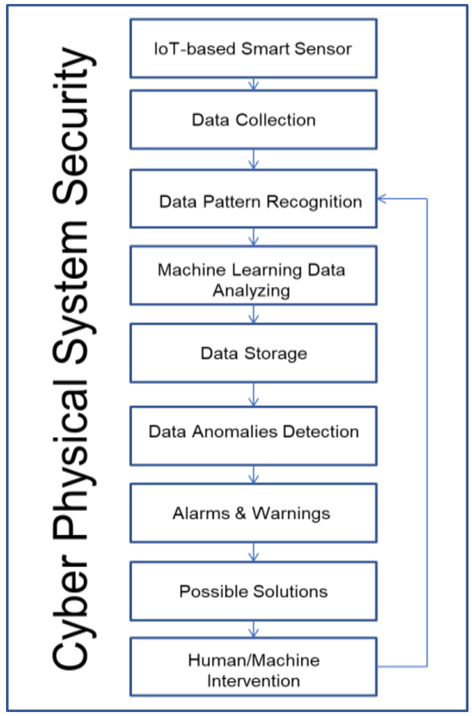


Figure 23: IoT-Based Smart Product for effective servitization block diagram

Moreover, the framework delivered by Yoval C. & Gonen S. in 2020 was validated by implementing it in the OMT-Digital Smart fuel Injection System. OMT has created the start-up company OMT Digital to quickly evolve its offer and include services based on its products. To achieve this goal, the two companies have worked together to create an intelligent injector able to communicate its operative characteristics to a local processing unit for performing fast data analytics and providing immediate feedback to the engine control unit and to the engine room crew, as well as transmitting the processed data to cloud-based storage for further analysis and knowledge generation (Marco C. & Marco F., 2019). As a result, a smart process control framework was elaborated.

OMT Digital aims to transform traditional mechanical injectors into smart injectors to be able to share, process, and store data for further analysis to improve injectors' performance and increase their lifetime. Their smart system comprises different layers, so a fully digital layer connects the injectors in an IoT system to the Hub. In this layer, the digitization of the analogue signal takes place. After that comes the processing of the signal, which is done in the fog node, and here is where the algorithms run, and the reduction of data occurs -process raw data to extract value-added data- and present directly to users' interface the status of the health of the system. Then, the same data further reduced is sent to the cloud when the connection allows.

The IoT intelligence-related services/data provided to the user are divided into three categories (C):

- **C1:** drift compensation and product development "automation system". OMT has GUI so they can see how all the injectors "in the world" are operating and get important data to help them develop the product further. This is one of the benefits that the "injector manufacturer" can get from this automation system (i.e., getting numerous data from all the operating injectors).
- **C2:** on-board maintenance, so if there is a problem in the injector, it needs to be fixed it quickly. The system here tells "on the user interface" that there is an abnormality somewhere. It advises about the actions that need to be done to solve the problem. So, the maintenance of the components can be achieved easier.
- **C3:** condition-based maintenance, which means the ability to measure the status of the injector over time to predict failure before it occurs and calculate its remaining life to decide what maintenance needs to be done and when.

By considering the literature analysis and OMT-Digital case and pursuing improvements to the process control framework proposed by Yoval C. & Gonen S. in 2019, a smart controller framework for the fuel injection system "FIS" of OMT-Digital is presented. Figure 24 describes its main five modules and information flows in which the model operates.

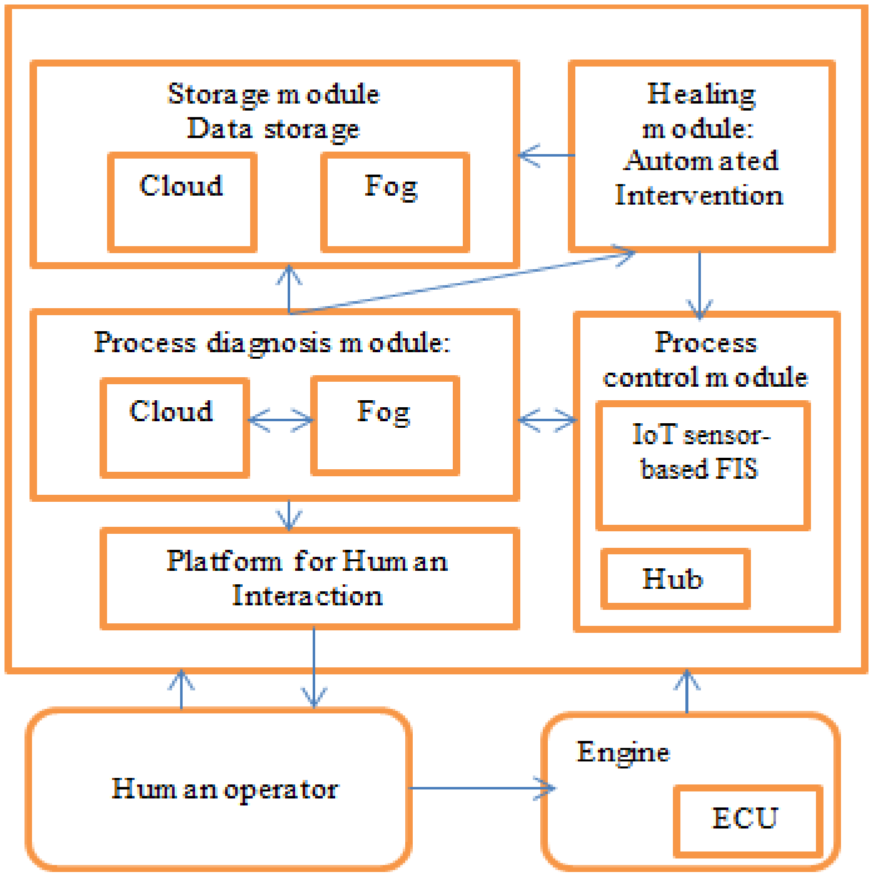


Figure 24: Smart controller framework for fuel injection systems

Process Control Module

This module is responsible for collecting the data, "mainly the temperature and the solenoid current," and sending it to the "process diagnosis" control. The injectors are connected to the system. Whenever the engine's control unit activates the injector, this triggers data generation and acquisition. Moreover, there is an analogue sensor in the injector, an analogue to digital convertor. Then this data is sent to the Hub and then sent via the internet to this computer (fog node). So, there isn't any particular algorithm in this phase. It's just data coming into the sensor and then delivered to the fog node.

Process Diagnosis Module

The processing of the collected data is done in this module. The collected data is sent to the fog node. The fog node will machine learning algorithms" or classical digital signal processing algorithms to process the data and transform it into more value-added data. The other level of data processing is done in the cloud.

In the ship, the real-time analysis is taking place, which means that if something is changing significantly, this will immediately be transferred with an alarm to people who are in charge on the ship will be informed so that they can perform immediate actions the resulted changes.

On the other hand, the development of the algorithms to estimate the components' lifetime is done on the cloud.

Healing module

Based on the required type of intervention, the corrective actions can either be performed automatically as part of the smart control or through the manual intervention of a human expert. For example, suppose there is a delay in the performance of the injectors. In that case, the system can compensate for this defect automatically by itself. However, in the case of more complex faults, the intervention of humans is required

Storage module

Here is where the data get stored, and it can be stored in two ways, in the fog node for up to a month of a capacity for local analytics on the ship. Once there is an internet connection, the data get automatically stored in a data lake in the cloud. It's used to give lifetime prediction and to give access to the data by different stakeholders

Human interaction module

This platform is used as one direction information flow to provide the user with valuable data. The stakeholders can access the cloud with the graphical user interface of OMT "OMT GUI". The crew on the ship can review the health of a specific engine with some KPIs through alarms on the platform, which reflects if there is something wrong. The ways to solve this issue are provided to the operator through the platform as well. And this is done locally without the cloud connection

3.3.1.1 Results & Discussion

The main discussion areas in this research are the importance of internet of things technology in manufacturing comes from its ability to collect real-time data and extract valuable knowledge from these huge amounts of data which can be supported through the implementation of a smart IoT-based servitization framework which was presented in this research together with a 10-steps approach diagram. These are highly connected to the assumptions and hypotheses that were mentioned before, so they were used to answer the research questions formulated earlier in this research.

Speaking about the first hypothesis, "**H1:** There is an increasing interest of the maritime sector in servitization," which is directly linked to the first and fifth assumptions "**A1:** Cyber-physical environment for integrating digital product design and manufacturing processes for higher quality and lower-cost operations, **A5:** Improved field service, maintenance and decision making is possible because of more information about when and how their product is being used", these were tested positive through the outcomes achieved by the company under investigation in this study after implementing the smart control fuel injection system proposed earlier. OMT is a company in the maritime sector which is achieving important benefits from implementing this IoT-based servitization framework within its operations. They start to build a good reputation in the market for having this technology “the smart control system”, and seen as a technologically advanced injection system developer, and this attracts a lot of new customers for the company “indirect revenue”, as well as the financial revenue from selling the service provided by the smart monitor FIS “direct revenue”. Also, having the technology of IoT-based servitization smart monitor system gives OMT the possibility to gain more projects of this kind and to be able to digitalize other products and not only the injector. These benefits also provide an answer to the higher-level question formulated earlier in this research:

RQ1: How IoT-enhanced CPS and servitization can add value to a manufacturer or a components provider in the maritime sector?

The second hypothesis, “**H2:** Engines and related systems (subsystems) will benefit from the integration of IoT, CPS, and OR techniques”, which was extracted from the second and third assumptions “**A2:** Transforming product-centric processes service-oriented ones through the help of digital technologies implementation, **A3:** The digital transformation can be achieved by the integration and the development of IoT, CPS, with other physical devices”, also found support since the IoT-based framework that was implemented in a CPS environment to support the smart fuel injection system produced by the OMT-Digital, showed that all the data were fed to machine learning and artificial intelligence algorithms to enable the prediction of the injector lifetime depending on the actual conditions of use; this also answers the second research question:

RQ2: How to improve the product manufacturing process by using operational collected data?

Regarding the third hypothesis, "**H3:** Cyber security issues will increase in importance", this is tested positive since the high amount of collected and shared data needs to be processed in a secured way; otherwise, the risk of cyberattacks will increase dramatically to the point where the implementation of these new technologies will affect negatively on the company. On the other side, if these real-time data were treated securely, this would expose any abnormalities that might occur. In the case study in this research, the collected real-time data "RTD" helped OMT detect injector operation anomalies such as the delayed start of injection, which is linked to higher fuel consumption. Their compensation by the control unit keeps the engine operating optimally. So the RTD is used to detect the performance and the lifetime of the injector. This data can support decision-makers who are either the ship stakeholders or the engineers in the crew of the ship and guide them toward a better understanding of the performance of the injectors and, therefore, better maintenance. This answers the following questions:

RQ1.1: How to use the collected real-time data RTD from IoT sensors?

RQ1.3: Who are the beneficiaries of the aggregated RTD?

However, since the proposed framework in this research doesn't cover the effect of tardiness in the detection of the real-time data, this leaves the following question without an answer:

RQ1.2: What is the effect of tardiness in aggregating IoT data?

Therefore, further development to the proposed framework can be suggested and validated in other real-case scenarios to answer this question.

Finally, understanding the value of the collected data and being able to extract knowledge out of it and transform these huge amounts of data into valuable services is the heart of servitization, and this supports the final hypotheses "**H4:** The success of servitization depends highly on data understanding" and its related assumption "**A4:** Operational research technologies "AI and ML" is used to support data intelligence development and analytics."

Moreover, the 10-steps approach diagram and the smart control framework for the case under investigation developed by this research can be considered the first steps toward implementing the IoT-based servitization concept in a CPS environment to collect and analyze data for further development and improvement in product performance and maintenance. However, the smart controller FIS framework proposed by this research differs from the one described by Yoval C. & Gonen S. in 2020 since it considers the storage process of the collected value-added data, which is a new module that was not covered in their framework. Also, the healing module is mainly responsible for performing the automatic intervention. However, it can't send any updates or modifications to the machine learning weights in the process control module. Moreover, the human interaction platform in the framework presented here is used just like a tool to provide information to the operator, so the operator can't send any data to the other modules within the framework. Finally, their framework assumes that the sensors practice self-awareness and maintain their own reliability, while it's not the case of the sensor developed by OMT-Digital.

Finally, this smart control framework has been presented at an international conference on Internet of Things, Big Data and Security IoTBDS2021 under the name of "Internet of Things Based Product-Service System in the Maritime Industrial Sector" (Abusohyon I. & Tonelli F., 2021). This paper is listed below in the appendix section of this thesis.

3.3.2 OMT & DT Framework

The literature shows some differences in the development of the digital twin in the manufacturing domain and maritime domain. However, the research and interest in the maritime domain are still new, while many researches have been focusing on the manufacturing domain in the past few years (Nicole T. et al., 2020).

Implementing Digital Twins is the origin of the difference between Digital Twin procedure-related manufacturing and maritime sections. The purpose of the maritime section is usually based on the opportunity provided by digital twin "opportunity-driven," while for manufacturing section is on the basis of needs that must be fulfilled and achieved by the help of digital twin "need-driven" (Erikstad S., 2019). Therefore, more research is needed to develop a need-driven approach for digital twin development in the maritime sector.

Moreover, the maritime domain is witnessing digital transformation, especially in the smart control and automation of processes, by extracting valuable knowledge of the large stream t of data collected from sensors and actuators. Therefore, the ability to access data remotely from hard-to-reach assets and handle these huge datasets is so important in the maritime domain

<u>OMT-Digital</u>

An innovative and agile start-up spun off by OMT Spa in 2018 to provide tailor-made digital solutions that enable value creation through data analytic, with a particular focus on the marine transport and propulsion markets. Its vision is to provide services based on its products, and it is based in Turin-Italy. Therefore, it has created create an intelligent injector able to communicate its operative characteristics to a local processing unit for performing fast data analytics and providing immediate feedback to the engine control unit and to the engine room crew, as well as transmitting the processed data to cloud-based storage for further analysis and knowledge generation (Marco C. & Marco F., 2019). Therefore, the digital twin framework resulting from this research was investigated within the boundaries of this new startup, "OMT-Digital". This startup has been chosen for this research because it aims to support its customer's digital evolution, which is equivalent to the aim of implementing the digital twin.

Starting from implementing the digital twin technology within their processes, it turned out that their purpose is to facilitate the designing of the injectors' prototypes and validate certain decisions about the system and identify possible problems or risks. To do so, they don't need an intelligent digital twin but a basic digital twin, the pre-digital twin level.

So basically, they are using the digital twin as a simulation tool to help them design the injector before having the actual physical model. This means that there isn't any data acquisition from the physical twin at the moment. However, OMT-Digital mentioned that in the near future, they are planning to invest more in the digital twin technology and to move toward the implementation of a higher-level digital twin such as the intelligent digital twin, to be able to improve the after-sales services and to perform the adaptive and condition-based maintenance.

Till then, the digital twin implementation produced by this research can't be fully studied and investigated in a real industrial case, "OMT-Digital," because of the reasons discussed above.

3.3.2 Artificial intelligence in Operation

The forthcoming industry 4.0 promotes the spread of the Internet of Things (IoT) technologies as the key enablers of a newly interconnected work environment where machines and human operators are supposed to cooperate within a common production system. The smart factory concept is thus expected to drastically change the interaction among human operators and machines, with advanced human-machine interfaces (HMI), augmented reality, and wearable devices are becoming part of the standard worker's equipment. Coherently with such view, the manufacturers of operating machines are implementing artificial intelligence features in their products, transforming automated machines into cyber-physical systems (CPS), with advanced interoperability functions, ideally allowing them to interact with the other systems, with the environment and with the human operators in the seamlessly integrated production site. This idyllic view of the smart production systems arises some fundamental questions about the role of the human operator in the work environment of the future and how this interaction will take place. The risk in such a sense is to consider industry 4.0 a technology-driven process mostly focused on machines, where human resources are only marginally involved. However, leaving the man in the background of a machine-cantered industrial revolution would eventually lead to a general deterioration of the worker's physical and psychological conditions, negatively impacting well-being and safety. The issues related to next-generation human-machine interaction and workers' wellbeing should also be discussed in consideration of the ageing process that is affecting the workforce of many industrialized countries, whose impact on manufacturing systems' performances has been highlighted by a recent study by Calzavara et al. (2020). The European population, in particular, is projected to grow from 507.2 million in 2013 to 522.8 million in 2060, with the percentage of seniors (65 years or older) forecasted to grow by 10%, while the working-age population is expected to drop by 9.4% over the same period (EC

2017). A similar trend is observed in the USA. In 2016, people over 65 years old comprised 18.6% of the adult working population, with a projected average growth of 0.6% per year until 2026.

Similarly, more than 25% of the population in Japan were aged 65 years and older in 2014. The percentage is expected to reach 40% by 2060 (Debroux 2016; Collins and Casey 2017). In a manufacturing environment, human operators' capacity to perform a task requiring physical and cognitive efforts generally diminishes with ageing (Gonzalez and Morer 2016; Strasser 2018). However, this decrease can minimize the system's productivity if the workplace is healthy and safe.

Based on such considerations, rethinking the role of the human operator in a general ergonomic framework is a major challenge to undertake within the 4th industrial revolution, in a renewed approach involving new technologies and methodologies. Indeed, in the current industrial practice, ergonomics is still frequently approached with standard worksheets filled by experts and processed with statistical tools rather than real-time quantitative measurements. In such regard, the enabling technologies of industry 4.0 offer an unprecedented occasion for improving the health and safety conditions of the workplace through real-time data gathering and analytics. The recent advances in sensing technologies demonstrate the possibility of developing miniaturized devices capable of measuring the workers' exposure to physical (e.g. vibrations) and cognitive (e.g. fatigue) hazards, their wellbeing status (e.g. the presence of stress markers in biological fluids), as well as the health and safety conditions of the workplace (e.g. wrong postures or the presence of dangerous substances). In addition, coherently with the paradigm of the smart factory, through the employment of smart devices, the operators can exchange information with a centralized system capable of warning them about their actual risk exposure, thus becoming a part of an interconnected production environment.

This research aims at contributing to the existing research in the context of operators' ergonomics and safety in smart production environments by targeting the following research objectives.

1. Demonstrating the effectiveness of state-of-the-art machine learning methods for activity recognition in the manufacturing industry
2. Demonstrating the technical feasibility and the effectiveness of the current technologies in monitoring the workers' conditions in real-time
3. Proposing a novel approach to occupational health and safety in the smart industry context through the digitalization of risk-related data

A methodology is thus proposed to recognize the activities performed by each operator during the work shift and to map the corresponding exposure towards health risks. Based on such information, a decision support system is finally proposed to prevent the occurrence of dangerous situations by sharing relevant information and triggering early warnings when necessary. The research, in particular, focuses on the health risks related to vibrations, which, according to Eurofound's (2015) sixth European working conditions survey (EWCS), affect an average of 19% of workers in Europe, with Agriculture, Manufacturing and Construction being the most critical sectors. In such contexts, the vibrations originating from tools or machinery can cause occupational diseases such as the hand-arm vibration syndrome (HAVS). Therefore, national and international institutions have issued specific regulations to enforce surveillance actions and prevention measures and assign specific responsibilities to the manufacturers of the power tools, to the employers, and partly to the workers themselves. In particular, the machinery directive (2006/42/EC) requires the manufacturers to implement appropriate technical solutions to reduce the vibration levels in their tools and equipment. The employers are in charge of monitoring risks in order to preserve the health of the operators, while the workers are responsible for using the tools according to the given instructions and reporting the occurrence of unusually high vibration levels during their activity. Such prescriptions nowadays are applied only to a limited extent, not necessarily due to the negligence of the subjects involved (which still exists in some industrial contexts), but rather due to the technical difficulties in measuring and assessing the risk exposure for workers and to the lack of suitable real-time measurement instruments (Podgorski et al. 2017, Bernal et al. 2017).

Consequently, the subjects involved are scarcely aware about the actual risk exposure of workers, and corrective actions are seldom triggered timely. It is hence necessary to provide organizations with adequate tools and systems capable of increasing their awareness about vibration hazards, thus introducing work breaks when necessary, restricting the operating time during the workday, scheduling tasks in order to alternate the use of vibrating and non-vibrating tools and triggering safety measures when necessary. The evolution towards smart production systems must consider such issues, promoting the employment of advanced technologies such as IoT and augmented/virtual reality to integrate the safety of workers into the general smart factory framework to initiate the Safety 4.0 era.

3.3.2.1 Theoretical background

The origin of the research about the interaction between human operators and machines can be traced back to the last century, when, after World War II, the spread of mass production systems promoted the principles of efficiency and productivity as the main drivers of industrialization. The initial research was thus mainly focused on optimizing the performance of the machines, while the workers had to adapt to the systems' processes. The shift towards a human-centric view of the work environment emerged only at the end of the last century, when occupational health and safety principles were placed at the core of the ergonomics science, in a modern approach towards human-machine interaction. Such a topic is recognized nowadays as an important and scientifically consistent research topic, attracting a significant research effort from scientists of different disciplines. In such regard, the recent establishment of the smart factory paradigm within the context of industry 4.0 has enriched the scope of ergonomics with new technological and methodological elements, fostering the development of a systematic and integrated approach towards the design of future manufacturing environments. According to such view, the topic of the "Smart Operator" or "operator 4.0" has been recently introduced (Longo et al. 2017, Ruppert et al. 2018, Romero et al. 2017, Kong et al. 2018) as the counterpart of the smart factory concept, to align and enhance operators' capabilities/competencies with the new smart production environment. This evolution of the operator's role is supported by the methodological and technological advances promoted by the fourth industrial revolution, including wireless interconnection technologies (IoT), Big Data Analysis, Artificial Intelligence, etc. Applying such technologies in conjunction with Human Activity Recognition (HAR) methodologies can open a wide landscape of new applications related to analyzing and classifying the operators' activities. HAR is a consolidated research topic focused on automatically detecting and recognizing a person's activities or a group of persons by analyzing relevant data related to their operations. The roots of the HAR system can be traced in the activity theory, originally developed by the Russian psychologist Leontev (1978) back in the '80s, which defines the fundamental theoretical reference framework for classifying human activities. The activity theory introduces a hierarchical structure where activities are described as an aggregation of actions, which, in turn, are understood as a set of atomic steps named operations. The early efforts in developing activity recognition systems began with formulating suitable methodologies to reconstruct the structure of different activities from the analysis of data related to the operations performed, fused with additional context information. Such approaches ultimately aimed at simulating the human ability to extract significant elements from redundant or confusing information, thus falling in the broader framework of machine learning (ML) methods. ML is a research field initiated in 1959 to develop computer systems with the ability to learn without being explicitly programmed *(*Samuel*, 1959).* Driven by the increase in computational capabilities offered by electronic calculators, the first practical applications of pattern recognition systems were mainly based on the stochastic discrimination of characteristic patterns in noisy datasets (Devijver and Kittler, 1982), such as texts, images or sounds. However, the integration with on-body sensing technologies started approximately 20 years later, with the studies of Randell et al. (2000). Nowadays, after more than 50 years of research, ML has become an important interdisciplinary research area involving sensor-based and video-based recognition systems. The former aims at recognizing activities through on-body or ambient sensors, while the latter refers to the use of images or videos. The original toolset of statistical methodologies has also been enriched with more complex and computationally demanding techniques allowing for real-time analysis of complex patterns in big amounts of data. Modern ML methods can thus be distinguished into two broad classes: supervised learning, involving human expert's knowledge in a preliminary stage, and unsupervised learning, where the reconstruction of an inherent structure of the data is entirely entrusted to the machine. The class of supervised machine learning methods typically includes regression (e.g. generalized linear models, support vector regression, decision trees, ensemble methods, trained neural networks) and classification techniques (e.g. support vector machines, k-nearest neighbor, discriminant analysis). In contrast, clustering (e.g. hierarchical, k-means, Hidden Markov Models) and association techniques belong to the class of unsupervised machine learning.

The proliferation of electronic sensing devices in the last decade promoted the spread of sensor-based HAR systems in several fields, including industry (Akhavian and Behzadan 2018, kaveh et al. 2016), medicine (Patel et al. 2012, Schrader et al., 2020), assisted living (Ghasemi and Pouyan,2016), etc. Recently, applications of Har technology have also been proposed in the context of ergonomics and safety (Nath et al., 2018, Malaise et al., 2019), where several typologies of body-mounted sensors have been employed within automatic ergonomic assessment methods based on the classification of the activities performed by workers. In particular, a consistent body of scientific literature focuses on vibration-based activity recognition methods, exploiting the data gathered by accelerometers integrated into the workers' equipment. The first relevant results in classifying human activities based on accelerometer data appeared at the beginning of the new millennium when Bao & Intille (2004) and Ravi et al. (2005) formulated the activity recognition problem as a modern classification problem. The first industrial experimentations appeared some years later when Joshua and Varghese (2011) explored accelerometer application in the construction industry for work sampling, while Ahn et al. (2013) used a set of features calculated from acceleration data to classify excavator operations into three classes. The limited computational capabilities and the high cost of the data gathering devices substantially hampered the spread of such methodology, which remained confined to the research domain. A major paradigm shift occurred in the last decade due to the popularization of smartphones featuring powerful miniaturized accelerometers based on Micro-Electro-Mechanical Systems (MEMS). Several smartphone applications of vibration-based HAR systems have thus appeared in the last years, with significant contributions also in the industrial context where vibration analysis has been employed to monitor and classify construction workers' activities (Akhavian and Behzadan 2016, Zhang et al., 2018).

While the technologies for activity monitoring are spreading in a pervasive manner, from a methodological point of view, the approaches reported in the literature generally refer to the classification of activities based on recognizing specific patterns in the features extracted from vibration signals. In particular, such approaches mostly rely on heuristic handcrafted features, also known as shallow features, including significant statistics extracted from the raw signal (e.g., std, avg, mean, max, min, median, etc.) in the time domain (Bao, & Intille, 2004; Heinz, et al. 2003; Kern et al. 2003, Ravi et al. 2005), or in the frequency domain (Krause et al. 2003, Nham et al. 2008). Classification methods, such as decision trees (Bao et al. 2004, Mannini & Sabatini 2010), k-Nearest Neighbor (Ravi et al. 2005), and Support Vector Machines (Anguita et al., 2012), are then trained to identify different activities. An extensive survey on wearable sensor-based HAR can be found in (Oscar et al. 2013).

Coherently with the recent literature reported above, the research here proposed is based on the application of HAR technology in the context of manufacturing industries to improve the health and safety conditions of the workplace, exploit the information gathered by a smart sensing device worn by the operators as a part of their standard equipment. The prototype device, developed specifically for this research, can gather and analyze the vibration data without hampering the activities normally performed by the workers according to their schedule and store the pre-processed information in a shared digital ledger accessible by all the stakeholders involved in safety surveillance. The novelty of the proposed approach is related to the combination of the activity recognition methodology with a referenced real-time vibration risk assessment approach (Aiello et al., 2012). A real-time mapping of the activities performed by the workers and their corresponding risk exposure can thus be obtained in order to promptly undertake preventive or corrective actions when dangerous situations are likely to occur. In particular, the EU Directive 2002/44/EC defines an "action value" as a threshold for triggering corrective actions and "exposure limit," which, once reached, forces the worker to stop his activity. Such values are established equal to 2.5ms^{-2} and 5ms$^{-2,}$ respectively. According to the Standard EN ISO 5349-1:200, the average daily vibration is calculated based on reference vibration levels generally provided by the tool manufacturers. However, this approach is questionable as the effective vibration intensity generated by mechanical machines largely depends upon several specific factors, including maintenance, operating conditions, etc. Hence, it is not unusual that the same tools generate substantially different vibrations when performing different tasks. A precise measurement of the actual vibration exposure originating from specific tasks in the industry context should thus be employed to obtain more realistic values. This research aims at proposing a novel system and related methodology to overcome the above-discussed issues by simultaneously mapping the different tasks performed by an operator during its work shift and the associated vibration dose, thus providing a reliable picture of the inherent operators' exposure to safety risks.

3.3.2.2 Methodology

Coherently with the above-discussed research objectives, the proposed methodological approach aims to map the activities performed by a set of operators in the manufacturing industry and associate their corresponding risk exposure to obtain an overall representation of the safety conditions in a smart factory. The methodology established is based on ML procedures exploiting the could interconnection functionalities and IoT technologies promoted by industry 4.0, which can be subdivided into two main steps: the analysis of the acceleration data streams gathered by a wearable sensing device and the assessment of the corresponding hand-harm vibration risk exposure. Such phases are discussed below.

Recognition and Classification of worker's activity

The methodology proposed for classifying the activities performed by the workers is based on the analysis of the vibration signals acquired by two accelerometers integrated into a wearable device through the implementation of a typical Activity Recognition Chain (ARC) as described in the reference framework of sensor-based HAR systems (e.g., Bulling et al. 2014) involving the following steps: **data collection, pre-processing, segmentation, feature extraction, and classification** (Figure 25). According to this approach, the input vibration data collected by a sensing device are validated and subdivided into segments of fixed, length-named windows. The relevant features are then extracted from each window and fed into a machine learning classifier to categorize them into a set of pre-established classes. In the proposed case, the classes are referred to as the different basic operations performed by means of rotating tools into a smart factory (e.g., grinding, polishing, cutting, etc.) within a general task assigned to the operator. The effectiveness of the classification substantially depends upon the self-learning capabilities of the classifier employed. It can be assessed by evaluating specific precision and accuracy indicators. The methodology was finally validated in the laboratory by performing experiments, and the classification accuracy was evaluated.

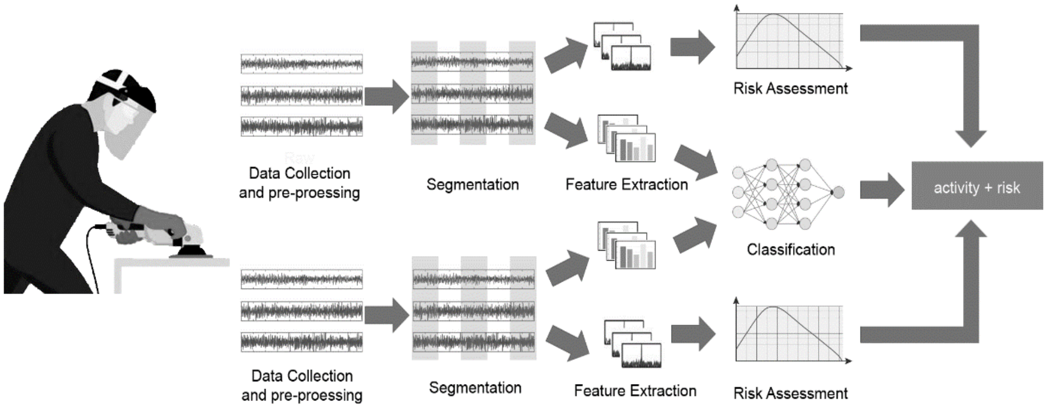


Figure 25: Schematic representation of the proposed approach

Data Collection

Data collection has been performed using a smart wearable data gathering prototype device specifically designed and developed for the purpose of this research. The system features two high-performance tri-axial accelerometers fixed to the operator's wrists and cable-connected to the main sensing device attached to his waist. The instant tri-axial raw acceleration data are recorded for each hand while the worker is performing his regular activities (related to the assigned tasks), thus obtaining two distinct data streams consisting of the timestamped X, Y Z accelerations values. The volume of the data generated and the consequent computational effort required for processing them is strictly related to the polling frequency, which must be accurately established considering the technical limitations of the hardware employed. A more detailed technical discussion of this issue is given below.

Pre-processing

The pre-processing step involves all the preliminary operations required to transform the raw acceleration measurements into valid input data, suitable for the subsequent feature recognition process. In the case considered, the data pre-processing step involves an evaluation of the consistency of the data read by the sensors, which could be affected by artifacts deriving from, e.g., out-of-range readings, electromagnetic noise and interferences in the data transfer, or from hardware failures. Corrupted data due to partial readings are filled with the last valid reading, thus obtaining regular triplets stored into time-stamped vectors as valid inputs for the subsequent processing steps.

Segmentation

This step involves the subdivision of the vibration data streams into windows of fixed length. It is performed before the feature extraction procedure to reduce the dimensions of the datasets. Data segmentation also reduces the computational effort required for extracting the relevant features in big datasets, which may otherwise result in significant delays, particularly when embedded systems with limited hardware capabilities are employed for real-time applications (Ravì et al. 2016), as in the case here considered. The establishment of an appropriate segmentation process depends upon the specific application considered, being generally recognized that longer time windows improve the accuracy of the recognition process but result in increased computational effort for feature extraction. Establishing an appropriate length for data segmentation is thus a substantial issue, and advanced techniques involving variable length and overlapping windows have been proposed in the literature to improve the results. A detailed discussion on such a topic can be found in Banos et al. 2014. Referring to the analysis of vibration levels, however, Preece et al. (2009) observed that existing studies reported in the literature generally do not consider time segments rarely exceeding 10s, with polling frequencies mostly varying from 20Hz to 100Hz (a detailed discussion on this issue can be found in Dehghani et al. 2019). Considering the advances in the computational capabilities of the CPUs designed for smart devices in the last decade, it is nowadays possible to process big amounts of data in a small time. The windows' length and polling frequency can thus be substantially increased. The sensing device employed in this study can generate two separate data streams (one for each accelerometer) at up to 1600 readings per second, with each measure consisting of three acceleration values in the X, Y and Z axes. In such conditions, a time frame of 1 minute can contain as much as 384 000 time-stamped values per stream. In the application considered in this study, the device seamlessly processed data segments of 40 secs in quasi real-time in the experimental tests.

Feature extraction.

Feature extraction is essentially a dimensionality reduction process based on transforming each raw-data segment into a restricted feature space through appropriate numerical methods and computational approaches. Clearly, choosing an appropriate set of meaningful features is critical in this phase to preserve the inherent knowledge for an accurate classification process. Contrarily, unnecessary features or redundant information would only affect the performance of the classification algorithms without scientifically improving the final result. In the case of data collected from inertial sensors, the features commonly extracted can be classified into time domain and frequency domain features. In this study, similarly, with several referenced works (Berke Erdas et al. 2016), seven popular time-domain features have been extracted for each axis in each window (Table 8), involving statistical attributes such as mean, standard deviation, as well as envelope metrics such as maximum and minimum, root mean square, skewness, kurtosis of the signal.

Table 8: Time domain Features extracted for activity recognition, W=generic data window

Feature name	Description	Formula
Mean	arithmetic mean of all the acceleration values belonging to the window	$\bar{x} = \sum_{x_i \in W} \frac{x_i}{N}$
Standard deviation	Dispersion of the acceleration values belonging to the window around the reference mean value	$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N}}$
Maximum	Maximum of the acceleration values	$Min = \min_{x_i \in W}\{x_i\}$
Minimum	Minimum of the acceleration values	$Max = \max_{x_i \in W}\{x_i\}$
Root Mean Square	square root of the arithmetic means of the squares of a set of numbers.	$RMS = \sqrt{\sum_{x_i \in W} \frac{x_i^2}{N}}$
skewness	distortion or asymmetry in a symmetrical bell curve.	$S = \frac{1}{N}\left[\frac{\sum_{i=1}^{N}(x_i - \bar{x})}{\sigma}\right]^3$
Kurtosis	Kurtosis is primarily a measure of the heaviness of the tails of a distribution relative to a normal distribution.	$K = \frac{1}{N}\left[\frac{\sum_{i=1}^{N}(x_i - \bar{x})}{\sigma}\right]^4$

Classification

The classification process is the last step of the activity recognition chain. It discriminates the feature space representation of the segments into one (binary classification) or more (multiclass classification) categories. In the context of ML, the classification process is implemented through the development of mathematical functions and algorithms named classifiers. When the classification process relies on an initial knowledge provided as a reference set of pre-classified instances, the corresponding classifier is an instance of supervised learning methods. Recognizing the different possible activities a tool operator performs in a manufacturing industry properly configures as a multiclass classification process. However, to simplify the classification process in this thesis, a preliminary analysis has been carried out to regroup the activities performed into two broad classes of heavy-duty (HD) and low-duty (LD) activities, as reported in Table 9.

Table 9: Classification of the manufacturing operations into High Duty (HD) and Low Duty (LD) operations

Task ID	operation	Tool type	Tool weight (kg)	Heavy duty	Light duty	Vibration level (ahw)
A	Surface finishing	Palm grip orbital sander	1.5-2.5		X	5-10
B	Rough solder grinding	Right angle sander	3.0 – 5.0	X		15-25
C	Metal trimming	Trimming shear	2.0 – 3.0	X		20-30
D	Paint repair	Jitterbug sander	2,5 – 5,0		X	4-8
E	Paint polishing	Polisher	2,0 – 3,0		X	4-8
F	Rust removing	Stone grinder	3,0 – 5,0	X		20-30
G	Metal cutting	rotating carbon blade cutter	10,0 – 20,0	X		25-40

Based on the above considerations, this thesis has developed a binary classifier to discriminate between HD and LD activities based on their vibration signature. The classification problem has thus been approached by means of the well-known K-Nearest Neighbor (KNN) classifier**,** which assigns each new instance to a specific class according to its distance from the k most similar instances already classified. Despite its simplicity, the KNN algorithm has revealed a robust and versatile classifier. It combines good accuracy with a limited computational effort and outperforms more complex classifiers in many real-time applications. In such regard, a crucial role in the classification accuracy is played by establishing a suitable distance metric and by the number of neighbours (k) considered. The influence of such parameters on the algorithm's performance is still a widely discussed topic. However, the Euclidean distance is the most used metric. Different metrics such as Manhattan or Hamming distance are rarely employed. The k parameter influences the shape of the decision boundary, with small values resulting in a higher influence of noise on the classification and large values substantially increasing the computational effort. Given the lack of appropriate optimization approaches, its value is generally established empirically by trial and error.

Risk evaluation

The second element of the methodology proposed concerns the real-time quantitative evaluation of the hand-arm risk exposure associated with the operator's operations. The procedure established for such a purpose is performed after the segmentation step. It analyzes the vibration data in each segment according to the guidelines provided in ISO 5349-1 (2001a) and ISO 5349-2 (2001b). According to such guidelines, the vibration dose transmitted to the operator's hands is related to the root-mean-square (rms) frequency-weighted acceleration value. The vibration spectrum must thus be extracted from the raw acceleration data by means of Fast Fourier Transformation (FFT) and analyzed in 1/3 octave bands. Subsequently, each band's root mean squared (rms) intensity must be calculated and multiplied by an appropriate weighting factor representing the corresponding physiological effect. The ISO 5349 weighting curve shows a peak value in a frequency range between 4 and 31.5 Hz. The effects caused by the vibration in the hand-arm system are the most critical, while it rapidly decades below 10% for frequencies above 125 Hz. The frequency weighted acceleration can thus be calculated according to equation (1).

$$a_{hw(x,y,z)} = \left[\sum_{j=1}^{n}\left(W_j \cdot a_{w,j(x,y,z)}\right)^2\right]^{\frac{1}{2}} \tag{1}$$

Where $a_{w,j}$ is the acceleration measured in the one-third octave band in m s^2, and W_j is the weighting factor of the corresponding one-third-octave band.

The evaluation of vibration exposure in accordance with ISO 5349 is finally obtained as the root-sum-of-squares (total vibration value) of the three-component values according to equation (2).

$$a_{hw} = \sqrt{a_{hw(x)}^2 + a_{hw(y)}^2 + a_{hw(z)}^2} \tag{2}$$

Where $a_{hw(x)}$, $a_{hw(y)}$, $a_{hw(z)}$ are the frequency-weighted acceleration values for the single axes.

The vibration exposure finally depends upon the magnitude of the total vibration value and the daily exposure expressed in terms of the 8-hour energy-equivalent acceleration or frequency-weighted total vibration value according to equation (3).

$$A(8) = a_{hw}\sqrt{\frac{T}{T_0}} \tag{3}$$

Where T is the total daily duration of the exposure (s), and T_0 is the reference duration of 8 h.

The method for obtaining energy-equivalent acceleration assumes that the daily exposure time required to produce adverse health effects is inversely proportional to the square of frequency-weighted acceleration. To facilitate the development of real-time risk evaluation tools, an effective approach is to consider an equivalent vibration score (*VS*) factor, calculated according to the following equation (4).

$$VS = a_{hw} \cdot T^2 \tag{4}$$

The employment of the vibration score rather than 8-hour energy equivalent acceleration has proven to be an effective approach in real-time risk assessment (Aiello et al. 2019). It allows updating the worker's risk exposure level at each new data segment acquired. Finally, decisions related to the worker's safety can be undertaken by comparing the instantaneous vibration score with the action threshold and maximum allowable dose, coherently calculated, as equations (5a) and (5b) are given below.

$$VS^{action} = 8 \cdot 5^2 = 200 \tag{5a}$$

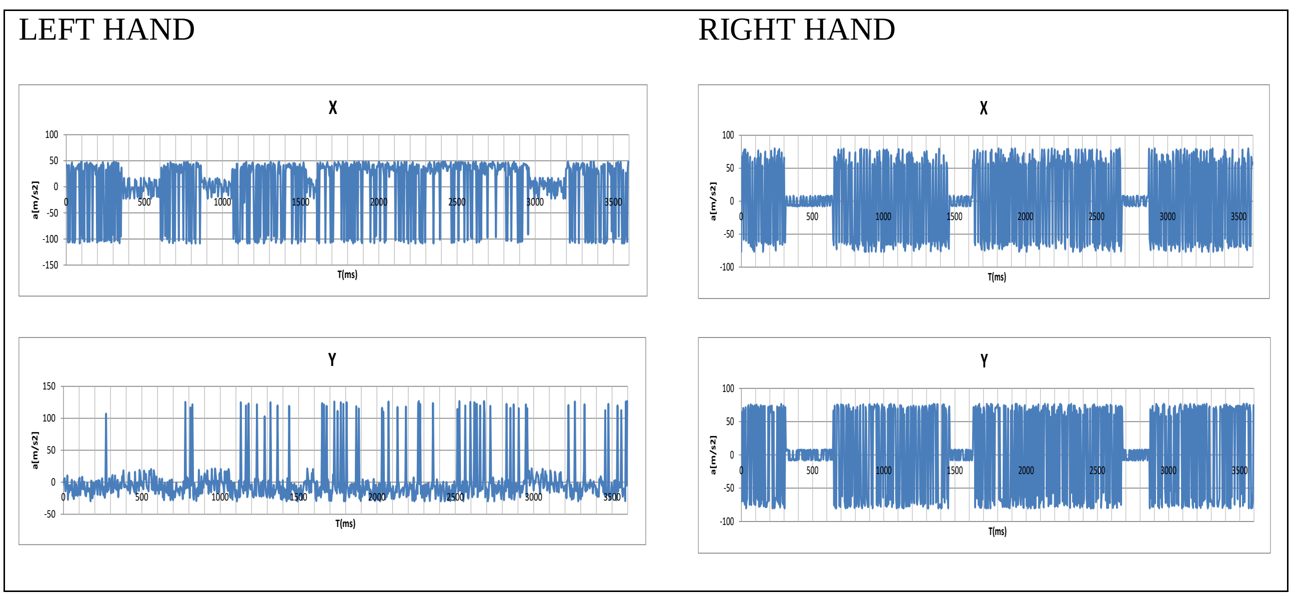
$$VS^{maximum} = 8 \cdot 2{,}5^2 = 50 \tag{5b}$$

Experimental analysis

To demonstrate the effectiveness of the proposed approach, experimental analysis has been performed through a set of lab experiments where the operations given in tab one have been simulated using real tools typically employed in the manufacturing industry. The vibration signals generated during the lab tests have been gathered through a device prototype specifically developed for this research. The device features two cable-connected triaxial accelerometers fixed to the operator's wrists. It is based on the Raspberry PI4 "system-on-chip" platform, featuring a 1.5 GHz 64-bit quad-core ARM Cortex-A72 processor, 4GB RAM, WLAN and full gigabit ethernet, integrated into a single board. The raspberry system has been connected with via I2C to two high-performance Bosch Sensortec BMI270 smart inertial measurement units (IMU) with a measurement range of +-16g and a maximum Output Data Rate (ODR) of 1.6 kHz. The device is finally connected to the WiFi network, enabling communication with a centralized system capable of gathering and analyzing the data transmitted by several devices. The system is finally equipped with a 20 000 mAh Li-po rechargeable battery for DC power supply, allowing for several hours of autonomous operations, thanks to the high energy efficiency of the BMI270 MEMS sensors and the low power consumption of the raspberry board. The Vibration signals acquired during several lab tests have been segmented into windows of 40 seconds containing 64000 values and stored in the local memory. The pre-processing and feature extraction activities are performed locally on the wearable device and risk assessment calculations. The system is thus structured according to a decentralized architecture. The wearable devices perform most of the data processing functions on data streams of 99 segments per hour per hand. Such a decentralized solution is highly scalable. Previous studies (Aiello et al. 2017) have demonstrated its effectiveness in monitoring the risk exposure of several workers simultaneously.

3.3.2.3 Results and Discussion

The experiments allowed generating a database of vibration streams originated by more than 20 hours of manufacturing operations simulated in the lab. A generic instance of such data streams is represented in Figure 26.



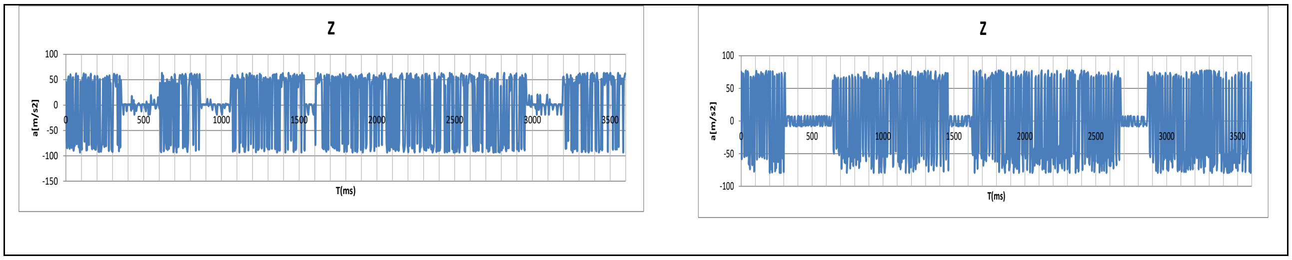


Figure 26: Example instance of raw vibration data

The data streams have been further subdivided into segments of 40 secs, obtaining a database of more than 2000 segments. The data thus obtained have been subsequently fed into the k-nn classifier in order to evaluate its performance in categorizing the data into HD and LD classes. For such purpose, a cross-validation process has been performed. The original dataset has been randomly partitioned into k subsets P_1, P_2, …, P_k of equal size. Each partition is then subdivided into a validation set and a training set and processed by the classifier. The classification accuracy has then been estimated, evaluating the proportion of instances correctly predicted by the classifier. The accuracies obtained for each partition have been finally averaged to obtain an overall score. In particular, in the case presented here, the overall dataset has been pre-classified into HD and LD operations; subsequently, 20 Partitions of unique 500 segments each were obtained, extracting random segments from the entire dataset. Each partition was subdivided into a training set and a validation set of 100 and 400 instances, respectively. The classification accuracy obtained has finally been evaluated according to the parameters reported in the following equations 6 to 9.

$$Accuracy = \frac{\#correct\ classifications}{\#\ dataset\ dimension} = \frac{TP + TN}{TP + FP + TN + FN} \quad (6)$$

$$Sensitivity\ = \frac{TP}{TP+FN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$F - score = 2\,\frac{Precision\ X\ Sesitivity}{Precision+\ Sensitivity} \tag{9}$$

TP (true positive) is the number of samples correctly attributed to the HD class, and TN (true negative) is the number of instances correctly attributed to the LD class. *FP* (False Positives) and *FN* (false negatives) are referred to as misclassified instances.

The classification results were thus obtained considering different values of k, to analyze the influence of this parameter on the accuracy of the classification and choose the optimum value. The results given in tables 10,11, and 12 show that increasing the value of k from 3 to 7, the average number of errors (FN+FP) increases from 7,55 to 35,60 (over 100 instances classified). At the same time, the overall accuracy decreases from 92% to 74%. A similar reduction can be noticed in all the other accuracy parameters except the sensitivity, which shows less significant variations. Based on these results, the k=3 classifier performed best. Such good performance is mainly due to the good results obtained in classifying HD instances. Indeed, although the average number of errors is similar in both classes (4,40 and 3,15 respectively), the number of instances classified in the two classes differs significantly, which is a consequence of the prevalence of HD operations in the lab experiments. It can also be observed that the performance of the k=5 classifier is worse compared to k=3 due to the substantial increase of the classification errors in HD. However, the performance in LD instances actually improves.

Table 10: KNN Classifier performance for K=3

run #	TP	TN	FP	FN	FN+FP	accuracy	Sensitivity	precision	F-Score
1	63	32	3	2	5	0,95	0,97	0,95	0,96
2	53	37	6	4	10	0,9	0,93	0,90	0,91
3	52	39	5	4	9	0,91	0,93	0,91	0,92

4	56	35	6	3	9	0,91	0,95	0,90	0,93
5	55	36	3	6	9	0,91	0,90	0,95	0,92
6	64	31	4	1	5	0,95	0,98	0,94	0,96
7	53	39	6	2	8	0,92	0,96	0,90	0,93
8	62	34	3	1	4	0,96	0,98	0,95	0,97
9	55	39	3	3	6	0,94	0,95	0,95	0,95
10	59	34	5	2	7	0,93	0,97	0,92	0,94
11	53	43	2	2	4	0,96	0,96	0,96	0,96
12	55	39	5	1	6	0,94	0,98	0,92	0,95
13	59	35	0	6	6	0,94	0,91	1,00	0,95
14	50	40	6	4	10	0,9	0,93	0,89	0,91
15	59	32	5	4	9	0,91	0,94	0,92	0,93
16	56	35	5	4	9	0,91	0,93	0,92	0,93
17	61	34	0	5	5	0,95	0,92	1,00	0,96
18	54	32	8	6	14	0,86	0,90	0,87	0,89
19	58	40	1	1	2	0,98	0,98	0,98	0,98
20	52	34	12	2	14	0,86	0,96	0,81	0,88
AVG	**56,45**	**36,00**	**4,40**	**3,15**	**7,55**	**0,92**	**0,95**	**0,93**	**0,94**

Table 11: KNN Classifier performance for K=5

run #	TP	TN	FP	FN	FN+FP	accuracy	Sensitivity	precision	F-Score
1	52	20	25	3	28	0,72	0,95	0,68	0,79
2	50	22	26	2	28	0,72	0,96	0,66	0,78
3	53	17	26	4	30	0,7	0,93	0,67	0,78
4	57	13	27	3	30	0,7	0,95	0,68	0,79
5	59	23	14	4	18	0,82	0,94	0,81	0,87
6	52	26	21	1	22	0,78	0,98	0,71	0,83
7	49	26	24	1	25	0,75	0,98	0,67	0,80
8	63	14	23	0	23	0,77	1,00	0,73	0,85
9	48	21	27	4	31	0,69	0,92	0,64	0,76
10	53	21	25	1	26	0,74	0,98	0,68	0,80
11	49	20	31	0	31	0,69	1,00	0,61	0,76
12	53	21	22	4	26	0,74	0,93	0,71	0,80
13	55	16	26	3	29	0,71	0,95	0,68	0,79
14	51	20	25	4	29	0,71	0,93	0,67	0,78
15	56	18	23	3	26	0,74	0,95	0,71	0,81
16	55	24	19	2	21	0,79	0,96	0,74	0,84
17	48	21	27	4	31	0,69	0,92	0,64	0,76

18	61	14	22	3	25	0,75	0,95	0,73	0,83
19	58	19	23	0	23	0,77	1,00	0,72	0,83
20	57	20	21	2	23	0,77	0,97	0,73	0,83
AVG	**53,95**	**19,80**	**23,85**	**2,40**	**26,25**	**0,74**	**0,96**	**0,69**	**0,80**

Table 12: KNN Classifier performance for K=7

run #	TP	TN	FP	FN	FN+FP	accuracy	Sensitivity	precision	F-Score
1	56	13	28	3	31	0,69	0,95	0,67	0,78
2	53	16	24	7	31	0,69	0,88	0,69	0,77
3	54	14	31	1	32	0,68	0,98	0,64	0,77
4	48	14	35	3	38	0,62	0,94	0,58	0,72
5	48	15	34	3	37	0,63	0,94	0,59	0,72
6	53	17	28	2	30	0,7	0,96	0,65	0,78
7	54	9	32	5	37	0,63	0,92	0,63	0,74
8	51	9	36	4	40	0,6	0,93	0,59	0,72
9	55	11	28	6	34	0,66	0,90	0,66	0,76
10	48	10	38	4	42	0,58	0,92	0,56	0,70
11	58	12	24	6	30	0,7	0,91	0,71	0,79
12	46	16	33	5	38	0,62	0,90	0,58	0,71
13	55	11	32	2	34	0,66	0,96	0,63	0,76
14	52	13	30	5	35	0,65	0,91	0,63	0,75
15	50	13	35	2	37	0,63	0,96	0,59	0,73
16	53	9	33	5	38	0,62	0,91	0,62	0,74
17	49	7	38	6	44	0,56	0,89	0,56	0,69
18	60	14	23	3	26	0,74	0,95	0,72	0,82
19	48	13	35	4	39	0,61	0,92	0,58	0,71
20	52	9	34	5	39	0,61	0,91	0,60	0,73
AVG	**52,15**	**12,25**	**31,55**	**4,05**	**35,60**	**0,64**	**0,93**	**0,62**	**0,74**

Finally, the vibration risk associated with the activities has been evaluated by performing a FFT transform of the vibration signals in each segment and calculating the weighted average vibration factor, considering the ISO weighting curve. Subsequently, the vibration score (VS) has been calculated according to eq. Four and the overall map of the single operations performed. Corresponding workers' exposure to vibration risk during the execution of a complex task has thus been constructed. Such result is depicted in the following Figure 27 referred to a task involving seven elementary operations performed in approx. 180 mins. The vibration signals are gathered through the monitoring device and subdivided into 270 segments of 40 secs each. The feature extracted from each segment were then fed into the k-nn classifier. The results show that all the operations were classified into HD and LD classes, thus mapping the complete task and associating the corresponding overall risk exposure.

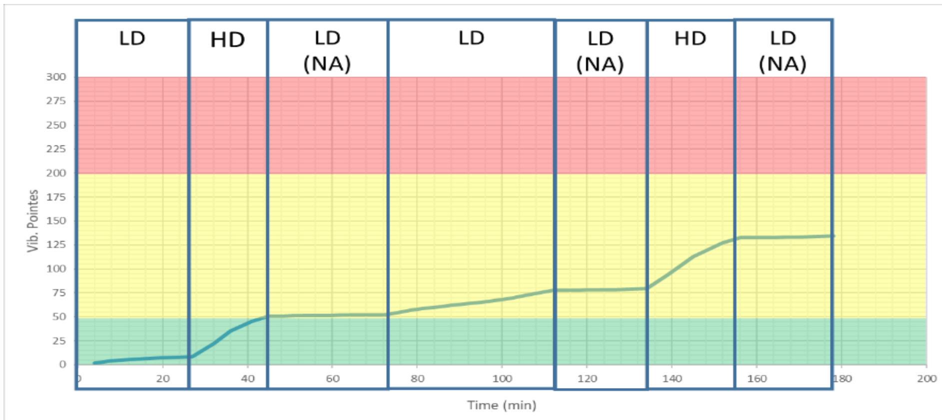


Figure 27: Map of the activities performed during a task and corresponding worker’s exposure to vibration risk. LD=Low Duty, HD=High Duty, NA=No Activity

Chapter 4: Conclusion

To take advantage of technology development, business owners need to adapt themselves to the changes stemming from the new technologies affecting all aspects of life and business. Utilizing these advanced components, such as the Internet of Things, cyber-physical system, and artificial intelligence, enables business owners to transform product-centric processes to smart control digital service-oriented ones. The first stage of this research is to do a theoretical thematic literature review on IoT and CPS servitization topics to shed the light on the main areas that the researchers are focusing on and bridge the existing gaps.

The result of the literature examination revealed five dominant areas. Detailing these five areas resulted in formulating a ten-step “ten modules” IoT-based servitization block diagram implemented within OMT-Digital boundaries. One of its main features is the “storage module” since this feature was neglected by the researchers in the literature who produced similar process control frameworks. The proposed framework supports companies to take the first steps toward remote monitoring servitization through the implementation of IoT and CPS to produce a fully integrated smart monitor system to improve assets' health and performance and reduce costs and waiting time. Moreover, a case study of a smart injector for the marine engine is analyzed to propose a working framework supporting the implementation of IoT and CPS to communicate the added-value data within the smart system built on five modules: process control module, process diagnosis module, healing module, a storage module, and human interaction module. Future research could include pursuing improvements to this framework and validating it in other industry 4.0 case studies

However, the literature analysis carried in this research shows that two categories "out of those five categories" regarding the integration between the digital product design and manufacturing process, and the interaction between human operators and the cyber-physical system are not well-studied by the researchers, so further attention for the integration between human operators, cyber-physical systems, and digital product design needs to be considered. Therefore, further research analysis has been conducted to bridge the gap in these two areas.

One of the main technologies used to integrate manufacturing processes and improve communication is the Digital Twin. This pushes the research path to more articles related to this technology and proposes a new framework that enables companies to align their processes with the competitive flow in the market.

To take full advantaging of Digital Twin, the pivotal step related to the creation phase of Digital Twins should be organized precisely. Since the influence of this step in the final performance of Digital Twin is undeniable, the main motivation behind carrying out this research work was identifying the entities that are impressive and designing them as the integrated framework. The qualitative empirical method was the base of an adopted methodology of the current study. Following this, an interview with fourteen specialists in the Digital Twin area was formed. The Mayring Content Analysis approach was employed in their response to extract the helpful information. The foundation of the questionnaire was set on this question: ``how a Digital Twin Implementation Framework in the first stages of the Digital Twin creation should be "considering data collection process". Analyzing the interviewees' responses revealed some striking insights related to the successful implementation of Digital Twin. A comprehensive framework that includes five main phases were designed by utilizing an accurate and deep intuitive understanding of interviewees' response. This framework provides a guideline for implementing the creation phase of Digital Twins. Implementing each phase faces challenges, and affective dimensions need to be properly evaluated and defined to overcome them. One of the striking advantages of the proposed framework is that all the possible challenges were identified via the interviews, and their proper reactions were proposed. In this regard, the users could avoid any challenge before its occurrence, which saves time and cost in the long run.

Several small and medium-sized enterprises, "SMEs," need to make the first move into digitalization. Digital Twin improves the system continuously and provides an exceptional opportunity for business owners to learn about possible scenarios that could lead to the development of the existing businesses. An increased profit margin stemming from continuous improvement plus more profit originating from business development are two distinguished benefits of Digital Twin implementation.

In addition to the importance of digital twin technology in the integration between different processes in the companies, the right implementation of cyber-physical systems "CPS" allows bidirectional communication and control among devices, so permitting to read and actuate sensors and actuators for these devices

As mentioned above, the interaction between human operators and the cyber-physical system is the second category researchers need to focus on. An industrial use case related to ergonomic evaluation has been studied.

The advent of industry 4.0 arises new challenges in the context of human-machine interaction, posing ergonomics and safety in the workplace at the core of a substantial multidisciplinary scientific debate. While the smart factory concept spreads in the manufacturing industry, operators frequently perform their activities in an uncomfortable, stressful, or dangerous environment. The industrial approaches towards ergonomics and safety frequently appear outdated and inadequate. In addition, the operators' physical and cognitive capabilities are reducing because of the workforce ageing phenomenon, which affects most of the organizations in industrialized countries.

With such premises, providing enterprises with new and more effective methods to enhance the health and safety condition of the work environment becomes mandatory to ensure adequate wellbeing conditions in the workplace and to prevent the occurrence of work-related pathologies.

This research proposes a new methodology for surveillance workers' well-being and preventing musco-skeletal pathologies related to hand-harm vibrations. The approach developed is based on state-of-the-art sensing technologies and machine-learning methods to automatically map the operators' activities and evaluate the actual vibration dose received. In particular, the study proposes a k-nn classifier for recognizing the workers' activities through the features extracted from vibration signals and a real-time vibration risk assessment methodology for associating their corresponding risk exposure. In addition, a wearable device has been developed, capable of transmitting relevant information about the workers' wellbeing and safety conditions taking advantage of IoT technologies in an interconnected work environment. The system and the methodology have been validated in the lab by simulating some operations frequently performed by operators in several industrial contexts.

The data gathered have been processed according to the methodology proposed and classified into heavy-duty and low-duty operations. The results obtained demonstrate the methodology's effectiveness with an overall accuracy of the classifier above 90% in the optimum configuration. With such a performance level, the system can be an effective tool to increase the workers' awareness about the safety condition of the workplace. However, it can also support the surveillance activity of the managers suggesting appropriate preventive and corrective actions. Finally, a paper about this has been produced "under the name of Operator safety in the smart factory: a Machine Learning approach towards real-time hand-arm vibration risk assessment" and submitted into an international journal. This paper is listed below in the appendix section of this thesis.

Saying so, the main objective of this research – as discussed in the Introduction chapter- has been completely achieved through the presentation of two different frameworks to guide manufacturers through the implementation of two important technologies, IoT and DT. Moreover, a new methodology based on machine learning algorithms has been presented to improve operators' safety and health conditions in smart industry context.

Appendix:

List of Published Papers & Courses with their Related CFU

Type	Activity	Description	CFU
Research	Article Co-author (Published)	Demartini, M., Galluccio, F., Mattis, P., **Abusohyon, I.**, Closed-Loop Manufacturing for Aerospace Industry: An Integrated PLM-MOM Solution to Support the Wing Box Assembly Process. Advances in Production Systems. Towards Smart Production Management Systems, pp. 423-430.	6
Research	Article Author (Published)	**Abusohyon, I.,** Tonelli, F., Internet of Things Based Product-Service System in the Maritime Industrial Sector. IoTBDS 2021-6th International Conference on Internet of Things, Big Data and Security	6
Research	Article Author (Published)	**Abusohyon, I.**, Crupi, A., Bagheri, F., Tonelli, F., How to Set Up the Pillars of Digital Twins Technology in Our Business: Entities, Challenge and Solutions. Processes 2021, 9, 1307. https://doi.org/10.3390/pr9081307.	6

Research	Article Author (Submitted)	**Abusohyon I.,** Garcia L., Tonelli F., Aiello G. Operator safety in the smart factory: a Machine Learning approach towards real-time hand-arm vibration risk assessment. Submitted to the International Journal of Computers & Industrial Engineering	6
Course	University Course	Courses of Engineering for Industrial Sustainability. Delivered by Prof. Flavio Tonelli.	6
Course	University Course	Machine Learning – A Computational Intelligence Approach. Delivered by Prof. Francesco Masulli & Prof. Stefano Rovetto.	6
Course	University Course	Data-Driven Modelling and Machine Learning. Delivered by Prof. Nunzio Bonavita.	2
Course	University Course	Italian Language Course “Level B2”. Delivered by Prof. Maria Teresa Caprile.	4

References

Abusohyon I. & Tonelli F. (2021). *Internet of Things Based Product-Service System in the Maritime Industrial Sector*. IoTBDS 2021-6th International Conference on Internet of Things, Big Data and Security

Agarwal A., Shankar R., & Tiwari M. K. (2006). Modeling the metrics of lean, agile and leagile supply chain: An ANP-based approach. Eur. J. Oper. Res., vol. 173, no. 1, pp. 211–225.

Ahn C. R., Lee S., & Peña-Mora F. (2013). The Application of Low-Cost Accelerometers for Measuring the Operational Efficiency of a Construction Equipment Fleet. *Journal of Computing in Civil Engineering.*

Aiello G, Vallone M., & Catania P. (2019). Optimising the efficiency of olive harvesting considering operator safety, *Biosystems Engineering*, 185, pp 15-24, 2019.

Aiello G., Catania, P., La Scalia, G., Vallone, M., & Venticinque, M. (2012). Real time assessment of hand-arm vibration system based on capacitive MEMS accelerometers. *Computers and Electronics in Agriculture, 85, 45 -52*.

Aiello G., Giallanza A., & Giovino I. (2017). Safety Optimized Shift-Scheduling System based on Wireless Vibration Monitoring for Mechanical Harvesting Operations, *Chemical Engineering Transactions*, 58, 349-354.

Akhavian R. and Behzadan A. H. (2018). Coupling Human Activity Recognition and Wearable Sensors for Data-Driven Construction Simulation. *Journal of Information Technology in Construction* (ITcon), vol. 23, no. 1, pp. 1-15, 2018.

Akhavian R., & Behzadan, A. H. (2016). Smartphone-based construction workers' activity recognition and classification. *Automation in Constuction*. 71, 198–209. doi: 10.1016/j.autcon.2016.08.015

Alam K. M. & El Saddik A. (2017). C2PS: A Digital Twin Architecture Reference Model for the Cloud-Based Cyber-Physical Systems. IEEE Access, vol. 5. pp. 2050–2062, 2017, doi: 10.1109/access.2017.2657006.

Andrea T. & Enrico S. (2019). Exploring the relationship between the product-service system and profitability. Journal of management and governance.

Ayani M., Ganebäck M., and Ng A. H. C. (2018). Digital Twin: Applying emulation for machine reconditioning. Procedia CIRP, vol. 72. pp. 243–248, 2018, doi: 10.1016/j.procir.2018.03.139.

Baecker J., Engret M., Krcmar H. (2020). Business Strategies for Data Monetization: Deriving Insights from Practice. In book: WI2020 Zentrale Tracks

Banos O., Galvez J.-M., Damas M., Pomares H., Rojas I. (2014). Window Size Impact in Human Activity Recognition. *Sensors* 2014, 14, 6474-6499.

Bao L., & Intille S. S. (2004). Activity recognition from user-annotated acceleration data. In Proceedings of the 2nd International Conference on Pervasive Computing, 1–17.

Basile F., Chiacchio P., Coppola J. & Gerbasio D. (2015). Automated warehouse systems: a cyber-physical system perspective. *IEEE*

Berke Erdaş C., Atasoy I., Açıcı K., Oğul H. (2016). Integrating Features for Accelerometer-based Activity Recognition, *Procedia Computer Science*, Volume 98, 2016, Pages 522-527, https://doi.org/10.1016/j.procs.2016.09.070.

Bernal G., Colombo S., Al Ai Baky M., Casalegno F. (2017). *Safety++: Designing IoT and Wearable Systems for Industrial Safety through a User Centered Design Approach.* In Proceedings of the 10th International Conference on Pervasive Technologies Related to Assistive Environments, Rhodes, Greece, 21–23 June 2017; pp. 163–170.

Bianchi N. P., Evans S., Revetria R., Tonelli F. (2009). Influencing factors of successful transitions towards product-service systems: A simulation approach. International Journal of Mathmetics and Computers in Simulation.

Biesinger, F., Meike, D., Kraß, B., & Weyrich, M. (2018). A Case Study for a Digital Twin of Body-in-White Production Systems General Concept for Automated Updating of Planning Projects in the Digital Factory. In 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA) (Vol. 1, pp. 19-26). IEEE..

Binos T., Bruno V., Adamopoulos A. (2019). Intelligent agent based framework to augment warehouse management systems for dynamic demand environments. *An intelligent framework in dynamic demand environments.*

Bulling A., Blanke U., Schiele B. (2014). Tutorial on Human Activity Recognition using Body-worn Inertial Sensors. *ACM Computing Surveys Journal* 2014; 46:1–33. doi: 10.1145/2499621.

Calzavara M., Battini D., Bogataj D., Sgarbossa F., & Zennaro I. (2020). Ageing workforce management in manufacturing systems: state of the art and future research agenda. *International Journal of Production Research*, *58*(3), 729-747.

Caron, F., Marchet, G., and Perego, A. (2000) Layout design in manual picking systems: a simulation approach, *Integrated Manufacturing Systems*, **11**(2), 94-104.

Cattaneo L. & Macchi M. (2019). A Digital Twin Proof of Concept to Support Machine Prognostics with Low Availability of Run-To-Failure Data. IFAC-PapersOnLine, vol. 52, no. 10. pp. 37–42, 2019, doi: 10.1016/j.ifacol.2019.10.016.

Choy KL, Lam HY, Lin C., Lee C. (2013). A Hybrid Decision Support System for Storage Location Assignment in the Fast-Fashion Industry. *2013 Proceedings of PICMET '13: Technology Management for Emerging Technologies.*

Christopher G., Martin B., David W., Edward G. (2019). Cyber physical systems and internet of things. National Institute of Standards and Technology Special Publication

CHUANG Y., CHIA S., WONG J. (2014). Enhancing Order-picking Efficiency through Data Mining and Assignment Approaches. *WSEAS TRANSACTIONS on BUSINESS and ECONOMICS.*

Collins S. M., & Casey R. P. (2017). “America’s Aging Workforce: Opportunities and Challenges”. Report from the Special Committee on Aging United States Senate.

Coppo M., Dongiovanni C., & Negri C. (2004). Numerical analysis and experimental investigation of a common rail-type diesel injector. J. Eng. Gas Turbines Power, vol. 126, no. 4, pp. 874–885, Oct. 2004.

Coronado P. D. U., Lynn R., Louhichi W., Parto M., Wescoat E., & Kurfess T. (2018). Part data integration in the Shop Floor Digital Twin: Mobile and cloud technologies to enable a manufacturing execution system. Journal of Manufacturing Systems, vol. 48. pp. 25–33, 2018, doi: 10.1016/j.jmsy.2018.02.002.

Damiani L., Demartini M., Cassettari L., G., Revetria R., Tonelli F. (2017). Digitalization of manufacturing execution systems: The core technology for realizing future smart factories. Proceedings of the Summer School Francesco Turco.

Damiani L., Demartini M., Guizzi G., Revetria R., Tonelli F. (2018). Augmented and virtual reality applications in industrial systems: A qualitative review towards the industry 4.0 era. IFAC-Papers OnLine p.624-630.

Davide Anguita, Alessandro Ghio, Luca Oneto, XavierParra, and Jorge L Reyes-Ortiz. (2012). Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine. In International workshop on ambient assisted living, pages 216–223. *Springer*, 2012

Debroux P. (2016). Elderly workers in Japan: The need for a new deal, management revue. *Socio-economic Studies*, 27, issue 1-2, pp. 82-96, 201

Dehghani A, Sarbishei O, Glatard T, Shihab E. (2019). A Quantitative Comparison of Overlapping and Non-Overlapping Sliding Windows for Human Activity Recognition Using Inertial Sensors. *Sensors (Basel). 2019* Nov 18;19(22):5026. doi: 10.3390/s19225026. PMID: 31752158; PMCID: PMC6891351.

Devijver P.A., & Kittler J., (1982) Pattern Recognition A Statistical Approach. Prentice-Hall, London. *International journal of remote sensing*

Ding K., Chan F. T. S., Zhang X., Zhou G., Zhang F. (2019). Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors. International Journal of Production Research, vol. 57, no. 20. pp. 6315–6334, 2019, doi: 10.1080/00207543.2019.1566661.

Erikstad, & Stein Ove. (2017). Merging physics, big data analytics and simulation for the next-generation digital twins. HIPER 2017, High-Performance Marine Vehicles, no. September, 139-149.

Eurofound: Sixth European working conditions survey. (2015). In: The European Foundation for the Improvement of living and working conditions; Retrieved from http://www.eurofound.europa.eu/surveys/data-visualisation/sixth-european-working-conditions-survey-2015.

European Commission (EC). (2017). The 2018 Ageing Report: Underlying Assumptions and Projection Methodologies. Retrieved from https://ec.europa.eu/info/publications/economy-finance/2018-ageing-report-underlying-assumptions-and-projection-methodologies_en.

European Union. (2006). Directive 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on Machinery and Amending Directive 95/16/EC (Recast); European Union: Brussels, Belgium, 1989; Volume 157, 24–86. Directive 2006/42/EC -The machinery directive

G. Zhang, Shang X., Alawneh F., Yang Y. & Nishi T. (2021). Integrated production planning and warehouse storage assignment problem: An IoT assisted case. *International Journal of Production Economics*

Gero J. S. & Kannengiesser U. (2004). The situated function–behaviour–structure framework. Design Studies, vol. 25, no. 4. pp. 373–391, 2004, doi: 10.1016/j.destud.2003.10.010.

Ghasemi V. and Pouyan A. A., (2016). *Human activity recognition in ambient assisted living environments using a convex optimization problem*. 2016 2nd International Conference of Signal Processing and Intelligent Systems (ICSPIS), Tehran, 2016, pp. 1-6, doi: 10.1109/ICSPIS.2016.7869899.

Glaessgen E. & Stargel D. (2012). The digital twin paradigm for future NASA and U.S. Air Force Vehicles," 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference20th AIAA/ASME/AHS Adaptive Structures Conference14th AIAA. DOI: 10.2514/6.2012-1818.

Gohari H., Berry C., & Barari A. (2019). A digital twin for integrated inspection system in digital manufacturing. IFAC-PapersOnLine, vol. 52, no. 10. pp. 182–187, doi: 10.1016/j.ifacol.2019.10.020.

Gonzalez I., & Morer P. (2016). Ergonomics for the Inclusion of Older Workers in the Knowledge Workforce and a Guidance Tool for Designers. *Applied Ergonomics*, 53, 131–142.

Grieves M. & Vickers J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," Transdisciplinary Perspectives on Complex Systems. pp. 85–113, 2017, doi: 10.1007/978-3-319-38756-7_4.

He Y., Guo J., & Zheng X. (2018). From surveillance to digital twin: Challenges and recent advances of signal processing for industrial internet of things. IEEE Signal Process. Mag., vol. 35, no. 5, pp. 120–129, Sep. 2018.

Heber D. T. & Groll M. W. (2017). How the blockchain fosters E/E traceability for MBSE and PLM in distributed engineering collaboration. DS 87-3 Proceedings of the 21st International Conference on Engineering Design (ICED 17) Vol 3: Product, Services and Systems Design, Vancouver, Canada, 21-25.08. 2017, pp. 321–330.

Heinz E., Kunze K.-S., Sulistyo S., Junker H., Lukowicz P., & Troester G. (2003). *Experimental evaluation of variations of primary features used for accelerometric context recognition*. In Eusai 2003 Computer Science (Vol. 2875, p. 252 - 263). Eindhoven, The Netherlands.

Hofmann W. & Branding F. (2019). Implementation of an IoT- and Cloud-based Digital Twin for Real-Time Decision Support in Port Operations. IFAC-PapersOnLine, vol. 52, no. 13. pp. 2104–2109, 2019, doi: 10.1016/j.ifacol.2019.11.516.

Isaksson A. J., Harjunkoski I., & Sand G. (2019). The impact of digitalization on the future of control and operations. Computers & Chemical Engineering, vol. 114. pp. 122–129, doi: 10.1016/j.compchemeng.2017.10.037.

ISO 5349-1, 2001a. Mechanical vibration—measurement and evaluation of human exposure to hand-transmitted vibration—Part 1: general Requirements, ISO, Geneva.

ISO 5349-2, 2001b, Mechanical vibration – guidelines for the measurement and assessment of human exposure to hand-transmitted vibration. Part – 2: Practical guidance for measurement at the workplace, ISO, Geneva

Jones D., Snider C., Nassehi A., Yon J., & Hicks B. (2020). Characterising the Digital Twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, vol. 29. pp. 36–52, doi: 10.1016/j.cirpj.2020.02.002.

Joshua L., Varghese K. (2011). Accelerometer-Based Activity Recognition in Construction. *Journal of Computing in Civil Engineering* 2011,25, 370–380

Kaveh S. Bastani, Kim Z., Kong J., Nussbaum M. A., & Huang W. (2016). Online Classification and Sensor Selection Optimization with Applications to Human Material Handling Tasks Using Wearable Sensing Technologies", *IEEE Transactions on Human-Machine Systems*, vol. 46, no. 4, pp. 485-497, 2016

Kern N., Schiele B., & Schmidt A. (2003). *Multi–sensor activity context detection for wearable computing*. Ambient Intelligence, First European Symposium Conference, EUSAI 2003, Veldhoven, The Netherlands, November 3.-4, 2003, Proceedings.

Keyur K. & Sunil M. (2016). A New Approach to Integrate Internet-of-Things and Software-as-a-Service Model for Logistic Systems: A Case Study. International Journal of Engineering Science and Computing.

Kharat R., Bavane V., Jadhao3 S. & Marode R. (2018). Digital Twin: Manufacturing excellence through virtual factory replication. 2018, doi: 10.5281/ZENODO.1493930.

Kong XT, Luo H, Huang GQ, Yang X (2018). Industrial wearable system: the human-centric empowering technology in Industry 4.0. *J Intell Manuf.* https://doi.org/10.1007/s10845-018-1416-9

Krause A., Siewiorek D., Smailagic A., & Farringdon J. (2003, October). Unsupervised, dynamic identification of physiological and activity context in wearable computing. In *Proc. iswc* (p. 88-97). Krause et al. 2003, Lee J., Azamfar M., Singh J., & Siahpour S. (2020). Integration of digital twin and deep learning in cyber - physical systems: towards smart manufacturing," IET Collaborative Intelligent Manufacturing, vol. 2, no. 1. pp. 34‑36, doi: 10.1049/iet-cim.2020.0009.

Leontev AN. (1978). *Activity, consciousness, and personality*. Englewood Cliffs, NJ: Prentice Hall, 1978, Mayr, HC, Al

Li D., Eric L., Ling L. (2018). Industry 4.0: state of the art and future trend. International journal of production research.

Lin H. & Ma Y. (2021). A New Method of Storage Management Based on ABC Classification: A Case Study in Chinese Supermarkets' Distribution Center. *SAGE Open.*

Liu M., Shuiliang F., Dong H. & Xu C. (2020). Review of digital twin about concepts, technologies, and industrial applications. Journal of Manufacturing Systems

Lokukaluge P. & Brage M. (2020). Ship performance and navigation information under high dimensional digital models. Journal of Marine Science and Technology.

Longo F., Nicoletti L. & Padovano A., (2017). Smart operators in industry 4.0: A human-centered approach to enhance operators' capabilities and competencies within the new smart factory context. *Computers & Industrial Engineering.* 113. 10.1016/j.cie.2017.09.016.

Lu Y., Liu C., I.-Kai K.. Wang, Huang H., & Xu X. (2020). Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing, vol. 61. p. 101837, 2020, doi: 10.1016/j.rcim.2019.101837.

Malaise A., Maurice P., Colas F., Ivaldi S. (2018). *Online Human Activity Recognition for Ergonomics Assessment. SIAS 2018 - 9ème conférence internationale sur la sécurité des systèmes industriels automatisés*, Oct 2018, Nancy, France.

Mannini A., & Sabatini A. M. (2010). Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors*,10(2), 1154–1175.

Marco C. & Marco F. (2019). Towards the digital engine: the OMT smart injector enables performance monitoring and condition-based maintenance. 29TH CIMAC World Congress.

Marco C., Francesco C., Marco F., Marco L. (2019). Fuel Injection 4.0: The Intelligent Injector and Data Analytics by OMT Enable Performance Drift Compensation and Condition-Based Maintenance. The 29th CIMAC World Congress 2019 in Vancouver, Canada.

Mayring P. (2000). Qualitative content analysis [28 paragraphs]. Fourm qualitative sozialforschung forum qualitative social research [on-line journal].

Milan Jemelka, Bronislav Chramcov, and Pavel Kříž (2016). Design of the storage location based on the ABC analyses. *AIP Conference Proceedings 1738*, 120026 (2016); doi: 10.1063/1.4951909

Miller A. M., Alvarez R., & Hartman N. (2018). Towards an extended model-based definition for the digital twin. Comput. Aided Des. Appl., vol. 15, no. 6, pp. 880–891.

Moritz S., Carl R., Bjornar H., Klaus-Dieter T. (2016). Utilising the Internet of Things for the Management of Through-life Engineering Services on Marine Auxiliaries. The 5th International Conference on Through-life Engineering Services.

Nakamoto S. (2019). Bitcoin: A Peer-to-Peer Electronic Cash System. bitcoin.org, Nov. 20, 2019. http://dx.doi.org/10.2139/ssrn.3440802.

Natalia k., Sebastian k., Michal G. (2014). Servitization Strategies and Product-Service-Systems. IEEE 10th world congress on services.

Nath N., Chaspari T., & Behzadan A. (2018). Automated ergonomic risk monitoring using body-mounted sensors and machine learning. *Advanced Engineering Informatics, 38, 514–526*. https://doi.org/10.1016/j.aei.2018.08.020

Negri E., Fumagalli L., & Macchi M. (2017). A review of the roles of digital twin in CPS-based production systems. Procedia Manufacturing, vol. 11. pp. 939–948, doi: 10.1016/j.promfg.2017.07.198.

Nham B., Siangliulue K., Yeung S., (2008). Predicting mode of transport from iPhone accelerometer data. *Machine Learning Final Projects, Stanford UniversityNham et al 2008*

Oscar D Lara, Miguel A Labrador. (2013). A survey on human activity recognition using wearable sensors. *IEEE Communications Surveys and Tutorials, 15(3):1192–1209, 2013.*

Pagoropoulos A., Kjær L., Bejbro J., Andersen1 and McAloone T. (2017). The influence of costs and benefits' analysis on service strategy formulation: Learnings from the shipping industry. Cogent Engineering..

Patel S., Park H., Bonato P. et al. A review of wearable sensors and systems with application in rehabilitation. *Journal of NeuroEngineering Rehabilitation* 9, 21 (2012). https://doi.org/10.1186/1743-0003-9-21

Peterson C., Aese G., Heiser D. (2004). Improving order-picking performance through the implementation of class-based storage.

Podgorski D., Majchrzycka K., Da̧browska A., Gralewicz G., Okrasa, M. (2017). Towards a conceptual framework of OSH risk management in smart working environments based on smart PPE, ambient intelligence and the Internet of Things technologies. *Int. J. Occup. Saf. Ergon.* 2017, 23, 1–20. [CrossRef]

Preece S.J., Goulermas J.Y., Kenney L.P., Howard D. (2009). A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data. *IEEE Trans. Biomed. Eng. 2009, 56, 871–879.*

Randell C., Muller H. (2000). Context Awareness by Analyzing Accelerometer Data; Proceedings of the Fourth IEEE International Symposium on Wearable Computers; Atlanta, GA, USA. 16–17 October 2000; Washington, DC, USA*: IEEE Computer Society*; 2000. p. 175

Ravi D., Wong C., Lo B. & Yang G. (2016*). Deep learning for human activity recognition: A resource efficient implementation on low-power devices.* 2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN), San Francisco, CA, 2016, pp. 71-76, doi: 10.1109/BSN.2016.7516235.

Ravi N., Dandekar P., Mysore M. (2005) *LittmanActivity Recognition from Accelerometer Data* 17th Conference on Innovative Applications of Artificial Intelligence (2005), pp. 1541-1546, 10.1007/978-3-642-02481-8_120

Reaidy P., Gunasekaran A., Spalanzani A. (2014). Bottom up approach based on Internet of Things for order fulfillment in a collaborative warehouseing environment. *Int. J. Production Economics*

Romero D., Wuest T., Stahre J., Gorecky D. (2017). *Social factory architecture: social networking services and production scenarios through the social internet of things, services and people for the social operator 4.0.* In IFIP International Conference on Advances in Production Management Systems; Springer: London, UK, 2017; pp. 265–273.

Rosen R., Boschert S., & Sohr A.(2018). Next Generation Digital Twin," atp magazin, vol. 60, no. 10. pp. 86–96, 2018, doi: 10.17560/atp.v60i10.2371.

Ruppert T., Jaskó S., Holczinger T., Abonyi, J. (2018). Enabling Technologies for Operator 4.0: A Survey. *Appl. Sci.* **2018**, *8*, 1650.

Sadowski A., Wojciechowski P., EngelsEth P. (2021). The contingent nature of warehouse flexibility. *International Journal of Productivity and Performance Management*

Salaheen F., Habib M., Miraz M., Hanafi Z. (2014). Challenges of warehouse operations: A case study in retail supermarket. *International journal of supply chain management.*

Samuel A. L. (1959). Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research and Development*, No. 3, pp. 211–229, 1959.

Schrader L., Vargas Toro A., Konietzny S. (2020). Advanced Sensing and Human Activity Recognition in Early Intervention and Rehabilitation of Elderly People. *Population Ageing* **13,** 139–165 (2020). https://doi.org/10.1007/s12062-020-09260-z

Shum, Kwok L., Watanabe, Chihiro (2008). The effects of technological trajectory in product centric firms upon the transition to smart service provision. The case of smart solar photovoltaic. Journal of services research.

Singh S., Shehab E., Higgins N., Fowler K., Tomiyama T., & Fowler C. (2018). Challenges of Digital Twin in High Value Manufacturing. SAE Technical Paper Series. 2018, doi: 10.4271/2018-01-1928.

Somayya M, R. Ramaswamy, Siddharth T. (2015). Internet of Things (IoT): A Literature Review. Journal of Computer and Communications.

Sooksakson N. & Kachitvichyanukul V. (2006). Performance Evaluation of Warehouse with One-block Class-based Storage Strategy. *APIEMS2009*.

Strasser H. (2018). The “art of Aging From an Ergonomics Viewpoint - Wisdoms on age. *Occupational Ergonomics,* 13 (S1): 1–24.

Suliman A., Husain Z., Abououf M., Alblooshi M., & Salah K. (2018). Monetization of IoT data using smart contracts. IET Digital Library.

Sullivana B., Desaib S., Solec J., Rossia M., Ramundoa L., Terzi S. (2020). Maritime 4.0 – Opportunities in Digitalization and Advanced Manufacturing for Vessel Development. Procedia Manufacturing

Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., & Nee, A. Y. C. (2019). Digital twin-driven product design framework, International Journal of Production Research, vol. 57, no. 12. pp. 3935–3953, doi: 10.1080/00207543.2018.1443229.

Tao, Fei, Cheng J., Qi Q., Zhang M., Zhang H., & Sui F. (2018). Digital Twin-Driven Product Design, Manufacturing and Service with Big Data. International Journal of Advanced Manufacturing Technology 94 (9): 3563–76.

Taticchi P., Tonelli f., Starnini E. (2009). A Framework for Evaluating Product-Service Systems Strategies. Proceedings of the 10th WSEAS Int. Conference on mathematics and computers in business and economics,

Taylor N., Human C., Kruger K., Bekker A. Basson A. (2020). Comparison of Digital Twin Development in Manufacturing and Maritime Domains. In book: Service Oriented, Holonic and Multi-agent Manufacturing Systems for Industry of the Future

Tharma R., Winter R., & Eigner M. (2018). An approach for the implementation of the digital twin in the automative wiring harness field. Proceedings of the DESIGN 2018 15th International Design Conference. 2018, doi: 10.21278/idc.2018.0188.

Thomas D. R. (2006). A general inductive approach for analyzing qualitative evaluation data. American Journal of Evaluation, vol. 27, no. 2. pp. 237–246, doi: 10.1177/1098214005283748.

Tonelli F., Taticchi P., & Sue E. S. (2009). A framework for assessment and implementation of product-service systems strategies: learning from an action research in the health-care sector. WSEAS Transitions on Business and Economics, 6(7), 303-310.

Uhlemann T. H.-J., Lehmann C., & Steinhilper R. (2017). The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0. Procedia CIRP, vol. 61. pp. 335–340, 2017, doi: 10.1016/j.procir.2016.11.152.

Vaismoradi M., Taurunen H. & Bondas T. (2013). Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study. Nursing and Health Sciences, 15, 398–405

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Wärmefjord K., Söderberg R., Lindkvist L., Lindau B., & Carlson J. S. (2017). Inspection Data to Support a Digital Twin for Geometry Assurance. Volume 2: Advanced Manufacturing. 2017, doi: 10.1115/imece2017-70398.

West T. D. & Blackburn M. (2017). Is Digital Thread/Digital Twin Affordable? A Systemic Assessment of the Cost of DoD's Latest Manhattan Project. Procedia Computer Science, vol. 114. pp. 47–56, 2017, doi: 10.1016/j.procs.2017.09.003.

Whittemore R., Chase S. K., & Mandle C. L. (2001). Validity in Qualitative Research. Qualitative Health Research. vol. 11, no. 4. pp. 522–537, 2001, doi: 10.1177/104973201129119299.

Xjanghorban T., Latifnejad R., & Taghipour A.(2014). Skype interviewing: the new generation of online synchronous interview in qualitative research. Int. J. Qual. Stud. Health Well-being., vol. 9, p. 24152, Apr. 2014.

Xu Y., Sun Y., Liu X., & Zheng Y. (2019). A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning," IEEE Access, vol. 7. pp. 19990–19999, 2019, doi: 10.1109/access.2018.2890566.

Yang L. (2017). Cyber Physical System (CPS)-Based Industry 4.0: A Survey. Journal of Industrial Integration and Management

Yoval C., & Gonen S. (2020). Framework for smart process controller implementation in an industry 4.0 setting.

Yu M. (2011). Multi-criteria ABC analysis using artificial-intelligence-based classification techniques. *Expert Systems with Applications*

Zdravkovic J. & Stirna J. (2019). Towards Data-Driven Capability Interface. IFAC-PapersOnLine, vol. 52, no. 13. pp. 1126–1131, 2019, doi: 10.1016/j.ifacol.2019.11.347.

Zhang M.Y., Cao T.Z., Zhao X.F. (2017). Applying Sensor-Based Technology to Improve Construction Safety Management. *Sensors* 2017,17, 1841

Zhou, M., Yan, J., & Feng, D. (2019). Digital twin framework and its application to power grid online analysis. CSEE Journal of Power and Energy Systems, 5(3), 391–398.

Zhuang C., Liu J., & Xiong H. (2018) Digital twin-based smart production management and control framework for the complex product assembly shop-floor. The International Journal of Advanced Manufacturing Technology, vol. 96, no. 1–4. pp. 1149–1163, doi: 10.1007/s00170-018-1617-6.