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Potential Applications of Collaborative Intelligence Technologies in Manufacturing:

Study of applicability of Collaborative Intelligence Technologies in Manufacturing Small-and-Medium Enterprises, Collaborative Intelligence Frameworks, application benefits and adoption barriers

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Abstract

The pacing adoption of Artificial Intelligence (AI) technologies has encouraged researchers to work on the potential change the collaboration between human intelligence and machine intelligence could make to various disciplines. The main goal of this thesis revolves around providing a systematic analysis of the scientific literature referring to the application of artificial collaborative intelligence (CI) in the Manufacturing sector. Aiming to provide a clear mapping of the concept CI, this work reviews the paradigm shift from Industry 4.0 to Industry 5.0, taking us from system-centric manufacturing towards human-centric manufacturing. With a deep focus on AI and Machine Learning, this works reviews the enabling technologies of the new paradigm. Also, this work reviews the recent research efforts towards developing frameworks supporting a bi-directional collaboration between humans and intelligent machines. Additionally, a detailed review on the past literature on Artificial CI empirical studies between 1999-2022 was carried out to highlight the evolution of the topic before and after both Industry 4.0 (I4.0) and Industry 5.0 (I5.0) introduction. Furthermore, this work provides a qualitative analysis of the readiness of manufacturing SMEs (MSMEs) to adopt the recent CI technological advancements. The parameters used for the analysis are the proposed system's usability in addition to both affordability and maturity of utilized technologies. The qualitative analysis indicated that compared to large enterprises, MSMEs are not yet ready to invest in the majority of recently introduced CI technologies, as it encounters difficulties finding finances, labor skills, and knowledge to be early adopters. This result paves the way for the second research question trying to study the potential impact of artificial CI on MSMEs from a different angle. A literature review on artificial CI a in MSMEs was carried out between 1999-2022 to highlight the popularity of the topic in the entrepreneurial sphere before and after both I4.0 and I5.0 introduction. Later on, adopting a 4-stage lifecycle, this work investigates the potential impact of the recent CI technologies upon the different lifecycle challenges of a MSME including new product development, labor skill gap filling and scaling up operations. Nevertheless, similar to the first research question, this work provides a qualitative analysis of the readiness of manufacturing SMEs to adopt the recent CI technological advancements according to the new perspective. Finally, this work summarizes the main challenges hindering the adoption of CI technologies.

Keywords: Collaborative Intelligence (CI), Artificial Intelligence (AI), Human-AI Collaboration, Machine Learning (ML), Manufacturing Small and Medium Enterprises (MSMEs), Industry 4.0, Industry 5.0, Human-Centric AI-based Manufacturing

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List of Abbreviations

Acronym	Stands for	Acronym	Stands for
AA	Adaptive Automation	**I5.0**	Industry 5.0
ADOP	Adaptive Operating Procedures	**Iaas**	Infrastructure as a Service
AGI	Artificial General Intelligence	**ICS**	Industrial Control Systems
AGV	Autonomously Guided Vehicle	**IIoT**	Industrial Internet of Things
AI	Artificial Intelligence	**IoE**	Internet of Everything
AIS	Artificial Immune System	**IoP**	Internet of People
AM	Additive manufacturing	**IoS**	Internet of Services
AMT	Automated Manual Transmission	**IoT**	Internet of Things
ANNs	Artificial Neural Networks	**IPA**	Intelligent Personal Assistant
AR	A Augmented reality	**LfD**	Learning from Demonstration
ATCs	Advanced Trained Classifiers	**LSTM-N**	Long Short-Term Memory network
BD	Big Data	**MAS**	Multi-agent Systems
CBR	Case-based Reasoning	**MES**	Manufacturing Execution System
CC	Cloud Computing	**ML**	Machine Learning
CEM	Customer Relationship Management	**MOTL**	Man-on-the Loop
CI	Collaborative Intelligence	**MSMEs**	Manufacturing Small and Medium Enterprises
CK	Conceptual Knowledge	**MTH**	Machine-to-Human
CM	Customized Manufacturing	**MTM**	Machine-to-Machine
CMfg	Cloud Manufacturing	**NLP**	Natural Language Processing
CNC	Computer Numerically Controlled	**NLU**	Natural Language Understanding
CNN	Convolutional Neural Network	**NPD**	New Product Development
Cobots	Collaborative Robots	**OLAM**	On-line Analytical Mining
CPS	Cyber-Physical Systems	**OLAP**	On-line Analytical Processing
CRAF	Customer Requirement and Forecast	**Paas**	Platform as a Service
CS	Cybersecurity	**PdM**	Predictive Maintenance
CSI	Collaborative Sensing Intelligence	**PDM**	Product Data Management
DIA	Digital Intelligent Assistant	**Pi-Mind**	Patented-Intelligence-Mind
DL	Deep Learning	**PK**	Procedural Knowledge
DM	Dialog Management	**RFID**	Radio-Frequency Identification
DNN	Deep Neural Networks	**RNN**	Re-current Neural Network
DSS	Decision Support System	**RQ**	Research Question
DT	Digital Twin	**RUL**	Remaining Useful Life
EBS	Electronic Brainstorming	**Saas**	Software as a Service
EC	Edge Computing	**SAM**	Smart Additive Manufacturing
FIS	Fuzzy inference system	**SCADA**	Supervisory Control and Data acquisition
FNN	Feed-Forward Neural Network	**SCM**	Supply Chain Management
GD	Generative Design	**SF**	Smart Factory
H-CPS	Human Cyber-Physical Systems	**SMEs**	Small and Medium Enterprises
HC-HRC	Human-Centric Human-Robot-Collaboration	**SOAP**	Simple Object Access Protocol
HEC	Human-Robot-Collaboration	**SOP**	Standard Operating Procedures
HITL	Human-in-the-Loop	**STT**	Speech-to-Text
HMI	Human-Machine Interface	**SVM**	Support Vector Machines
HMM	Hidden Markov Model	**TPs**	Total number of Publications
HTH	Human-to-Human	**TTS**	Text-to-Speech
HTM	Human-to-Machine	**UAVs**	Un-manned Aerial Vehicles
I4.0	Industry 4.0	**VR**	Virtual Reality

1. Introduction to the Research

Manufacturing is regarded as one of the key driving forces of the global economy as it "represents a cornerstone of many national economies, a crucial sector to the generation of structural change, productive jobs and sustainable economic growth" (Herman, 2016). According to (HitHorizons, 2021), the European manufacturing sector yielded around € 12,647 billion in 2021, which represents 16.13% of turnover of all companies available in the database. Also, according to (Statista, 2021), the manufacturing sector has provided about 17% of the European jobs opportunities in 2021. Considering the various rising trends such as globalisation, resource scarcity and digitalisation, European manufacturing sectors should necessitate facilitating innovation-driven transformations to achieve more competitive, sustainable and modern production. Therefore, as emphasized by (EuropeanCommision, 2016), industrial "modernisation" has therefore been proved of crucial importance for both "economic dynamism" and "the lasting creation of growth and jobs". Following the integration of the Internet, communications, computers and other information-based technologies and digitalised management methods, the traditional manufacturing industry has "gradually evolved from large-scale production line to personalized, customized, and digital" (Tingting, et al., 2021).

Undoubtedly, AI is currently one of the standout technological trends that are currently attracting a huge interest from researchers and entrepreneurs. Today's manufacturing systems are becoming increasingly complex, dynamic and connected. The factory operation encounters challenges of "highly nonlinear and stochastic activity due to the countless uncertainties and interdependencies that exist" (Arinez, et al., 2020). Recent advancements in AI, especially Machine Learning (ML) have shown a promising potential to revolutionize the manufacturing domain through incorporating advanced analytics tools for mining and processing the endless amounts of manufacturing data collected, known as Big Data (BD).

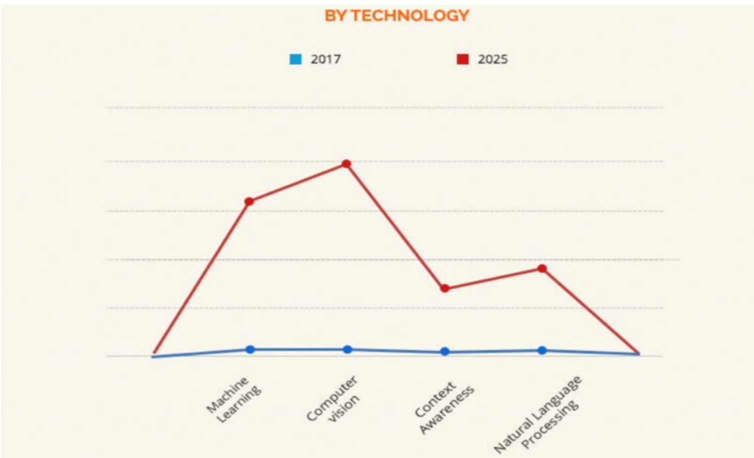

Figure 1 Forecasted Adoption of AI Technologies in the Manufacturing Market (Khandelwal, 2018)

1.1 Manufacturing Small and Medium Enterprises (MSMEs)

The digitalization of manufacturing is the core of Industry 4.0 initiative. AI and ML are popular topics of Industry 4.0. Many publications regarding these topics have been published, but they are primarily focused on larger enterprises (Hansen & Bogh, 2021). For small and medium-sized enterprises (SMEs) and start-ups, "the issue is often a lack of internal research and development capabilities, expertise, and funding to support such assessments" (Spoehr, et al., 2021). However, according to (EuropeanCommision, 2016), SMEs are considered the economic backbone of many countries, as they represent over 99% of all businesses and "contribute on average with more than 50% of the value to the economy in the European Union and with almost 100 million employees, represent approximately 70% of the European workforce" (Powell, et al., 2021). This makes the adoption of Industry 4.0 and the digitalization of manufacturing a fundamental challenge for most SMEs, many of which already struggle to remain competitive in a rapidly evolving business climate. Thus, it is increasingly important that these kinds of companies also have easy access to these technologies and can make them operational. In other words, smaller enterprises will have to gradually deal with topics such as AI and ML.

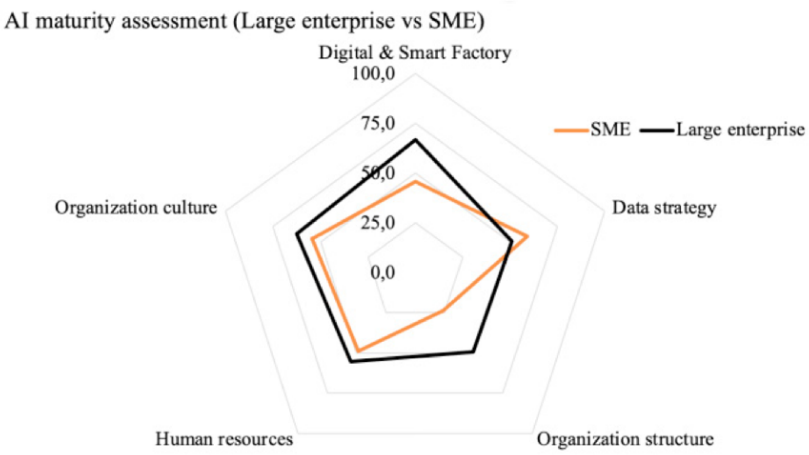

Figure 2 Comparison between AI adoption in SMEs and Large enterprises (Bettoni, et al., 2021)

Accordingly, in the medium term, SMEs should turn their attention to harnessing the potential of advanced manufacturing technologies. Fortunately, technologies such as "high speed and high precision computer numerical control (CNC) machines, collaborative robots (cobots), or 3D printers are currently economically more feasible for SMEs" (Rauch, et al., 2019). Although the widespread deployment of these technologies in industrial environment will expectedly continue for some years to come, this shift will also be mastered by those who adapt to it at an early stage.

1.2 Manufacturing Start-ups

Start-ups, which are a critical subsegment of SMEs, have become important sources of innovation. In most cases, “startups tend to be a lot riskier than their small business counterparts as they are often starting something very new and run the risk of over-inflating too soon due to their fast growth” (Amery, 2018).

The innovative manufacturing start-ups represent one of the main sources of innovation that stimulate the growth of the western economies. Following years of offshoring manufacturing activities in an attempt to cut costs, science and engineering-based manufacturing firms have opened the gate to achieve a sustainable, competitive manufacturing base. "We are always looking to grow businesses that sell products outside the community and therefore bring money in. Manufacturing is one of the strongest industries in terms of improving your local economy," says Chris Reddin, executive director of the Georgia Center of Innovation for Manufacturing center. In Italy, for example, (Statista, 2021) revealed that 75 percent of all startups operated in the sector of business services as of March 2021. This was by far the most common sector in the country. The industry of manufacturing, energy, and mining followed, with 17 percent of the total.

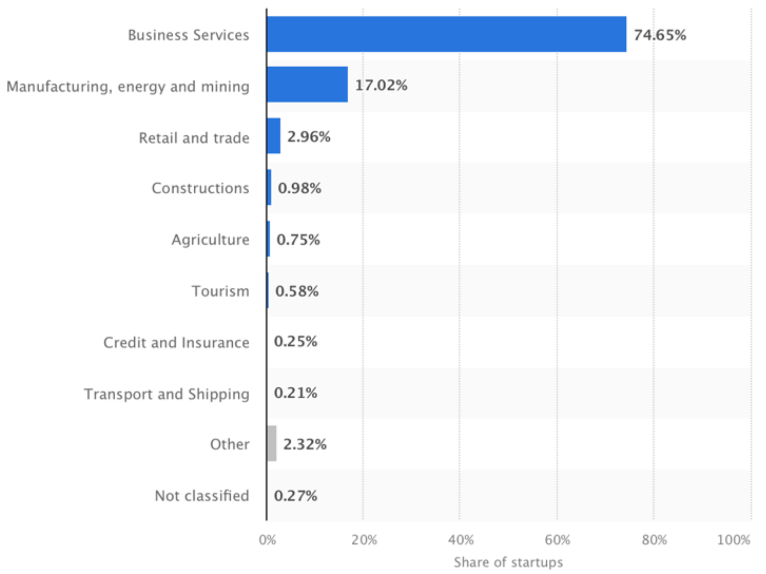

Figure 3 Distribution of innovative startups in Italy in 2021

Despite the integral role manufacturing start-ups play in the economy, research relating to the manufacturing strategy development process of start-ups is surprisingly not matching the pacing digitalisation advancements. As a result, this paper overviews the potential impact of augmenting the human capabilities with artificial intelligence technologies on the different stages of the small and medium enterprises’ lifecycle. However, a start-up life-cycle would be applied to the research to account for the uncertainty and dynamicity of the initial and final stages.

The paper is organized as follows:

Section 1 presents a brief introduction to the research. Section 2 provides the proposed methodology of literature research. Section 3 presents the results of the analysis of Research Question 1 and section 4 provides the detailed literature research revolving around the different angles of the research question mentioned above. Section 5 presents the results of the analysis of Research Question 2 and Section 6 provides the detailed literature research revolving around the different angles of the associated research question. Finally, in Section 7, the main challenges of CI are summarized.

RQ1: What is the potential impact of collaborative intelligence (CI) upon the Manufacturing Sector?

RQ2: What is the potential impact of CI upon MSMEs ?

1.3 A Recap of the Recent Waves of the Industrial Revolution

Over the past years, the global economic recession has been pushing for a big change within the industrial sector. Offshoring activities aiming for lower cost labor has not become the fittest strategy to foster competitiveness. Instead, companies should be committed to the "real value-added" it offers to the market (Alcácer & Cruz-Machado, 2019).

Industry 4.0 (I4.0) is an initiative introduced in 2011 to make the German manufacturing industry more competitive *('Industrie 4.0').* Later, this initiative has been rapidly adopted in a global manner. According to (Lu, 2017), I4.0 can be portrayed as Cyber-Physical Systems (CPS) production relying upon heterogenous BD, knowledge integration, and interoperable service-oriented manufacturing process alongside the deployment of high technologies such as the Internet of Things (IoT), Internet of Services (IoS), Radio-Frequency Identification technologies (RFID), cognitive computing, Cybersecurity (CS), Cloud Computing (CC), and advanced Robotics. In a production context, (Leyh, et al., 2017) refer to I4.0 as the intelligent flow of the workpieces machine-by-machine in a factory, on a real-time communication between machines. Thus, I4.0 aims to amplify the smartness of the manufacturing industry, improve the mass productivity by interconnecting machines and devices that can intelligently communicate and interact throughout the product's lifecycle, and elevate the manufacturing system's adaptability by developing flexible and collaborative systems to solve problems and make the best decisions (Peruzzini, et al., 2017). The goal is to enable autonomous decision-making processes, tracking assets and processing sensory data in real-time, and facilitate equally real-time connected value creation networks through early involvement of stakeholders, and vertical and horizontal integration (Leyh, et al., 2017).

Figure 4 Industry 4.0 Technological Pillars (Puskas & Bohács, 2019)

1.3.1 Reference Model of I4.0

Different German institutions worked together to develop a reference model for I4.0. The 3D model shown in Figure 5 represents the development of a shared language and a structured framework that introduces the core bases of I4.0, incorporates existing standards, and fill the gaps by guiding the implementation of the enabling technologies (ZVEI, 2015) .

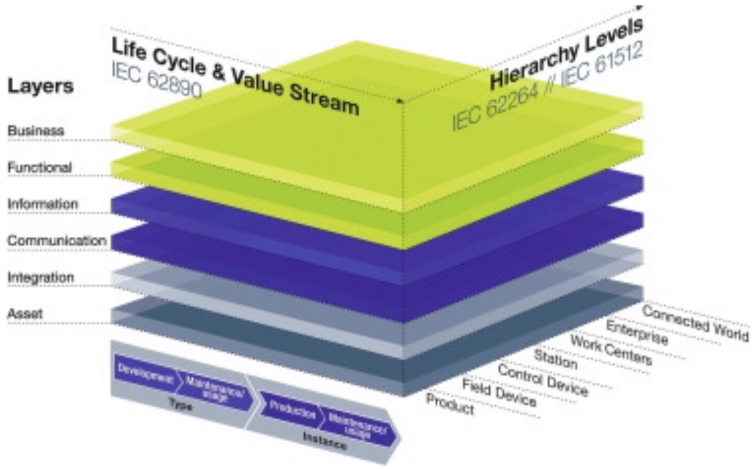

Figure 5 I4.0 Reference Model (RAMI4.0) (ZVEI, 2015)

Briefly, the horizontal right axis is labelled by "Hierarchy level", as it represents the hierarchy levels adopted from the IEC 62264 standard, including the entire functionalities in the industry. The hierarchy levels range from the "product" to the last stage of the I4.0 development enterprise environment, which is labelled by "connect world". The last stage of the IEC 62264 standard deploys IoT and IoS to connect enterprise, customers, and suppliers (Pauker, et al., 2016). The horizontal left axis, labelled by Life Cycle & Value Stream, represents the life cycle of facilities and products according to the IEC 62890 standard. The structured layers on the vertical axis represent the decomposition of a machine into its properties, guiding a "step-by-step migration from the actual to the future manufacturing environments" (Pauker, et al., 2016). The layers structured on the vertical axis are summarized below:

- Asset Layer: It resembles real components including both physical (i.e Conveyor, pallets, robots,…etc) and non-physical (i.e Software) elements. As well, this layer resembles the human factor, which is a part of the transformation to the virtual domain achieved by the "Integration Layer" via Human-Machine Interface (HMI) (Zezulka, et al., 2016).

- Integration Layer: It provides information for the digitization of the assets in a processable form to be managed by computer aided controls . This layer collects information through the various technologies connected to Information Technologies, including sensors, RFID readers, and HMI (Marcon, et al., 2017).

- Communication Layer: It manages standardization of communication by directing uniform data format and predefined protocols to the “Information Layer” (Zezulka, et al., 2016). As well, this layer provides services for control of the “Integration Layer” (Marcon, et al., 2017).

- Information Layer: It regularly processes and integrates the data gathered from different sources alongside receiving and transforming events to match the data which are available for the “Functional Layer” (Zezulka, et al., 2016).

- Functional Layer: It supports formal descriptions of functions, develops a horizontal integration platform of different functions, and generates rules and decision-making logic. Remote access is restricted to the Functional layer due to the importance of data integrity (Zezulka, et al., 2016).

- Business Layer: It ensures the integrity of functions in the value stream, facilitates mapping of the business model and links between different business models (Zezulka, et al., 2016).

1.3.2 The Key Technologies of I4.0

In a manufacturing context, as pointed earlier, I4.0 aims to develop “intelligent and communicative systems including machine-to-machine communication and human-machine interaction. Now and in the future, companies have to deal with the establishment of effective data flow management that is relied on the acquisition and assessment of data extracted from the intelligent and distributed systems interaction. The main idea of data acquisition and processing is the installation of self-control systems that enable taking the precautions before system operation suffered” (Salkin, et al., 2017). As well, I4.0 fosters interoperability, agility, flexibility, decision-making, and efficiency (Havard, et al., 2020).

This subsection presents the nine building blocks of the I4.0 frameworks as detailed by (Salkin, et al., 2017):

1.3.2.1 The Industrial Internet of Things (IIoT)

Following the continuous advancements with respect to mobile devices such as RFID readers, Wireless sensor Networks (WSN), CC, and different communication networks, IoT has witnessed a noticeable maturity within various fields (Sadiku, et al., 2017). As implied by its name, IoT can be branched into a couple of terms: “internet” and “things”. Firstly, “Internet” refers to a “A global system serving users worldwide with interconnected computer networks using Standard Internet Protocol suit (TCP/IP)” (Alcácer & Cruz-Machado, 2019). On the other side, the “things” refers to anything like an object, service or a human (Madakam, et al., 2015). Thing-to-Thing, Thing-to-Human and Human-to-Human establish a network inside IoT and exchange data through the internet (Sadiku, et al., 2017). According to (Bortolini, et al., 2017), IoT refers to the “ubiquitous presence, even in the industrial environment, of several things or objects able to co-operate and interact with each other for a common purpose”. Thus, IoT promotes the digitalization and virtualization of the entire physical “things” (Peruzzini, et al., 2017). Hence, the digitalized information collected from heterogenous sources (i.e. virtual copy of the physical world or sensors) can be incorporated to enhance production parameters (Peruzzini, et al., 2017).

Among the efforts to define an IoT design architecture, and adopted from the works of (Li, et al., 2015) and (Hammoudi, et al., 2018), (Alcácer & Cruz-Machado, 2019) presented a 4-layered IoT Framework as briefed below and elaborated in Figure 6:

- Sensing Layer: It senses the conditions associated with the connected “things” in a unique and integrable manner. The “things” include actuators, sensors, RFID tags, wearable devices, …etc.

- Network Layer: It provides the infrastructure required for transferring the processed data via the communication networks from the sensing layer to the service layer alongside supporting the exchange of data by triangulating an automatic mapping of the connected “things” within the network.

- Service Layer: It deploys middleware technology to improve the services requested by users and applications on a regular basis. Also, this layer maintains the interoperability of the heterogenous devices via an adequate management of data and a well-structured ontology database.

- Interface Layer: It facilitates the interconnection and management of the networked "things" beside ensuring a user-friendly, understandable, and clear interaction between the user and the system. deploys middleware technology to improve the services requested by users and applications on a regular basis. Also, this layer maintains the interoperability of the heterogenous devices via an adequate management of data and a well-structured ontology database.

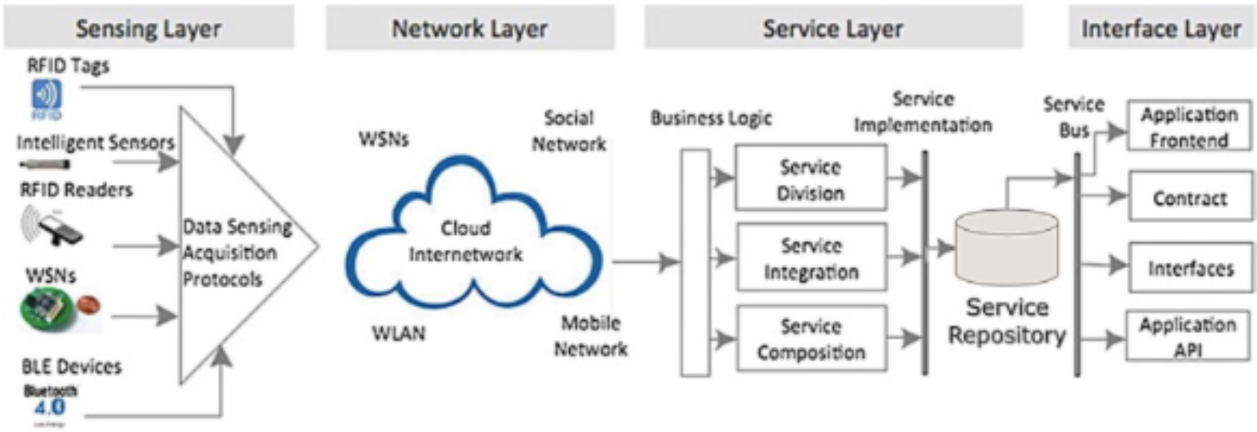

Figure 6 Generic Service-oriented Architecture of IoT (Li, et al., 2015)

In a manufacturing context, the IIoT refers to the networking of industrial devices via the internet to satisfy industry's need for real-time data availability and high reliability by harnessing the advancements of several technologies such as sensory devices and BD analytics (Andulkar, et al., 2018). A typical IIoT framework is described in detail in section 4.8.1.

On the other hand, as an extension of IoT, the IoS can be viewed as the connectivity and interaction of the "things" forming valuable services (Alcácer & Cruz-Machado, 2019).

1.3.2.2 Cloud Computing (CC)

CC provides an option for firms who prefer to invest in IT outsourcing resources. (Shetty & Panda, 2021) characterized CC for SMEs as a "disruptive innovation, possessing the required elements such as on-demand, low cost, and low infrastructure that threaten the existing premise-based IT market". According to (Yandong & Yongsheng, 2012), the cloud can be deployed in four different models: public (usually on a data center location, managed by vendors and available for all public), private (usually on a private, secure, and centralized data center and available only for internal), hybrid (combination of public and private clouds) and community (shared by multi organizations and supported by a specific sharing of interests and concerns community). Among the efforts to highlight the available types of cloud service models, (Alcácer & Cruz-Machado, 2019) established a 3-layered system of the available types of service models along with the associated management overview as briefed below and portrayed in Figure 7:

- Infrastructure as a Service (IaaS) supplies clients with required computing resources, virtual infrastructures, networks or storage to deploy and run arbitrary software.

- Platform as a Service (PaaS) enables users to develop and run their own applications using programming languages on the remote cloud infrastructures without worrying about capacity, server reliability, resource's availability, and maintenance.

- Software as a Service (SaaS) is a cloud infrastructure where complete applications are hosted at the backend rather than being hosted in the end users' terminal or in a local data center (Hammoudi, et al., 2018). The hosted applications (i.e. Computer-Aided-Design software) are accessible from heterogenous users' devices via an interface (i.e. web browser), which reduces the total cost of the service.

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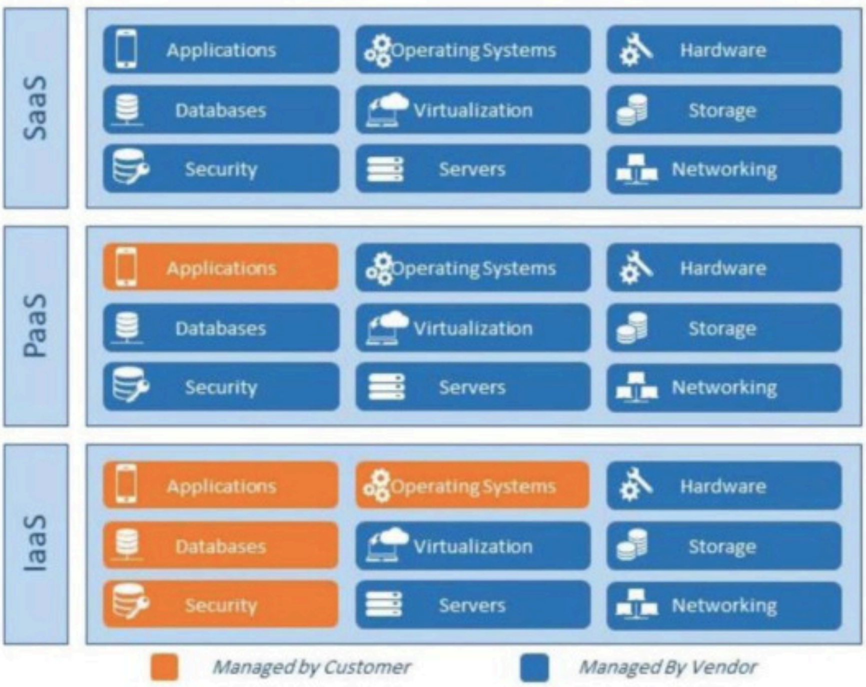

Figure 7 Management Overview of the Service Models of Cloud Computing (Alqaryouti & Siyam, 2018)

In a manufacturing context, aiming to enhance the current manufacturing systems, cloud Manufacturing (CMfg) concept was introduced to harness the CC technology. Further details about the CMfg concept will be presented in section 4.

1.3.2.3 Big Data (BD)

As highlighted earlier, massive amount of different types of generated data (i.e. structured, semi-structured, or unstructured data). can be gathered via interconnected heterogeneous devices/machines (Bortolini, et al., 2017). According to (Cemernek, et al., 2017), BD refers to a "term describing large volumes of high velocity, complex and variable data requiring advanced techniques and techniques to enable the capture, storage, distribution, management and analysis of the information" Data gathering or storage are fundamental aspects of BD, but the core feature of BD is the value-adding information obtained by cost-effective data analysis, which could guide the managers' way towards cost efficiency and effective decision-making over a product's entire lifecycle (Yin & Kaynak, 2015)

Building on the 4 V's defined by (IBM, 2012) and the 5 V's adjusted by (Yin & Kaynak, 2015), (Alcácer & Cruz-Machado, 2019) has added further dimensions to better characterize and process vast amounts of unstructured heterogenous data gathered in various formats including video, audio, text, or others. Provided below the proposed a 10 V's model of BD to describe the various dimensions:

Volume	Large data volume size consuming large storage (i.e. multi terabytes)
Variety	Different types of data, generated from a wide range of sources in different formats
Velocity	Refers to the rate of generating, processing, analyzing, and accordingly taking actions
Veracity	Resembles the possible unreliability of some data sources
Vision	Data generation occurs according to a visionary purposeful process
Volatility	The expiry of data's validity should be monitored along the data lifecycle
Verification	Data generated must be verified with respect to the pre-set engineering measurements
Validation	Refers to ensuring the transparency of assumptions made during the vision process
Variability	Data flow rates measured by its variation
Value	The defining value of BD reflects the insightful information resulted from the process

Table 1 The 10 V's of Big Data (Alcácer & Cruz-Machado, 2019)

Advanced data analysis is fundamental to explore large volumes of off-line/real-time data (i.e. ML algorithms). The knowledge extracted from the explored data guides the manufacturers to a better understanding, comprehension, and decision-making throughout the different stages of a product's lifecycle, which would elevate the manufacturing competitiveness in the global market (Tao, et al., 2018). As shown in Figure 8, the data gathered from the lower levels of the manufacturing cycle (i.e. Shop Floor) can guide the management upper level's decision-making concerning market forecasting, demand analysis, and operation monitoring.

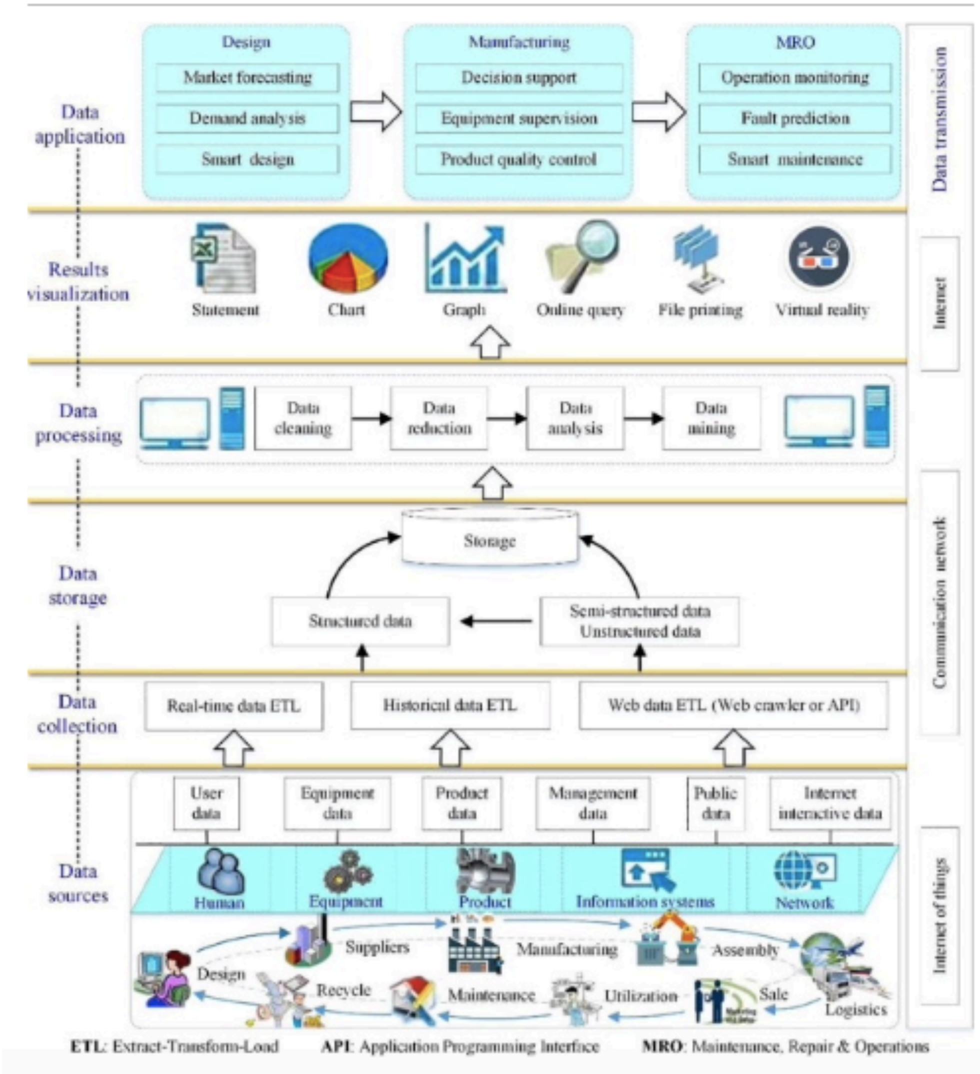

Figure 8 A Complete Data Life-cycle in a Manufacturing Context (Tao, et al., 2018)

Besides being a key to digital manufacturing, BD analytics is the foundation of meeting the scope of mass customization (Mourtzis, et al., 2016). Needless to mention, IoT and CC are vital enablers of BD analytics as they provide the data and required infrastructure respectively.

1.3.2.4 Simulation

Simulation refers to “an operation imitation, over time, of a system or a real-world process [as] it uses a system's artificial history and its observation, drawing inferences over the operational features of the representation of the real system” (Alcácer & Cruz-Machado, 2019). Before the application of a new business system, computer simulation could be incorporated to better understand the dynamics of the new paradigm and determine the complexity of the potential uncertainties prior to the accompanied investments and implementation efforts (RODIČ, 2017). As well, to improve an existing product or a production system, discrete event and 3D motion simulation could be deployed to enhance both the product and the production process development, which could promote a customized product manufacturing environment (Kuhn, 2006). Additionally, in accordance with the overall system’s robustness, simulation technologies have been effectively employed in making long-term decisions on the system capacity configurations and material handling systems via its off-line analysis of what-if scenarios (Negahban & S. Smith, 2014). On the other side, the real-time simulation has proved its effectiveness when it comes to short-term decision-making concerning manufacturing operations planning and scheduling, real-time control, operation policies and maintenance operations (Negahban & S. Smith, 2014). According to (Cedeño, et al., 2018), a real-time simulation refers to an efficient computational system running at the same rate as the physical system, which necessitates the presence of ample real-time data provided by IoT.

The new simulation modeling paradigm revolves around the concept of Digital Twin (DT), which stretches simulation to entire product life-cycle stages, integrating real-time data with simulation models for better performances in productivity and maintenance based on realistic data (RODIČ, 2017) . Further details on DT concepts will be provided in section 4.

1.3.2.5 Augmented Reality

Augmented reality (AR) refers to “the integration of additional computer generated information into a real-world environment. Most current AR applications integrate computer graphics into the user's view of his current surroundings” (Paelke, 2014). Such technologies necessitate the availability of various electronic devices including cameras, hand-held optical devices, head-worn optical devices, Projectors, holograms, processing unit, sensors, QR markers,..etc (Syberfeldt, et al., 2016). Unlike Virtual Reality (VR), AR does not entirely fake conditions to imitate the real situation with a virtual one (Lavingia & Tanwar, 2019). AR aims to enhance the user's experience and performance by providing him the information that has a direct upon the task in hand by deploying electronic devices to provide either direct or indirect view of a real-world integration with virtual entities (Palmarini, et al., 2017). Additionally, this technology has the potential to improve users' experiences in various sectors including entertainment, marketing, health care, and most importantly, the manufacturing industry. In a manufacturing context, AR has shown promising effects in various points of the production process's lifecycle. To illustrate, AR can be used to provide a live reflection of the on-going status of a warehouse or a production line, thus facilitating monitoring, communication, and planning (Pintzos, et al., 2014). Also, AR and VR have gained popularity in prototyping and collaborative design, as they promote a fast development of visual prototypes that can be edited by multiple users, thus making it easier to meet the customers' demands of customized products (de Sá & Churchill, 2012). As well, integrated with AI/ML technologies, AR has been deployed to develop an interactive Human-Machine-Interface as a mean of personalized up-skilling of operators in performing different manufacturing tasks (Karamalegos, 2018). By the way, further details on the systems designed to train and upskill workers would be provided in section 6. Furthermore, maintenance is one of the most promising fields of AR, as it fosters the operator's performances by supporting both his technical maintenance activities and decision-making (Palmarini, et al., 2017). As shown in Figure 9, AR can also help filling the "gaps" between product development, manufacturing cycles, and sales as it enables reproducing digital information and knowledge of the different phases at the same instant (Alcácer & Cruz-Machado, 2019).

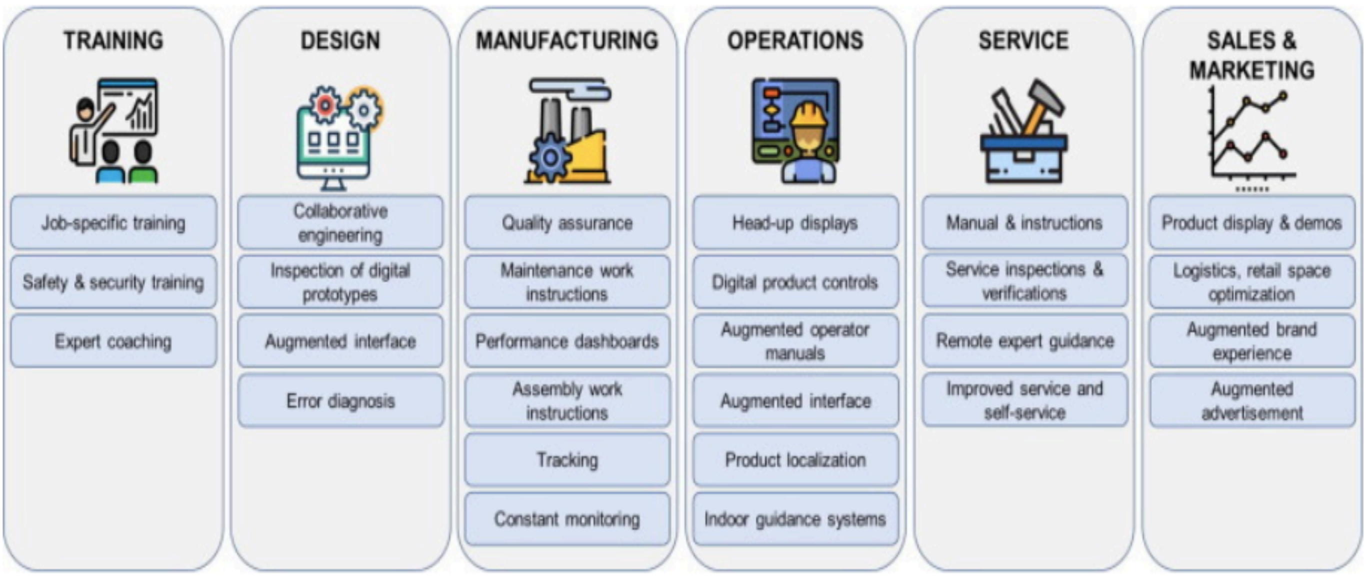

Figure 9 Value of Industrial AR across I4.0 (Alcácer & Cruz-Machado, 2019)

1.3.2.6 Additive Manufacturing (AM)

Although the innovative technologies associated with I4.0 has provided various solutions to develop products and services, but still the manufacturing costs and time-to-market are attracting a huge interest of different stakeholders, as both parameters are integral determinants of competitiveness. Hence, the research efforts towards additive manufacturing (AM)/3D printing/rapid prototyping has evolved over the past decades from a rapid prototyping technology to advanced manufacturing (Korner, et al., 2020). The AM paradigm has attracted interest because it provides various applications that could potentially replace many conventional manufacturing processes (Jiang, et al., 2017). According to (Forster, 2015) , AM refers to "a collection of technologies able to join materials to make objects from 3D model data, usually layer upon layer, as opposed to the subtractive manufacturing methodologies". According to (Tofail, et al., 2018), AM facilitates handling greater customization without extra tooling or manufacturing cost, manufacturing of complex geometries, producing lattice structures, and minimizing the material wastes. (Alcácer & Cruz-Machado, 2019) added that AM promotes the creation of prototypes to support the independence of value chain elements, thus diminishing the time allocated to design and manufacturing. Additionally, (Shin, 2016) highlighted that AM supports manufacturing of various scales including nanoscale (bio-fabrication), micro-scale (electronics), macro-scale (personal products, automotive), and large-scale (architecture and construction).

The integration of AM, AI/ML technologies, BD analytics, and IoT has played an integral role in the emergence of the smart additive manufacturing (SAM) feature. To note, further details about SAM will be provided in section 4.

1.3.2.7 Horizontal and Vertical Systems Integration

Taking the information flow and different levels of automation into consideration, I4.0 promotes a "collaborative scenario" of "systems integration" between engineering, production, supply chain operations, and others (Saucedo-Martínez, et al., 2018). In general, real-time data exchange is supported in I4.0 via three types of systems integration as briefed below:

- Horizontal integration: represents a vital key behind "high-level collaboration" between different companies, incorporating information systems to "enrich product lifecycle" (Salkin, et al., 2017), paving the way for an "interoperable" and "inter-connected ecosystem within the same value creation network" (Tupa, et al., 2017).

- Vertical integration: represents a vital key behind sharing data and information between different layers of the same company's organizational hierarchy to enrich planning, scheduling, and production (Foidl & Felderer, 2016). Additionally, this integration approach is a vital enabler of producing customized products in small lot sizes, as it "digitizes" the entire processes within the organizational hierarchy after taking the real-time data collected from the manufacturing processes. In other words, vertical integration could be cornerstone of achieving the concept of the smart factory (SF) (Salkin, et al., 2017).

- End-to-End integration: According to (Salkin, et al., 2017), based on the former integration approaches, End-to-End integration aims to bring product design, manufacturing, and the end customer altogether on the same line over the product's entire lifecycle (Alcácer & Cruz-Machado, 2019). To further explain the three integration types, Figure 10 portrays the relationship between the three integration approaches in a manufacturing context.

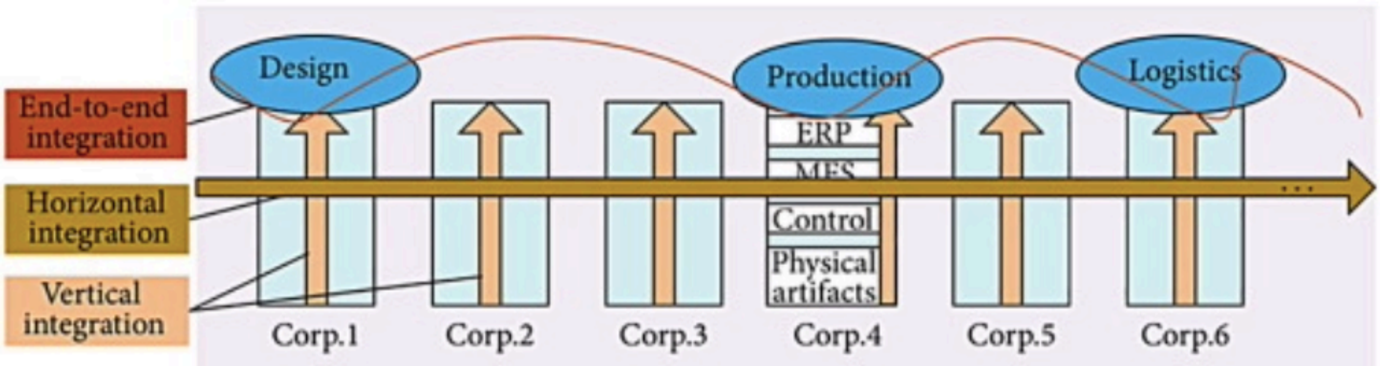

Figure 10 Relationship between the Three Integration Types in a Manufacturing Context (Wang, et al., 2016)

1.3.2.8 Autonomous Robots

Manufacturing paradigm is shifting rapidly from mass production towards customized production, which urges elevating the manufacturing businesses' adaptability, flexibility, and reconfigurability (Pedersen, et al., 2016). Seen as one of the forms of AI by (Wu, et al., 2018) , robots have the potential to flexibly facilitate manufacturing a wide variety of products, thus reducing the overall production costs (Salkin, et al., 2017). Undoubtedly, continuous advancements and integration of computing capabilities, communication technologies, and AI/ML algorithms, have contributed to nurturing the smartness of machines, processes, and products. To illustrate, adaptive robots have found fertile ground in various stages of a product's lifecycle, ranging from product development to assembly tasks (Salkin, et al., 2017).

Additionally, I4.0 has promoted the full autonomy of robots by developing them to mimic a human operator's decision-making process under dynamic, unstable working environments, thus diminishing the human's role in the manufacturing cycle (Ben-Ari & Mondada, 2017). Also, researchers have directed their attention to the potential of setting up a collaborative environment of autonomous industrial robots. To be specific, researchers focus on two typologies of collaborative environments: Human-Robot-Collaboration (HRC) and multiple autonomous robot's collaboration. To illustrate, as shown in Figure 11, (Hassan & Liu, 2017) proposed a multiple autonomous robot's collaboration approach relying upon robots with complementing capabilities performing spray painting tasks. The author emphasizes that teaming up multiple autonomous industrial robots would offer a wider range of manufacturing applications. On the other side, collaborative robots refer also to the possibility of bringing cobots and humans to work together in close proximity, which would offer affordably flexible solutions in the manufacturing industry (El Makrini, et al., 2018). Further details on HRC will be provided in section 4.8.8 and section 4.

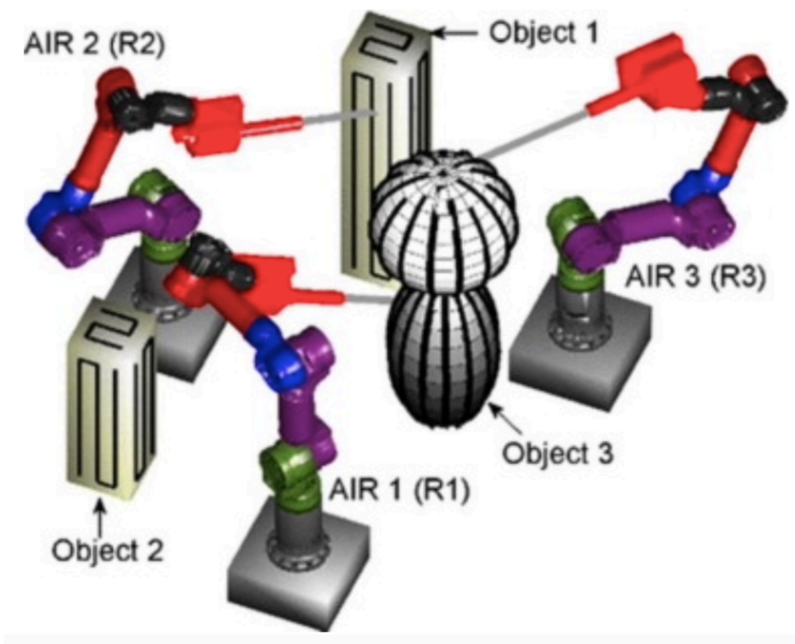

Figure 11 Autonomous Industrial Robots Performing Paint Spraying (Hassan & Liu, 2017)

1.3.2.9 Cybersecurity (CS)

The expanding need for networking devices globally over the internet alongside the valuable information generated by I4.0 have raised various concerns over the past years. In particular, the IoT frameworks, virtual environments, and remote access to cloud technologies have introduced new risks associated with the security of data exchange within "vanishing enterprise boundaries" (He, et al., 24-29). In some cases, manufacturing operations can be shut down by a cyber-attack, leading to operational losses and occasional threat to the operators' safety (Tsuchiya, et al., 2018). Such concerns bring the term "Cybersecurity" (CS) to the surface. According to (Kannus & Ilvonen, 2018), CS refers to "a new term on a high level of information security, and through the word "cyber" it spreads to apply also on industrial environments and IoT". In other words, CS is a technology developed to protect, detect, and react to internal/external attacks launched against industrial control systems (ICS) including Supervisory Control and Data acquisition (SCADA) for example (Ani, et al., 2017). According to (Benias & Markopoulos, 2017), the main reasons behind successful cyber attacks against ICS networks include irregular updating of anti-virus soft wares embedded in devices, misalignment of security protocols over the different points of the supply chain, and deployment of outdated industrial devices. Restricting access to data to authorized users is a priority to protect against external cyber-attacks (Alcácer & Cruz-Machado, 2019). As well, the deployment of cost-effective private-cloud architectures could be a reliable solution to foster CS and maintain safety of ICS.

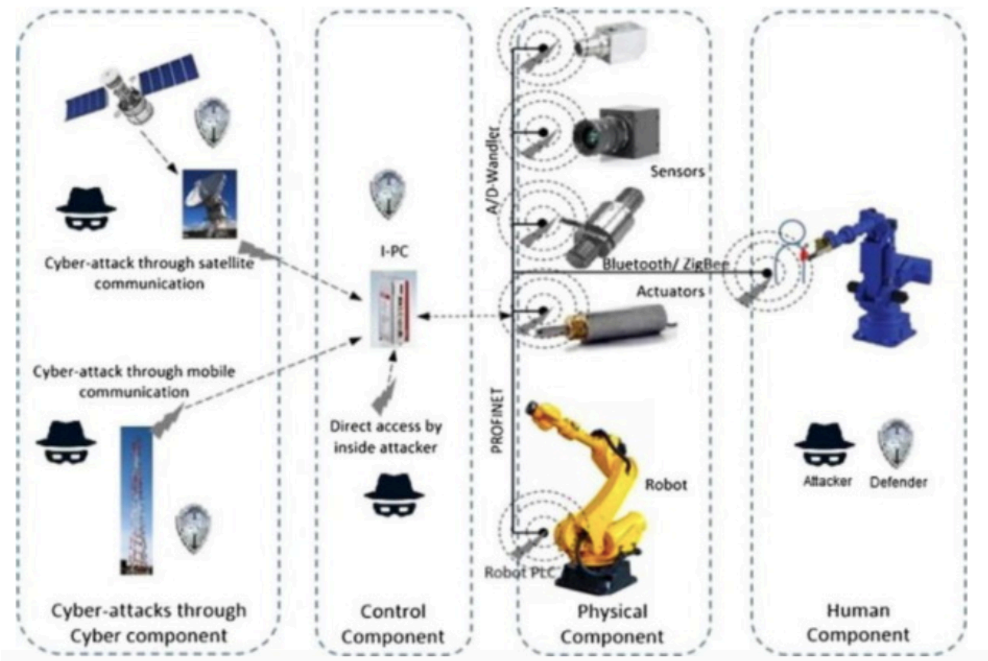

Figure 12 Potential Cyber-attack routes in an Industrial Context

1.4 Overview of Human-machine Relationships

The First and Second Industrial Revolutions have introduced machines to be simply used by human workers in an independent, co-existent manner. During the Third Industrial Revolution, reconfigurable machines and production lines were introduced to support a cooperative relationship between humans and machines, as they likely share physical and informational resources without working simultaneously on the same task. Later on, I4.0 introduced intelligent machine to collaborate with humans in an interactive way under a unified team identity. However, I4.0 diminished the role of the human factor in the manufacturing cycle, which raised concerns over the past years, leading to the emergence of I5.0. In this direction and triggered by the recent introduction of I5.0 projects, (Lu, et al., 2022) has portrayed the evolving human-machine relationships over the different industrial revolutions in a 5C journey: Coexistence, Cooperation, Collaboration, Compassion and Coevolution.

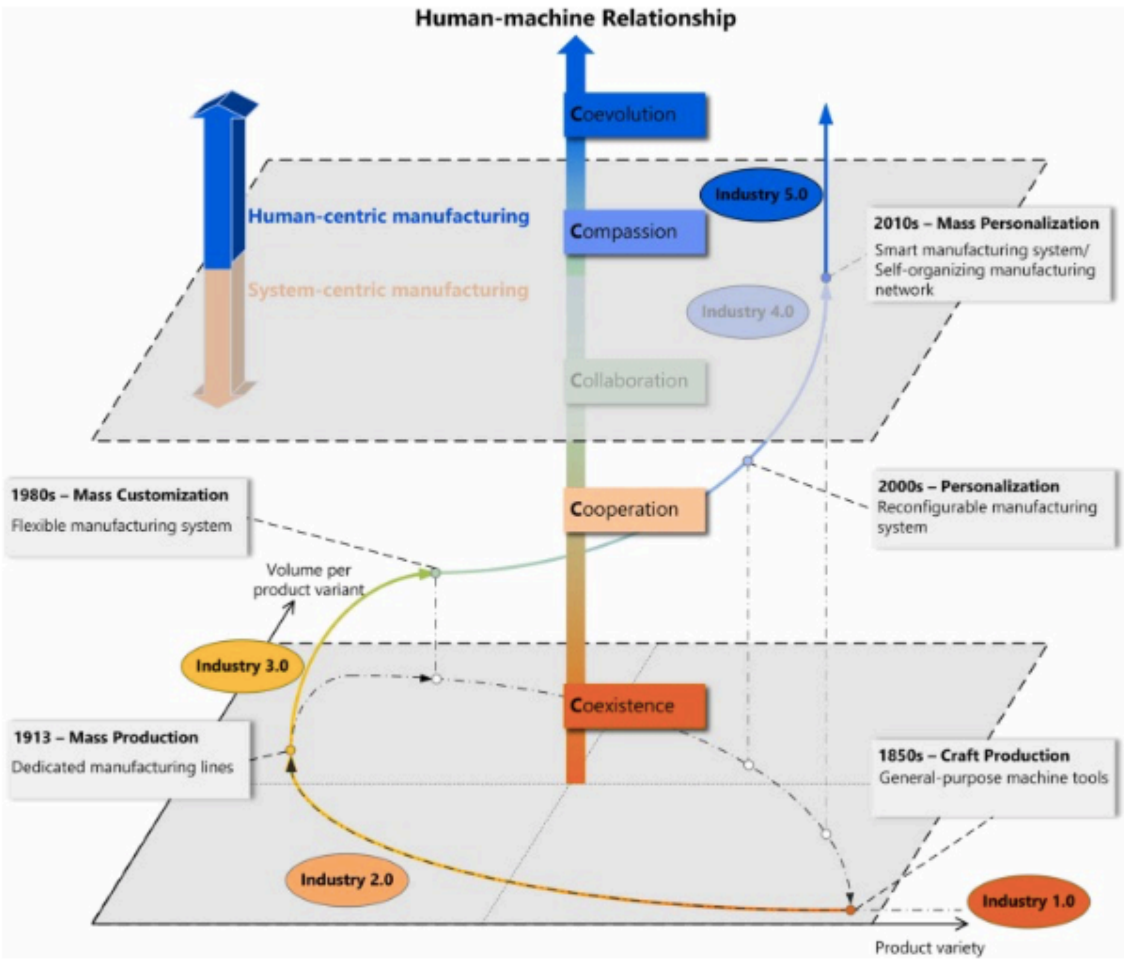

Figure 13 The evolution of Human-machine Collaboration towards industry 5.0 (Lu, et al., 2022)

1.5 Overview of Collaborative Intelligence

The emergence of the I4.0 has necessitated deepening the concepts of CI. Viewing CI only as a framework incorporated to enable the knowledge sharing and collaboration between experts has become obsolete. The continuous advancements of AI technologies have urged increasing the research efforts towards harnessing the benefits of the collaboration between the human factor and intelligent machines. Needless to mention, machines alone are not enough; human factor is the focal point of the company's growth. To illustrate, according to (Wilson & Daugherty, 2018) ,companies aiming to replace the human factor with the new technologies won't achieve the long-term benefits of the industrial digitalisation. However, companies would benefit more through incorporating AI technologies to complement and augment human capabilities. Thus, the concept of human–machine collaboration is developing. To illustrate, Humans are responsible for executing three crucial roles: training machines to perform certain tasks, explaining the 'counterintuitive or controversial' outcomes of the executed tasks and maintaining the 'responsible' use of machines (i.e ensuring a safe and ergonomic ecosystem of humans and robots).

1.5.1 Humans Assisting Machines

1.5.1.1 Training

In fact, programmable technological applications have been present in our lives for ages. Differently, thanks to the recent advancement with respect to both the availability of huge data sets and software developments (i.e computing power and open-source code libraries), AI-powered systems acquire their 'knowledge' through learning large amounts of data. For example, a ML algorithm runs on a training dataset and develops an AI-based model. To a great extent, ML systems are self-programmable. However, the human factor is still crucial to the guidance of the learning process. To elaborate, Humans are responsible for picking the convenient algorithms, formatting data, defining learning parameters, and troubleshooting problems. In other words, AI-powered applications are taught the know-how of performing their jobs by humans. Despite being at early stages, but organisations are expected to deepen their hierarchies by adding experienced staffs to fill the AI-powered systems training roles.

Cortana, developed by Microsoft, is one of the most popular AI powered assistants. In fact, the bot "required extensive training to develop just the right personality: confident, caring, and helpful but not bossy. Instilling those qualities took countless hours of attention by a team that included a poet, a novelist, and a playwright” (Wilson & Daugherty, 2018). On the same line, Apple’s Siri and Amazon’s Alexa were trained by humans to develop the personalities to ensure that they accurately reflected their companies’ brands.

Following the big players’ lead, AI-training start-ups have entered the tech-market aiming to provide AI assistants capable of displaying more sophisticated human capabilities. To demonstrate, the start-up Koko, which is based on a technology developed at the MIT Media Lab, provides a “peer-to-peer network for users to deal with symptoms related to stress, anxiety and depression” (Mack, 2016) through asking the user further relevant questions to provide better advice instead of the routine replies.

1.5.1.2 Explaining

Lack of trust and acceptance has been a major concern that slowed down the investments towards collaborative AI-powered systems. Being allowed only to oversee the input and output of a system with no exposure to the structure of the algorithmic process leading to the output conclusion has intensified the fears and misconceptions between humans and their AI assistants. Such dilemma necessitates the presence of ‘explainers’ to eliminate the blur between the out-of-sight algorithm and the non-expert end user. Also, such role necessitates an expertise of the working context (i.e Law, Manufacturing, Health Services, ..etc). As AIs increasingly reach conclusions through processes that are opaque (the so-called black-box problem), they require human experts in the field to explain their behavior to figure out how an AI agent weighed inputs into, for example, a sentencing or medical advice.

1.5.1.3 Sustaining

Undoubtedly, the incorporation of AI systems in our day-to-day activities would necessitate the creation of various job opportunities. To illustrate, apart from training or explaining the output of the models, qualified employees should be thrown to the mix to “ensure that AI systems are functioning properly, safely, and responsibly” (Wilson & Daugherty, 2018). For example, in an industrial context, a safety engineer should put a framework in place to predict and prevent harm by collaborative AI systems.

1.5.2 Machines Assisting Humans

The importance of the human factor to the development and sustainability of AI systems across its lifecycle is undeniable. However, as mentioned before, the relationship between a human being and an AI-powered assistant is bi-directional. In fact, smart machines are helping humans expand their abilities in three ways. They can 'amplify' our cognitive strengths; 'interact' with customers and employees to free us for higher-level tasks; and 'embody' human skills to magnify our physical capabilities.

1.5.2.1 Amplifying

Beside the apparent results of AI-powered systems on the side of analysts in terms of data-driven decision-making abilities, smart machines have proved big impact upon creative product development. An illustrative example of AI's power to revolutionize product development is Renault. Following a shift in consumer demand, the French automaker is equipping a growing number of new vehicle models with an automated manual transmission (AMT)—a system that behaves like an automatic transmission but allows drivers to shift gears electronically using a push-button command. AMTs are widely known among consumers, but, due to technical complexity, designing them could be challenging and time-consuming. Aiming to streamline its AMT development process, Renault decided to acquire Simcenter Amesim software from Siemens Digital Industries. The simulation technology depends on artificial neural networks (ANNs), which are simply AI 'learning' systems loosely modeled on the human brain. Simply, engineers drag, drop, and connect icons to create a graphical model of the product. When displayed on a screen as a sketch, the model illustrates the relationship between all the various elements of an AMT system. Accordingly, engineers can anticipate the behavior and performance of the AMT and suggest any necessary refinements early in the development cycle, avoiding undesirable problems and delays. In fact, According to MIT Technology Review Insights, "by using a virtual engine and transmissions as stand-ins while developing hardware, Renault has managed to cut its AMT development time almost in half" (Siemens, 2021).

1.5.2.2 Interacting

Unlike traditional channels, Human-machine collaboration opens the door for companies to maintain a relatively more effective interaction with employees and customers. Interactive AI systems have been proved of promising effects over the different stages of the value chain. AI agents like Cortana, for example, can ease communications between people or on behalf of people, such as by "transcribing a meeting and distributing a voice-searchable version to those who couldn't attend" (Wilson & Daugherty, 2018). Simply, the AI agent incorporates advanced interfaces such as voice-driven natural-language processing to drive interactions between or on behalf of people. In a manufacturing context, such systems could be used as a personal assistance providing a step-by-step workflow. Also, the system could be supported by a real-time adaptation to be compatible with real-life situational context (i.e adapted to workers skill levels) Thus, standard operating procedures (SOP) become Adaptive operating procedures (ADOP).

1.5.2.3 Embodying

As pointed above, some AI agents are present in the form of digital entities like Cortana, Alexa and Siri. However, in other applications, the intelligence is embodied in a robot that augments a human worker. Lightweight robots equipped with sensors, motors and actuators engage in physical tasks, as they are now capable of recognizing people and objects, thus ensuring a safe collaborative work alongside humans in factories, warehouses, and laboratories.

In manufacturing, for example, robots are transforming from being potentially viewed as ‘dangerous’ and ‘dumb’ industrial machines into smart, context-aware ‘cobots’. A cobot arm might, for example, handle repetitive actions that require heavy lifting, while a person performs complementary tasks that require ‘dexterity’ and ‘human judgment’, such as assembling a gear motor. Also, autonomous guided vehicles are considered one of the most effective cobots in the industrial sector as they collaborate with human operators to provide the right material at the right time. On the same line, Hyundai is further developing the cobot concept with exoskeletons. In short, “these wearable robotic devices, which adapt to the user and location in real time, will enable industrial workers to perform their jobs with superhuman endurance and strength” (Wilson & Daugherty, 2018).

To sum up, CI will automate processes and machines, empowering humans to act efficiently in case of unexpected situations. Important to note, most critical situations will still necessitate the human’s decisive skills. The AI will digest all historical machine and process data and suggest actions. Humans, on the other side, will be able to make smart decisions relying upon the proposals of the AI. As a result, human workers and AI work alongside and bring various benefits to functions such as assembly, maintenance, quality, and logistics.

1.6 Human-AI collaboration in industry 5.0: a human-centric AI-based approach

Human-centric AI-based manufacturing has been emerging as a necessity for future industries to be prepared to encounter the dynamic market challenges. Human-centric AI-based manufacturing would foster the factories' flexibility, agility and competitiveness (Maderna, et al., 2022). As previously indicated, although the interactive collaboration between humans and intelligent machines has been introduced in I4.0, but still the majority of past and current research is system-centric, aiming to optimize system performance, limit humans to a subservient role and ensure a safe working environment for all actors (Lu, et al., 2021). However, taking the main goal of industry 5.0 (I5.0) into consideration, Human-centric AI-based manufacturing aims to reignite the human's pivotal role in the manufacturing cycle, while maintaining their cognitive and psychological wellbeing beside better opportunities for personal growth. According to (MAY, et al., 2015), human-centric manufacturing "aims to define new social sustainable workplaces where the human dimension is a key cornerstone, highlighting the requirements for shifting from a traditional task-centric production to a worker-centric production". Thus, this thesis aims to review the recent research efforts directed towards understanding the collaboration framework between the human operator and AI-powered machines.

Relevantly, (Lu, et al., 2021) proposed an anthropocentric human–machine symbiosis framework that augments human capabilities and well-being in an industrial working environment. Briefly, the proposed framework presents a reference model of human-centric manufacturing, focusing on the simplest form of human-centric manufacturing systems, where humans work with empathic machines in a symbiosis relationship. Simply, "human and machine agents form intelligent teams to collectively sense, reason and respond to incoming manufacturing tasks to ensure productivity and workforce well-being" (Lu, et al., 2022). According to (Lu, et al., 2021), this reference model prioritizes: (a) *human centrality* – the ability to focus on human desire and judgment; (b) *social wellness* – the ability to detect and respond to human physical and mental performance to maximize human wellness; and (c) *adaptability* – the ability to learn from the environment and change behavior based on that learning.

Additionally, this reference model represents the interactions between humans and machines by three fundamental blocks as follows:

1.6.1 Human-machine understanding – empathy skills

Human centricity necessitates an accurate evaluation of human physical state, cognitive workload, and the psychological reactions to elevate operator's performance via human–machine collaborations. Thus, this work will review the recent technologies incorporated to enable the machines to understand its human partner's state.

1.6.1.1 Understand human states

So far, different tools and techniques have shown a promising potential in understanding the three human states, as reviewed by (Mark, et al., 2021). This work reviews the most relevant topics in this direction.

In the first place, physical and mental state can have a significant impact upon operator's work performance (M. Marcora, et al., 2009), as they could cause difficulties in completing manufacturing tasks, higher stress levels, lower satisfaction and ultimately diminishing productivity (Peruzzini, et al., 2020). In a human–machine collaboration framework, dynamic human physical, cognitive, and psychological states can be indirectly inferenced from signals, such as emotional prosody, facial expressions, body poses, eye gaze, and pupil dilation (Lu, et al., 2021). In the future, machines would have to develop the skills to "observe a human counterpart's physical and mental state, establish a human-centric world model, and generate empathic behaviors that would be perceived as compassionate interactions in human environments" (Lu, et al., 2021). In this direction, (Romero, et al., 2016) proposed a vision for the "Operator 4.0" in the context of human cyber-physical systems (H-CPS), adaptive automation (AA), and intelligent multi-agent systems towards human-automation symbiosis work systems for a socially sustainable manufacturing workforce. Briefly, the authors define H-CPS as systems engineered to both "improve human abilities to dynamically interact with machines in the cyber and physical worlds by means of 'intelligent' human-machine interfaces, using human-computer interaction techniques designed to fit the operators' cognitive and physical needs" and "improve human physical, sensing and cognitive capabilities, by means of various enriched and enhanced technologies (i.e. wearable devices)". Importantly, both H-CPS goals would be accomplished through computational and communication techniques, thus enabling adaptive control systems while maintaining the human-in-the-loop (HITL) feature. On the same line, AA refers to "the idea of having machines adapt to the cognitive and physical demands of users in a momentary and dynamic manner" (A. Hancock, et al., 2013), thus allowing a "dynamic and seamless transition of functions (tasks) allocation between humans and machines that optimally leverages human skills to provide inclusiveness and job satisfaction while also achieving production objectives" (Romero, et al., 2016). Finally, an intelligent agent is an entity (human, artificial or hybrid) capable of observing information about the surroundings, developing situational awareness, making decisions, modifying its plan of action and negotiating with other agents for various purposes (Kasabov & Kozma, 1998).

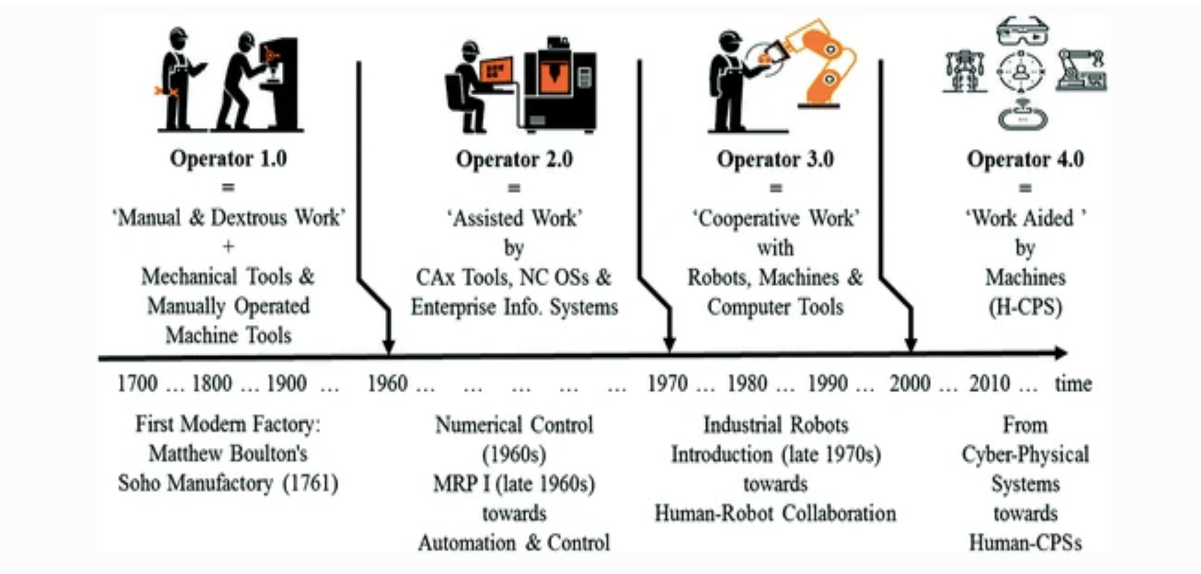

Figure 14 Evolution of Operator X.0 Generations (Romero, et al., 2016)

Through the utilization of the mentioned conceptual tripod, the "operator 4.0" vision proposed three automated frameworks dedicated to aiding workers for enhancing their capabilities: Sensorial Assistance Systems, Physical Assistance Systems, and Cognitive Assistance Systems. In brief, A sensorial capability is defined as the ability of the worker to acquire information from the surrounding environment, which provides the base for creating the fundamental knowledge for decision-making and adequate orientation during a workflow (Attwood, et al., 2004). To illustrate, according to (Mark, et al., 2019), sensorial assistance systems are already being utilized in many factories to support disabled workers' sensorial awareness. For example, warning lights mounted on top of doors or equipment are incorporated to indicate the manufacturing plants' status and aid persons with hearing problems to boost risk awareness early enough and react appropriately. Also, to follow-up the operators' health in real time, smart watches (integrated with sensors) can be utilized in industrial eco-systems (Lughofer & Sayed-Mouchaweh, 2019). In the future, new algorithms should be developed for "cooperative and collaborative learning of situations for collective sense-making and decision-making by sensor agents (including agent networks)" (Romero, et al., 2016), thus facilitating the utilization of the situational knowledge base of participating agents to filter irrelevant data, strengthen weak but relevant signals, and negotiate signal bandwidth for priority communication. Ideally, ML technologies could be incorporated to develop situational awareness. To illustrate, Advanced Trained Classifiers (ATCs) is a ML technique that can be embedded in an intelligent sensor agent to support human-automation symbiosis, learn about the operator's behaviour in action, proactively intervenes when an operator needs assistance, and accordingly pick the adequate type and level of sensing (aided) capabilities to facilitate optimal sensing performance by the operator (Woźniak, et al., 2014) .

On the other side, a physical activity refers to any movement exerted by the human body's skeletal muscles that require expenditure of energy. In an industrial context, it resembles "the operator's ability and capacity to perform physical activities required for daily work and can be characterized by physical functions such as the ability to assemble, manipulate, and lift—together with their non-functional properties, e.g., precision, dexterity, speed, and strength" (Romero, et al., 2016) . The vision of Operator 4.0 highlights the fact that human's capabilities are dynamic, as they change over time and according to the surrounding context (i.e. the operator may get exhausted over the working day). Therefore, developing a physical assistance system would necessitate a dynamic, real-time assessment of the operator's physical state. Again, relying upon a group of ML techniques, ATCs could provide a real-time assessment of the worker's physical performance and adequately decide the timing to intervene without obstructing the workflow's rhythm, thus reducing accidents, injuries and production's scrap rate. As well, to involve persons with disabilities in the industrial environment, various physical assistance systems have been made available on the market. To illustrate, (Mark, et al., 2019) stated that "collaborative robots can be used to compensate physical disabilities of workers, as they can be integrated in a standard manual workstation as an additional and individual aid component to give lifting support or to hold parts while the operator is executing".

Finally, a cognitive capability is the "operator's capacity and ability to undertake the mental tasks (e.g. perception, memory, reasoning, decision, motor response, etc.) needed for the job and under certain operational settings" (B. Carroll, 1993). Due to the expected dynamicity of the future factories' working environment, cognitive assistance systems that both models and monitors an operator's mental workload has emerged as a "central topic in optimizing industrial worker's cognitive state and increasing manufacturing performance" (Lu, et al., 2022). Integrated with AR technologies and intelligent HMI, such systems would level up the operator’s mental performance in terms of a boosted cognitive workload (i.e. diagnosis, situational awareness, decision-making, planning, etc.), thus improving the worker’s well-being and the production system’s overall performance (Romero, et al., 2016). As well, research efforts have been directed towards utilizing the objective cognitive measures (i.e. blood pressure, eye movement, and breath rate) together with ML technologies and data analysis methods to better estimate a human’s cognitive state. For example, (F. Wilson & A. Russell, 2003) proposed using statistical machine learning to fit a model which enables prediction of mental workload from the physiological signals, and then use that model to make mental workload estimates from newly-gathered physiological signals. Furthermore, similar to the previously mentioned assistance systems, relying upon a group of ML techniques, ATCs could provide a real-time assessment of the worker’s cognitive performance and adequately decide the timing to intervene without obstructing the workflow’s rhythm., thus reducing accidents, injuries and production’s scrap rate (Woźniak, et al., 2014).

To sum up, the main goal behind developing empathy skills in smart machines revolves around laying the foundations for a trust-based relationship, which have been seen as a fundamental component of interactions and productive collaborations between humans and machines (Lee & Moray, 1992). On the other side, it is also essential for humans to understand and keep an eye on the health of smart machines, leading to a better human–machine relationships. Followingly, dynamic task allocation and adjustment based on human and machine states of health can help maximize human–machine team performance.

1.6.2 Human-machine collaborative intelligence

Developing empathic understanding between humans and machines opens the door for collaborative intelligence. System-centred manufacturing control strategies, such as man-on-the loop (MOTL) control systems, support a paradigm shift from a direct human intervention to indirect human supervision (Cimini, et al., 2020). Such strategies proved to be insufficient to meet the expectations of the future factory (Lu, et al., 2021). As well, AI advancements are stirring people’s concerns of being displaced on the shop floors (Frank, et al., 2017). However, research suggested that better system performance is achieved when humans and AI systems join forces to form CI (Wilson & Daugherty, 2018). Interactive collaboration strategies between humans and empathic machines necessitates the development of the best-fit collaboration mechanisms and action plans in a dynamic setting. Hence, manufacturing control needs to adapt in learning, reasoning, and control (Lu, et al., 2022).

1.6.2.1 Learning and reasoning

In a human-centric manufacturing paradigm, both machines and humans need to learn and update their knowledge on a regular basis (Li, et al., 2021). The Co-evolution direction suggests that "humans and machines need to fully take their respective advantages to learn their own knowledge and learn from each other" (Lu, et al., 2022). This sub-section spots the light on the learning content and sources, the methods of learning and reasoning, and knowledge update and transfer within agents.

1.6.2.2 Learning content and source

In essence, the learning material is knowledge. Knowledge can be branched into conceptual knowledge (CK), which resembles the rules and relationships that establish a domain , and procedural knowledge (PK), which resembles the know-how of performing a specific task (Canobi, 2009).

In a manufacturing context, the sources of knowledge are various and not easy to classify. However, the data format of learning sources can be collected in the form of either structured or unstructured data. Structured data are "organized data which have a known structure, size, and format,making it suitable for indexing and automated metadata creation allowing for thecreation of searchable, indexable, and retrievable data management systems" (Merritt, et al., 2019) , while unstructured data is simply the opposite. Although the management of different data formats is relatively more critical to the learning process of machines, humans still learn through unstructured data in the form of visual, auditory, textual, and tactile information. To this purpose, based on the learning sources, data format, and knowledge type, (Lu, et al., 2022) briefed a comparison between the different manufacturing stages including product design, manufacturing plan, manufacturing process and maintenance. To illustrate, the conceptual knowledge required for the product design stage can be acquired from design manual, engineering drawing, or defect report in both structured and unstructured data (text, image, audio and video). Regarding a manufacturing plan, both conceptual and procedural knowledge need to be acquired from an ERP system or a production schedule in both structured and unstructured data (text and image). To learn the core manufacturing processes and accompanied maintenance tasks, both conceptual and procedural knowledge need to be acquired from G-code, inspection data, or operation logs in both structured and unstructured data (text, image, audio, video, and sensor data).

1.6.2.3 Learning methods

The construction of cognitive schemas is the pivotal component of human learning (N. Pirnay-Dummer & M. Seel, 2017). Briefly, Cognitive-behavior therapists define schemas as "cognitive structures that organize thought and perception. Schemas are also viewed as having an integral influence on emotion and behavior" (Dattilio, 2007). To a certain degree, machine's learning of knowledge is similar to constructing cognitive schemas in human learning. However, instead of constructing a cognitive schema, "an important tool in database theory and technology is the notion of the database schema" (Burgin & Mikkilineni, 2021).

Humans learn conceptual knowledge via different methodologies including: inductive learning and elaboration learning. Inductive learning is "a learning method which applies inductive consequence. Inductive consequence applies inductive methods to summarize general knowledge from sufficient specific examples, and to distill general law of things" (Wang, et al., 2009). Inductive learning is applied for understanding and distinguishing general concepts, similar to the pattern recognition task for machines (Paolanti & Frontoni, 2020). On the other side, elaboration learning integrates new information with existing cognitive schemas in memory (Willoughby, et al., 1997). In other words, elaboration learning is applied for understanding new information based on established general knowledge, similar to meta learning tasks for machines (Vanschoren, 2019). To note, Meta-learning refers to "the science of systematically observing how different machine learning approaches perform on a wide range of learning tasks, and then learning from this experience, or meta-data, to learn new tasks much faster than otherwise possible" (Vanschoren, 2019).

Alternatively, humans learn procedural knowledge via different methodologies including knowledge compiling and Knowledge strengthening. Knowledge compiling refers to "figuring out the workflow from procedural information" (R. Anderson, 1993). In other words, knowledge compiling revolves around simplifying general knowledge into more fundamental knowledge, so it can be reusable in other situations (Corney, et al., 2010). To some extent, Knowledge compiling works in a similar manner to partial tasks of machine reasoning (Lu, et al., 2022). Simply, machine reasoning refers to "the ability to dynamically react to change and by doing this, reusing existing knowledge for new and unknown problems. With machine reasoning, problems are solved in ambiguous and changing environments" (Buest, 2017). On the other side, knowledge strengthening refers to enhancing skills from repetitive practice (Palmeri & J., 1999). In fact, knowledge strengthening is similar to reinforcement learning to a great extent , which improves skills through continuous trial and error. In other words, reinforcement learning is the problem faced by an agent that must learn behavior through trial-and-error interactions with a Dynamic environment (Kaelbling, et al., 1996).

1.6.2.4 Reasoning

In an industrial environment, the ultimate purpose of learning is not limited to obtaining knowledge, but stretches towards utilizing it to make decisions via reasoning (Leighton, 2004). This sub-section reviews reasoning tasks separately to emphasize the process and decision-making method in manufacturing processes.

In fact, there are several ways to start with information and arrive at an inference; hence, there are several theories to explain the process of human reasoning. Surely, each theory has its own strengths, weaknesses, and applicability to the real world. Human reasoning methodologies can be branched into three types: inductive reasoning, deductive reasoning and abductive reasoning (Ratajczyk, 2017). Similar to human reasoning, machine reasoning systems are based on a couple of pillars: knowledge base and inference engine. Briefly, knowledge base refers to “different ways of representing knowledge, including logical rules, knowledge graphs, common sense, text evidence, etc.” (Lu, et al., 2022). On the other side, inference engine refers to a “system component that applies logical rules to the knowledge base for translating information into a new idea” (McNally, 2022). In other words, an inference engine is responsible for delivering a solution to a particular problem (Duan, et al., 2020). Widely known reasoning methods can be branched into: symbolic reasoning, probabilistic reasoning, neural-symbolic reasoning, and neural-evidence reasoning (Lu, et al., 2022). In the manufacturing process, the majority of machine decision-making processes involve machine reasoning.

1.6.2.5 Knowledge update and transfer

Knowledge is an integral factor behind up-skilling human and machine agents in a SF. The knowledge update of each entity and the knowledge transfer between different entities deepens human-machine teaming towards “Co-evolution” (Lu, et al., 2021). Commonly, Knowledge update and transfer take place in different directions: human-to-human (HTH), human-to-machine (HTM), machine-to-human (MTH), and machine-to-machine (MTM).

In the HTH direction , operators regularly acquire new knowledge together via different learning sources to match the ever-changing requirements of factory technological upgrades. In the HTM direction, machines use the vast amounts of data to learn human knowledge and mimic his physical tasks. Thus, a machine could better collaborate with humans, ensure his safety, reduce his work stress, and understand both of his short-term and long-term.

In the MTH direction, humans acquire new knowledge discovered by intelligent machines. To illustrate, Hanson Robotics is building humanoid robots with AI-based generative design solutions and this knowledge can be transferred to human designers (Daley, 2021). However, knowledge transfer is not simple due to the complicated interpretability of deep learning (DL) algorithms. So, it would be of great benefit to develop interpretable and explainable AI accompanied with user-friendly HMI to facilitate transfering new knowledge from machines to humans and make the human operator reach the top of his needs' pyramid (Personal growth).

In the MTM direction, machines regularly update their knowledge base from different learning sources and share it with other machines to achieve swarm intelligence (Lu, et al., 2022). Simply, Swarm intelligence refers to "a swarm of agents (biological or artificial) which, without central control, collectively (and only collectively) carry out (unknowingly, and in a somewhat-random way) tasks normally requiring some form of intelligence" (Beni, 2020). Transferring knowledge between the same type of machines for performing the same task is quite simple. However, transferring knowledge between machines of different types for performing different tasks is still challenging (Lu, et al., 2022). Therefore, deeper studies of transfer learning and swarm learning might provide solutions to the mentioned challenges.

1.6.3 Human-machine communication

The third component of human-centric manufacturing is "natural bidirectional communication" (Lu, et al., 2022) between humans and machine agents. Human operators depend on a set of natural language and non-verbal gestures to work as a team, transfer knowledge and accomplish tasks cooperatively. Therefore, to develop a productive collaboration between humans and machines, empathic machines that are adaptive to individual users' communicative input should be built. Despite working in a dynamic environment with continuously varying contexts, such machines could "fluidly collaborate and interact with humans and learn from or teach humans in a natural way" (Lu, et al., 2022), thus paving the way for a healthy and collaborative communication between both agents, opening the gate for satisfying the human's needs, and achieving compassion and co-evolution. According to (Lu, et al., 2021), voice commands, physical interactions, text, image, video, AR, and VR can be utilized for bidirectional communications between humans and machines and are generally simple to use if developed properly. Gesture, body pose, and brainwave recognition are applicable to HTM communication. Efficient communication in human-centric manufacturing necessitates the advancement of the traditional communication strategies to intelligently decide the content to be exchanged (i.e Suggestion, Warning, Feedback, Encouragement,..etc), timing of exchange and channel through which data should be exchanged.

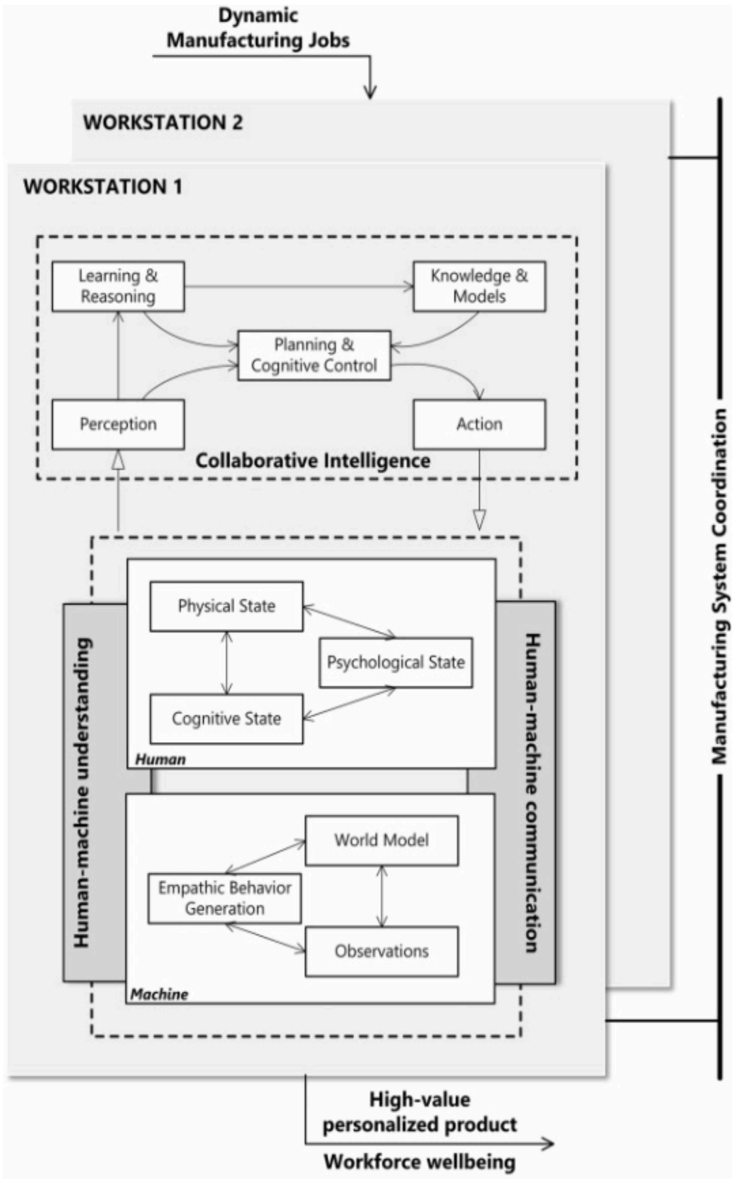

Figure 15 Human-centric manufacturing framework (Lu, et al., 2022)

1.7 A Practical Typology of the Operator 4.0 Vision

This section aims to review how the I4.0 technologies can practically support a collaborative environment between human intelligence and machine intelligence by providing an accurate evaluation and a boost to the human physical state, cognitive workload, and the psychological reactions to elevate the operator's performance. In this direction, building on the work of (Lu, et al., 2022), (Romero, et al., 2016) presented an Operator 4.0 typology that depicts how the I4.0 technologies can assist operators to become 'smarter operators' in their future factory workplaces.

1.7.1 Super-Strength Operator

This type of operator 4.0 revolves around augmenting a human operator's physical performance with a powered industrial exoskeleton. Powered Industrial Exoskeletons refer to "wearable lightweight, flexible and mobile, representing a type of biomechanical system where the human-robotic exoskeleton powered by a system of motors, pneumatics, levers or hydraulics works cooperatively with the operator to allow for limb movement, increased strength and endurance" (Romero, et al., 2016). Powered exoskeletons could help operators find the right balance between manual and automated operations in production systems, which would help them avoiding compromising efficiency for flexibility. To illustrate, in assembly areas, where workers likely approach manual tasks (i.e. Lifting heavy objects), powered exoskeletons may promote the collaboration between humans and technology to simplify the workflow and reduce the physical stress, thus boosting the human operator's stamina, saving the human's cognitive and creative efforts for more complicated activities, and improving the overall system's performance (Romero, et al., 2016). Additionally, such technology would be a determinant factor behind extending the careers of aging workers and taking advantage of their experiences, as it optimizes their physical performance and diminish the chances of work-related injuries. Needless to mention, integrating powered exoskeletons with AI/ML technologies could open up bigger opportunities. According to (Zaroug, et al., 2018), "a major challenge in current exoskeleton designs is the need to synchronise user intention with exoskeleton function to achieve smooth interaction between the user and device. The fusion of intelligent ML algorithms into the exoskeletons controller has potential to improve the human machine interface and user experience". For example, Hidden Markov Model (HMM) and Support Vector Machines (SVM) have shown promising performances in performance in motions classification (Zaroug, et al., 2018).

1.7.2 Augmented Operator

As highlighted in section 1.3, AR technology may help optimize the human operator's cognitive workload by offering him a real-time digital assistance system for completing manual activities without exhausting his memory into paper-based instructions and computer screens, thus diminishing the chances of human errors. Moreover, through the deployment of IoT and SCADA systems, AR technology can introduce a new HMI to manufacturing IT applications and assets, providing real-time status of processes and machines to the operator to further support his decision-making (Palmarini, et al., 2017).

Additionally, AR can re-shape the maintenance of assets via "diagnostic intelligence" based on data collected from mounted sensors to provide workers with a live "intra-factory overview" of production lines for monitoring, identifying, analyzing, diagnosing and resolving problems in the right moment, thus optimizing the operational efficiency (Romero, et al., 2016). To note, further details about the integration of AR with AI/ML technologies, VR, RFID readers, and QR codes were provided earlier in a separate subsection.

1.7.3 Virtual Operator

In general, VR refers to "the re-creation (partially or entirely) of a scene/object/event so as to give a perception of physically being there" (Toshniwal & Dastidar, 2014). In a manufacturing context, VR can "digitally replicate a design, assembly or manufacturing environment and allow the smart operator to interact with any presence (i.e. a hand tool) with reduced risk and real-time feedback" (Romero, et al., 2016). Thus, VR technology can integrate interactive virtual reality, accurate simulations of real-life scenarios, and other innovative technologies to develop the operator's cognitive workload, optimize the operator's decision-making, and facilitate up-skilling the operators via personalized training programs (Palmarini, et al., 2017). Similar to AR, manufacturing companies can utilize VR to "digitalize, analyze and simulate all the aspects of a product, as its geometric structure, physical behavior, etc., including the simulation of all the processes related to the product lifecycle" (Schina, et al., 2016). At the product manufacturing phase, VR introduces the concept "virtual factory" as "an integrated simulation model of the major sub-systems of a factory in order to evaluate different factory layouts, production line configurations, production balance (i.e. automation vs. mechanization) and production schedules in order to optimize the production master plan by means of what-if analyses, decision support systems and estimation methods" (Romero, et al., 2016). To foster the SF concept, (ZHU, et al., 2020) developed a cost-effective 3D-printed glove HMI with triboelectric finger bending sensors, palm sensors for sliding detection, and piezoelectric stimulators for feedback. The author integrated AI algorithms with AR/VR technologies to achieve a glove-based system capable of performing advanced object recognition.

1.7.4 Healthy Operator

This type of operator 4.0 revolves around augmenting a human operator's physical performance and cognitive workload with wearable trackers (i.e. Smart watch). Simply, wearable trackers are "devices designed to measure exercise activity, stress, heart rate and other health-related metrics as well as GPS location and other personal data" (Romero, et al., 2016). Such technologies have offered big opportunities to various fields. For example, military applications integrate wearable devices with data analytics to early anticipate potentially problematic situations (Sharma, et al., 2017) . In a manufacturing context, integrating wearable trackers with data analytics and AI technologies could help operators avoid undesirable dilemmas. To illustrate, utilizing "workforce analytics" keeps operators and upper level of management attentive to health-related metrics, which helps avoiding unexpected threats to operators' sanity in case of rising stress levels (Romero, et al., 2016). Also, such technologies could enable operators to plan and schedule their working times based on health-related metrics. According to (Naughton, 2020) , "wearable devices and AI-powered vision systems provide the capability to monitor workers safety, including the adherence of hygiene and social-distancing guidelines". Thus, taking data privacy concerns into consideration, utilizing such technologies could play an integral role in reducing the human errors, enhancing the overall system's productivity, and maintaining proactive safety frameworks for the operators under unexpected events.

1.7.5 Smarter Operator

This type of operator 4.0 revolves around augmenting the human worker with an Intelligent Personal Assistant (IPA) to boost his cognitive workload. Simply, IPA is a software agent that incorporates "a significant body of sophisticated AI technologies for knowledge representation, reasoning, planning, plan execution, agent coordination, adjustable autonomy, explanation, and learning" to facilitate "dynamic procedure learning, integrated task and calendar management, and real- time execution monitoring and prediction" (Myers, et al., 2007). Using NLP and NLU, IPAs could offer a voice-interaction technology to the human operator, which promotes productivity and operational efficiency by "allowing the operator to go hands-free to complete certain tasks" (Romero, et al., 2016). Among the tasks the IPAs assist the human workers to complete are: searching and retrieving from a digital library according to a natural voice input (i.e. Amazon's alexa), scheduling, pinpointing reminders, and planning for critical events in operations, managing inventory based on automatic stock-checks, and performing preventive maintenance based on predictive models developed to track a machine's degradation pattern to alert for proactive intervention.

1.7.6 Collaborative Operator

This type of operator 4.0 relies upon augmenting the human worker's physical performance with a Cobot. Cobots "mark a departure from traditional industrial robots which functions separated from their human co-workers. Cobots, on the other hand, are designed for direct interaction with human workers, to handle shared payload, and to function safely without conventional safety cages or similar protective measures" (Knudsen & Kaivo-Oja, 2020). Co-bots are capable of "performing a variety of repetitive and non-ergonomic tasks and that have been specially designed to work in direct cooperation with the smart operator by means of safety (i.e. force sensing and collision) and intuitive interaction technologies, including easy shop-floor programming" (Romero, et al., 2016) . The availability of such technologies would help nurturing the human worker's productivity and job satisfaction, as it frees him from doing routine/repetitive tasks to boost his self-esteem by completing creative tasks instead. Needless to mention, "intelligent robotics perception system is very important for a collaborative robot to make decisions, plan, and operate in real-world environments, by means of numerous functionalities and operations from occupancy grid mapping to object detection" (Galin & Meshcheryakov, 2020). In fact, such robotic perception systems deploy AI/ML algorithms, ranging from classical to deep learning techniques including supervised classifiers and ANN (Galin & Meshcheryakov, 2020). Further details on Cobots will be presented in section 4.

1.7.7 Analytical Operator

This type of operator 4.0 revolves around supporting the human operator's cognitive workload with BD analytics. BD Analytics is "the process of collecting, organizing and analyzing large sets of data (big data) to discover useful information and predict relevant events" (Romero, et al., 2016). Clearly, BD analytics may assist human workers completing more accurate forecasts, achieving greater transparency of operational KPIs, and keeping track of real-time status of assets, thus taking corrective actions prior to problematic situations and elevating the overall system's operational efficiency

The integration between data analytics and AI/ML technologies have attracted a significant interest over the past years, as it led to the emergence of Intelligent BD analytics as shown in Figure 16. In this direction, (Bashar, 2019) proposed an intelligent BD analytics framework that integrates text analytics, ML processes, and data mining NLP to predict the hidden knowledge in the data available through cheap sensors and the Industrial IoT. The proposed system proved its success with respect to improvising the process of manufacturing, by retaining the product consistency, optimal throughput and increasing the productivity.

The analytical operator is relevant to different other applications as many of them hugely depend on advanced data analytics. This applies to the collaborative operator, who often deploys image recognition to facilitate working near CoBots. Also, the healthy operator depends on the analytics of the health-related data gathered.

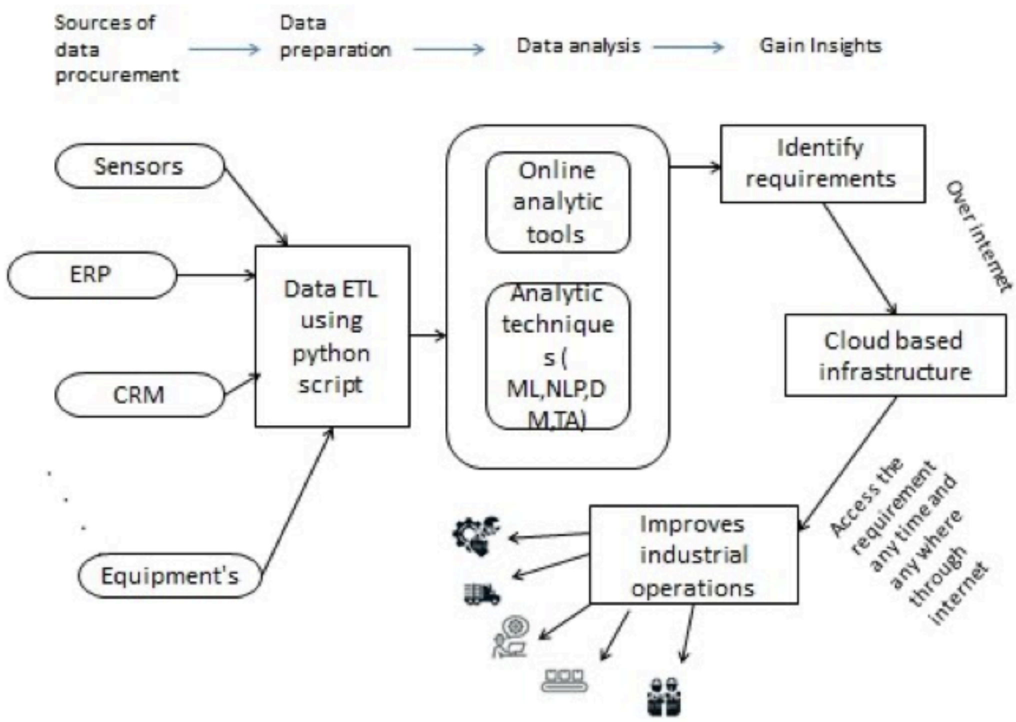

Figure 16 Intelligent Big Data Analytics in a Manufacturing Context (Bashar, 2019)

2. Research Schema

In accordance with the above considerations, this thesis provides a systematic literature review of research about CI and its potential impact upon the manufacturing industry and the MSMEs within a time frame between 1999 and 2022. By the end of a preliminary research, it has been clear that the frequency of the term "Collaborative Intelligence" in the different forms of resources (Academic Papers, Conferences Proceedings and Blogs) has experienced a rising trend over the past years. To illustrate, using Web of Science search engine, the year 2015 has seen the start of an upward trend of publishments referring to the two key words: "Collaborative Intelligence" and "Artificial Intelligence" as shown in Figure 17.

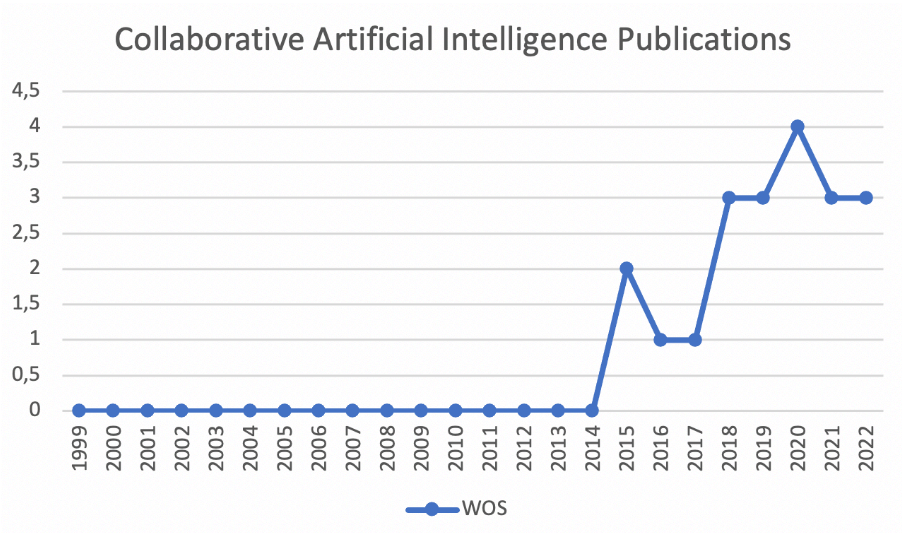

Figure 17 A Time Series of Collaborative Artificial Intelligence Publishments

Additionally, a different combination of keywords in different search engines has always resulted in different results, which necessitated the development of a classification system that facilitates analysing both the research trend and gaps with respect to the topic of interest. Furthermore, a classification system would highly help identifying the links between the topic of interest and the different sectors, thus orchestrate highlighting the potential impacts of CI on the manufacturing sector. Nevertheless, this work would open the door for the inclusion of various kinds of resources including Academic Publishments, Conferences Proceedings, Journals, Consultants' Blogs and Companies' Brochures, which would better portray the potential futuristic impacts of the topic under analysis upon the new manufacturing businesses. So, this paper aims to provide a detailed, up-to-date overview of the research conducted on the topic. However, this research does not solely revolve around providing a complete systematic analysis of the past literature on AI and CI. Instead, it focuses on setting a starting point for integrating the knowledge gathered from various research resources concerning this topic in order to suggest a schema for future research, open up a set of questions for further mining and draw a portrayal of the expected transformation of the topic under analysis in the coming years.

2.1 Methodology

The methodological approach incorporated a mixed bibliometric and content analysis techniques. In this paper, a mapping review was initially conducted through the SCOPUS database, Google and Google Scholar search engines. Regarding the publication time span, the time from 1999 to 2022 was considered in an attempt to measure the change of the level of attention towards Collaborative Intelligence before and after the introduction of I4.0. The research methodology employed throughout this study was a systematic literature review.

The main phases of the study were as follows:

1. *Phase 1: Research and Classification.* The present phase was broken into three steps:

- Step 1: Generalized Identification of Resources
- Step 2: Classification of Resources
- Step 3: Selection of Relevant Resources

In phase 1, bibliometric data was collected (step 1). Then, a classification of resources according to the different research questions was performed to outline the research in an organized manner (step 2). At the end of this phase, a selection process of resources in accordance with the prioritized research areas was conducted to spot the light on the documents to be analysed in detail (step 3).

2. *Phase 2: Analysis.* Once phase 1 was concluded, the next phase emphasized the analysis of the results. The approach used for the bibliometric analysis included:

- The use of an indicators for the parameter studied

The indicator chosen to perform the analysis was total papers (TPs), which is the total number of publications.

3. *Phase 3: Discussion*. By the conclusion of the second phase, a third one that provides a discussion of the results and a summary of the conclusions would be introduced.

Important Note: The same methodology was applied for each research question (RQ1 AND RQ2)

In Figure 18, the main phases and steps followed for the analysis are shown.

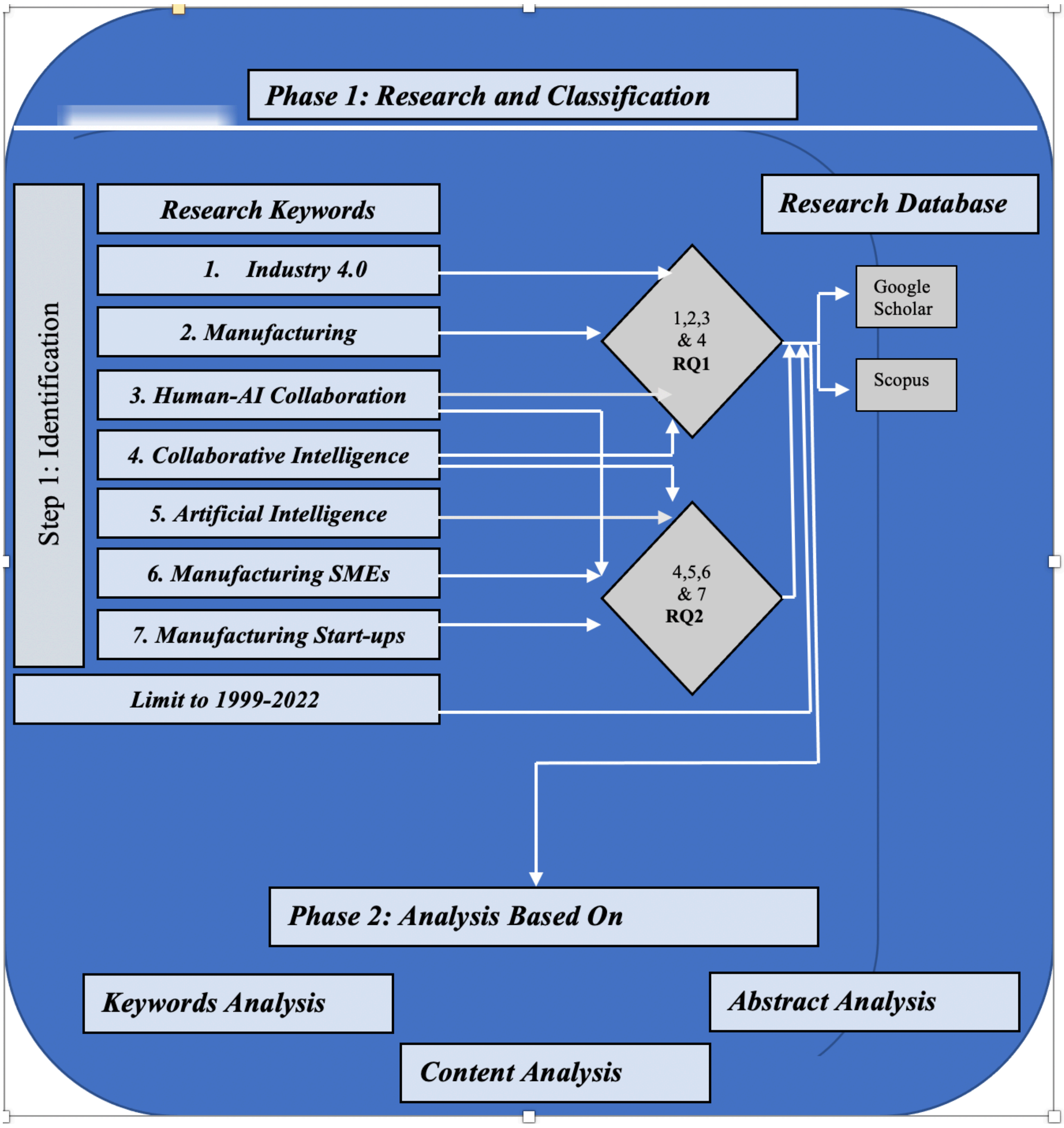

Figure 18 A summary of the Research Methodology

3. Results of the Bibliometric Analysis of Research Question 1

3.1 Phase 1: Research and Classification

The first phase consisted of the search for documents, which included the activities of collecting material belonging to the academic universe. This first phase was divided into three steps as follows.

3.1.1 Identification (Step 1)

For a comprehensive research of the research question, phenomenon, an investigation on the Scopus (SCP) and Google Scholar databases was carried out using Boolean operators. The research began by making a search query with the general key words "Collaborative Intelligence" OR "Human-AI" AND "Manufacturing" OR "Industry 4.0" as shown in Table 2.

Keywords	***Time Period***
Collaborative Intelligence	1999-2022
Human-AI	
Manufacturing	
Industry 4.0	

Table 2 Research Combination of Keywords

The search returned in total 3058 documents.

The results extracted by Google Scholar are numerically superior to Scopus (SCP): 3030 for the first and only 28 for the latter (Table 3).

Research Carried out in 2021		
Source of Research	Google Scholar	Scopus
Results	3030	28

Table 3 Research Results

In fact, the scarcity of sources on Scopus has directed the attention to the possibility of relaxing the search criteria. For example, the term “Artificial” could be used to replace the term “Collaborative”. In this case, Google Scholar yields about 17,000 search results compared to only 30 results in Scopus in the period between 2013-2022. Clearly, this indicates the low popularity of the term “Collaborative Intelligence” between researchers.

Anyway, the analysis will study the results before the relaxation of research keywords, because this thesis aims to analyse the research behaviour after the term “Collaborative Intelligence” was first coined by (Epstein, 2015). Important to mention, this time, the author was referring to the Artificial CI.

Important to note, the clear difference between the amount of search results of the two databases lies behind the unmatching effectiveness of Google Scholar and Scopus when it comes to locating recent gray literature sources (Gray literature is defined as “Information produced on all levels of government, academia, business and industry in electronic and print formats not controlled by commercial publishing”). To demonstrate, Google scholar is known for its relatively vast amount of search results as it “aims to summarize all electronic references on a subject” to “reach the widest audience available” (Falagas, et al., 2007). In other words, Google scholar is often recommended as a source of grey literature, which perfectly fits this paper’s systematic review of an under-researched topic. However, despite the availability of an ‘advanced’ search engine in Google Scholar, but it still does not enable the researcher to gain any information regarding the number of conference papers included in the academic search engine as provided by Scopus. On the same line, Google Scholar does not provide the ‘abstract and information on free full text availability’, which puts Scopus ahead with respect to this feature as it enables the researcher to be ahead of time in the inclusion phase.

The term “Collaborative Intelligence” was first introduced in 1999 to portray the potential behavior of an intelligent business "ecosystem" where CI represents "the ability to build, contribute to and manage power found in networks of people." (Gill, 2012). The introduced term has viewed social networks as “the foundation for next generation problem-solving ecosystems, modeled on evolutionary adaptation in nature's ecosystems” (Gill, 2012). Apparently, before the outbreak of I4.0 trend, CI research was only limited to conceptual efforts.

Despite being introduced by the end of the last century, but the attractiveness towards artificial CI research has just gained momentum in the last decade following the pacing developments of AI technologies. Consequently, some evolutionary terms started to float to the research community’s surface, including ‘SME 4.0’ and ‘Manufacturing 4.0’, in an attempt to prepare the entrepreneurial community to be capable of transforming their current paradigm and reaping the benefits of the upcoming wave of digitalization.

This analysis aims to highlight the link between the trends of research regarding CI, I4.0, and I5.0. Through a time-indexed time series of research documents pointing to the associated research question (RQ1), the link between the three trends has been emphasized. To demonstrate, provided below a graph (Figure 19) that provides a proof that the literature has been enriched with publishments following the attention directed to I4.0 and relevant topics. Growth is evident after 2011 when new technologies began to be researched and put into action more frequently. In fact, the I4.0 was first coined at Hannover Messe in 2011 by the Director and CEO of the German Research Center for Artificial Intelligence, Professor Wolfgang Wahlster, as a part of his ceremonial speech (Lydon, 2011). Since then, research attention has been directed towards the potential advancements in different sectors, especially the Manufacturing industry. As well, the deep analysis of the research efforts has revealed the 'significant trimming of the time needed to go from one [industrial] revolution to next one" (Rada, 2017). To elaborate, the development time for the first three industrial revolutions was around a century. However, it took only 40 years between the development of Industry 3.0 and I4.0, and only 4 years has seen the introduction of I5.0.

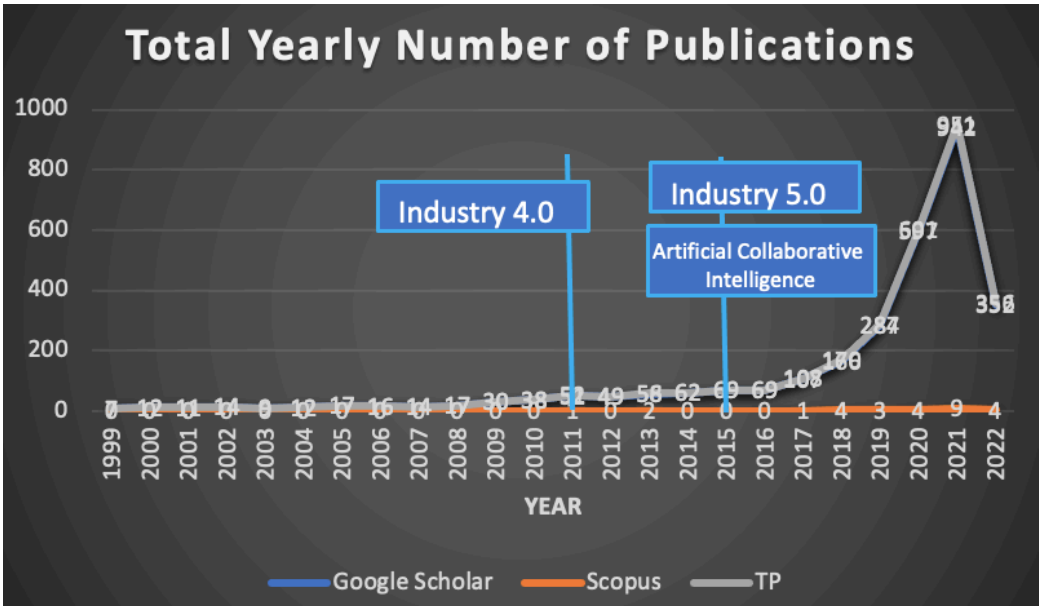

Figure 19 A Time-Series of Research Publications

In fact, this research indicates that over the time period considered (1999–2022), the number of published documents remained almost negligible until 2011, from which it undergoes a slight increase. We can relate this increase to the introduction of I4.0 initiative. Clearly, the published documents associated with RQ1 showed a noticeable increase by the end of 2015, which aligns with the introduction of Artificial CI and I5.0 in the scientific community as highlighted before. Another important note lies behind the clear overlapping of the "TP" and "Google Scholar" curves, which highlights the low share of research results provided by "Scopus" in this research question.

3.1.2 Screening (Step 2)

Following the completion of the identification phase, the thesis presents an overview of the topics and areas interface through a screening process. The screening phase revolves around an analysis of the accessible published documents. In other words, this phase required narrowing down the number of documents to be the focus of the study. So, an analysis of 'free access' documents was provided. In addition, the 'access through your institution' option provided by Direct Science, Research Gate, El-Sevier, and others, has enriched the list of accessible documents. Luckily, the inaccessible documents (due to hyperlink failures or un-authorized sign in) has shown a negligible effect upon our analysis, as less than 30 out of 3058 documents were excluded. Furthermore, in our study, we didn't believe we have to restrict our research to a specific subject area (Provided by Scopus only), as our research keywords are already restricted to the manufacturing sector.

To cut it short, the screening phase hasn't excluded a noticeable number of documents and almost all research results will enter the next phase.

3.1.3 Inclusion (Step 3)

By the completion of the screening process, the inclusion step was kick-started. This step prioritizes the selection of a portion of the documents extracted from the last step to be included in the sample on which bibliometric analysis was performed. In fact, according to earlier plans, this phase was supposed to rely upon a keywords analysis in addition to an abstract analysis. However, due to the unavailability of 'abstract preview' option in Google Scholar, we examined the full text of each document one at a time to ensure its eligibility to go through the analysis phase. For each article, we examined whether the document refers to the Human-AI collaboration theme in an entrepreneurial context or not. Also, this phase aims to check if any of the documents included case studies or real applications, suggestions for new AI and CI algorithms and architectures, or possible future scenarios.

Therefore, the final sample to be analyzed consisted of 102 documents for Google Scholar and 8 for Scopus.

3.2 Phase 2: Analysis

This section presents and discusses the findings of this review.

First, an overview of the selected studies is presented. Second, the review findings according to the research criteria, one by one in the separate subsections, are reported.

3.2.1 Top Highly Influential Analysis

This section spots the light on the most highly cited documents in Google Scholar and Scopus. In fact, in this case, a few research databases haven't provided a count of the citations. Also, the majority of documents had been recently published (between 2020-2022), which resulted in relatively lower accesses compared to earlier ones. Additionally, we need to point out that some researchers do not tend to cite the document through its publisher's database, which could sometimes lead to a misleading image. In consequence, in specific cases, we though it could be of relevance to mine the count of views and downloads to provide a clearer image. Anyway, (Spoehr, et al., 2021) has the highest citation count of 74. Briefly, this paper seeks to identify the contributions of AI to supply chain management (SCM) in various fields including production and logistics. Interestingly, the document publication year is 2021, about a year after Covid-19 outburst. To clarify, a study by PWC has claimed that "Fifty-Two percent of companies accelerated their AI adoption plans because of the Covid crisis", which correlates the huge shift of the research efforts. As well, despite being published less than a year ago, the document has been cited by many other researchers, which further stresses the viewpoint regarding the topic's research progressing maturity in the past couple of years. On the same line, the study reveals that research efforts associated with RQ1 have jumped 5 times between 2019-2021, which emphasizes the market's shift towards the adoption of Artificial CI technologies and justifies the recognizable interest of the scientific community in the topic.

The citation analysis has also revealed that the first book that we can identify among the most downloaded in the I4.0 period dates to 2021. (Helo & Hao, 2021) spots the light on several areas of value creation for the application of Artificial CI technologies in the supply chain. It also proposes an approach to designing business models for AI SCM applications. This book has seen 11724 downloads. Moreover, although it has been published a couple of months ago, (Lu, et al., 2022) caught much attention among the scientific community. To elaborate, 416 users have accessed and viewed the document. It contributes by presenting "arguments on the concept, needs, reference model, enabling technologies and system frameworks of human-centric manufacturing, providing a relatable vision and research agenda for future work in human-centric manufacturing systems” (Lu, et al., 2022).

3.2.2 Publications by Years

Consistent with the analysis in Section 3.1.1., the study points out that the number of documents included in the analysis is apparently negligible for the entire period before the introduction of the terms Artificial CI and Industry 5.0 in 2015. However, as expected, the relevant research shows a slight increase, starting in 2016. The data shown in Figure 20 also shows a relatively fewer documents in the period between 2015-2018, compared to the apparent boom in research afterwards.

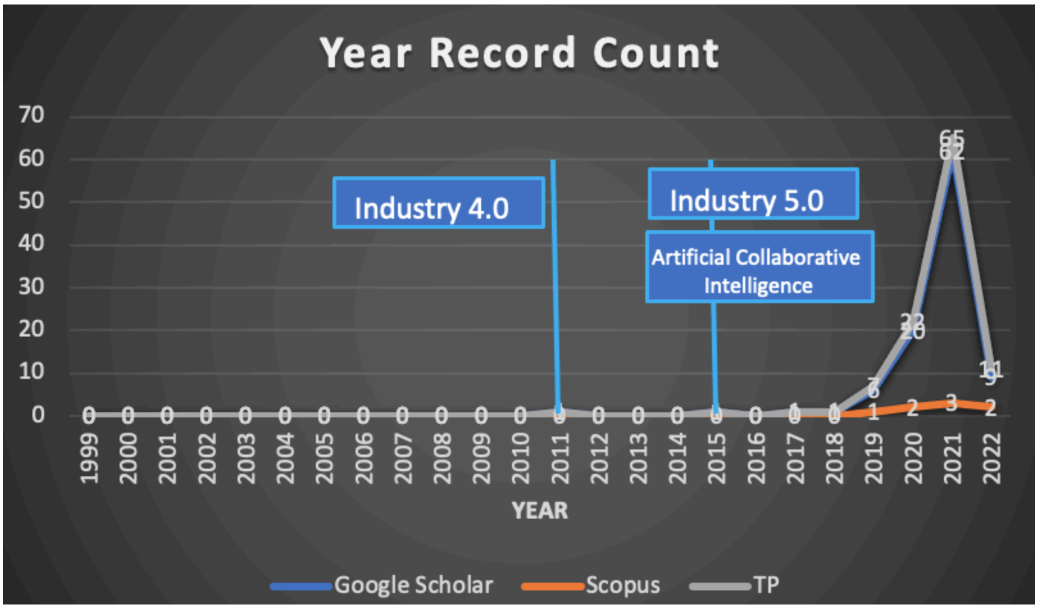

Figure 20 A Time Series of the Inclusion Results

In addition to the highlighted effects of Covid-19 on the research behaviour, certain technologies have taken significant steps. Autonomous driving, NLP, and quantum computing are example of the technological leaps that matured between 2020 and 2021.

With reference to 2022, the figure refers to the first four months of the year, so it is expected that during the year, there will be a further increase in the documents in the literature.

3.2.3 Country Analysis

This section’s main focus is determining the countries contributing the most to the research relevant to RQ1. To note, prior to conducting this specific analysis, we had to exclude all documents in Chinese and Japanese languages. In other words, this section might be slightly biased towards Europe, United States and United Kingdom.

In brief, the countries that give the most contribution are: The United Kingdom (16.1%), Sweden (15.2%) and the United States (13.4%). Following its 10-year plan to make the country a global 'artificial intelligence superpower', The United Kingdom has retained its leading position among the field's big players during the past couple of years. Interestingly, when it comes to Europe, Sweden comes on top of the list of contribution. To demonstrate, although I4.0 was first introduced in Germany, but Sweden "is at the global forefront of I4.0. With clean energy, advanced technologies and a thriving culture of collaboration, there is no better place to lay the groundwork for sustainable and digitally powered operations" (BusinessSweden, 2021).

In addition, it is worth mentioning that Europe has contributed with 54.5% of the available resources. This high contribution could be related to the fact that "since 2017, France, Germany, and Italy relations have intensified their trilateral cooperation to promote digitizing the manufacturing industry" (Yang & Gu, 2021), which arguably brought the I4.0 research and corresponding topics to lead the line. Following this trend, we anticipate a recognizable evolution of smart production and entrepreneurial initiatives and therefore a further maturation of scientific research.

3.2.4 Key Take-aways of Analysis

This section highlights the main outcomes of the second phase:

- Google Scholar is superior to Scopus in terms of the availability of resources corresponding to the input combination of keywords
- The research efforts associated with the research question have seen a slight increase starting from 2011 (Introduction of I4.0)
- A standout increase in research efforts have been noticed starting from 2021
- Research efforts associated with RQ1 have jumped 5 times between 2019-2021 following the outburst of Covid-19 pandemic
- Countries that give the most contribution to research are: The United Kingdom (16.1%), Sweden (15.2%) and The United States (13.4%)
- Europe has contributed with 54.5% of the available resources
- Asia has contributed with 20.54% of the available resources

- One of the trending keywords that emerged during the research is "Industry 5.0"
- The research was adjusted to make a search query with the general key words "Collaborative Intelligence" OR "Human-AI" AND "Manufacturing" AND "Industry 5.0" as shown in Table 4.

Keywords	***Time Period***
Collaborative Intelligence	1999-2022
Human-AI	
Manufacturing	
Industry 5.0	

Table 4 The adjusted Research Combination of Keywords

The search returned in total 61 documents.

The results extracted by Google Scholar are numerically superior to Scopus (SCP): 60 for the first and only 1 for the latter (Table 5).

Research Carried out in 2021		
Source of Research	Google Scholar	Scopus
Results	60	1

Table 5 Research Results of Adjusted Combination of Keywords

- The research efforts have then enjoyed a relatively larger increase after the introduction of the terms 'Industry 5.0' and 'Artificial Collaborative Intelligence' (ACI) were first introduced in 2015

4. Literature Survey of Research Question 1

4.1 Industry 5.0: A New Evolution of the Fourth Industrial Revolution

I5.0 refers to the conceptual leverage of the collaboration between the cognitive creativity of the human factor and the increasingly powerful, smart, and accurate machines. The term I5.0 has been introduced for the first time by Michael Rada (Known as the father of I5.0) by the end of 2015 (Rada, 2017). Despite being still far away from implementing I5.0 due to industry leaders' on-going belief in I4.0 ideology, but different research studies believe that I5.0 will reignite the necessary 'human touch' in the manufacturing industry (Nahavandi, 2019). Expectedly, I5.0 would further facilitate mass personalization, which could be a differential competitive advantage in the near future. To elaborate, following the rapid, consecutive technological advancements, customers are expected to demand customized products in accordance with their personal needs as indicated in Figure 21.

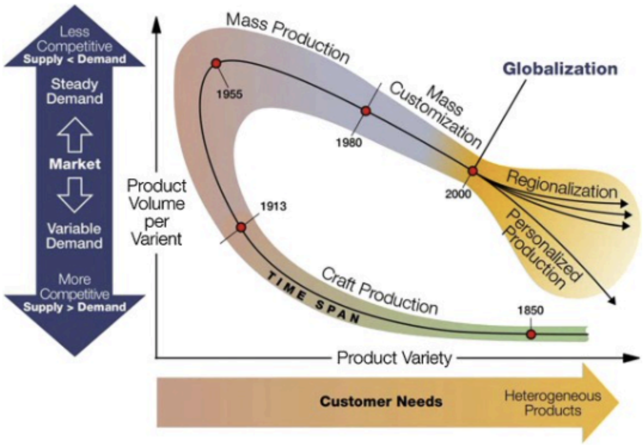

Figure 21 Manufacturing Paradigm Shift Towards Mass Personalization (Lu, et al., 2020)

Additionally, I5.0 would hugely enhance manufacturing efficiency and create a transparent channel between humans and machines, applying a shared responsibility for interaction and regular activities tracking. Nevertheless, the collaboration between humans and machines would expectedly increase the production capacity at a rapid pace. By the means of assigning routine/repetitive tasks to machines and freeing the human factor to be responsible for executing the non-routine/creative tasks, I5.0 would supposedly leave a huge, positive impact upon the quality of products and production processes.

Normally, I5.0 necessitates the availability of more skilled jobs compared to I4.0 as a result of the transformation in the way of doing things in businesses. I5.0 spots the light on mass customization, where humans will be guiding robots. Alternatively, in I4.0, robots are coordinated to facilitate large scale production, whereas I5.0 focuses mainly on a personalized customer satisfaction. I4.0 focuses on CPS connectivity, while I5.0 links to I4.0 applications and establishes a relationship between cobots. I5.0 incorporates predictive analytics and operating intelligence to develop models that help making better decisions in unstable conditions. In I5.0, most of the production process will be automated, as real-time data will be gathered from machines/devices in collaboration with highly skilled specialists.

4.1.1 Core Values of Industry 5.0

I5.0 is based upon a tripod of interconnected core elements provided below:

Human-centricity: shifting from the I4.0's technology-driven approach, the human-centric paradigm re-locates the human needs at the core of the productions cycles and makes sure the technologies incorporated intersect with those needs (i.e autonomy, safety and well-being). Thus, human operators would be considered as "investment" instead of being viewed as "cost" (Jafari, et al., 2022). In return, operators would need to keep upskilling and re-skilling themselves to better fit the job requirements of I5.0 (Breque, et al., 2021).

Sustainability: I5.0 necessitates the development of "circular processes" needs to develop circular processes that re-use, re-purpose and recycle natural resources, reduce waste and environmental impact, and ultimately lead to a circular economy with better resource efficiency and effectiveness" (Breque, et al., 2021).

Resilience: I5.0 supports the development of a more robust industrial ecosystem in order to be capable of managing unexpected situations and crisis. To demonstrate, "Geopolitical shifts and natural crises, such as the Covid-19 pandemic, highlight the fragility of our current approach to globalised production. It should be balanced by developing sufficiently resilient strategic value chains, adaptable production capacity and flexible business processes" (Breque, et al., 2021)

Figure 22 Core elements of Industry 5.0 (Xu, et al., 2021)

4.1.2 Features of Industry 5.0:

4.1.2.1 Smart Additive Manufacturing (SAM)

Additive manufacturing (AM) is “the sustainable approach adopted for industrial production, which builds the product part layer by layer instead of a solid block, thereby developing lighter but more robust parts one layer by layer” (Maddikunta, et al., 2022) . AM is considered one of the essential components of I4.0, as it could be an answer to the uprising mass customization. To elaborate, by including benefits in products with a focus on the customer satisfaction, AM might become a “key technology for fabricating customized products due to its ability to create sophisticated objects with advanced attributes” (Dilberoglua, et al., 2017). In accordance with I4.0 values, AM “facilitates transparency, interoperability, automation and practicable insights” (Haleem & Javaid, 2019). The recent technological advancements with respect to AI, IoT, CC, BD, CPS, 5G, DT and EC have significantly supported the development of smart manufacturing, thus achieving higher degrees of sustainability, profitability and productivity. As an additional feature that differentiates I5.0, SAM incorporates AI technologies and computer vision to provide better graphical representation and more accurate product design in 3D printing. SAM is defined as “a fully integrated, collaborative additive manufacturing system that responds in real time to support ubiquitous and intelligent design, manufacturing, and services of 3D printed products” (Wang, et al., 2020). Simply, SAM defines the different processes to manufacture a product by adding materials in various layers, thus helping the reduction of material consumption, and saving of energy resources. To harness the full potential of I5.0, SAM is “merged with integrated automation capability to streamline the processes involved in supply chain management and reduces the delivery time of the products” (Maddikunta, et al., 2022). According to (Montazeri, 2019), the fundamental research aspects necessary to promote such a SAM paradigm are as follows:

- Pragmatic Experimentation: Repeat experiments trying to initiate a particular type of part defects (i.e., porosity) and determine the quality of the parts using offline measurement techniques (i.e., X-ray).

- In-Process Heterogeneous Sensing: Mount multiple types of sensory devices inside the AM system and collect sensor data during the process.

- BD Analytics and AI: Advanced analytical algorithms to extract and correlate features and patterns from the vast amount of heterogeneous sensory data to specific defect types.

- Process Knowledge (Modeling): Develop theoretical models to emphasize the reasons behind the defect occurrence.

- Process Innovation: Recommend manufacturing strategies to avoid defects in future parts with minimal experimentation. For example, “devise closed-loop controls” could be developed to “ensure that the defect in a layer is corrected before the next layer is deposited” (Montazeri, 2019).

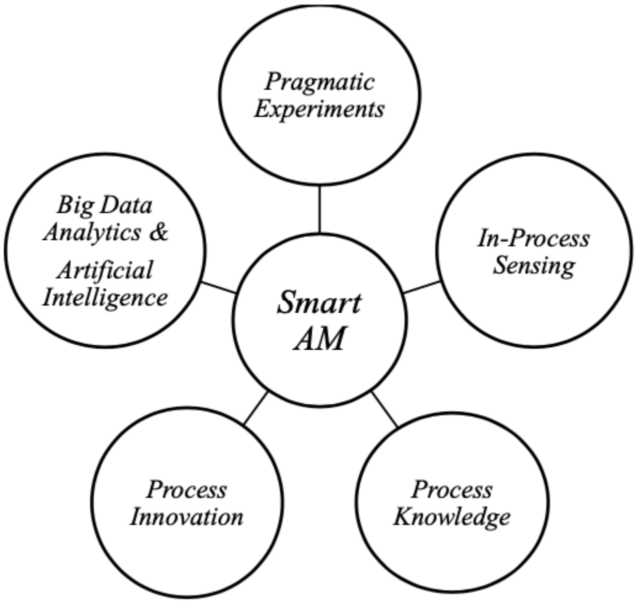

Figure 23 Fundamental aspects of Smart Additive Manufacturing (Montazeri, 2019)

4.1.2.2 Predictive maintenance (PdM)

Considering the steady steps towards the economic globalization, the industries would likely need to be prepared to encounter different challenges. Such challenges urge the manufacturing industry to utilize the recent technological transformation trends. Predictive maintenance (PdM) is considered one of the most promising technologies in I4.0. To foster both productivity and efficiency, the manufacturers directed their attention to adopting the evolving technologies, such as CPS approaches and advanced analytical methods (Zonta, et al., 2020). In I4.0, PdM facilitates performing maintenance cycles prior to a component/machine’s failure, thus avoiding unexpected downtimes and negating the need for costive scheduled maintenance (Compare, et al., 2019). Clearly, instead of the vague assumption of a machine’s continuous availability, PdM promotes a transparent manufacturing sphere in terms of a fair estimate of the production system’s state after uncovering and evaluating the uncertainties. This feature necessitates the deployment of "state-of-the-art prediction tools" to transform the data collected from smart sensor networks into insightful information of uncertainties to support the human operators with taking smart decisions. On the other side, I5.0 aims to re-locate the human operator in the center of predictive maintenance framework. Briefly, to maximise the potential of PdM, it "should be integrated into the Digital Twin of the asset, [so] any number of views can be configured to display valuable information required for different tasks" (Ash, 2019). To illustrate, through visualizing a DT, an automotive engineer could quickly identify the close-to-failure component and assess the option of replacing it during the scheduled service instead of risking the waste of time due to its failure between services.

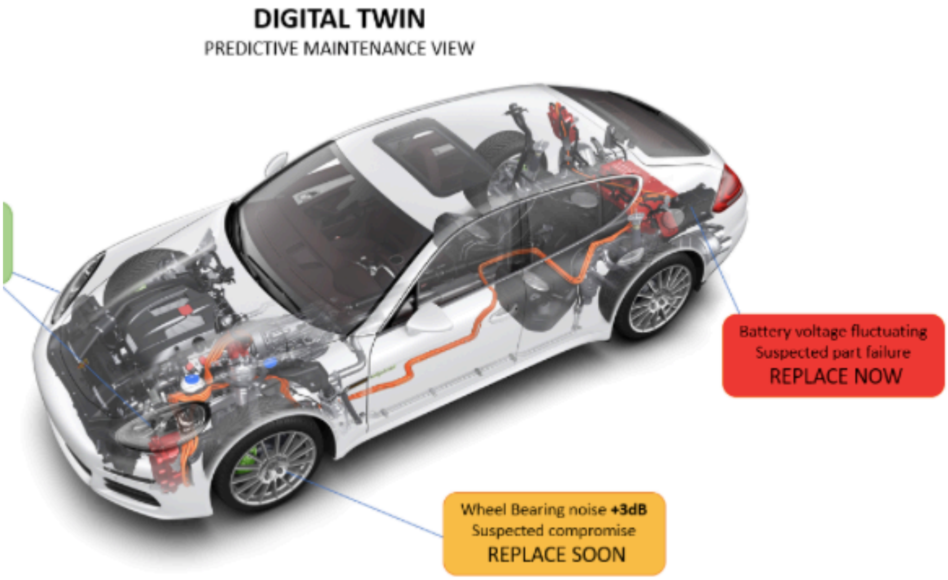

Figure 24 Digital-Twin Supported Predictive Maintenance in Industry 5.0 (Ash, 2019)

4.1.2.3 Hyper customization

I4.0 has shown success when it comes to networking autonomous machines, promoting intelligent supply chains and diminishing the role of the human factor in the industrial ecosystem. Although customization of products is an aspect of the I4.0 paradigm, but "the effort is not adequate to satisfy the personalization demands for different verticals" (Dev, et al., 2021). On the other side, relying upon the human-machine interaction and hyper customization, I5.0 aims to enhance the personalization capabilities integrated in the industrial ecosystem where the customized prerequisite of clients could be satisfied with minimum cost and highest efficiency (Dev, et al., 2021). Simply, Hyper customization is "a personalized marketing strategy which applies cutting-edge technologies such as AI, ML, cognitive systems and computer vision to real-time data in order to provide more specific product, service and content to every customer" (Maddikunta, et al., 2022). The collaboration between human intelligence, AI and cognitive systems aids manufacturers to respond to market changes and mass customize the products as “many variants of the functional material is shared with other personnel with the motive of customizing the product with different variants for customers choice” (Maddikunta, et al., 2022). Needless to mention, hyper-customization necessitates the transition to an agile manufacturing system that can manage both human intervention and dynamic customer preferences. Also, the feasibility of hyper customization hugely relies upon the cost effectiveness of the developed products (Yetış & Karaköse, 2020).

4.1.2.4 Cyber physical cognitive systems (CPCS)

The advanced connectivity of smart devices provided by IoT has paved the way for I4.0 to transform the manufacturing cycles from complete manual systems into advanced CPS-based industrial applications (Lu, 2017). Needless to mention, cloud technologies are deployed to provide an efficient, safe and private storage and exchange of data (De Oliveira, et al., 2019). Additionally, cognitive methods are utilized in various applications such as surveillance, industrial automation, and environment monitoring to foster the performance of the system and thus referred to as cyber physical cognitive system (C-PCS) (Alp Topal, et al., 2020). Briefly, C-CPS “contain nodes with cognitive capabilities that are able to sense, analyze the environment, and act based on their analysis results” (De Oliveira, et al., 2019). Additionally, it encompasses a cyber physical element which supports interconnection of all process elements (Tang, et al., 2018). In C-CPS, knowledge and learning are integral elements of the decision making process (De Oliveira, et al., 2019). As previously mentioned, unlike I4.0, the fifth industrial revolution aims to bring back the human factor to the production loop through facilitating the collaboration between AI-based technologies and skilled operators, thus promotes the manufacturing sector’s readiness to satisfy a customer’s personalization demands. Accordingly, the C-PCS has been modeled and utilized in HRC manufacturing to execute the assembly of components in real-time (Maddikunta, et al., 2022). To further emphasize the human’s role, “decision making can only be improved by human interference” (De Oliveira, et al., 2019), which highlights the importance of operators’ past experiences to both improving and running the CI-based systems in I5.0.

4.1.3 Key Enabling Technologies of Industry 5.0:

4.1.3.1 Edge computing (EC)

Edge computing (EC) opened the door for data processing at the network edge and this has been developed as a result of the intense and increased development of the IoT as well as the myriad of emerging different cloud services. A worth noting fact is that EC is beneficial in multiple ways. To explain more, it can help in the transition phase to I4.0 as well as I5.0. EC gives the advantage of meeting expectations of different attributes like the data protection, latency costs and response time (Deng, et al., 2020). In addition to the mentioned benefits, EC diminishes communication overhead and ensures the productivity of applications in remote areas. From the security perspective, EC excludes the public cloud from the process of data processing and this cuts down the security risks regarding the I5.0 significant events. In order to capitalize on the beneficial operations done by EC data processing, cache coherency, computing offloading, transferring and delivering requests (Deng, et al., 2020), the design of the edge must be done precisely to make it private, reliable and secure. From the perspective of real life applications, EC offers real-time communications for next-generation I5.0 applications such as un-manned aerial vehicles (UAVs), autonomous vehicles (Abdirad, et al., 2020), and remote patient monitoring. Additionally, with the help of EC, I5.0 are capable of capitalizing on more feasible resources for both hardware and software resources which supports this industry in the process of exchanging information linked to their field. On another side, EC filters the data needed by the servers to solve the problem of lack of efficient analysis of data due to its tremendous large amounts. It also takes part in efficient decision making by the allowance of preventive analytics which pinpoints machine failure and help in avoiding it.

4.1.3.2 Digital twins (DT)

A DT is a digital replication of an object or physical system and there are many examples for such representations like wind farms, jet engines and smart cities (Lu, et al., 2020). Similar to the EC, the development of IoT helped in capitalizing on the functionality of DT by mapping physical objects to their digital alternatives in order to have a simulation. This resulted in resolving many problems before happening because the digital version projected the inevitable problems and eliminated them. Also, “The rapid advancement of AI, ML, and big data analytics has enabled DT to reduce maintenance costs and improve performance of system” (Tao, et al., 2018). According to (Lu, et al., 2020), DT can be used for different manufacturing actors summarized below:

- DT for manufacturing assets: A manufacturing asset can be "connected" and "abstracted" to the cyberspace via its DT, thus operators can take advantage of near real-time data gathered from the asset to monitor its operating conditions and make "proactive optimal" operational decisions. This is considered a big step towards mass personalization as it supports the manufacturing system's "flexibility" and "resilience" along with providing a more robust operator's "situational awareness".

- DT for people: DT can also keep operators linked at the shop floor through abstracting their physical characteristics (i.e. weight, health) and real-time status (i.e. activity data, emotional status) to develop models understanding "personal wellbeing" and "working conditions" of operators in a factory. The developed models can facilitate designing "human-centered human-machine collaboration strategies" to boost the physical and psychological states of operators, thus leading to a better overall productivity. Such technology would also encourage operators to up-skill themselves using personalized training programs replicating "physical factory setups" with varying "virtual what-if scenarios", thus supporting "resource optimization" and "operational efficiency".

- DT for factories: DT can also replicate a real-time environment of a factory. By supporting it with smart sensing devices and BD analytics, a manufacturing firm can possess a "self-organizing" factory with a transparent "operational visibility", thus facilitate an early identification of faults' reasons, production bottlenecks, and materials' requirements.

- DT for production networks: By networking manufacturing assets, people and factories via DT, the entire manufacturing ecosystem can be virtually represented. Furthermore, networking "distributed Digital Twins" between manufacturing firms will open the door for the integration between "virtually connected production networks" and BD capabilities to offer chance of anticipating future needs in a network of DTs.

What DT can offer is enabling I5.0 to overcome technical issues by pinpointing these issues in an earlier phase and this helps in eliminating defects and increasing the accuracy, precision of the decision making process. Hence, this will increase profitability and lessen losses. This advantage of early error detection also enhances the customization attribute in order to improve the user experience because it offers updating physical objects based on the detected errors through the virtual simulation.

4.1.3.3 Collaborative Robots (Cobots)

Apart from the traditional work of robots, the collaboration between humans and machines in work has become crucial to fulfill the potential of the emerging trends in automation and robotics. This resulted in producing a new type of robots widely known as cobots. These cobots are programmed to work hand in hand with people which will increase the pace of many businesses operations and tasks. In 1996 professor Edward Colgate and Michael Peshkin of Northwestern University developed the primary version of cobots (Van, 1996). Nowadays, the cobots are tremendously different from the primary cobots. The newest version of the cobots are reliable because they are designed with sensors that open the door for the human workers to detect any misplaced object in their path. The reason behind this is that sensors make the cobots stop when humans interfere to remove any unneeded objects. This is opposite to the first wave of cobots where there were no motors in addition to the presence of brakes and this crippled the working process (Simões, et al., 2020).

A major challenge for robots and their lack of critical thinking is the Customization or personalization of products. Here comes the functionality of the collaboration between robots or cobots and humans. With cobots' ability to accelerate the pace of multiple operations as well as increasing the mass production, businesses can benefit from the mix between humans and cobots to maintain a mass amount of personalized, accurate and precise products in a faster way than ever. A case of utilizing cobots to personalize products is smart applications that summarize the profile of patients as well as creating an efficient health routine based on data and information (Simões, et al., 2020). In addition to the real life examples of assistant robots to doctors in surgeries, there is a perfect example of what is called "The Davinci surgical system". This system is used in urology and gynecology surgeries, as well as in other surgeries as surgeons capitalize on its technical benefits to have better surgeries and more successful and efficient ones. Hence, I5.0 capitalizes on cobots to redefine the relationship between robots and humans to cut down labor costs and increase productivity, pace, efficiency and reliability.

4.1.3.4 Internet of everything (IoE)

The interconnection between data, information processes and how people can use it can open the door for a new wave of better personalized and customized experiences for business and nations on a wider scale. The Internet of Everything (IoE) can enhance the user experience based on the data provided and what is called IoE-generated data. This also can happen in an efficient way through wireless sharing of information between the consumer and the second party which can be the patient and the doctor in case we are talking about a medical use of the IoE. In addition to the fact that I5.0 capitalizes on IoE to have better customization of experiences in general, it can also enjoy the privilege of IoE to get better optimization criteria in attributes of latency and operating costs by overcoming bottlenecks on communication channels. Another edge IoE gives to the I5.0 is cutting down the supply chain waste as well as getting an efficient and optimized production process.

4.1.3.5 Big data analytics (BD analytics)

A major trending and important thing that provides a tremendous help to I5.0 is the BD analytics. BD analytics is mainly collecting a huge amount of varying data analyzing it. There are a variety of techniques used to analyze this BD. For example, BD technologies such as ML, AI, social networking, data mining, and data fusion are commonly utilized to analyze BD (Hämäläinen & Inkinen, 2019). One of the major benefits of using BD analytics is utilizing the collected data to discover and understand the pattern and behavior of customers, which leads to more customized customer buying criteria including pricing of the product. Additionally, BD analytics will help cutting down overhead costs by optimizing production (Fukuda, 2020). This model takes us to a very important role BD analytics play, which is the detection of user reactions and social behaviors based on analyzing his/her reactions. Consequently, companies like Facebook, Twitter utilize this benefit to model personalized products and initiatives to maintain user satisfaction and hence profits. BD analytics provide multiple benefits from different perspectives. It can provide a competitive advantage by simulating real time decisions in addition to predicting inevitable events in the industry and then act accordingly. Another crucial key benefit of BD Analytics is the mass customization process without any chance of failure to happen during product development via handling huge amounts and volumes of data. This takes us to the next use of BD Analytics, which is enhancing the continuous process improvement by analyzing large amounts of data regarding the whole cycle of manufacturing (Majeed, et al., 2021).

4.1.3.6 Blockchain

Blockchain technology provides I5.0 with varying and multiple advantages. To overcome the challenge of handling a huge amount of different devices connected to each other in a centralized management style, Blockchain can offer help by designing decentralized and distributed management platforms via supporting distributed trust (Viriyasitavat & Hoonsopon, 2019). In addition, Blockchain can provide I5.0 with a safe way of interaction between peers to keep records in an unchangeable block that applies transparency and this is crucial to the ecosystem of I5.0 (He, et al., 2020). To apply security enforcement, smart contracts are used in addition to the possibility of enabling data receiving and gathering through using blockchains. Another important additional value blockchains provide is digital identities. These identities can be assigned to its owner whoever it's a person or an entity. This is done in order to have efficient subscriber management and a safe authentication process of different stakeholders. This benefit is not limited to better authentication processes but it can be improved to manage services as well as properties. Furthermore, “Blockchain technology can also be used to register IP rights and to catalog and store original work” (Mushtaq & Ul Haq, 2018). In collaboration with smart contracts, Blockchains can make the contract and agreement phase between stakeholders more feasible and faster by the use of automation.

4.1.3.7 6G and beyond

It is clear that the growing demand and growth in the technology fields must cast our attention to the inevitable problem of required bandwidth and here comes the importance of 6G. 6G can help I5.0 applications in maintaining perfect optimization criteria. For example, it will provide low latency and high reliability. To overcome the challenges of mobility and handover management in I5.0 when 6G is used, several “AI techniques can be used to obtain optimal mobility predictions and optimal handover solutions to ensure efficient connectivity” (Yang, et al., 2020). 6G provides solutions to multiple challenges by using Quantum communication and complex strategies of energy consumption to overcome the challenges of the demand of high data rate for the use of multiple applications as well as energy waste respectively.

4.1.4 Applications of Industry 5.0

4.1.4.1 Cloud Manufacturing (CMfg)

Cloud manufacturing (CMfg) represents a further shift of the current traditional paradigm. By integrating the recently advanced technologies such as cloud platforms, EC, IoT, semantic web, virtualization, and service-oriented technologies, CMfg has the potential to revolutionize the traditional manufacturing paradigm into an advanced manufacturing process. To elaborate, the incorporated technologies facilitate inserting a manufacturing company's resources (i.e. software tools, knowledge, equipment, … etc) into a cloud, thus enabling different actors to access it from anywhere (Adamson, et al., 2017). In other words, in a CMfg process, "multinational stakeholders will collaborate together to operate efficient and low cost manufacturing process" (Maddikunta, et al., 2022). According to (Mutlu, et al., 2017), designers would be able to further protect their intellectual properties (i.e manufacturing design documents) through exploiting the cloud's storage capacity and robust access control. Beside the levitated levels of reliability, multi-tasking, high quality, cost effectiveness, and on-demand capabilities provided by CMfg, it could have a positive impact upon the environment as it could enable "an 83% reduction in transportation emissions by shifting production from a single central location to distributed micro-factories around the world" (Fast Radius, 2021). Additionally, manufacturers would find it easier to localize their manufacturing plants closer to both the suppliers of raw materials and cheaper workforce. Throughout the past years, research efforts have been directed towards the possibilities of controlling both the machines and processes in the manufacturing life cycle by a CMfg platform. Relevantly, in an attempt to distinguish CMfg from the previous networked manufacturing models, (Liu, et al., 2016) proposed a model for multitask-oriented service composition and scheduling, in which key factures of CMfg such as service orientation, involvement of logistics, and dynamical change of service availability are taken into account. Also, (Tao, et al., 2014) proposed a five-layered structure to collect the working condition information of manufacturing processes via IoT sensors and support a resource intelligent perception and access system. Simply, the proposed framework can form a massive intelligent information interaction network to achieve intelligent identification, monitoring, and management of manufacturing resources. Concurrently, among manufacturing ventures, the effective deployment of IoT can aggregate all types of inside and outside resources. The proposed system architecture is briefed as follows:

- Resource Layer: It integrates all manufacturing resources included in the entire life cycle of manufacturing. Manufacturing resources include hardware manufacturing resources, computational resources, intellectual resources and other resources.
- Perception Layer: It provides intelligent perception and identification of the entire manufacturing resources via various sensing devices and adapters in product life cycle, thereby providing robust support for manufacturing service platform to intelligently identify and manage manufacturing resources. Sensing devices include two-dimensional barcode, RFID readers, sensors, video capture and GPS, and others. The adapters include software interface adapter, sensor adapters, model adapters, knowledge adapters, network adapters, storage adapters, technical resource adapters, and others.
- Network Layer: It provides the reliable, high-speed, and secure communication protocols to access various resources in a product' s entire life cycle, including 2G networks, 3G networks, 4G networks, satellite networks, cable networks, corporate internal wireless networks, and others.
- Service Layer: Supported by the network layer, it provides two categories of services: the CMfg service and the CMfg platform operational service. CMfg service represents the "results of service encapsulation of manufacturing resources and capacities, which can be invoked by end users" (Tao, et al., 2014). The latter represents the main services provided by the CMfg platform to realize the different operators to CMfg services, which includes knowledge management, transaction management, information assessment, billing management, resource calendar management, network management, virtual machine management, directory management, registration services, and others.
- Application Layer: It refers to the on-demand deployment of different CMfg services throughout the entire manufacturing life cycle, including design, manufacturing, experimentation, simulation, management, maintainance, and recycling.

On another note, (Xu, 2012) proposed the potential business models in CMfg, including pay-as-you-go business model. Following the emergence of I5.0, the next generation of CMfg systems have the potential to cover various and complex requirements of engineering, production, and logistics. The technological advancement of AI/ML technologies, EC, and 5G communication networks paves the way for an exponential expansion of future CMfg systems' capabilities.

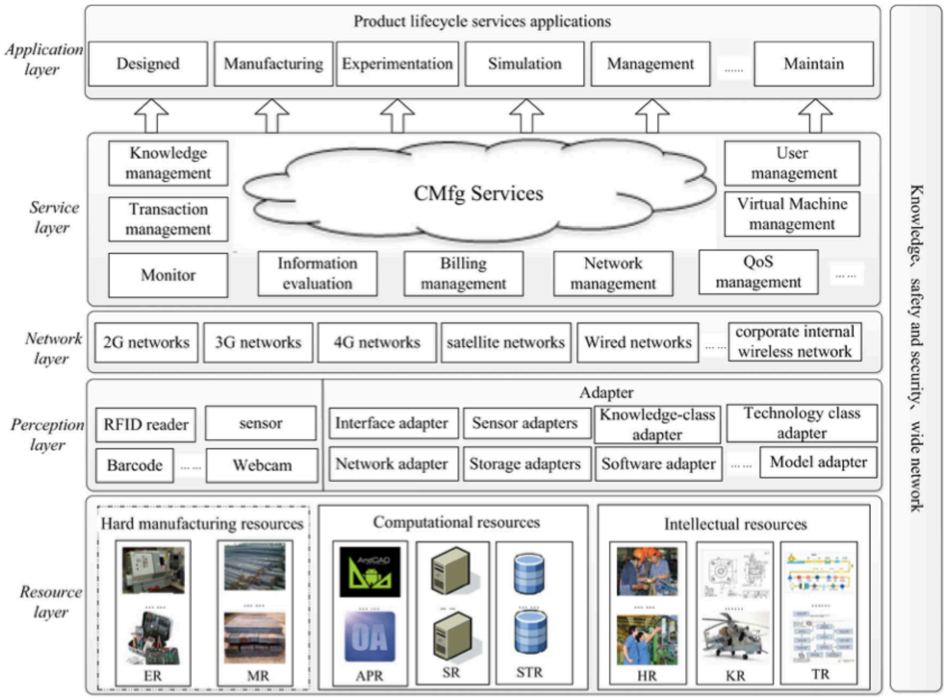

Figure 25 Architecture of IoT-Based Intelligent Perception and Access of Manufacturing Resources Toward Cloud Manufacturing (Tao, et al., 2014)

4.1.4.2 Supply chain management (SCM)

The alignment between the I5.0 innovative technology enablers (i.e DT, cobots, 5G Networks, 6G Networks, ML, IoT, EC, and others) and human's intelligence could facilitate both satisfying the customers' demand for personalized and customized products and reducing the associated lead time (Li, 2020). Expectedly, such paradigm shift would be the key for Supply chain management (SCM) to integrate mass customization into their production facilities.

Bearing in mind that this technology "is still on diapers" (Suarez-Valdes, et al., 2019), DT can be incorporated to develop a virtual replica of the SCM including warehouses, inventory status, assets, and logistics. To illustrate, the DT "encapsulates factories, suppliers, contract manufacturers, factories, transportation lanes, distribution facilities, and customer locations" (Maddikunta, et al., 2022). DT replicates the entire life-cycle of the SCM, ranging from the design phase, to the manufacturing, operations, and delivery contexts (Suarez-Valdes, et al., 2019). Through a real-time simulation of SCM systems, DT has the ability to sense and gather the real-world data via IoT smart sensors. AI technologies, ML algorithms, and big data analytics can then be deployed to anticipate the potential obstacles to be encountered during different stages of SCM. DT could also help businesses optimize complex, interlinked, and constrained trade-offs including quality, capacity, cost, and inventory, thus help improving the adopting companies' profits and diminishing the operational expenses.

Accordingly, management personnel can take pre-emptive corrective procedures to diminish the losses and faults during different phases of SCM, which supports the manufacturing ventures to “create as soon as possible globally competitive products of the new generation” (Simchenko, et al., 2019). In this direction, inspired by the six-layer DT architecture presented by (Kruger, et al., 2019), (Marmolejo, 2020) proposed a DT for a pharmaceutical company to enhance the robustness of the SCM process using solvers, simulators and analytic tools. The proposed system architecture is briefed as follows:

- The physical Twin: This layer revolves around incorporating inventory measurement devices under RFID technology environments encapsulating labels that can be mounted to any product. RFID technology working principle is mainly based on the interaction of 2 fundamental elements: the TAG and a reader. The tag consists of an antenna that enables the device to connect to the system and a microchip that collects information. In case the RFID tag receives energy obtained by the reading antennas, the chip deploys this energy as a power source and activates all its internal circuits (Want, 2006).
- The Local Data Source: The data gathered from the physical twin is uploaded by professionals in the form of compatible databases. Aiming to reduce dependency on external actors, the authors highlighted their preference of implementing an internal database to join the information of the cyber-devices.
- Local Data Repositories: For simplicity and costs minimization, the system relies upon local databases (simple spreadsheets hosted in each area or department involved in the digital twin). Despite not being able to take advantage of the features provided by cloud storage (i.e. Reliability, data-exchange-safety, everywhere-data-accessibility), but the authors preferred using local storage to negate the necessity of a backup, high-speed connection, and maintenance of all hardware.
- The IoT Gateway Interface: This layer plays an integral role in enabling electronic devices to communicate and exchange data, to be later analyzed and transformed into insightful information that facilitates the optimization SCM operating processes.
- The Cloud-based Information Repositories: A private cloud is incorporated to provide a secure platform to execute the simulation models using the data stored in the local repository.
- The Emulation and Simulation Platform: A “powerful and flexible simulation tool is the key to developing a digital twin in the supply chain” (Marmolejo, 2020). Needless to mention, using modeling tools that are “multi-method in nature” could be the key

for an efficient and robust DT, as it would require the deployment of relatively fewer software packages during its development.

The application phase focused on modelling and analyzing different operating scenarios of the inventory, supply, manufacturing, and product distribution process for a pharmaceutical company.

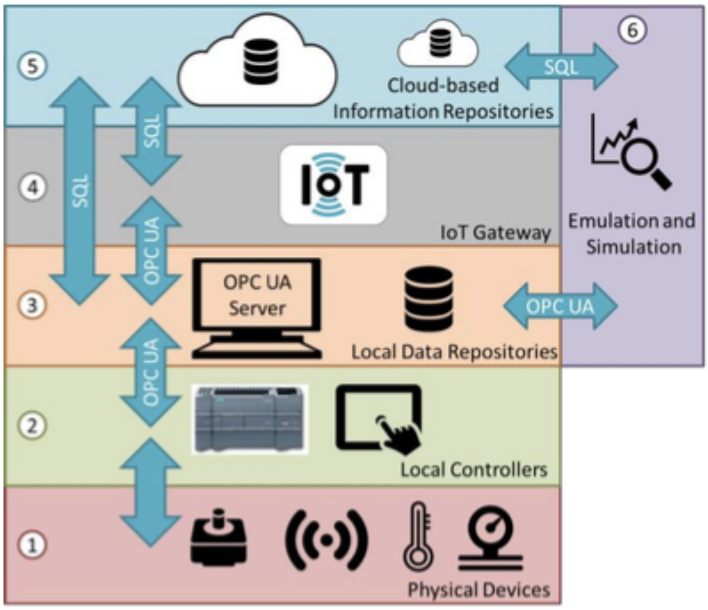

Figure 26 A six-layered Architecture of Digital Twins (Kruger, et al., 2019)

On another note, Co-bots can play an integral role in SCM through replacing the human factor when it comes to handling routine/repetitive tasks including packaging, routine quality checks, material handling, assembly of the materials, delivery/picking of the products/returns to/from the customers, thus freeing the human's intelligence to meet the complexity of jobs within the SCM lifecycle and reducing the overall labor costs (Simões, et al., 2020). Accordingly, cobots streamline all the processes in SCM, such as systematic inventory management, tracking of stocks, order fulfillment and return of the products (Kopacek & Kent, 2020).

4.1.4.3 Manufacturing/production

The gradual introduction of robotics and automations over the past industrial revolutions has catalyzed changes regarding the paradigm of the global manufacturing industry. Over time, robots have been successfully replacing humans completing risky, monotonous, or physically demanding industrial tasks including welding and painting in car factories and loading/unloading heavy objects in warehouses (Yli-Ojanperä, et al., 2019). As mentioned earlier, I5.0 aims to augment the human intelligence with the ever-evolving cognitive computing skills to perform collaborative operations as machines grow smarter and more connected, which could stimulate a radical change of the industrial ecosystem. As a consequence, research efforts have been directed towards investigating the implications of I5.0 in a manufacturing context.

Relevantly, (Nahavandi, 2019) presented different practical developments achieved by researchers for use in I5.0 applications and environments. Also, the study further emphasizes the necessary technological advancements to further support I5.0 such as networked sensor data interoperability, multiscale simulation and dynamic modeling, production tracking, virtual training, autonomous systems, and machine cognition. As well, the author portrayed the impact of I5.0 on the manufacturing sector and overall economy from societal and economic angles. To illustrate, contrary to the cultural concerns, the author agreed with the argument of (Millier, 2017) claiming that I5.0 will generate more job opportunities in the era of human-machine collaboration rather than displacing human workers. On another note, (Sherburne, 2020) envisioned the potential incorporation of I5.0 in textile industry. Their qualitative presents the development of functional fiber computing for the textile industry in the context of I5.0.

4.1.4.4 Disaster Management

As implied by its name, disasters refer to instant, catastrophic accidents that threatens lives or assets. On the other hand, disaster management refers to "the body of policy and administrative decisions, the operational activities, the actors and technologies that pertain to the various stages of a disaster at all levels" (Lettieri, et al., 2009). In other words, natural/industrial disaster management/prevention strategies are necessary to help diminish/control the aftermath of a disaster. In this direction, (Sukmono & Junaedi, 2020) proposed harnessing I5.0 in the context of disaster management of natural earthquakes. On another note, integrating human's intelligence with IoT, and AI opens big opportunities regarding the disaster management field. To illustrate, (Chen, et al., 2016) proposed a system that fosters collaboration between human workers, IIoT, and AI technologies to improve the capability of detecting the leakage of toxic gases in an industrial context. Further details of the proposed systems will be covered in the following sections. As well, further applications of I5.0 core values with a focus on collaborative intelligence would be covered in detail in the next sections.

4.1.5 The main differences between Industry 4.0 and Industry 5.0

Although the European Union "sees Industry 5.0 as a complement to Industry 4.0" (i-SCOOP, 2022), but still the blurry line between both initiatives should be kept clear. As mentioned before, the main goal of I4.0 lies behind achieving complete process automation using smarter and connected machines. On the other side, I5.0 prioritizes balancing the machine-human interaction. Also, technology has been always the pivot of I4.0, while optimizing the collaboration between human intelligence and AI has been always earmarked as the future driver of growth by I5.0 (Wilson & Daugherty, 2018). Thus, I4.0 aims for a complete virtual environment, but I5.0 is pushing for the transition back to real environment. Accordingly, contrary to I4.0, I5.0 would open up more job opportunities for skilled workers to cooperate with machines. Finally, I5.0 would make the industry prepared for the upcoming trend of customers demanding personalized products, which is unfortunately not the case for I4.0

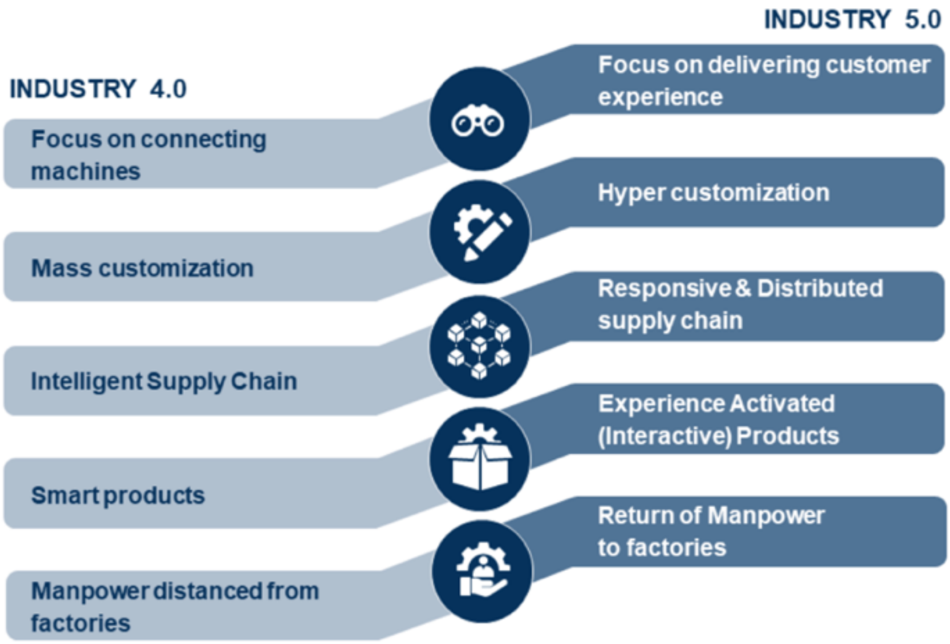

Figure 27 A comparison between Industry 4.0 and Industry 5.0 (Zutshi, 2019)

4.2 The Main Pillar of Collaborative Intelligence: Artificial Intelligence (AI)

Recently, the term "Artificial Intelligence (AI)" has registered its position among the hottest topics in the scientific community. Despite its recent popularity, AI has been primarily introduced in the middle of the last century. However, today's technological advancements in terms of digital memory capacities, computing processing power and network bandwidths have paved the way to start reaping its benefits.

Generally, AI is "a sub-discipline of computer science that involves computers that apply human-like reasoning abilities. Accurate and sophisticated patterns within big datasets are better and more easily recognised by specific AI techniques such as machine learning (ML)" (Kaur & Kaur, 2021). From a technical point of view, AI technologies are employed aiming to enhance the efficiency and effectiveness of industrial processes. The primary goals of AI are to reduce costs, save time, improve quality, and improve the robustness of industrial processes. Furthermore, AI facilitates the "revamping of production processes and their adjoining processes from the ground up, the enriching of one's own products or services through or with AI, and the implementing of novel business models" (Ahlborn, et al., 2019). Clearly, these targets should be easier to hit once the industrial operations are equipped with adaptation and problem-solving abilities. In other words, in addition to the currently employed if/then algorithms and the classic automation and control procedures, AI is expected to add a whole new level of "mastering of complex situations in industrial processes" (Ahlborn, et al., 2019).

The AI technologies employed nowadays are generally divided into rational or behaviour-oriented models. In case of a work environment that involves an interaction between humans and machines, behaviour-oriented AI technologies are used. To demonstrate, NLP for machine translation is one of the widely used behaviour-oriented models. Otherwise, specifically in industrial processes where either sophisticated planning processes or behaviour recognition are necessary, developing rational AI technologies would be more relatively convenient. For example, computer vision, action planning and optimisation are among the most widely known rational AI technologies (Ahlborn, et al., 2019). By the way, apart from the above classification, various sources have provided different ways of classifying AI-based systems.

This research provides the two widely known methodologies of classifying AI technologies

4.2.1 Artificial Intelligence Classification Type I

4.2.1.1 Narrow Artificial Intelligence

The systems with narrow AI are employed solely to execute selective tasks without being able to take decisions on behalf of humans. “It is used for single task only and is also known as weak AI” (Patel, et al., 2020). In fact, narrow AI systems play an important role in our daily lives. To demonstrate, apple’s Siri is one of the technologies that integrate narrow AI systems in our daily routines.

4.2.1.2 General Artificial Intelligence

Having the ability of imitating human beings in terms of reading and analysing data is referred to as “Artificial General Intelligence (AGI) and is strong AI” (Patel, et al., 2020**).** However, such systems have not yet come to light because scientists find it highly complicated to define the human intelligence regarding their ability to see things, differentiate them and control their imagination. In other words, AGI has not been achieved so far, and hopefully through the researchers’ continuous work, it could be achieved before 2040.

4.2.1.3 Super AI

Obviously, this type “surpasses the human intelligence it can perform all the activities better than humans using cognitive properties” (Patel, et al., 2020). However, it is still seen as a ‘hypothetical concept of AI’, which represents the ability of AI systems to completely replace humans by being capable of thinking and making judgements.

4.2.2 Artificial Intelligence Classification type II

4.2.2.1 Reactive Machines

Being the first AI-based system machines, such machines have been only capable of “automatically responding to a limited set or combination of inputs” as “they do not involve memory-based operations” (Hassani, et al., 2020), and therefore they cannot learn patterns. In other words, reactive machines cannot predict or forecast future events. IBM’s Deep Blue is an example of reactive machines, which was widely known in 1997 for beating the Russian chess Grandmaster Kasparov (Kovacs, et al., 2016).

4.2.2.2 Limited Memory

Unlike the Reactive Machines, such machines have developed the capability of learning from historical data to react to future events. To demonstrate, most of the currently employed AI-based applications in our lives are considered as sub-categories of Limited Memory machines including: chatbots, virtual assistants and autonomous vehicles (Hassani, et al., 2020).

4.2.2.3 Theory of Mind

These AI-based machines are considered a hypothetical upgrade to the previously mentioned systems, as they are supposed to develop an ability to "better understand entities with which they interact by discerning their needs, emotions, beliefs, and thought processes" (Joshi, 2019). However, such systems are still thought of as a conceptual framework. A famous, under-developed robot based on this technology is Sophia, which was developed by Hanson Robotics to go on press tours as an exhibition to help people imagining what robots are capable of doing. To demonstrate, despite not being able to understand human emotions, but still Sophia can "hold basic conversation and has image recognition and an ability to respond to interactions with humans with the appropriate facial expression, as well as an incredibly human-like appearance" (Hassani, et al., 2020).

4.2.2.4 Self-aware AI

Self-aware systems are a further development that represent the future of AI. These machines will have a "human-level consciousness" (Hassani, et al., 2020) along with the "ability to understand thoughts and feelings of humans and act accordingly" (Joshi, 2019). However, this is still considered as a hypothetical concept that might take years to come to light due to its utter complexity that make some see it as the 'ultimate goal of AI' that would lead to AI breakthrough that "could turn society on its head, enhance how we live in the day to day exponentially and even save lives" (Hassani, et al., 2020)

From an industrial point of view and taking the complexity of developing AI-based systems that can imitate the human's consciousness into consideration, much of the research has been directed to developing the machines to be capable of learning data to improve the entire industrial life cycle. On the same line, it is widely known that in order to consider something as intelligent, it must first have "the capacity to learn and solve problems independently" (Ahlborn, et al., 2019) Clearly, beside other technologies, ML is considered as one of the main sub-areas of AI that targets enabling machines to "perform their jobs skillfully by using intelligent software" (Mohammed, et al., 2017) through the employment of statistical learning algorithms., which, in fact, necessitate the availability of vast quantities of data**.** ML is branched into 3 sub-categories as shown in Figure 25: supervised learning, unsupervised learning, and reinforced learning.

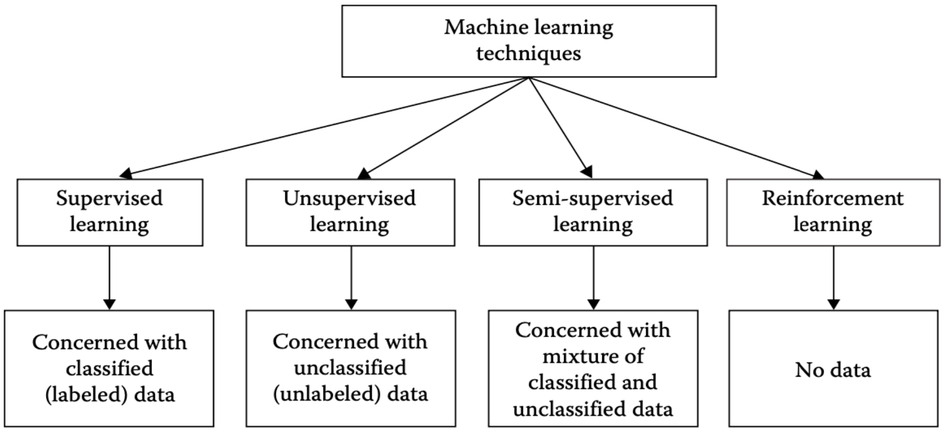

Figure 28 Mapping of Machine Learning Technologies (Mohammed, et al., 2017)

Alternatively, the "learning of hierarchical structures of characteristics in successively higher, hidden network layers" is commonly known as deep learning (Ahlborn, et al., 2019). Relying upon the quality of the provided streams of data, the AI systems can either perform 'one-time analytical purposes' or 'repetitive re-learning purposes' that facilitates an autonomous elimination of complexities and detection of events or patterns, which could be further used to "explain events, make predictions, or enable actions to be taken" (Ahlborn, et al., 2019) without the need for a human's input.

4.2.3 A glimpse of the AI-based methodologies applied in the Industrial sector

Figure 26 summarizes the seven main AI-based methodologies which are currently applied in industry. The main three methodologies which are commonly applied in industry are ML, NLP, and vision technology. In this section, we will explain the three methodologies in more detail as well as briefly discuss a few others that have potential to grow and play an important role in Entrepreneurial sector in the nearby future. We will also dive deeper into the most common algorithms used in ML and their main applications in the industrial sector.

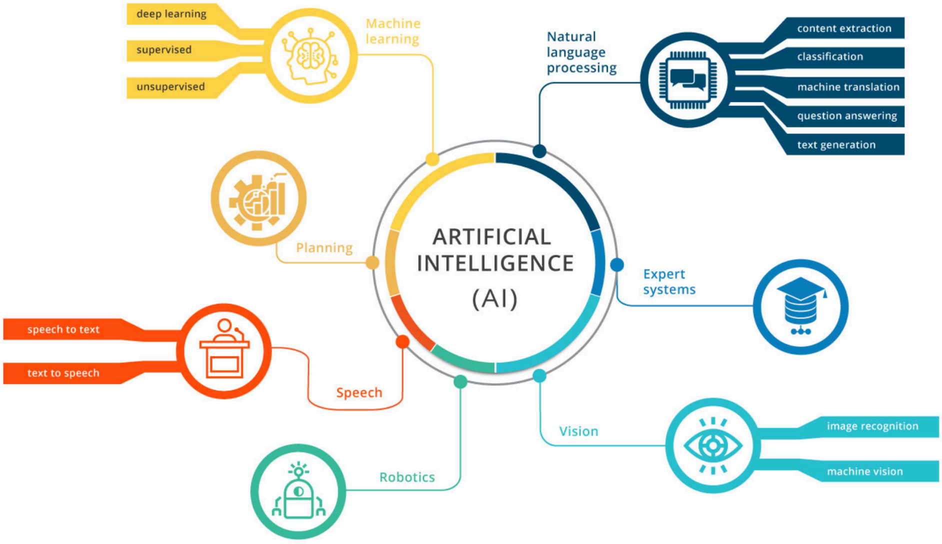

Figure 29 A doughnut plot showing the seven technologies of Artificial Intelligence with machine learning, natural language processing and vision technologies are the leading contributors (Rohm, 2022)

4.2.3.1 Knowledge based systems (Expert Systems)

Expert systems are considered one of the early developed AI programs that gather knowledge from experts' input "in a very specific, limited domain of human expertise" (Laudon & Laudon, 2014), in order to automatically respond to similar situations through applying a set of If-then-False rules provided by knowledge engineers. An example of knowledge-based systems was developed in the early 1970s at Stanford University by Ted Shortliffe for medical diagnosis and therapy to prescribe antibiotics to patients according to their health state (Shortliffe, 1977).

4.2.3.2 Machine Learning (ML)

Machine learning (ML) is the most prominent branch of AI and is one of the most widespread. The main goal of machine learning is to use data and algorithms to imitate the learning ability of humans and to gradually improve any predictions that they make. ML algorithms can be classified into supervised learning and un-supervised learning. Supervised learning are ML algorithms that can only operate on labelled datasets. The labelled datasets are used to train the algorithms into classifying unlabelled data or making predictions. Unsupervised learning on the other hand uses ML algorithms to cluster unlabelled data. These algorithms can detect hidden patterns in unlabelled data without any human inputs (IBM Cloud Education, 2020) .

We will discuss a few of these algorithms in the following section:

4.2.3.2.1 Logistic Regression

Logistic Regression is a powerful supervised ML algorithm which is used for the classification problems. it is a predictive analysis algorithm and based on the concept of maximum likelihood and is used when the output is categorial. In ML, a classification problem is defined as an attempt into classifying the data into predefined distinct groups. Logistic regression can be applied on both structured and unstructured data. Structured data involves a dataset where the target is already defined while unstructured or unlabeled data involves having a dataset where the target needs to be identified (Swaminathan, 2018).

There are three main types of logistic regression. The first type being the most familiar one and the one explained here in further detail is binary logistic regression and is basically a response function which has only two 2 possible output values such as pass or fail. The second type is multinomial logistic regression which involves three or more outcomes that have no order. Vegan, vegetarian, and non-vegetarian can be thought as three outcomes for multinominal logistic regression. The third is that of ordinal logistic regression whose output has three or more categories with ordering such as TV rating on a scale from 1 to 5 (Seth, 2020).

Binary logistic regression regression essentially uses a logistic function defined below to model a binary output variable. Logistic regression differs form linear regression by that the logistic regression's output range has to bounded between 0 and 1. In addition, another difference ascertained by the name of linear regression is that logistic regression does not require a linear relationship between inputs and output variables. This is due to applying a nonlinear log transformation using a sigmoid curve. A sigmoid curve is used to define the relationship between the logit of the odds ratio (defined as the ratio of probability of success to probability of failure) and the input parameters. Figure 27 shows a plot of the sigmoid function with the output value ranging from 0 to 1 as most probabilities. Sigmoid function (y) is defined as follows where x is the input parameter.

$$y(x) = \frac{1}{1 + e^{-x}}$$

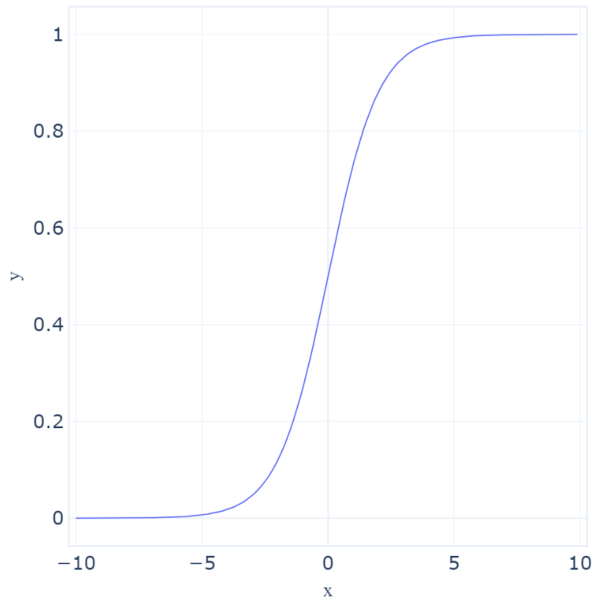

Figure 30 A Plot of the sigmoid function (Seth, 2020)

For logistic regression with multiple inputs:

$$z = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + \cdots + \beta_n X_n$$

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

4.2.3.2.2 Bayesian Inference (Naive Bias)

A very common statistical tool used as a building block both supervised and unsupervised ML algorithms is Bayesian inference. Bayesian inference is simply a statistical inference method in which the probability for a hypothesis is updated using recently available data through applying Bayes' theorem. It is mainly used to deduce properties about a population or a probability distribution as more evidence or information about this population starts to become available (Brooks-Barlett, 2018).

Bayes' theorem is based on the principle of conditional probability. Conditional probability is the likelihood of an event, given the knowledge of the occurrence of a previous event (Wikipedia, n.d.). Conditional probability is calculated by the quotient of the probability at which A and B both take place, although not necessarily at the same time and the probability of B as defined below where A and B are considered here as independent events:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

It is worth noting that the easiest implementation of Bayesian inference usually involves using Gaussian distributions. Gaussian distribution has a unique characteristic which is that it is conjugate to itself with respect to a Gaussian likelihood function. This in principle means that if I multiply two Gaussian distributions with each another, I'll get another Gaussian function. The gaussian distribution is defined as where μ is the mean and σ is the standard deviation:

$$f(x{:}\,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-0.5\left(\frac{x-\mu}{\sigma}\right)^2}$$

Figure 28 shows the workflow of applying Bayesian updating to solve a problem. The very beginning of this workflow is defined in dotted box of Figure 13 **a)** which describes the general framework of Bayesian statistics and introduces a Bayesian research cycle. In the Bayesian research cycle, an overview of the literature is used to implement a Bayesian model on real data and includes selecting appropriate prior distributions as well as carrying out prior predictive checking and determining the likelihood distribution through data collection (van de Schoot, et al., 2021). The rest of Figure 28 shows all the subsequent steps in the Bayesian workflow that follows the Bayesian research cycle. The subsequent step to the Bayesian research, as highlighted in the Bayesian updating workflow, is determining the Prior distributions. The selection of priors is often regarded as one of the most delicate steps when implementing a Bayesian model as it has significant impact on the results (the posterior distribution). Selecting the appropriate prior distribution is ascertained using the prior predictive checking process. The likelihood function is then determined and is then multiplied with the prior to reach the final posterior distribution which can be used for inference. This process is explained further by diving deeper into the equations used in the Bayesian updating scheme.

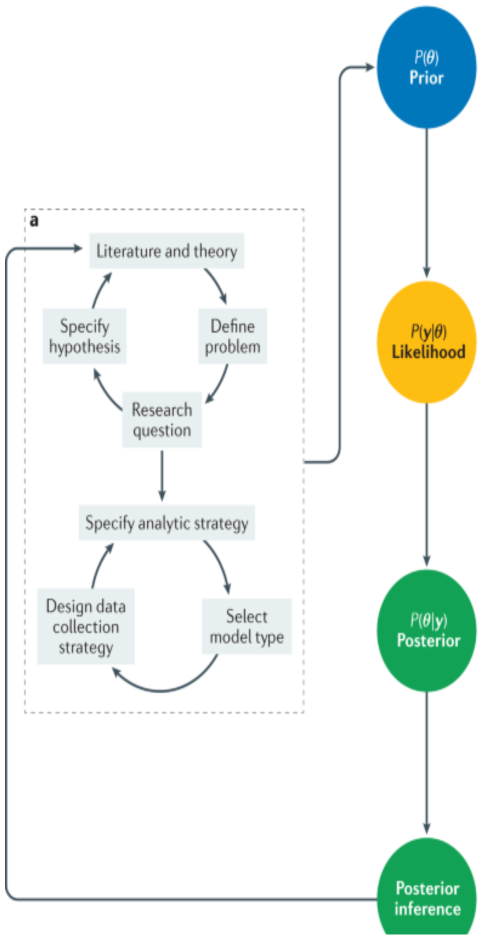

Figure 31 Standard Bayesian workflow (van de Schoot, et al., 2021)

A typical Bayesian updating scheme involves three main steps. The first is finding or estimating a given parameter in a statistical model using, available knowledge. This is called the prior distribution, which is typically determined before data collection. The second step is determining the likelihood function using deductions made about the parameters from the collected observed data. The last step is multiplying the prior distribution and the likelihood function using Bayes' theorem to get a well-defined posterior distribution as highlighted in the equation below where $P(data|\theta)$ is the likelihood function, $P(\theta)$ is the prior distribution and $P(\theta|data)$ is the posterior distribution. Figure 29 shows an example of Bayesian updating where the newly collected observations of aircraft masses affected the mean and standard deviation of the prior distribution forming an posterior distribution with a an updated mean and standard deviation that betters fits the newly available data. A real-life application of Bayesian inference is the Kalman filter. The Kalman filter uses an analytical implementation of Bayesian recursions through which a robot to infer its position and orientation. Kalman filters rely on linear Gaussian state space models to calculate the probabilities of multiple beliefs.

$$P(\theta|data) = \frac{P(data|\theta) * P(\theta)}{P(data)}$$

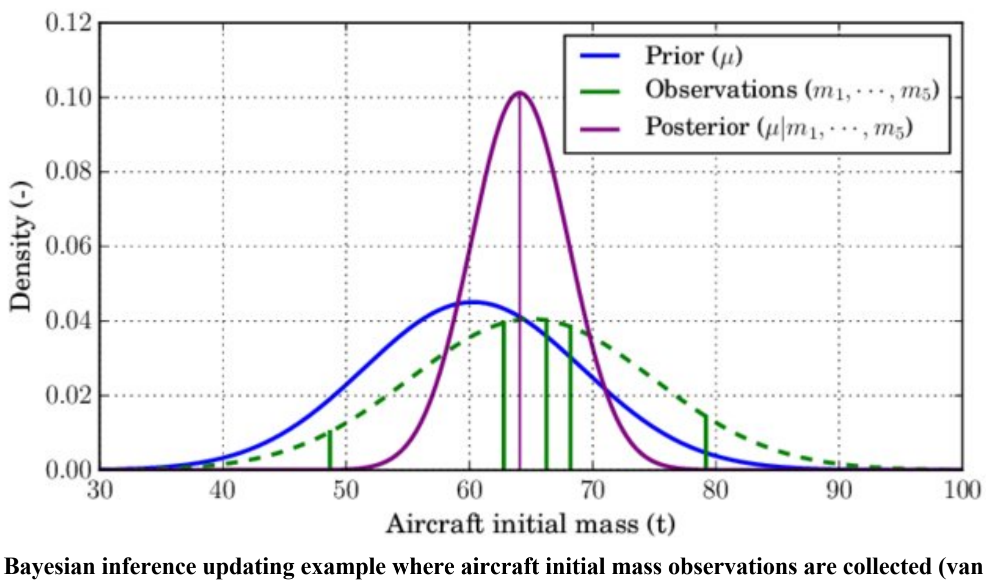

Figure 32 Bayesian inference updating example where aircraft initial mass observations are collected (van de Schoot, et al., 2021)

4.2.3.2.3 Deep Learning (DL)

Deep learning (DL) is a "scalable machine learning" algorithm which focus on using deep neural networks (DNN) to process large amounts of data and analyse it. Due to its inherent ability to process BD, DL made a substantial impact across various industries such as fraud detection, predictive maintenance and spam detection (IBM Watson Studio, 2021). The difference between DL and ML is that the latter is relatively more dependent on human intervention to learn. Humans need to choose the set of features the model uses to learn. DL algorithms on the other hand can ingest unstructured raw data and automatically determine the features which distinguish different categories of data from one another. DL perform a task repeatedly and works on improving the accuracy of its prediction through deep layers that allow for progressive learning. The main algorithms adopted in ML methods are based on neural networks.

4.2.3.2.4 Neural networks

Artificial Neural Networks (ANNs) are "computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems" (Basheer & Hajmeer, 2000). In general, neural networks are an artificial abstract of the way a human's brain functions as they are conceptually built of "structures comprised of densely inter-connected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for dataprocessing and knowledge representation" (Basheer & Hajmeer, 2000). To demonstrate, such systems are formed of Input stimuli which are connected through a network of nodes to output nodes (The output conclusion). However, ANNs are not expected to mimic the operation of the human's biological systems, as they are just inspired from the functionality of the biological networks that could facilitate solving complex problems after learning the historical data. On the same line, ANNs have proven their functionality when it comes to "classification and optimisation situations" (Meziane, et al., 2000). Furthermore, ANNs have been widely accepted by the scientific community due to its "remarkable information processing characteristics of the biological system such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and their capability to generalize" (Basheer & Hajmeer, 2000). Figure 20 shows a simple neural network model consisting of two hidden layers ($\boldsymbol{L_2}$, $\boldsymbol{L_3}$) and an input layer ($\boldsymbol{L_1}$) which takes in four inputs ($\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \boldsymbol{X_4}$) and producing an output layer ($\boldsymbol{L_2}$) which has two outputs ($\boldsymbol{Q_1}, \boldsymbol{Q_2}$). The first hidden layer ($\boldsymbol{L_2}$) has five neurons while the second hidden layer ($\boldsymbol{L}_3$) has three neurons. The network here is called a fully connected network, also known as Feedforward Neural Network (FNN). There are usually three steps involved in setting up a neural network. The first is writing the output as a linear combination of the inputs after assigning each individual input a corresponding weight and each output equation a bias element. We then assign random values to the inputs to calculate the output. Calculating the output is usually referred to as forward propagation. The second step is calculating the loss term which is the error between the predicted output values and the actual values. The third step is trying to minimize the loss or error term as much as possible by adjusting the corresponding weights to have a neural network that is an accurate representation of the problem solved. This step can be referred to as backward propagation. It is worth mentioning that to model any non-linearity, a transformation equation is applied to our linear equations and is called an activation or a squashing function. There are various types of activation equations and an example of an activation equation is the sigmoid function which can bring nonlinearity to model a binary classification problem (Neha, 2021).

Generalized equation of a neural network:

$$Q_1 = Bias + W_1X_1 + W_2X_2 + \dots + W_nX_n$$

Generalized a neural node before and after applying a squashing function which here is a simple sigmoid transformation:

$$N_1 = Bias_1 + W_{11}X_1 + W_{21}X_2 + W_{31}X_3 + + W_{41}X_4$$

$$h_1 = sigmoid\ (N_1)$$

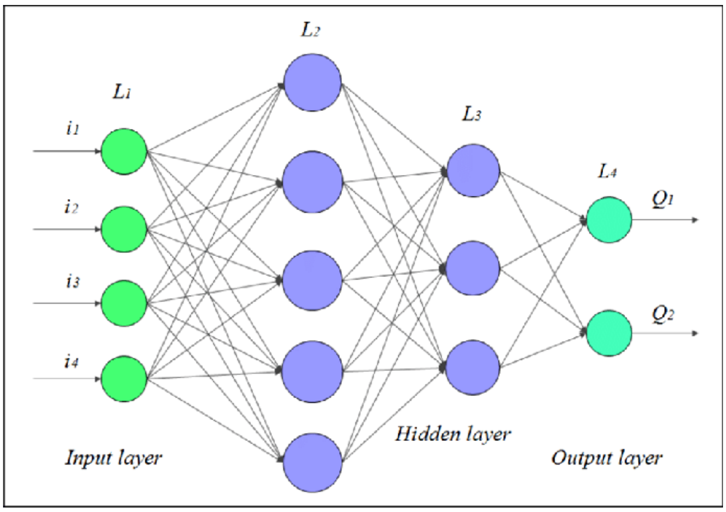

Figure 33 A neural network of 4 inputs (i_1,i_2,i_3,i_4) and 2 outputs (Q_1 Q_2) consisting of two hidden layers (L_1, L_2) (Neha, 2021)

4.2.3.2.5 Natural Language Processing (NLP)

Natural language processing (NLP) is a field of AI, which adopts algorithms that make human language intelligible to machines (IBM Cloud Education, 2020). NLP can be used to carry our various tasks such as speech recognition, automatic summarization, translation, named entity recognition. NLP combines linguistics and computer algorithms to learn the rules and structure of language and create intelligent systems capable of understanding, analyzing, and extracting meaning from text. One of the basic elements of NLP is Tokenization used to break up a string of words into semantically meaningful units called tokens. Another component is speech tagging which adds to a speech category to each token within a text. Dependency grammar is another component which focuses on the way words in a sentence are connected while Constituency Parsing has a main goal of visualizing the entire syntactic structure of a sentence by identifying phrase structure grammar. Lemmatization and stemming are techniques used by NLP to find the root form of words. Finally, Named entity recognition is one of the most popular tasks in NLP and is associated with extracting entities such as names, location, etc from within a text. Text classification is another crucial task where text is understood by organizing it into predefined categories (tags). One of the most powerful marketing tools related to text classification is sentiment analysis, which categorizes unstructured data by sentiment and that can help marketeers identify how their target audience feel about their product.

4.2.3.2.6 Computer Vision

Computer vision algorithms are a ML or DL model that are used to identify and label images (IBM Resrach, 2020). They analyze images by breaking them down into pixels which are then labelled. A mathematical operation called convolution using a convolutional neural network (CNN) are applied to these labels to makes predictions about the input image. A convolutional neural network identifies hard edges and simple shapes, then fills in information as it runs iterations of its predictions. The ML algorithms adopted in computer vision help enable a computer to teach itself about the context of visual data. If the computer is fed enough labelled images or patterns, the computer will go through the data and teach itself to distinguish one shape from another. Algorithms enable the machine to learn by itself, rather than someone programming it to recognize an image. It worth noting that a CNN is used to understand single images while a recurrent neural network (RNN) can be used for analyzing videos. An ample of RNNs is Long Short-Term Memory (LSTM) Network which is a sequential network which allows for information to persist and can be used for video classification.

4.2.3.2.7 Ensemble learning

Ensemble learning is multiple ML models combined altogether which collectively can solve a problem better than any of its individual components (Rocca, 2019). In ensemble learning theory, base models or as we call them weak models are combined and are considered the building blocks of the ensemble as shown in Figure 31. These weak models are usually overfitted i.e., characterized by low variance or underfit i.e., characterized by high bias and so do not perform so well by themselves. Therefore, the goal of an ensemble of weak models is to reduce the limiting characteristic of its building blocks component by reducing bias and/or variance. The ensemble leads to a strong learner that achieves better bias/variance characteristics as shown in Figure 31.

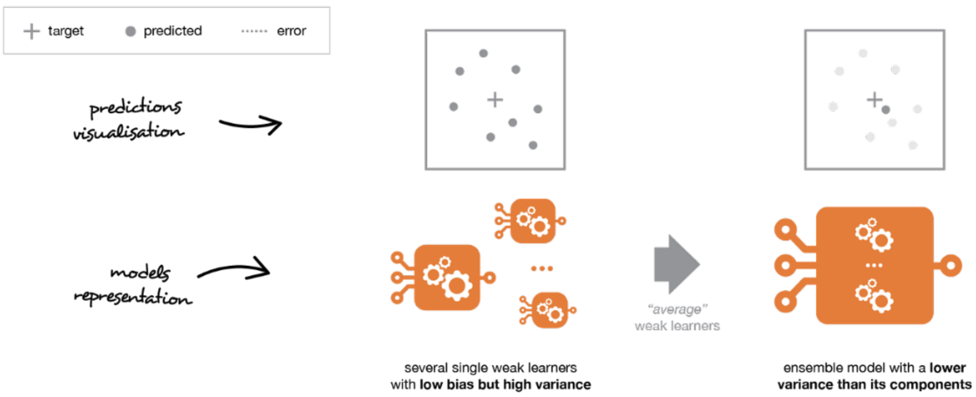

Figure 34 Combining weak learners with low bias but high variance generating an ensemble model with lower variance than its components (Rocca, 2019)

4.2.3.2.8 Fuzzy logic

Fuzzy logic is considered as one of the interesting techniques under the umbrella of AI technologies. According to literature, fuzzy logic principles were introduced by Lotfi Zadeh in 1965 (Hellmann, 2001). Since then, this technique has proved its success in dealing with complex situations as it enables the “representation and processing of uncertain or vague information” (Meziane, et al., 2000) including linguistic statements and ill-defined system models. In other words, engineers and scientists have exploited this technique to “model human common-sense reasoning and decision making” (Ansari, 1998).

4.2.3.2.9 Genetic algorithms (GA)

Genetic Algorithms (GA) are advanced AI algorithms based on the ‘population genetics’ for finding solutions for complex search and global optimisation problems. To elaborate, in case of being conveniently encoded, GAs could provide solutions to real world problems through replicating the principles of “natural selection and survival of the fittest” (Busetti, 2001).

4.2.3.2.10 Case-based reasoning (CBR)

Case-based reasoning is one of the recently emerged knowledge-based problem solving and decision support techniques. However, unlike traditional knowledge-based systems, CBR system “solves a problem by remembering a previous similar situation and by reusing information and knowledge of that situation” (Aamodt & Plaza, 2001) instead of depending only on input knowledge of a certain domain. To demonstrate, CBR systems could be of great use in the medical sector. For example, this system can replace a physician in case of examining a patient of similar symptoms to a former one through reasoning by recalling past cases

4.2.4 Artificial Intelligence Rewarding Impact upon the Manufacturing Sector

The industrial sector is responsible for one third of the world’s GDP and half of the world’s energy consumption. Through the integration of recent information technologies (social, mobile and analytics) with emerging operational technologies ranging from sensors to robotics, the manufacturing sector could find itself in front of a huge opportunity to reduce waste, improve margin and move towards a sustainable future (Buchmeister, et al., 2019). In the following section, a selection of applications is briefed to highlight the potential change that could positively affect the manufacturing sector:

4.2.4.1 Product Design

Instead of the traditional, human-dependant design operations, AI technologies are currently leading an encouraging development as they provide the process with “real-time data coming from customer interactions or from the ecosystem in which the firm lies” (Verganti, et al., 2020). For example, real-time data could include “data describing restrictions and various parameters such as material types, available production methods, budget limitations and time constraints. The algorithm explores every possible configuration, until an optimal design solution is reached” (Buchmeister, et al., 2019). As a consequence, such data streams can enrich AI engines to develop its problem-solving capabilities, which would directly lead to the possibility of cancelling out the human role in the design process.

4.2.4.2 Digital Twin (DT)

Leveraging on the continuous advancements within the data analytics and IoT field, a digital twin (DT) has emerged as one of the hottest scientific topics in the industrial field, as it could potentially revolutionize the manufacturing sector through enabling a remote interaction between managers, manufacturers and machines along with providing a real-time analysis and accurate decisions. Briefly, a DT is "an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" (Glaessgen & Stargel, 2012). Undoubtedly, IoT has skyrocketed the amounts of usable data from the different fields including healthcare, smart city environments and manufacturing. Additionally, data analytics field is considered as a valuable resource for predictive maintenance and fault detection and the future health of manufacturing processes. However, DT still necessitate the effective presence of both ML and AI skills.

4.2.4.3 Virtual Manufacturing (VM)

Virtual Manufacturing (VM) is another interesting topic that has been the centre of the scientific community's attention for a long time, as it has the potential to break through the traditional operational strategies and assumptions by integrating manufacturing with information technology. To illustrate, such simulation systems provide the opportunity to "prove out" the production processes, resulting in "pre-production hardened systems" (Radharamanan, 2002) that helps avoiding the risk of going through actual production processes, thus would consequently help increasing production flexibility, eliminating the fixed costs and reducing wastes in terms of both time and materials. Additionally, VM could effectively revolutionize the decision-making process of acquisition managers through offering reliable, accurate schedules, risks and expenses.

4.2.4.4 Manufacturing Automation

Manufacturing automation is considered as an integral enabler of the transformation of manufacturing processes. Through its integration with the various advanced technologies including BD, IoT, VR, and AI, automation has the ability to stimulate the evolution of "the manufacturing value stream" as "software and machinery are increasingly more capable"

(Bradford, 2020). Undoubtedly, automation can be implemented in different levels according to the needs and resources of the industry introducing it. To illustrate, various industries have incorporated automation technologies in different aspects including "CNC machining, maintenance, material movement, scheduling, management and administration" (Bradford, 2020). According to research, new levels of automation are expected to drive the industrial sector to see unprecedented levels of accuracy and productivity through increasing capacity, improving quality, eliminating costs and diminishing lead time. Furthermore, Automation and Robotics would facilitate working in less human-friendly environments therefore reduce the accompanied health risks. To demonstrate, robotics would expectedly develop voice and image recognitions, which would pave the way to "re-create complex human tasks" (Buchmeister, et al., 2019).

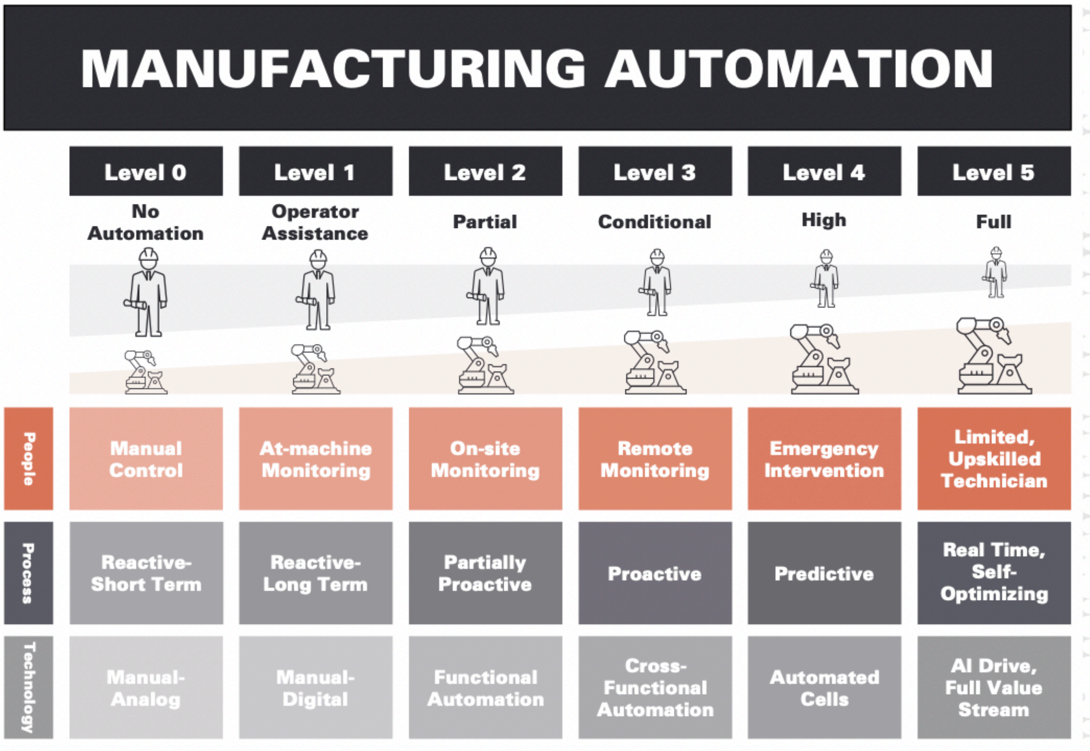

Figure 35 Hierarchical Representation of Manufacturing Automation (Bradford, 2020)

4.2.4.5 Quality

Needless to mention, quality has a substantial impact upon the sustainability and competitiveness of manufacturing entities. As mentioned above, AI algorithms are employed to eliminate scrap and enhance quality as "Machine learning and deep learning algorithms today contribute to the growing automation of quality control in production chains, helping considerably reduce the number of faulty parts, and the high costs resulting from them"

(Kang, et al., 2020) through early alerting manufacturing operators in case of detecting a progressive production faults that would in return invoke product quality defaults. Nevertheless, unlike human operators, advanced Machine-vision tools are capable of locating microscopic defects during the operations and autonomously responding through "using a machine-learning algorithm trained on remarkably small volumes of sample images" (Buchmeister, et al., 2019)

4.2.4.6 Smart Maintenance

In the manufacturing sector, unexpected machinery downtime is considered one of the most worrying dilemmas and cost-incurring events. In this regard, predictive maintenance has emerged to take its place among the top priorities in the industrial environment. To elaborate, "Predictive maintenance uses advanced AI algorithms in the form of machine learning and artificial neural networks to formulate predictions regarding asset malfunction" (Buchmeister, et al., 2019). As a consequence, such systems open the door for apparent reductions in maintenance expenses and extension of Remaining Useful Life (RUL) of equipment. Finally, Predictive maintenance algorithms enable saving time, resources, and labour costs to optimize the manufacturing value chain.

4.3 The Futuristic Picture: Collaborative Intelligence

Despite being viewed in the media as a threat towards human's jobs, AI is in real a promising field of research that mainly revolves around providing workers the space to nurture their effectivity fulfilling their roles. AI and ML algorithms will mostly show their worth when they are incorporated alongside human skills to complement and augment capabilities without replacing them as "Machines are not taking away human skills; they're amplifying and assisting our skills, while giving us room for creativity" (Damer, 2018). This will introduce an entire field of collaboration in which the "speed, scalability and quantitative capabilities of AI work are in harmony with the strengths that set humans apart: leadership, teamwork, creativity and emotional intelligence" (Damer, 2018).

Through the exploitation of the continuous technological advancements (internet in particular), collaboration has become possible through "sharing information, resources, and responsibilities by distributed agents to jointly plan, implement, and analyze the activities required to achieve individual and common goals" (Zhong, et al., 2015), as we have become capable of communicating and interacting with others remotely. So, despite being a recent research field, but CI has already been a part of our lives in various daily business activities.

For example, humans regularly exploit various developed web applications for remote communication and knowledge sharing. Also, entities within the same organisational hierarchy have established knowledge supply networks through internet-based technological advancements.

Collaboration can also be implemented in different ways. To illustrate, collaboration can come into action either blindly or in an intelligent way. Undoubtedly, being applied blindly does not guarantee the target achievement (ex: efficiency). So, apparently, the difference is made through the combination of the two words: Collaboration + Intelligence.

So, errors and failures in any collaboration-based system emerge due to the lack of effective knowledge exchange. In this manner, CI can be more effectively pointed to as a quantitative measure to "calculate the *collab-orability* (collaboration-ability) of agents in addressing the following challenges: How to define and identify the best collaborators? When and why to collaborate with other agent(s)? What resources to share? What collaborative network structure to use? How to handle and prevent potential failures?" (Zhong, et al., 2015).

Settling on a single definition for Collaboration Intelligence (CI) has been a highly sophisticated task. Consequently, it was a simpler task to find a definition for the two words (collaboration+ intelligence) in a separate way.

4.3.1 Collaboration

"Collaboration", in a raw meaning, is "*the action of working with someone to produce or create something*" (Zhong, et al., 2015). To put it into a technological context, we can portray it as any work that is done between a human being and a machine (ex: driver-car) to achieve targets that are/may not be achievable in an individual manner. Generally, collaboration can be implemented in two different contexts: Mandatory collaboration and Optional collaboration. To elaborate, some cases necessitate collaboration between entities to achieve a target, while in other cases, a collaboration would be considered as an option to improve a target.

On the same line, researching the term collaboration has seen much overlapping between it and other terms including coordination and cooperation. Consequently, it was essential to provide a map of those 3 keywords to highlight their similarities, inter-relationships and differences.

• *Coordination*: Refers to exploiting communication and knowledgen sharing to reach common goals among entities through working harmoniously.
• *Cooperation*: In addition to the attributes of coordination, it maintains a resource-sharing dimension to support goal achievement.

• *Collaboration*: In addition to the attributes of both coordination and cooperation, collaboration refers to "the sharing of *information*, *resources*, and *responsibilities* among entities to jointly plan, execute, and analyze the activities required to achieve individual and common goals" (Zhong, et al., 2015) .

4.3.2 Intelligence

Unlike the clear definition of collaboration, 'Intelligence' has different definitions as it linked to a range of contexts and mechanisms starting from communication mechanisms, cooperation to integration and collaboration. So, in general, intelligence refers to a system's ability to satisfy the collaboration's objectives regardless of its complexity.

4.3.3 Collaborative Intelligence

Back in time, people have intended to design machines because they wanted assistance. Accordingly, in order to put complete trust in an AI-based model, users would be eager to be fully aware of the machine's source of knowledge and the pattern of its reasoning. As mentioned before, a CI model is designed to partner a person to accomplish a target. So, some tasks are expected to be assigned to the machine and others are more reasonably assigned to the human users. To demonstrate, a Cobot vacuum cleaner could be incorporated alongside the user's efforts in order to collect tiny dirt particles that are beyond a human's sight ability. CI is viewed as a two-sided relationship between the user and the machine as both sides would request assistance in light of particular situations. With respect to the vacuum cleaner Cobot, despite adding to the process's efficiency, but it is still not expected to completely substitute its user's role as their skills are complementary. For example, an interesting angle of the system is represented by the vacuum cleaner's ability to identify situations where the user could help (e.g: switch off in case of an incompatible working situation) and accordingly request assistance (Epstein, 2015). Apparently, such system could shape the basis of an interesting CI. So, a CI must develop the ability to 'model the human view of the world' in order to collaborate effectively with human users. In other words, a CI should be aware of the unsymmetric relations that represent an integral part of the human perceptions that differentiate him to machines. For example, in a psychology experiment, people regularly reported that Cuba was similar to Russia, but Russia was not similar to Cuba. In fact, “most AI research treats object similarity as a symmetric relation” (Epstein, 2015). Furthermore, a CI should be capable of conducting reasonable and productive dialogues with his human partner after being equipped with ‘extensive knowledge’ and ‘self-awareness’. CI models should also be capable of learning from its partner and changing its strategy in the middle of a process. Needless to mention, human users interact with multiple agents, deal with different data sources, and go after multiple goals. To do so, they normally employ “multiple reasoning methods and multiple heuristics” (Epstein, 2015).

Important to mention, the term “collaborative intelligence” has been interpreted differently over the years, in correspondence to the technological advancements at the time. To demonstrate, three different definitions of CI are provided below:

4.3.3.1 Internet Crowd-based Collaborative Intelligence

Internet Crowd-based Collaborative intelligence technologies have been developing since the breakthrough of collaborative social media platforms by the end of the past decade. Based on real life cases, “Large-scale crowds exhibit extraordinarily intelligent capabilities through the participation and interaction of individuals on the Internet, which constitutes a new type of intelligent system” (YunhePan, 2016). Such CI systems have been incorporated to the benefit of various fields including the medical and academic fields. For example, the EyeWire game developed by the Connectome Project at Princeton University is capable of determining single cell and neural connections using a similar methodology, with a total of 165 000 citizen scientists from 145 countries collaborating in the game to “describe with colors how nervous tissue in mammalian retinas detects structure-function relationships involving motion” (YunhePan, 2016). Other examples include Wikipedia, Baidu Q&A, and Zhihu Q&A. Internet Crowd-based Collaborative intelligence computing can revolutionize the knowledge base available to human society as it could be an integral factor in critical applications. The related theory and technology has surpassed the preliminary stages throughout the recent past years towards unprecedented maturity of CI.

4.3.3.2 Human-centric Collaborative Intelligence

Since the introduction of AI, the main question that hit people’s minds revolves around the ability of machine intelligence to surpass human intelligence in the future. Undoubtedly, such questions arise due to fears of the possibility of AI replacing human’s jobs. However, studies clarified that “Human intelligence constitutes a form of natural biological intelligence that is different from that of AI" (YunhePan, 2016). Therefore, a human-centric CI systems would be built on a cooperation between computer and humans, that could surpass their individual intelligence. In fact, such systems were explained thoroughly by (Wilson & Daugherty, 2018). Based on their research involving 1,500 companies, which focuses on real-life implementations of human-centric CI systems, they concluded that corporates "achieve the most significant performance improvements when humans and machines work together" (Wilson & Daugherty, 2018). According to the research, such systems have undeniable positive impacts upon flexibility, speed, scale and decision making. For example, they stated that SEB, a major Swedish bank, now incorporates a virtual assistant called Aida to interact with millions of customers. Aside from being able to handle natural-language conversations, "Aida has access to vast stores of data and can answer many frequently asked questions, such as how to open an account or make cross-border payments" (Wilson & Daugherty, 2018).

In addition, wearable devices, intelligent-driving vehicles, exoskeleton devices, and human-machine collaborative surgeries have been put into action, indicating that the human-centric CI system has its door wide open for future development.

4.3.3.3 Autonomous Collaborative Intelligence Systems

Since the birth of AI, autonomous robotics development has been the centre of attraction for researchers. However, this direction was hindered by many technological obstacles. To demonstrate, even after the development of robots capable of walking using four legs, the US military turned its attention to the engineering of unmanned combat vehicles. Needless to mention, such research iterations have led to the introduction of autonomous aircrafts and vehicles.

Successful steps in developing automated intelligent mechanical equipment have promised higher degrees of effectiveness, easiness and economic benefits. Therefore, autonomous-Collaborative intelligence systems will be an important developmental direction for future generations of AI, as it has the potential to revolutionize the decision taking systems incorporated within the life cycle of start-ups, small and medium enterprises and larger corporates.

To sum up, the vast computing developments are leading us to an "open, dynamic and ubiquitous environments in which devices, services, and software agents are all expected to seamlessly integrate and cooperate in support of human objectives, anticipating needs, negotiation for services, acting on users' behalf and delivering services in any where, and any time" (Epstein, 2015). Apparently, there are huge gaps between collaborative intelligence components (human and machine) as they view the world differently, they process differently, and they communicate differently. Therefore, for a successful collaboration between a machine and a human user, different key issues should be carefully analysed.

4.3.4 Pillars of Collaborative Intelligence

The collaborative intelligence is the resultant of the seamless connection and interaction between the three pillars: collaboration technology environment, rally the area of knowledge and intellectual cooperation (Lee & Lan, 2007)

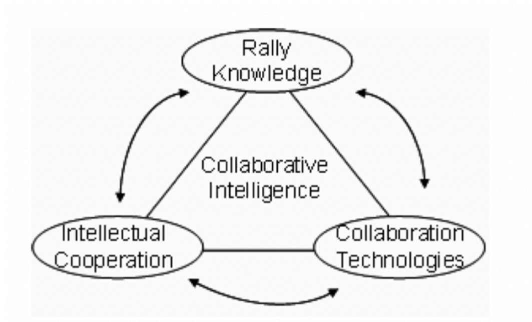

Figure 36 Pillars of Collaborative Intelligence (Lee & Lan, 2007)

4.3.4.1 Collaboration Technology Environment

Collaboration technologies include software, hardware and networks that facilitate the communication, collaboration and problem solving of a group of users within a collaborative environment. The collaborative environment technologies include:

• **Synchronous technologies:** Advancements that enable group of people to work together with being necessarily active at the same place/time including chat, video/chat conferencing and shared white boards.
• **Asynchronous technologies:** Advancements that enable group of people to work together without being necessarily active at the same place/time including e- mail, Weblog and discussion forums.

4.3.4.2 Rally the Area of Knowledge

The emergence of web 2.0 and big companies (e.g Google and Amazon) has revolutionized the cyber space, as it enables users to create new webpages, share information and "dynamics links using open source technologies" (Lee & Lan, 2007) following Google's development of "scaleable architecture for servers" (Lee & Lan, 2007) in a successful attempt to connect PCs in a faster manner compared to the former offerings by Yahoo! and MSN that focused solely on the development of massive servers to handle vast amounts of data streams.

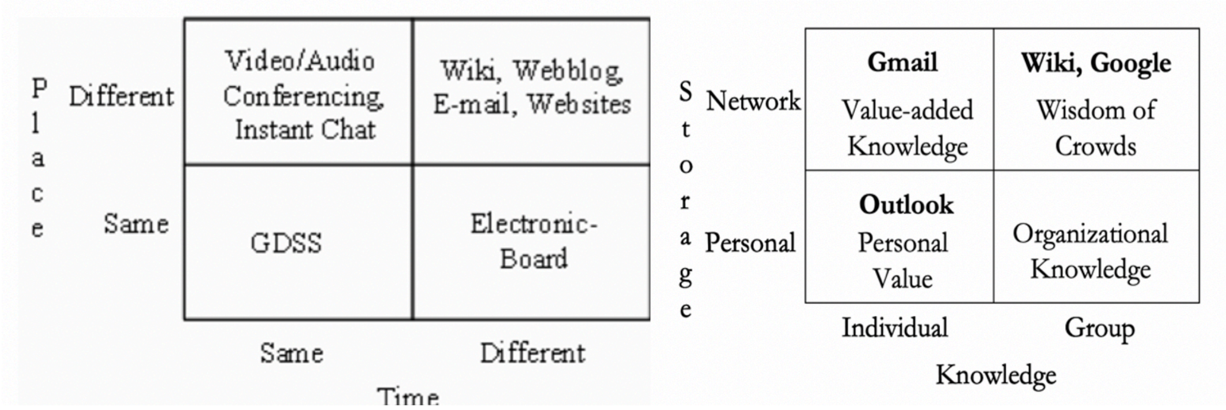

Figure 37 The Revolutionized Cyber Space

4.3.4.3 Intellectual Cooperation

As a matter of fact, through its "core philosophy" of "openly service", Web 2.0 has opened the door for users to "cooperate to create a new world of dynamic knowledge" (Lee & Lan, 2007), which represents an integral block of the CI chain.

The intellectual cooperation spots the light on the collaborative advantages resulting from both "inter-personal" and "inter-organizational" interactions that took advantage of the recently extended social networks, which results in "network value and effect". Value networks are "complex sets of social and technical resources to generate economic value. This value takes the form of knowledge, intelligence, a product (business), services or social good" (Lee & Lan, 2007).

4.3.5 A General Approach For Collaborative Agents Modeling

Step 1: Problem Determination and Assessment

This primary step identifies and describes the problem under analysis through modelling the conceptual framework of the desired system from a user's perspective along with determining the services and functionalities that the model should be capable satisfying.

Step 2: System Architecture:

This step revolves around determining the system components and connectors. This step is an advanced-level portrayal of the system that makes the system more "understandable, intellectually manageable, guide development implementation and evolution of the system for future modification" (Houari & Far, 2005).

Step 3: Capturing the Targets

The targets of the system are specified according to the requirements. In this stage, collaboration, activity and sequence diagrams are employed to provide a precise representation of the system from the user's eyes. To elaborate, this step prioritizes identifying the services the system should provide to its partner.

Step 4: Extracting the plans

From the user's point of view, internal diagrams that highlight the functionalities of the system's internal entities in order. Undoubtedly, this step helps unveiling more details that are not clear to extract only through the external perspective. A collaborative agent's plans refer to groups of activities hierarchised under sets of roles, which are responsible for specifying the model's ability to achieve a target.

Step 5: Identifying the (Knowledge)

Knowledge is the missing piece of puzzle, which is responsible for complementing the plans to successfully fulfil the target. In fact, knowledge is stored in the form of either "a set of assertions which comprise standards propositional operators" (Houari & Far, 2005) including conjunctions, disjunctions and negations or "a set of quantifiers". It can also be stored in the form of "other devices for quantifying assertions with a level of uncertainty, as well as ontological assertion" (Houari & Far, 2005).

Step 6: Specifying the Interaction

Collaborative agents should be developed to interact with partners, other agents and external environment in order to fulfil their assigned duties. For such requirements, a unique kind of messaging protocol should be developed to stimulate the agent to trigger a certain sequence of actions. The hypothesized protocol should emphasize a set of rules that orchestrate the relation between "an agent with other agents to achieve a desired final outcome in sharing the knowledge and performing actions that satisfy the desired goals to fulfill some utility functions" (Houari & Far, 2005). Messages can be coded in XML (eXtensible Markup Language) format and transmitted using the Simple Object Access Protocol (SOAP).

Step 7: Agents Adaptation

The ability to learn is considered one of the attributes of an intelligent autonomous agent that could be developed through the incorporation of different machine learning techniques built in an algorithmic form. For example, a trained neural network learning algorithm can be created by the generation of knowledge for the agent in the form of if-then rules, which are used for training the model.

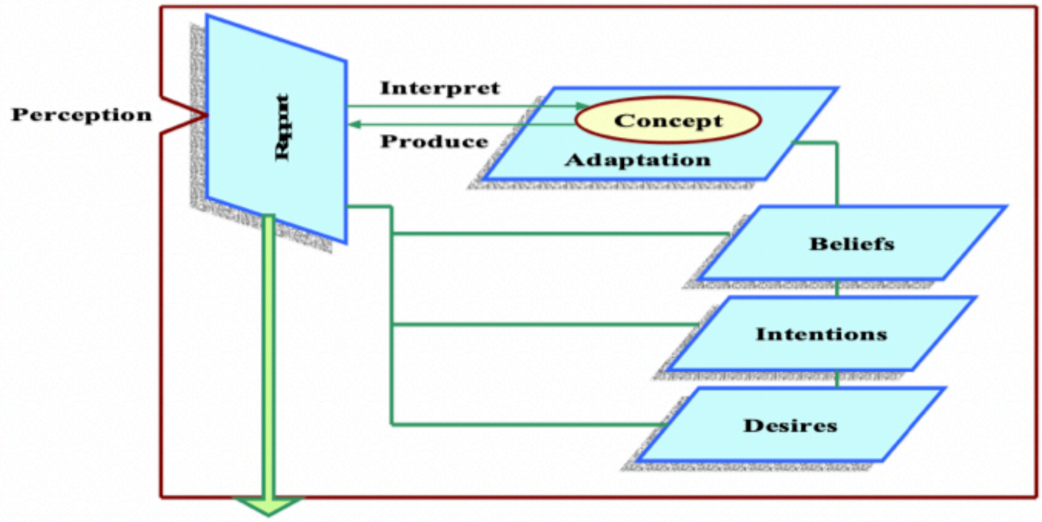

Figure 38 A conceptual Framework of Agents Adaptation (Houari & Far, 2005)

4.4 Discussion

4.4.1 Latest Research Findings on Collaborative Intelligence in an Industrial Context

In light of the continuously changing demands of the industrial production field in terms of safety, efficiency, and environmental friendliness, various sensors and wireless devices have been widely employed in the industrial environments, which paved the way for a gradual nurture of the Industrial Internet of Things (IIoT) related research. Simply, IIoT is based upon the daily collection of vast amounts of data by different devices at different times, to be later collaboratively analysed facilitating the generation of "effective solutions to achieve safe, highly efficient and eco-friendly industrial production/service" (Chen, et al., 2016). According to research, some proposals related to taking advantage of the cooperativity of big data analytics have already come to light.

4.4.1.1 Collaborative Sensing Intelligence Framework (CSI)

Building on the availability of "massive spatio-temporal data from different devices and different time points", (Chen, et al., 2016) has extended the research to the collaborative sensing intelligence (CSI) framework, which is expected to enhance the efficiency of monitoring and controlling, leading to a favourable elimination of costs and energy consumption in the industrial production sector. Also, such proposed systems can play a vital role in improving the mechanical productivity of assets. To demonstrate, thanks to the different sensors and wireless devices incorporated, we can extend our expectations to reach a fully automatically controlled maintenance system of machines even in "remote and hard-to-reach areas" (Chen, et al., 2016).

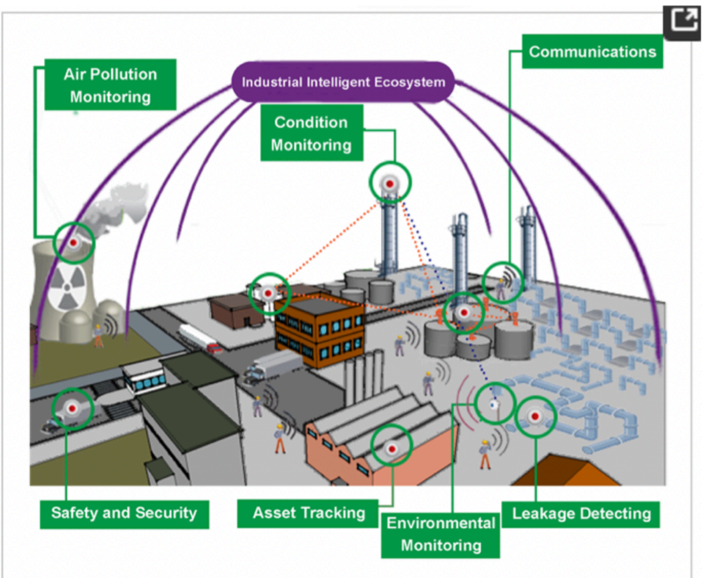

Figure 39 A Graphical Representation of an Industrial Intelligent Ecosystem (Chen, et al., 2016)

4.4.1.1.1 Key Components of CSI

The CSI framework is composed of three main components: Sensing data collection, Integrated analytics, Information mining and Knowledge discovery.

4.4.1.1.1.1 Sensing data collection

In a data-driven industrial environment, vast amounts of data have been expected to be gathered by the sensors and wireless devices, which are mounted everywhere. Additionally, this component is the primary block of integrated analytics, which makes collecting enough spatio-temporal data highly essential.

4.4.1.1.1.2 Integrated analytics

This is the core component of CSI. An effective, collaboration-based integration of unsimilar data from various sources is undoubtedly an integral factor behind a successful data mining/discovery, which would result in useful information/knowledge. In fact, the collaboration of different objects has been a clear obstacle that hindered the practical development of this component. Industrial production is formed of a "series of processes and actions, and these processes and actions are location- and time-related. A spatio-temporal Markov chain can be used to process the relationships between these processes and actions" (Chen, et al., 2016). According to previous work, based on such processing, the collaboration between different objects could come to reality.

4.4.1.1.1.3 Information mining and knowledge discovery

Based on a successful Integrated Analytics, the industrial processes rules and workflow can be learned, which could lead to the formation of actionable knowledge organised in terms of a particular logical sequence. According to literature, "Based on the mined information and the discovered knowledge, various intelligent algorithms can be designed to solve the problems and to meet the requirements of industry" (Chen, et al., 2016).

4.4.1.1.2 An Industrial Application of CSI: Dynamic Detection of Toxic Gases

Leakage of toxic gases in large-scale petrochemical plants has always been one of the most concerning dilemmas to both humans and the surrounding environment (Wang, et al., 2014), which earmarked CI as a potential solution to develop an intelligent leakage detection system for timely crisis management and control.

Currently, in the majority of large-scale petrochemical plants, only static wireless sensor nodes are independently deployed to alert workers to a potential leakage of toxic gases (Chen, et al., 2016) .Briefly, a static node triggers an alarm only in case of sensing a reading for a particular toxic gas that exceeds a pre-set threshold in a certain location, which limits such detecting systems' functionality. To elaborate, such systems find it difficult to locate the exact coordinates of leakage source as it cannot track the concentration variations of toxic gases (i.e. concentration varies by time and location), which necessitates a collaboration between the different sensor agents. Also, such systems find difficulties triangulating the real-time geographical locations of operators, which complicates the efficient monitoring of the workers' health. Thus, a collaboration between operators and sensor agents is essential to facilitate predicting the impact of the potential leakage upon the workers' health. On another note, due to the fact that each sensor is designed to detect a particular toxic gas, a costive system of different sensor types must be deployed in various positions to detect different gases. However, such systems are still not applicable to all possible scenarios. To illustrate, in such dynamic environments, different toxic gases might react together forming new combinations of different characteristics, which might not be detected by the mounted sensors. Accordingly, as shown in figure 37, (Chen, et al., 2016) proposed a CSI framework to provide a solution to the mentioned problems after collecting and analyzing massive spatio-temporal data from various devices in IIoT environments.

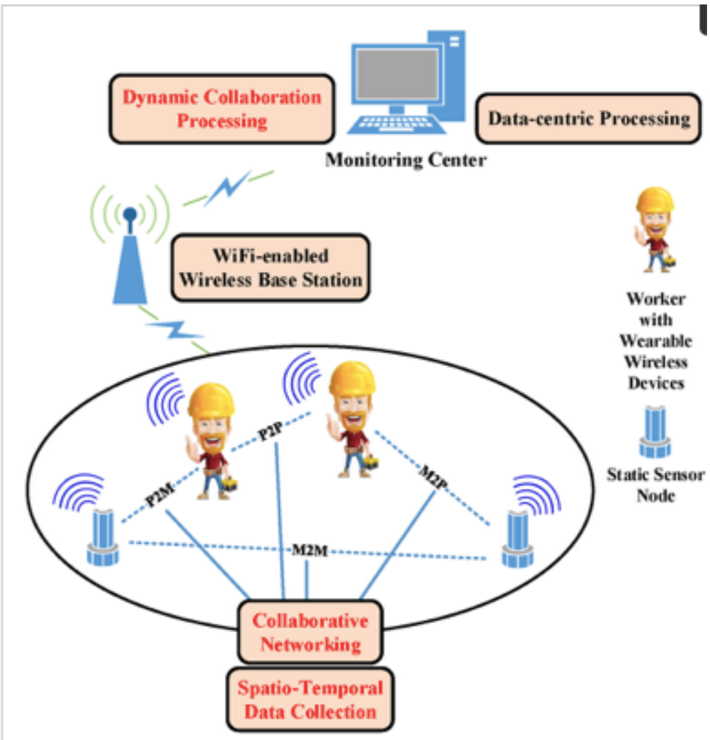

Figure 40 An Application of CSI Framework to Improve the Detectability of Toxic Gases in Large-scale Petrochemical Plants (Chen, et al., 2016)

Simply, this framework is composed of four elements: sensor-embedded wearable wireless devices, static wireless sensor nodes, WiFi-enabled wireless base stations, and a remote monitoring centre. The wearable wireless devices are worn by operators and collaborate with static wireless sensor nodes to sense the ambient environment and gather spatio-temporal data. The data are re-directed to the remote monitoring centre via WiFi-enabled wireless base stations. According to the collected data, the monitoring center occasionally initiate a dynamic collaborative networking among several wireless devices to provide a problem-solving network to detect the potential leakage of toxic gases.

4.4.1.2 Collaborative robots and complex robotic cells

As pointed earlier, industry 4.0 could be an answer to a couple of the main challenges encountering the manufacturing enterprises: shorter product life-cycles and increasing demand of highly customized products. Needless to mention, demand patterns change frequently in particular industries including furniture, footwear, and others. Expectedly, a change of demand patterns would be painful to the start-ups and SMEs, as they cannot afford the huge flexible production lines acquired by the bigger incumbents. Fortunately, ample research efforts have been directed towards the potential impact of CI upon the traditional manufacturing paradigm. The new manufacturing paradigm is based on modular factory structures composed of smart devices within a networked IoT environment (Román-Ibáñez, et al., 2018). In traditional manufacturing industries, robots are employed mainly for assembly tasks. The research paper (Morenilla, et al., 2021) presents a literature review of "Systems for the autonomous or collaborative assembly of furniture sets and sewing of garments using robots, robotic monitoring systems in footwear industry as well as unfolding of garments". Scalability, safety and security concerns are covered in the development of these systems.

A planning and assembly system for furniture pieces is introduced, where KUKA robots are responsible for geometric and symbolic planning, re-assignment of roles, and coordination of workflow to accomplish a successful assembly of a table. Interestingly, for heavy objects that cannot be managed by a single robot, a "set of robots is coordinated to complete the task" (Knepper, et al., 2013). Additionally, AI-powered systems for the autonomous assembly of furniture sets (e.g., tables, chairs) employing a set of robots are presented in (Huang, et al., 2018) and (Knepper, et al., 2013). Briefly, such systems mimic basic operation skills in mechanical assembly using ML, Learning from Demonstration (LfD) in particular. So, KUKA could be comfortably assigned the cutting process, while humans guide the assembly of the final product assisted by an AI interactive interface. Clearly, such systems necessitate the development of a "a library of 3D models taking into account the modularity and scalability of components of furniture sets" (Morenilla, et al., 2021). On the same line, "human multimodal cues for furniture assembly were analyzed" to extract information in an attempt to improve the communicational and social skills of cobots (Kontogiorgos, et al., 2018).

To sum up, research efforts towards cobots have intensified throughout the past decade. Clearly, cobots could be an answer to different challenges hindering the growth of MSMEs. To elaborate, new, affordable cobots with advanced levels of cognitive and communicational skills could facilitate the set-up of flexible manufacturing systems, which could withstand shorter product life cycles and frequently varying demand for highly customized products.

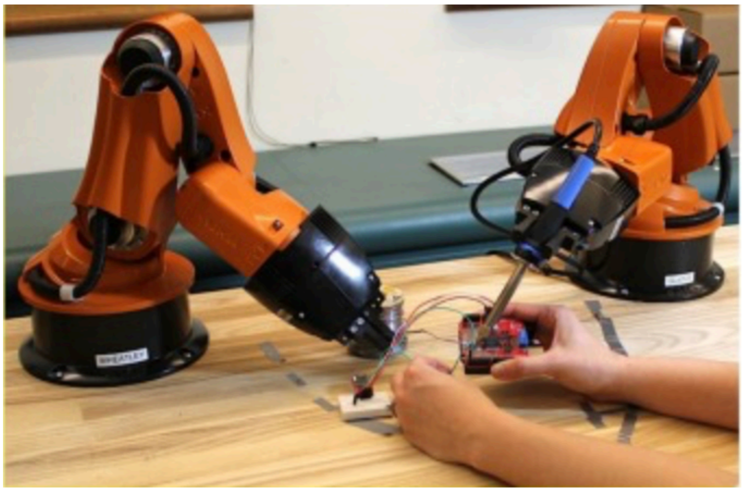

Figure 41 A Work-space of Human-AI Collaboration Invalid source specified.

4.4.1.3 AI-based human-centric decision support framework

Adaptability to variations under unstable business environments has recently emerged as a competitive differential for manufacturing enterprises. This goal highlights the necessity of developing adaptivity to eliminate uncertainties. One of the main uncertainties within the manufacturing sector lies behind the reliability of its assets. As a matter of fact, assets likely degrade over time due to wear of mechanical components, bad weather conditions and accidents. As a result, research efforts have been directed towards harnessing artificial intelligence technologies to develop a decision support framework for predictive maintenance. (Chen, et al., 2021) proposes an AI-based human-centric decision support framework for predictive maintenance in asset management, which can facilitate prompt and data-driven decision-making under unstable environments. In addition to its adaptivity, developers should ensure "that such decision support framework establishes a strong human–machine teaming component to ensure user acceptance within real-world environments; allowing business actions and informed decision to be made promptly" (Chen, et al., 2021)

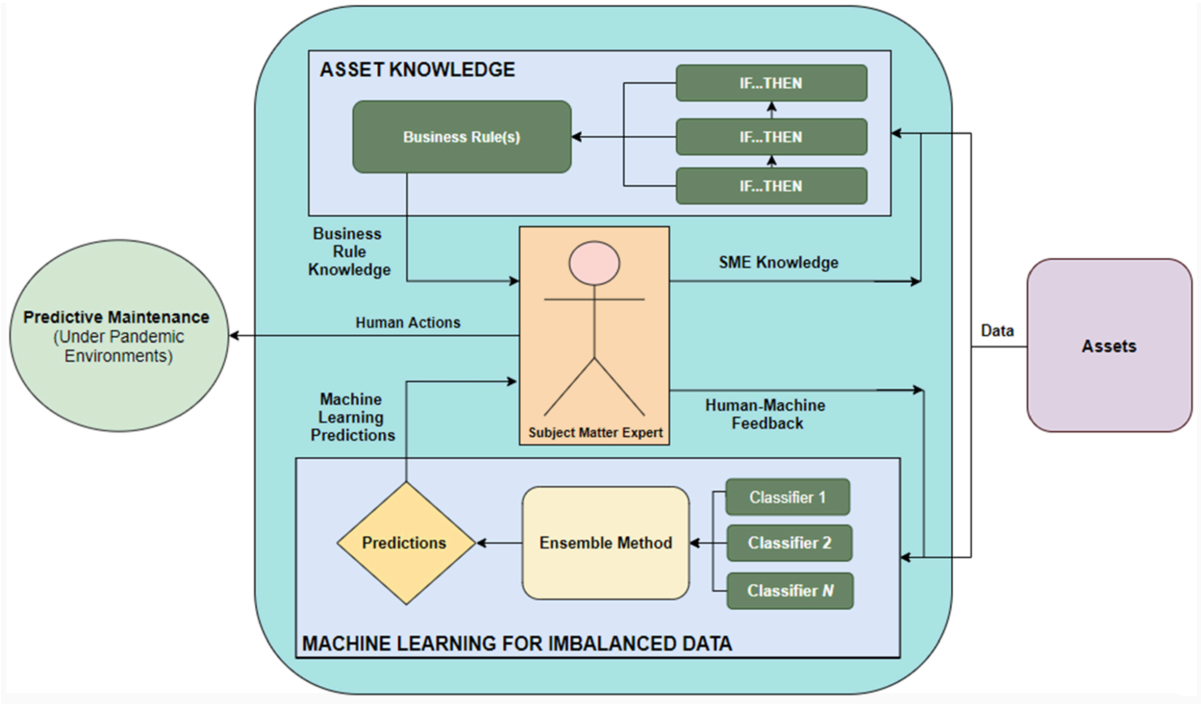

Figure 42 AI-based human-centric decision support framework (Chen, et al., 2021)

The proposed framework is divided into the following key interconnected components:

- Assets: Primarily, an asset under real-time monitoring "needs to be an IoT-enabled entity with sensory data extraction capabilities, and from which data samples are collected from" (Chen, et al., 2021)

- Asset Knowkedge: embedded within this decision support framework a component responsible for gathering and adopting tacit knowledge from technical experts. This component must be regularly updated to ensure the delivery of the latest knowledge and guidelines to the experts/non-experts users to adapt to situational changes in the right time. The main mission of this component revolves around transforming the gathered knowledge into well-structured business rules. Furthermore, deploying AI models facilitates extracting meaningful patterns from huge data sets to complement the prepared business rules, thus "leading to a knowledge base that aims to bridge human–machine trust in using the decision support framework" (Chen, et al., 2021). Supposedly, the knowledge base consists of statistical features that indicate whether the collected sensory data samples captured from the asset under analysis is normal or abnormal. Normally, "bridging human–machine trust enables business actions to be undertaken" (Chen, et al., 2021). Nevertheless, this component includes a precaution directory to deal with highly unpredictable fault diagnostics which can be double checked by business rules, ML inference, and technical experts.

- Machine Learning for imbalanced data: In particular cases, the AI-powered maintenance systems might output biased and misleading decisions. This phenomenon goes back to feeding the system with imbalanced data during the training stage. In brief, the developed Ensemble model exhibits better learning and representation of the majority class. For example, the collected data from a machine's sensors are commonly biased towards being referring to a non-failure state. A human-feedback loop of this framework is proposed to facilitate the re-assessment of ML predictions in case of a misalignment between machine predictions and the operator's intuition of the asset under his watch.

- Predictive Maintenance: A critical feature of this AI-powered decision support framework is taking the feedback from technical operators into account within the working cycle of the algorithm. In case of a misalignment between the set business rules and ML predictions, technical operators are involved to re-assess the outcome and accordingly update the ML models. To illustrate, assuming the presence of class imbalance, the proposed framework is capable of outputting results and re-accept a double-checked input from the co-operator, thus strengthening the collaborative trust between humans and machines, which could stand out as a differential in highly unpredictable scenarios (i.e Pandemic).

To further stress the point, the human factor has been an integral component of the proposed framework throughout starting from structuring the business rules to the validation and update of the system's outcomes. Thus, developing such systems should not be considered as a threat to the human's role. On the contrary, such systems promote a "human–machine teaming" (Van Diggelen, et al., 2019) loop to strengthen the trust-based partnership between human operators and AI models.

4.4.1.4 Shop Floors with Virtual Intelligent-Assistant (ChatBot)

The term "Internet of things" was first coined by British entrepreneur Kevin Ashton in 1999. Since then, we have been witnessing the outburst of devices connectivity in various fields. However, the industrial applications barely harnessed IoT before the global maturity of I4.0 in 2013. In 2015, another term, "Internet of People" (IoP) floated to the surface to complement the IoT concept. Simply, IoP "connects the workforce to the internet using interfaces" (Mantravadi, et al., 2020). Conceptually, IoT "promotes people-centric design enhancements with the principles of being social, personal and proactive" (Miranda, et al., 2015).

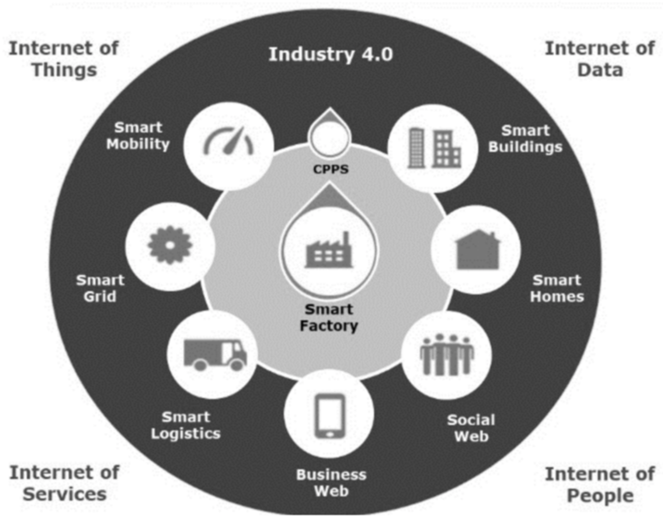

Figure 43 Internet of Everything (Da Silva, et al., 2020)

After a detailed identification of the specific requirements for a user-friendly Manufacturing Execution System (MES), (Mantravadi, et al., 2020) provided a validated prototype of an interactive chatbot supported with a prediction system to foster human-AI collaboration concepts and promote collaborative technical assistance. The author incorporates techniques such as NLP and ANN, which are key parts in making a chatbot 'intelligent' to collaborate with the MES user. The chatbot's main target is enhancing production coordination by "assisting the shop floor workforce and learning from their inputs, thus acting as an intelligent assistant" (Mantravadi, et al., 2020). This source presented a programmable chatbot as a proof of concept, where the new interface layer provided live updates related to production in natural language and complemented MES with predictive capability.

Input: Natural language query from the user
Output: Requested data value from MES on natural language form, chat log
Algorithm: User interaction

1. **while** user has a question
2.   user enters query
3.   detected and extract keywords
4.   **for** each keyword *k* in query
5.   lookup *k* in MES data fields
6.   save *k* for Algorithm 2
7.   **return** MES data value *v*
8.   **end for**
9.   concatenate *v* with predefined reply string
10. **end while**

Figure 44 Chatbot Interaction Algorithm (Mantravadi, et al., 2020)

In a factory's dynamic environment, a chatbot can be linked either to the sensors mounted to the physical assets on the shop floor or to external data sources to provide responses relevant to procurement planning, inventory management and shipping upon request. According to (Sankar & Balakrishnan, 2016), a chatbot with a prediction system can also be linked to a 'database supported knowledge base'. Expectedly, implementing such systems necessitate the availability of both interoperable devices and a unified IT infrastructure.

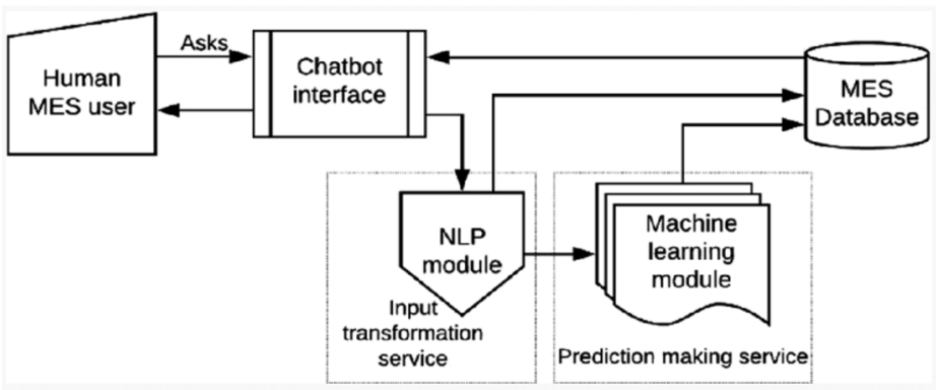

Figure 45 MES based Technical Assistance System (Sankar & Balakrishnan, 2016)

4.4.1.5 Pi-Mind Technology

Smart factories have become one of the hottest research topics in the past years. SF is a futuristic view of the industrial sector in which "the products, resources and processes are decided and controlled by CPS" (D. Evjemo, et al., 2020). (Terziyan, et al., 2018) depicts its own vision of a smart factory as an "ecosystem, which embeds cognitive aspects and biased decision-making into existing automated schemes of the operation". Needless to mention, this futuristic vision urges the development of convenient communication and collaboration infrastructure to connect providers and consumers of successful industrial decisions.

In brief, Patented-Intelligence-Mind technology is a "compromise between completely human-expert-driven decision-making and AI-driven decision-making [as it] enables capturing, cloning and patenting essential parameters of the decision models from a particular human expert making these models transparent, proactive and capable of autonomic and fast decision-making simultaneously in many places" (Terziyan, et al., 2018). The proposed technology deepens the human impact in smart manufacturing processes and supports human-AI 'shared responsibility' for the consequences of the decisions articulated. Additionally, the technology takes advantage of 'capturing' and 'utilization' of the "traditionally human creative cognitive, intuitive and emotional capabilities" (Terziyan, et al., 2018), which in many exhibits a better performance compared to rational decision-making. In other words, Pi-Mind technology refers to a group of models, methodologies, and tools based on principles of value-based biased decision-making and creative cognitive computing to complement the axioms of decision rationality in industry.

Figure 46 Pillars of Pi-Mind Powered System (Terziyan, et al., 2018)

The technology of Pi-Mind simulates a DT of a human decision-making schemes in different situations, which offers its user a variety of actions according to his personal preferences.

The proposed technology enables a shift from human employees functioning approach to the service-oriented one in the majority of decision points of industrial ecosystems. Thus, Pi-Mind technology can be employed as an answer to the real-time need of outsourcing a technical expert as it adds a new dimension on top of Collective Intelligence emergent from the collaboration of artificial agents and human individuals. To elaborate, although most industrial contexts limit human operators to technological parameters, predefined processes or series of actions and the rules for their execution, yet each human operator embraces a unique degree of freedom in making decisions after earning his own skills and abilities.

The degree of freedom displayed in an operator's decision-making process is the core principle behind the application of Pi-Mind technology. Beside his own situational cognitive assessment, an employee could find it more convenient to outsource consultation from colleagues, experts and domain specialists. Luckily, thanks to Pi-Mind robots, flexible problem-solving can be executed instantly without involving real human individuals.

Despite the expected diminishing of the demand for domain specialists, but Pi-Mind would supposedly make their "ubiquitous presence" instantly available and increasingly impactful within the smart manufacturing ecosystem. To clarify, the Pi-Mind technology's main target doesn't lie behind replacing human factor in industrial processes; it is about globalizing every individual's impact within I4.0

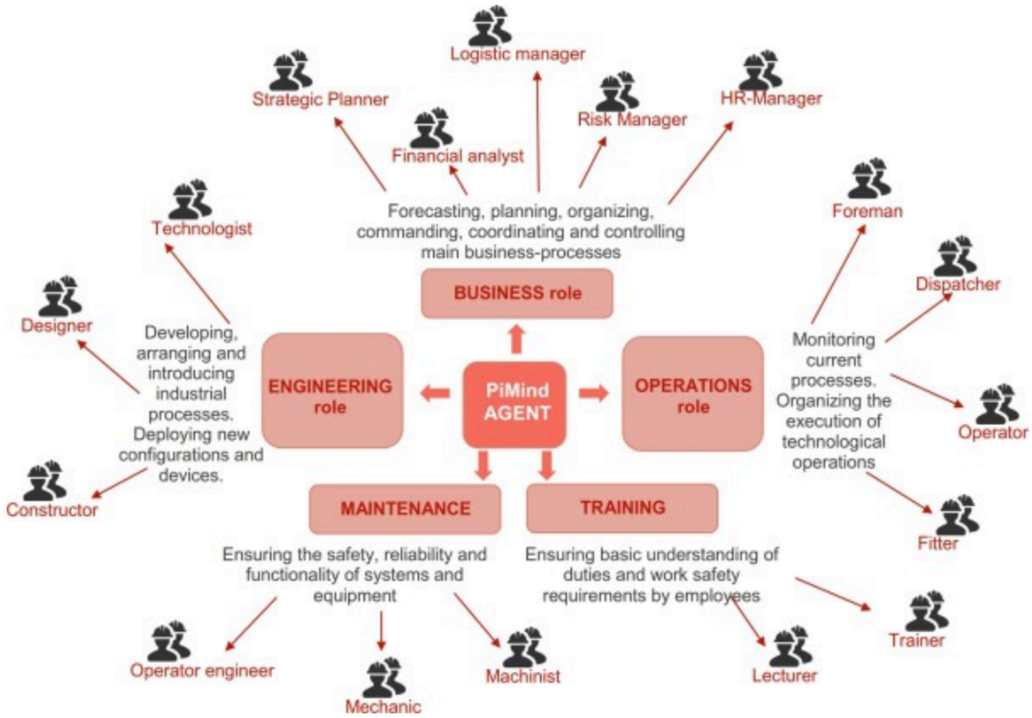

Figure 47 Industrial Applications of Pi-Mind (Terziyan, et al., 2018)

According to the author, Pi-Mind technology could be an answer to unexpected events during assembly and testing tasks. Briefly, Pi-Mind robot can assist a worker with creative decision-making in the scenarios where improvisation is needed or even encouraged. In addition to his personal Pi-Mind robot, the recommendations received from the artificial clones of different external experts can be taken into consideration to stimulate the convergence towards an integrated, compromised and possibly unique decision for a certain problem. Thus, the worker takes advantage of the diversity of opinions before reaching to an optimal decision.

4.4.1.6 Augmented Manufacturing Analytics Framework for Human-AI Collaboration in Quality Control

Augmented analytics is becoming one of the hot research topics, which focuses on the improvement of analytics through the development of “conversational interfaces” and the employment of digital intelligent assistants (DIA) representing the human knowledge, thus facilitating the interaction with gathered data and extracted information.

(Bousdekis, et al., 2021) outlines a framework for implementing quality analytics for decision augmentation through optimized human-AI interaction. The framework embraces the entire data analytics lifecycle (descriptive, predictive, and prescriptive analytics) targeting the extraction of an “increased value from quality data and prescribing appropriate mitigating actions through a voice-enabled DIA” (Bousdekis, et al., 2021). Although the descriptive analytics analyzes historic events and predictive analytics anticipates future events, but both could not further bolster the decision-making process (Chen, et al., 2012). On the other hand, prescriptive analytics, a relatively less mature field, has been increasingly gathering research interest as it facilitates data-driven optimization for decision support and planning (Lepenioti, et al., 2020). According to (Frazzetto, et al., 2019) , prescriptive analytics could potentially have the biggest positive impact upon businesses by supporting it with insights about proactive corrective actions for the anticipated undesired events. However, this field necessitates the presence of highly skilled workers with respect to data science and ML, which slows down the pace of adoption. To address this issue, (Bousdekis, et al., 2021) suggested that combining prescription with augmented analytics could enable users with average data science and ML skills to identify and communicate the most important insights or changes in the business by interacting through spoken and written language through the incorporation of NLP and conversational interfaces.

To develop a reliable voice-enabled DIA system, the author integrated four core components presented by (Deriu, et al., 2021) and (Maedche, et al., 2019): Speech-to-Text (STT) to transcribe voice inputs, Natural Language Understanding (NLU) to extract intents and entities, Dialog Management (DM) to track dialog states and decide the next actions, and Text-to-Speech (TTS) to generate a computer voice output. The proposed system is capable of augmenting tasks associated with product and process quality control. To demonstrate, this framework supports the detection of abnormal behaviors and root causes of defects, forecasting their impact on both the product and process quality and prescribing appropriate actions in the form of voice-first advice. Specifically, the framework foresees stream processing to perform real-time data processing for: (i) identifying potential reasons behind defects and highlighting correlations between products and defect rates; (ii) anticipating future quality defects and their potential impact; and (iii) prescribing mitigating actions to optimize relevant manufacturing performance indicators, such as Overall Equipment Effectiveness (OEE), uptime and scrap rate.

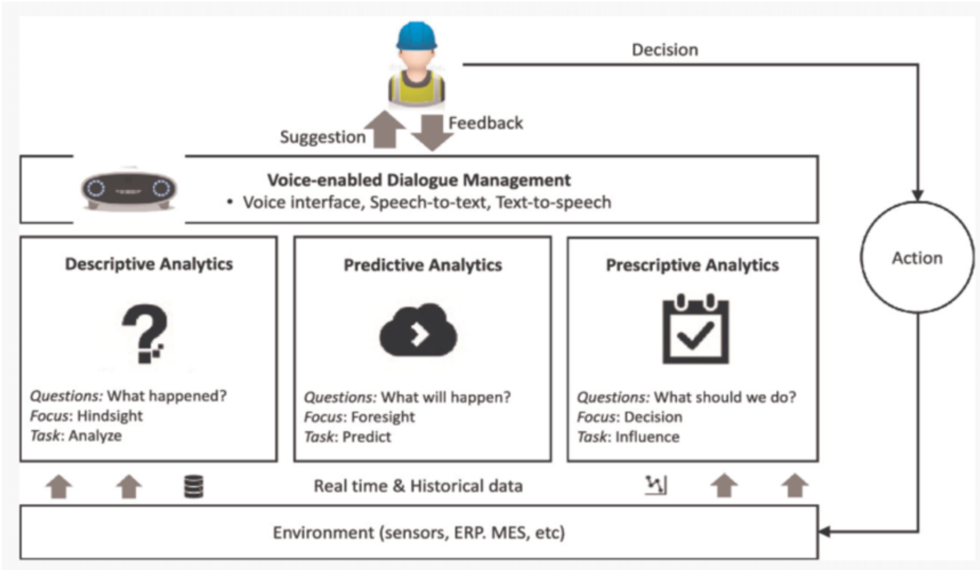

Figure 48 Augmented Manufacturing Analytics Framework

The system employs DIAs to spot the operator's plans, queries and instructions within the industrial ecosystem. Normally, DIAs should be backed to deal with trivial interaction obstacles in the manufacturing industry. To demonstrate, DIAs should be capable of fulfilling its job even in the presence of noise, different languages, and workers wearing voice-hindering masks or safety googles. Its STT component has to be reliable under these conditions, which is a technical challenge. To this purpose, a reliable STT model is embedded within the framework. However, important to note, the application of reliable STT trained models is quite challenging and expensive.

Furthermore, DIAs would be interoperable on different mobile devices to be usable regardless of the location of the user. Bearing in mind the time-pressing nature of manufacturing tasks, the DIA's outcome is developed to be fast, unambiguous and user-friendly. Since time pressure is a typical work condition, the DIA's dialogs must be fast, unambiguous, and easy to use to avoid the need for time-consuming graphical interfaces.

4.4.1.7 Artificial Intelligence-Driven Customized Manufacturing Factory

Although the industrial sector has witnessed promising technological leaps, but yet the manufacturing industry encounters various challenges to effectively respond to the rapid customization of personalized products. Thus, a shift of the current manufacturing paradigm has become a necessity. In relevance to the highlighted concerns, (Wan, et al., 2020) focuses on the implementation of a customized manufacturing (CM) factory. Briefly, a CM factory takes advantage of technological advancements with regards to learning capacity of AI technologies, smart interconnectivity and inter-operability of Cyber-physical objects, dynamic re-configurability of manufacturing execution systems, vast amounts of data and the deep integration between physical and informational systems. To cut it short, the deployment of AI and industrial IoT facilitates smart manufacturing as AI-powered tools enhance manufacturing efficiency and improves the chances of proactively introducing higher value-added products/services to the customer. However, adopting AI technologies still draws some concerns and challenges. To illustrate, AI and ML technologies necessitate the availability of high computer servers to facilitate the real-time processing of the massive amounts of gathered data (Sze, et al., 2017). On the manufacturing businesses' side, fulfilling such requirements might stand as a financial liability. Also, in such a hyper-competitive market, manufacturing firms fear outsourcing their data to external partners (Cloud computing services) to avoid leaking data.

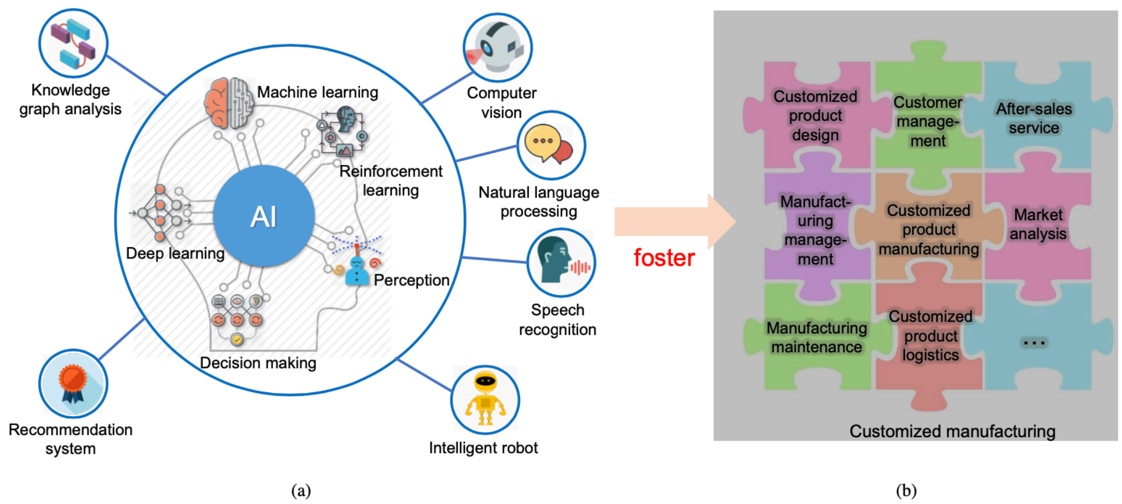

Figure 49 Incorporation of AI technologies in Customized Manufacturing (Wan, et al., 2020)

4.4.1.7.1 AI-driven customized manufacturing

As shown in Figure 46, the deployment of AI technologies could add value to the manufacturing industry across different parts of the value chain, ranging from customized product design to customized product logistics. Thus, complementing the human intelligence with AI technologies could benefit the manufacturing industry's flexibility, scalability, efficiency and sustainability.

Followingly, as named by (Wan, et al., 2020), "AI-driven CM" augments the human capabilities through learning and analysing order quantities, lead time and production anomalies. As well, ML technologies could learn data collected from the production assets to analyse it and learn when to alert the human operator to intervene, thus reducing downtime, anomalies and scrap rate. As well, ML algorithms can be employed to streamline the variability and uncertainty of supply chains through analysing data collected from the market and anticipating the sudden variations of customer preferences.

4.4.1.7.1.1 AI-Assisted Customized Manufacturing Factory

As depicted by (Wan, et al., 2020) in Figure 47, an AI-assisted CM framework includes smart devices, smart interaction, AI layer, and smart services. Provided below a brief description of the 4 building blocks of the system:

- Smart Devices: this block represents the "the physical layer" of the system (i.e robots, conveyors, ..etc). Being a part of automatic control systems, smart devices must be ready to meet a real-time request. There, ML algorithms can be employed in low power devices. For, example, supporting Field Programmable Gate Array (FPGA) "has shown a great improvement in both power consumption and performance in Deep Neural Networks (DNNs) applications, which offer high accuracies for important image classification tasks and are therefore becoming widely adopted" (Fallahlalehzari, 2020)

- Smart Interaction: this block links the device layer, AI layer, and services layer. Briefly, this layer consists of basic network devices (i.e routers) and communication protocols to connect different manufacturing processes. AI is incorporated in this block to predict, optimize, and control both mobile network reliability and congestion.

- The AI Layer: this block consists of AI algorithms operating at various computing platforms such as edge or cloud servers (Lu & Xu, 2018). To demonstrate, training a DL model for image processing can be executed in the cloud. Then, edge computing servers run the trained DL model and execute simple algorithms for assigned manufacturing processes.

- Smart Manufacturing Services: this block resembles data visualization, predictive maintenance, predictions, and market analysis. For example, a "recommender system can provide customers with details of CM products, and the information including the performance of a production line, market trends, and efficiency of the supply chain".

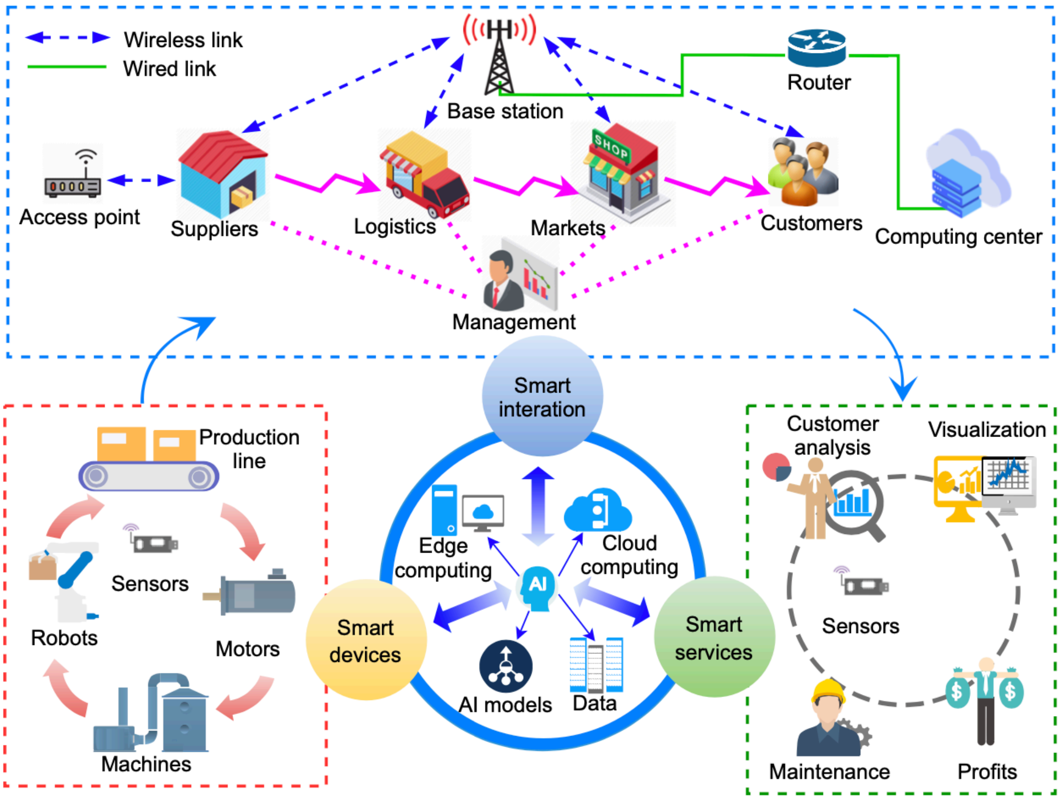

Figure 50 AI-assisted CM Architecture (Wan, et al., 2020)

4.4.1.7.1.2 Cooperative multiple agents

Multi-Agent Systems (MAS) "consist of autonomous entities known as agents" that "collaboratively solve tasks" and "offer more flexibility due to inherent ability to learn and make autonomous decisions" (Dorri, et al., 2018). According to (Wan, et al., 2020), "the multiple agents are deficient in processing massive data". However, the recent advancements in edge computing has opened the door for integrating multiple agents with AI to collaboratively execute complex tasks such as image-based product recognition (Park & Jeong, 2019) .

(Wan, et al., 2020) portrayed a working scenario of the cooperative AI-powered multi agents. First, the recommender system sends the product orders to the manufacturing system in accordance with the customers' preferences (Order Submission). Secondly, inside a remote CC service, the AI-assisted task decomposition algorithm receives the product orders to generate both the operations sequence and the estimated manufacturing time. Similar to a real-life scenario, a product preparation can be sub-divided into different tasks, which are forwarded to the agents via the industrial network. After a negotiation phase, agents communicate their roles to the edge server, which supervises the agreed plan according to corresponding conditions and constraints. Thirdly, the AI-assisted cost-evaluation algorithm computes the production cost according to provided historical data. Only then, the edge agents intelligently assign the tasks to the main cooperative group of agents to complete the product order by sending them the selection results. Throughout the production phase, the assigned device agents forward their status data to edge servers to provide a real-time monitoring of the assets. By the way, an AI-based algorithm picks free agents to form a cooperative subgroup to intervene in case the main cooperative group fail in some tasks (i.e Carrying Materials). So, the AI-assisted MAS almost provides a self-organisable smart factory.

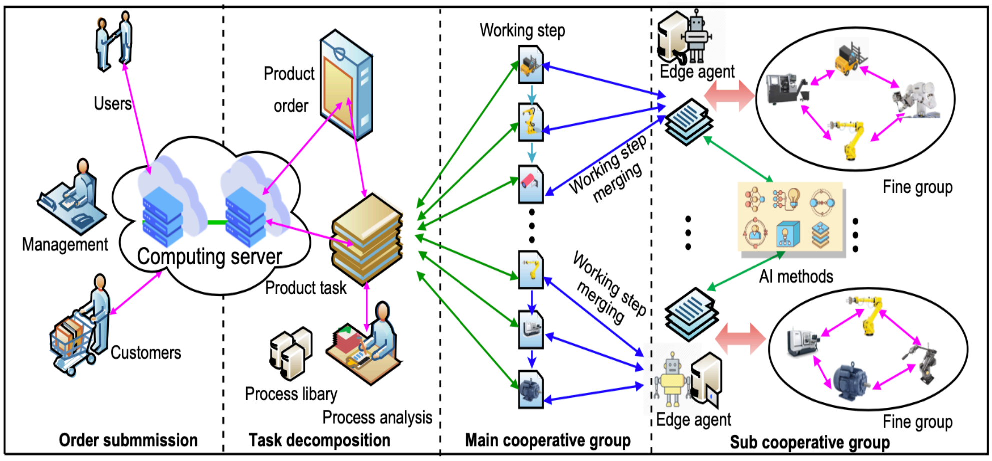

Figure 51 An AI-assisted Cooperative Multi Agents Framework (Wan, et al., 2020)

However, (Wan, et al., 2020) insisted that AI-driven CM does not intend to exclude the human factor from the entire production sphere. However, AI-driven methods augment the operators' capabilities to free their cognitive capacities on planning and optimizing the overall production system instead sparing time in repetitive tasks.

4.4.1.8 Human-centric AI-based Smart Manufacturing System

Re-locating the human factor in the heart of the industrial loop has been the main motivation behind the new vision of the manufacturing systems provided by (Lu, et al., 2022), as the authors simply proposed a framework for a human-centric manufacturing system in an unstructured and de-centralized manufacturing environment to support an "ultra-flexible manufacturing automation of personalized products". By building on the authentic vision of smart manufacturing presented by (Lu, et al., 2020) , the proposed framework contextualizes human-centric manufacturing system towards mass-production of highly personalized products by feeding a collaborative human-machine team a dynamic and unique list of manufacturing tasks. In brief, the authors create a library of elementary manufacturing activities (i.e. Threading, finishing, machining, ..etc). Then, the authors develop two models for every elementary task. The first model is responsible for identifying the necessary manufacturing skills and determining the corresponding manufacturing resources (including human operators). By the deployment of the technologies reviewed earlier in section 1.6, the second model simply creates a "human wellbeing impact profile that quantifies the physical, cognitive and psychological load of a task placed onto humans if it were feasible to be carried out by industrial workers. The physical load will be assessed at the level of individual human body joints and muscle groups" (Lu, et al., 2022).

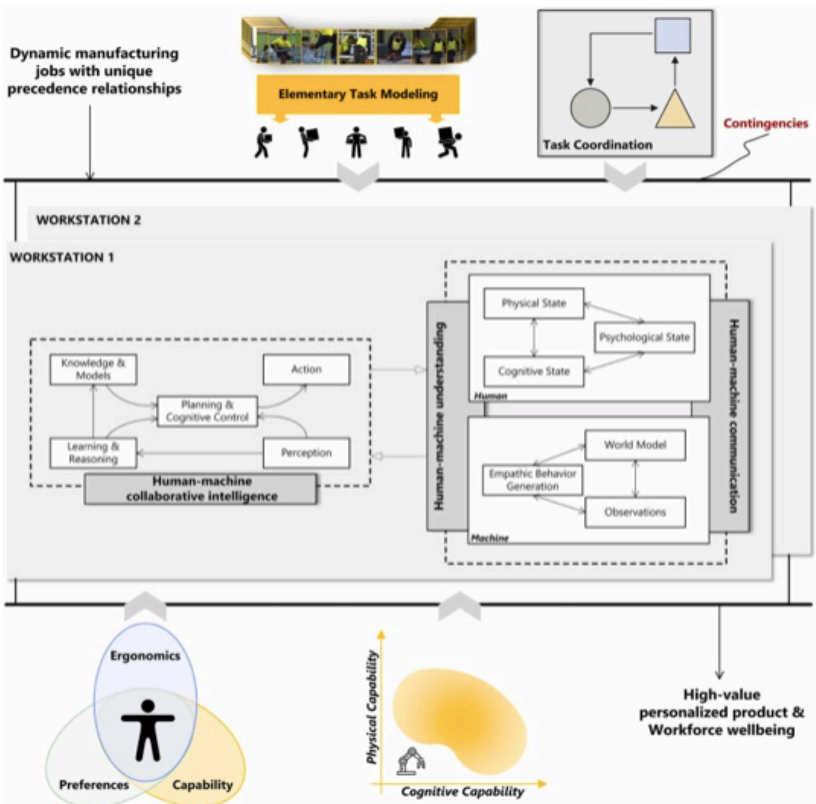

Figure 52 A Human-centric AI-based Smart Manufacturing System Framework (Lu, et al., 2022)

In addition, by adopting the conceptual reference model provided by (Lu, et al., 2020) a human DT will be developed to “model the capabilities, behavior pattern and wellness index of a worker” (Lu, et al., 2022). The “capability information” will provide machines the required data to decide on the possibility of delegating a manufacturing task to a specific operator from a skill-oriented point of view. Additionally, the wellness index resembles the operator’s physical, cognitive, and psychological stamina. As well, the behavior pattern focuses on the human’s adequate work-rest schedule, teamwork attitude and cognitive decision-making model. As pointed in section 1.6, modelling this tripod will support machines with a better, full-round understanding of human state variations in real-time, thus building a human-machine relationship based on “bi-directional empathy” and “proactive communication” (Lu, et al., 2022).

This human-centric AI-based smart manufacturing system's efficient control and optimization concern directs the attention to the “distributed cooperative multi-agent (both humans and machines) task allocation problem”, which should be handled in a totally different manner to the way researchers handle traditional manufacturing systems (Lu, et al., 2022). To clarify, in the “self-organize” proposed system, the operator’s wellness and working autonomy should be optimized while attaining an acceptable overall system productivity. Hence, the commonly used “centralized production scheduling algorithms” would not work well with the randomness accompanied with the operators’ freedom and contingencies. Instead, distributed learning-based algorithms, such as multi-agent reinforcement learning, could possibly equip the model with the necessary schema to respond appropriately to the dynamicity of human-machine collaboration.

4.4.1.8.1 Human-centric human-robot collaboration

Considered as an integral element of human-centric AI-based Smart manufacturing interactions at the machine level, (Lu, et al., 2022) proposed a human-centric human-robot collaboration (HC-HRC) framework to further upgrade the standard human-robot collaborative practices and consequently satisfy both human-centricity and production efficiency. Successful HC-HRC necessitates the maturity of three pillars including dynamic human understanding, empathic robot control, and dynamic task scheduling.

The three pillars are briefly summarized below:

4.4.1.8.1.1 Dynamic human understanding

Dynamic human understanding revolves around the design of a personalized DT for each operator to model his change of states and scenario-based intent (Lu, et al., 2020). The DT assesses human states by learning and classifying multimodal human body external signs to accurately estimate the impact of the assigned work upon the operator's physical, cognitive, and psychological state (Busch, et al., 2017). Concurrently, the DT regularly scans the operator's external body movements to predict both the short-term human intent and the manufacturing job's final objective according to learned sequences of actions by CNNs as proposed by (Zhang, et al., 2021). Accurate and continuous modeling of the human states and intent will lead to complete dynamic human understanding, fueling empathic skills which drive human-robot compassionate collaboration.

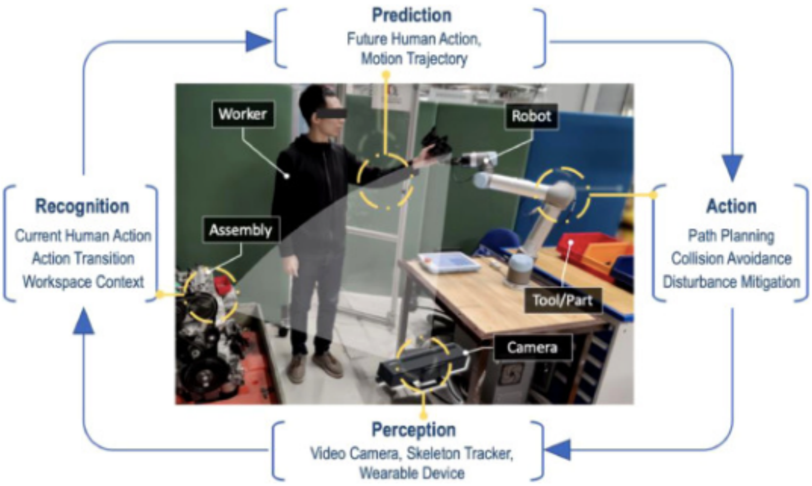

Figure 53 An example for dynamic human understanding by robots (Zhang, et al., 2021)

4.4.1.8.1.2 Empathic robot control

Empathic robot control relies upon "leveraging empathic skills for task-level action generation and subsequent mixed-imitative robot control" (Lu, et al., 2022). These empathic skills stimulate the maturity of a shared shopfloor model as it harmonizes human-machine shared actions following a successful definition of the self-organizing robot behavior based on understanding the operator's states and short/long term goals. In other words, the operator's autonomy alongside overall system's smooth performance is provided by empathic robots, which learns to self-adjust according to the human's changing states and intents, thus guaranteeing a “proactive robot assistance to satisfy human needs beyond safety” (Lu, et al., 2022).

4.4.1.8.1.3 Dynamic task scheduling and planning

On the job floor, dynamic task scheduling refers to “proactive task allocation/reallocation between humans and robots using human-robot collaborative intelligence for optimizing human wellness and handling contingencies” (Lu, et al., 2022). Task assignment algorithm and schedule optimize the operator’s wellbeing alongside the system’s productivity according to the fed data concerning both the agent’s information (i.e. human’s physical state, human/machine availability, human/machine capability) and the task’s accompanied constraints (Nikolakis, et al., 2018). The task allocation is dynamically scheduled using self-organizing shared autonomy between humans and machines. Unlike the available HRC research, the required “self-organizing shared autonomy” and “self-healing” task allocation strategy would generate “wellbeing-sensitive” task schedules according to human understanding to both collaboratively complete “on-demand” manufacturing jobs and intelligently adapt to unexpected contingencies (Lu, et al., 2022). Thus, the dynamic task scheduling is a clear example of harnessing CI to satisfy the human operator’s needs regarding esteem and self-actualization.

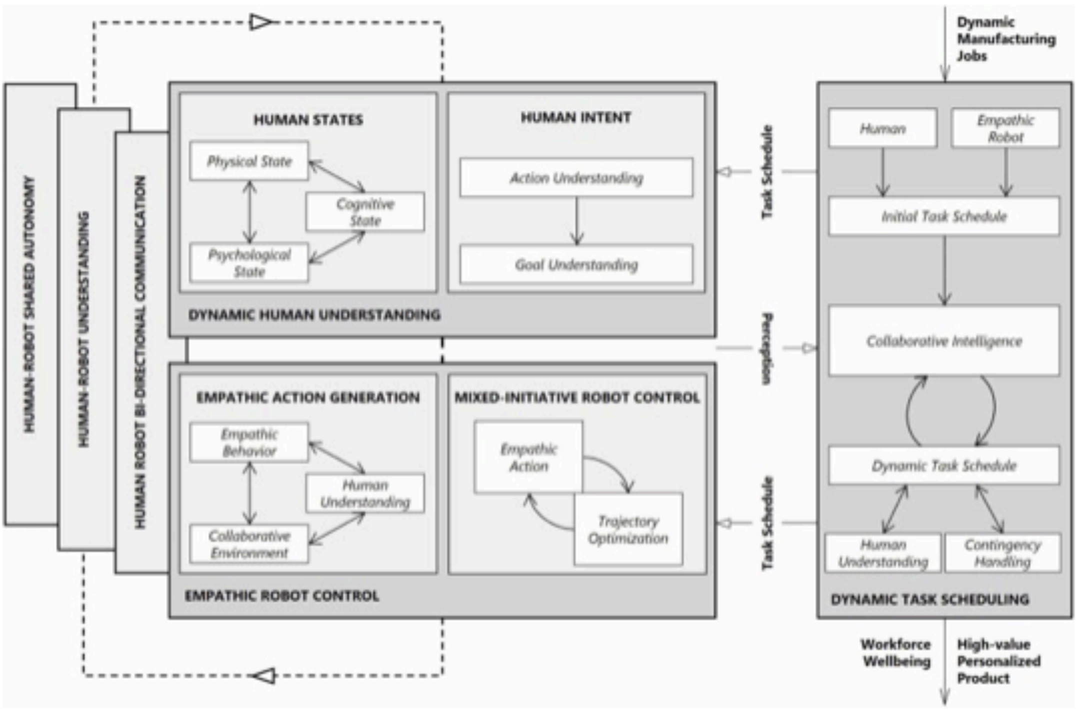

Figure 54 Human Centric AI-based Human Robot Collaboration (Lu, et al., 2022)

Technologies Involved \ Applications	Collaborative Sensing Technologies	Collaborative robots and complex robotic cells	AI-based human-centric decision support framework	Shop Floors with Virtual Intelligent-Assistant (ChatBot)	Pi-Mind Technology	Artificial Intelligence-Driven Customized Manufacturing Factory	Human-Centric AI-based Smart Manufacturing System
Smart IoT Devices							
Wearable Devices	✓						✓
Smart Sensors	✓	✓	✓	✓	✓	✓	✓
AI/ML Algorithms							
Spatio-temporal Markov Chains	✓						
Learning from Demonstration (LfD)		✓					
Ensemble model /Reinforcement learning		✓	✓			✓	✓
Image/Pattern Recognition		✓		✓			✓
ANN/Classifiers/CNN/ DNN/ Bayesian			✓	✓	✓	✓	✓
NLP/NLU				✓		✓	✓
STT/TTS						✓	✓
DBPS							
In-house Computing	✓						
Cloud Computing		✓	✓	✓	✓	✓	✓
Edge Computing						✓	✓
Communication Networks							
4G		✓	✓	✓	✓		✓
5G		✓			✓	✓	✓
WiFi/Bluetooth	✓						
DT/AR/VR					✓		✓

Table 6 An Analysis of the Technological Requirements of the Potential CI Applications in Manufacturing (According to the author's Findings)

Attributes / Technologies Involved	**Affordability**	**Maturity**
Smart IoT Devices		
Wearable Devices	LOW	MEDIUM
Smart Sensors	HIGH	HIGH
AI/ML Algorithms		
Spatio-temporal Markov Chains		HIGH
Learning from Demonstration (LfD)		MEDIUM
Ensemble model /Reinforcement learning		HIGH
Image/Pattern Recognition		HIGH
ANN/Classifiers/CNN/ DNN/ Bayesian		HIGH
NLP/NLU		HIGH
STT/TTS		MEDIUM
DBPS		
In-house Computing	HIGH	HIGH
Cloud Computing	HIGH	HIGH
Edge Computing	LOW	MEDIUM
Communication Networks		
4G	HIGH	HIGH
5G	LOW	MEDIUM
WiFi/Bluetooth	HIGH	HIGH
DT/AR/VR	LOW	MEDIUM

Table 7 A Qualitative Analysis of the Affordability and Maturity of Technologies Involved in the Researched Applications (From the author's Perspective)

Note: The maturity and affordability of these technologies is the authors' subjective assessment of their current technological readiness and availability in the Market. No solid quantitative comparison between these technologies in the context of human-machine communication is available yet. Usability will then be ranked according to the author's subjective assessment of the technology's effectiveness, easiness of use, and usefulness to the case.

4.2 A Qualitative Analysis of the Usability and Maturity of the Researched CI Technologies in Manufacturing

Application	Usability	Maturity
Collaborative Sensing Intelligence	HIGH	HIGH
Collaborative robots and complex robotic cells	HIGH	HIGH
AI-based human-centric decision support framework	HIGH	MEDIUM
Shop Floors with Virtual Intelligent-Assistant (ChatBot)	HIGH	MEDIUM
Pi-Mind Technology (PIM-T)	MEDIUM	MEDIUM
Augmented Manufacturing Analytics Framework for Human-AI Collaboration in Quality Control	HIGH	MEDIUM
Artificial Intelligence-Driven Customized Manufacturing Factory	HIGH	MEDIUM
Human-Centric AI-based Smart Manufacturing System	HIGH	LOW

HIGH MEDIUM LOW

Table 8 An analysis of the applicability, usability and maturity of the different technologies in a manufacturing context (From the author's perspective)

4.4.3 A Qualitative Analysis of the Human Intelligence and Artificial Intelligence Contribution

Application	Human Intelligence	Artificial Intelligence	Collaborative Intelligence
Collaborative Sensing Intelligence	LOW	HIGH	HIGH
Collaborative robots and complex robotic cells	MEDIUM	MEDIUM	HIGH
AI-based human-centric decision support framework	MEDIUM	MEDIUM	HIGH
Shop Floors with Virtual Intelligent-Assistant (ChatBot)	MEDIUM	MEDIUM	HIGH
Pi-Mind Technology	MEDIUM	MEDIUM	HIGH
Augmented Manufacturing Analytics Framework for Human-AI Collaboration in Quality Control	MEDIUM	MEDIUM	HIGH
Artificial Intelligence-Driven Customized Manufacturing Factory	MEDIUM	MEDIUM	HIGH
Human-Centric AI-based Smart Manufacturing System	MEDIUM	HIGH	HIGH

Table 9 A Qualitative Analysis of the Share between the Contribution of Human Intelligence and Artificial Intelligence Towards Collaborative Intelligence Towards (From the Author's Perspective)

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5. Results of the Bibliometric Analysis of Research Question 2

5.1 Phase 1: Research and Classification

The analysis of the first research question has concluded that the recently researched CI-based technologies could offer a game-changing edge to the manufacturing industry with respect to quality control, product design, productivity, scalability, and decision-making. However, apart from small-scale cobots and chatbots, according to the conducted qualitative analysis, large enterprises are relatively more well-positioned to invest in the majority of the researched questions, which further justifies the importance of posing RQ2. The first phase consisted of the search for documents, which included the activities of collecting material belonging to the academic universe. This first phase was divided into three steps as follows.

5.1.1 Identification (Step 1)

For a comprehensive research of the research question, phenomenon, an investigation on the Scopus (SCP) and Google Scholar databases was carried out using Boolean operators. The began by making a search query with the general key words "Collaborative Intelligence" OR "Human-AI collaboration" OR "Artificial Intelligence" AND “Manufacturing SMEs” as shown in Table 10.

Keywords	***Time Period***
Collaborative Intelligence	1999-2022
Human-AI Collaboration	
Artificial Intelligence	
Manufacturing SMEs	

Table 10 Research Combination of Keywords

The search returned in total 2184 documents.

The results extracted by Google Scholar are numerically superior to Scopus (SCP): 2170 for the first and only 14 for the second one (Table 11).

Research Carried out in 2021		
Source of Research	Google Scholar	Scopus
Results	2170	14

Table 11 Research Results

Despite the arguable scarcity of resources with respect to the associated research question, but still, we could gather a fair amount of information and insights.

Important to note, the clear difference between the amount of search results of the two databases lies behind the unmatching effectiveness of Google Scholar and Scopus when it comes to locating recent gray literature sources (Gray literature is defined as “Information produced on all levels of government, academia, business and industry in electronic and print formats not controlled by commercial publishing” (LibGuides, 2022)). To demonstrate, Google scholar is known for its relatively vast amount of search results as it “aims to summarize all electronic references on a subject” to “reach the widest audience available” (Falagas, et al., 2007). In other words, Google scholar is often recommended as a source of grey literature, which perfectly fits this paper’s systematic review of an under-researched topic. However, despite the availability of an “advanced” search engine in Google Scholar, but it still does not enable the researcher to gain any information regarding the number of conference papers included in the academic search engine as provided by Scopus. On the same line, Google Scholar does not provide the “abstract and information on free full text availability”, which puts Scopus ahead with respect to this feature as it enables the researcher to be ahead of time in the inclusion phase.

This analysis aims to highlight the link between the trends of research regarding Collaborative intelligence, Industry 4.0, Industry 5.0 and manufacturing SMEs. Through a time-indexed time series of research documents pointing to the associated research question, the link between the four trends has been emphasized. To demonstrate, provided below a graph (Figure 52) that provides a proof that the literature has been enriched with publishments following the attention directed to I4.0 and relevant topics. Growth is evident after 2011 when new technologies began to be researched and put into action more frequently. Clearly, the published documents associated with RQ2 showed a noticeable increase by the end of 2015, which aligns with the introduction of I5.0 in the scientific community as highlighted before. On the same line, the term “SME 4.0” was introduced by (Rauch, et al., 2018) to create an international and interdisciplinary research network to transfer the concepts of Industry 4.0 concepts and technologies to SMEs. On the other side, the term “Start-up 4.0” was recently introduced by (Kaczam, et al., 2021). Interestingly, the recent introduction of the term “start-up 4.0” justifies the severe shortage of research towards the applications of CI in start-ups before 2022. Thus, a focus has been directed towards filtering the research efforts restricted to the key word “manufacturing start-ups”, which surprisingly returned zero results. Hence, the coming sections will draw the attention to the potential impact of CI technologies upon manufacturing SMEs.

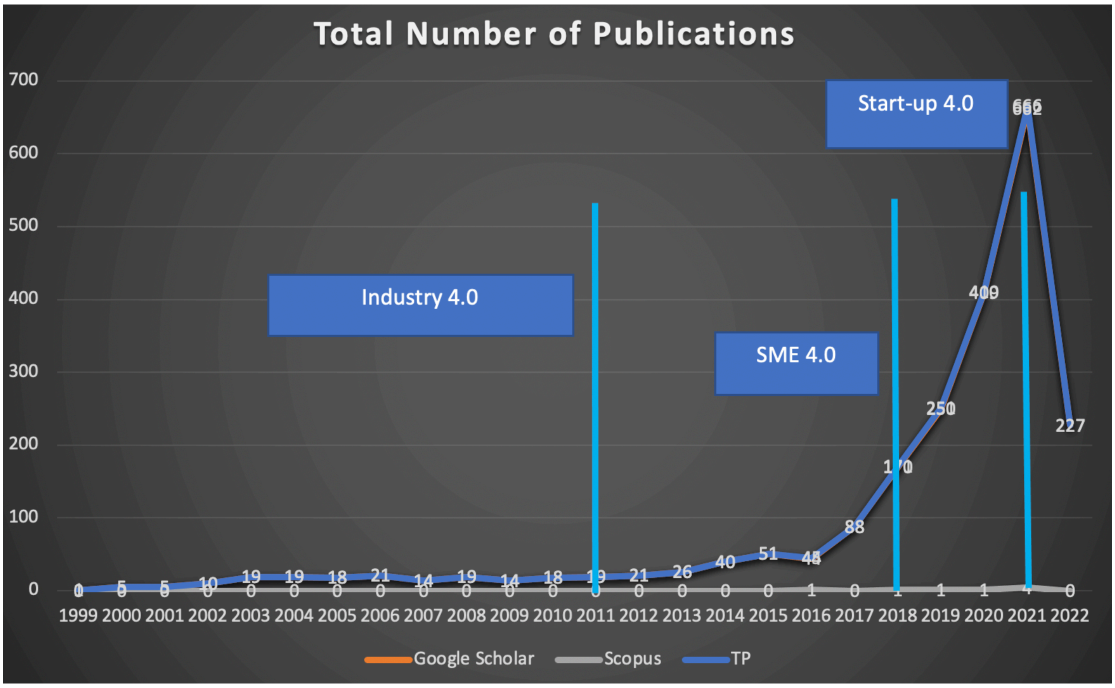


Figure 55 A Time-Series of Research Publications

In fact, this research indicates that over the time period considered (1999–2022), the number of published documents remained almost constant until 2011, from which it undergoes an increase. This turning point has emerged by the introduction of I4.0 technologies and pacing growth of relevant research activities, which signalled the necessity of directing the research efforts towards the potential impact of CI upon the entrepreneurial community, which saw the emergence of the trend "SME 4.0" by the beginning of 2018. As well, the figure highlights the apparent maturity of research towards the applications of CI in SMEs between 2018 and 2022, which signifies the presence of a lag between manufacturing SMEs and Large enterprises' adoption of CI technologies, and concurrently highlights the effect of the core values of I5.0 upon the industry's directions. Another important note lies behind the clear overlapping of the "TP" and "Google Scholar" curves, which highlights the low share of research results provided by "Scopus" in this research question.

5.1.2 Screening (Step 2)

Following the completion of the identification phase, the paper presents an overview of the topics and areas interface through a screening process. The screening phase revolves around an analysis of the accessible published documents. In other words, this phase required narrowing down the number of documents to be the focus of the study. So, an analysis of "free access" documents was provided. In addition, the "access through your institution" option provided by Direct Science, Research Gate, El-Sevier, and others, has enriched the list of accessible documents. Luckily, the inaccessible documents (due to hyperlink failures or un-authorized sign in) has shown a negligible effect upon our analysis, as less than 20 out of 2184 documents were excluded. Furthermore, in our study, we didn't believe we have to restrict our research to a specific subject area (Provided by Scopus only), as our research keywords already restrict the results to the manufacturing sector.

To cut it short, the screening phase hasn't excluded a noticeable number of document and almost all research results will enter the next phase.

5.1.3 Inclusion (Step 3)

By the completion of the screening process, the inclusion step was kick-started. This step prioritizes the selection of a portion of the documents extracted from the last step to be included in the sample on which bibliometric analysis was performed. In fact, according to earlier plans, this phase was supposed to rely upon a keywords analysis in addition to an abstract analysis. However, due to the unavailability of "abstract preview" option in Google Scholar, we examined the full text of each document one at a time to ensure its eligibility to go through the analysis phase. For each article, we examined whether the document refers to the Human-AI collaboration theme in a manufacturing context or not. Also, this phase aims to check if any of the documents included case studies or real applications, suggestions for new AI and CI algorithms and architectures in MSMEs, or possible future scenarios.

Therefore, the final sample to be analyzed consisted of 54 documents for Google Scholar and 8 for Scopus.

5.2 Phase 2: Analysis

This section presents and discusses the findings of this review.

First, an overview of the selected studies is presented. Second, the review findings according to the research criteria, one by one in the separate subsections, are reported.

5.2.1 Top Highly Influential Analysis

This section spots the light on the most highly cited documents in Google Scholar and Scopus. In fact, in this case, some research databases haven't provided a count of the citations. Also, a noticeable number of documents had been recently published, which resulted in arguably lower citations compared to earlier ones. Additionally, we need to point out that some researchers do not tend to cite the document through its publisher's database, which could sometimes lead to a misleading image. In consequence, in specific cases, we though it could be of relevance to mine the count of views and downloads to provide a clearer image. Anyway, (Michalos, et al., 2014) has the highest citation count of 162. This document presents the vision and architectures, proposed by the EU project ROBO-PARTNER. Briefly, this project promotes "a hybrid solution, involving the safe cooperation of human operators with autonomous and self-learning/adapting robotic systems, through a user-friendly interaction" (Michalos, et al., 2014), to help increase the collaborative robots' adoption rate by SMEs.

Interestingly, the document publication year is 2014, about two years following I4.0 was introduced, which further proves that the count of citations is proportional to the length of time a document has been out to light.

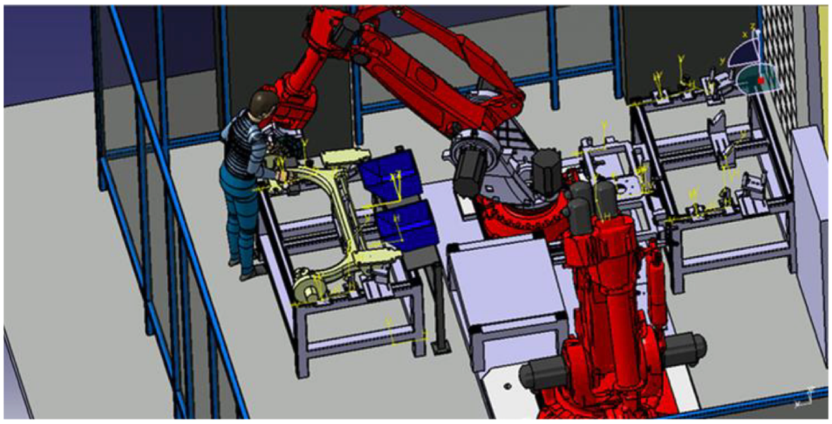


Figure 56 Human-Robot Collaborative Assembly

Obviously, most documents before I4.0 generally have more citations than the most recent documents. However, it is significant to note that a noticeable share of recent documents have a very high number of citations bearing in mind the year of publication. This reflects the interest in the topic from the scientific community.

The citation analysis has also revealed that the first book that we can identify among the most accessed (1067 accesses) in the I4.0 period dates to 2021. Briefly, (Iftikhar, 2021) elaborates on machine learning project development life cycle for manufacturing SMEs. Also, the paper presents new insights and suggestions for SMEs to facilitate a successful adoption of ML technologies. On another note, (Mohamed & Weber, 2020) received much attention among the scientific community. Simply, based on a case study of 53 British manufacturing SMEs, it presents several perspectives including digital technology trends, challenges facing the UK SMEs, and the state of their adoption in AI technologies, data analytics and big data.

5.2.2 Publications by Years

Consistent with the analysis in Section 3, the study points out that the number of documents included in the analysis is apparently low for the entire period before the introduction of I4.0 in 2011. However, as expected, the relevant research shows sudden increase, starting in 2013. The data shown in Figure 54 also shows a scarcity of documents in the period between 2012-2018, compared to the apparent boom in research afterwards.

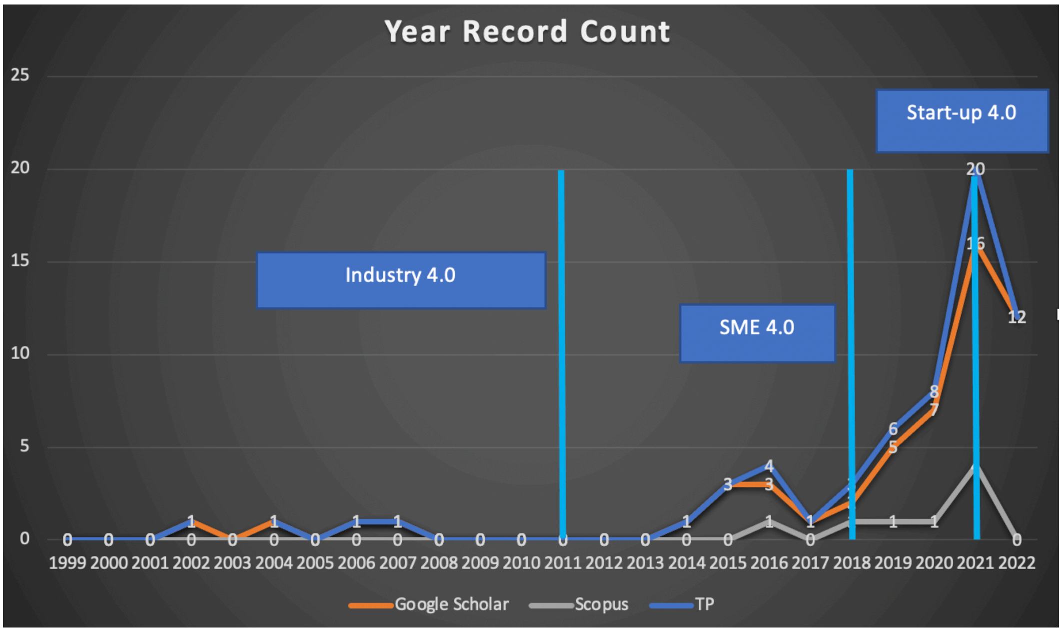


Figure 57 A Time Series of the Inclusion Results

The undeniable maturity of research could go down to the introduction of 5G technological services in 2019. Thanks to its increased bandwidth, 5G is expected to pave the way for new applications in IoT and MTM areas, thus making it more affordable for SMEs to catch up with the Larger enterprises' investments in the new technologies.

With reference to 2022, the figure refers to the first quarter of the year, so it is expected that during the year, there will be a further increase in the documents in the literature.

5.2.3 Country Analysis

This section's main focus is determining the countries contributing the most to the relevant research effort. To note, prior to conducting this specific analysis, we had to exclude all documents in Chinese and Japanese languages. In other words, this section could be slightly biased towards Europe, United States and United Kingdom.

In brief, the countries that give the most contribution are: The United Kingdom (11.3%), China (9.7%) and Germany (9.7%). Unsurprisingly, when it comes to Europe, Germany comes on top of the list of contributors. To demonstrate, I4.0 was first introduced in Germany, which justifies the correlation between both trends.

In addition, it is worth mentioning that Europe has contributed with 43.5% of the available resources. This high contribution could be related to the fact that "the EU's manufacturing base presents an excellent opportunity for broad AI adoption to get ahead in digitalization and the Internet of Things" (Brattberg, et al., 2020), which arguably helps closing the gap between Europe, China and the United States in terms of research. Following this trend, we anticipate a recognizable evolution of smart production and entrepreneurial initiatives and therefore a further maturation of scientific research.

5.2.4 Key Take-aways of Analysis

This section highlights the main outcomes of the second phase:

- The research efforts associated with the research question have seen a slight increase starting from 2011 (Introduction of I4.0)
- The research efforts have then enjoyed a relatively larger increase after the emergence of the term SME 4.0 in 2018
- The term Start-up 4.0 was first introduced in 2021, which justified the scarcity of research resources associated with manufacturing start-ups
- Most documents before I4.0 generally have more citations than the most recent documents
- Countries that give the most contribution to research are: The United Kingdom (11.3%), China (9.7 %) and Germany (9.7 %)
- Europe has contributed with 43.5% of the available resources, while Asia contributed with 22.6%

6. Literature Survey of Research Question 2

6.1 Vulnerable MSMEs: Collaborative Intelligence to the Rescue?

Unlike SMEs, a startup' main goal is designing a product that offers customers a differential value proposition. Scholars have indicated that "Start-up companies are relatively new to the market with the intent to explore a new idea or a product, usually leveraging technology" while "SMEs, on the other hand, establish operations involving known products and services mainly for local markets" (Raghu, 2017). The literature consistently insists that startups are "priority channels for social and economic development, industrial change, and renewal" (Passaro, et al., 2020). Such newly established companies are widely known as "temporary organizations" as they are highly prone to failure (above 60% of start-ups around the world fail during the first stage of operations) (Passaro, et al., 2016). In brief, despite the successful exploitation of "innovation-oriented" market opportunities and the establishment of a repeatable and a scalable business model (fast growth rate of revenues, operations, and employees), but still most of them fail to expand and they probably encounter the fate of being taken over by larger corporates due to the severe competition, their operation in changeable and unpredictable environments in addition to the scarcity of resources. So, unlike large corporates, even in case of possessing a brilliant business idea, MSMEs encounter various challenges of different intensities and complexities throughout their several life cycles stages. The main challenges include the limited financial resources, technological misalignment, and inability to compete large corporates for skilled labor. Specifically, to MSMEs, few other challenges might complicate the way towards a sustainable growth. Manufacturing businesses offer services in a highly competitive context as they are likely pressurized by global competition in terms of new offerings, novel production technologies, enhanced materials and organizational innovations. In return, manufacturing ventures rely upon innovation to either cope with the competition at least or create a competitive advantage through improving productivity (or cost reduction) and enhancing flexibility. According to (Sarkar, 2020), a recent review of the data of 27 years of US Manufacturing businesses' failure rates has revealed that "80% of US manufacturing companies have failed within 25 years of starting up. A fact that is not as widely publicized and hence less spoken about is that the option of failure continues beyond the first five-year period. It continues even beyond the first 10-year period. The US Bureau of Labor Statistics data shows that about another 30% of companies fail between year five and year fifteen. And, only about 20% of companies make it into their 25th year of existence". On the same line, (D. Vaisman & S. Nikiforova, 2018) estimated that new manufacturing businesses are subjected to the hypercompetition threat, as it reduces the life cycle of competitive advantage, leading to regular changes across the positioning of market players.

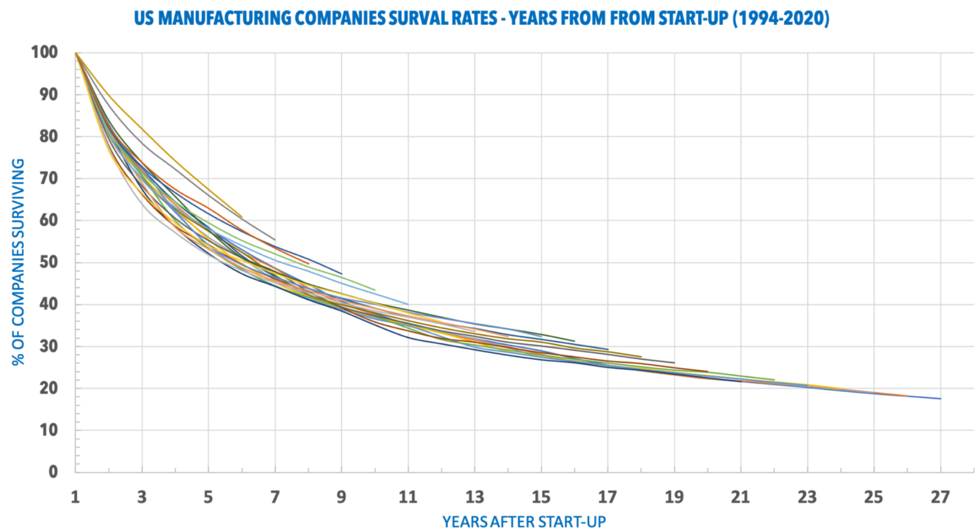


Figure 58 New Manufacturing Businesses Survival Rate (Sarkar, 2020)

Similar to other sectors' new businesses, new manufacturing ventures go through different stages of their life cycle. To illustrate, almost all new ventures encounter financial challenges and varying market demands. However, each new business is relatively more affected by particular factors than others of different sectors and different sizes. Assuming that "there are three major business sizes: small, mid-market, and large enterprise" (Novak, 2019), this work primarily aims to focus on MSMEs and start-ups. However, as pointed before, supported by the fact that SMEs are far superior to start-ups with respect to the economic impact, the scarcity of research efforts directed towards the impact of CI upon manufacturing start-ups has furtherly guided the work to re-direct the attention to MSMEs instead.

In consequence, this work spots the light on the common reasons behind the failure of MSMEs over the different stages of its life cycle and the potential impact of augmenting the human capabilities with AI technologies upon the efforts towards solving them. To this purpose, a life cycle analysis approach has been provided based on a systematic literature review.

Stages	Ideation	Intention	Startup	Expansion
Definition	Potential idea generation	Entrepreneurial intention readiness, opportunity validation, and pre-startup activities	New venture creation	Consolidation, scalability, and self-sustainability
Required resources and capabilities (organizational level)	Technical resources and entrepreneurial culture	Financial, technical, and managerial resources	Financial, technical, physical, and managerial resources	Financial, technological, physical, and managerial resources
Key factors (individual startupper level)	Creativity, intuition, prior experience	Entrepreneurial and risk-taking orientation, self-confidence, motivation	Entrepreneurial and risk-taking orientation, self-confidence, leadership	Leadership, coordination ability, strategic orientation
Key Activities	Discovering idea, market opportunity intuition, resource needs and availability	Market opportunity validation, engagement/commitment, team building, resource searching/validation	Business planning, product and commercial development, searching for additional funding resources	Massive customer acquisition, back-end scalability improvements, new personnel and first executive hiring, internationalization
Milestones	Idea viability	Prototype	Industrialization	Scale-up

Figure 59 A 4-stage Start-up Life Cycle Approach (Passaro, et al., 2020)

Briefly, the mentioned approach views a start-up's life cycle as "a sequence of stages from the ideation up to the consolidation/expansion stage, which can favor the analysis, planning, and management of flourishing startups' sustainability" (Passaro, et al., 2020). However, the author inspired it from the past literature about the SMEs lifecycle and adjusted it to accommodate the higher risk associated with start-ups' early and late stages (i.e. New product development and expansion), which . With no doubt, this interpretative approach facilitates the identification of a new business ecosystem actors, which would improve the chances of acquiring the essential resources and completing the key milestones necessary to experience a successful transition from a life cycle stage to another. Specifically, in an industrial context, this approach helps highlighting the main obstacles that might hinder the growth and maturity of a manufacturing SME.

The model was derived by adopting a four-stage life cycle approach (adjusted to a manufacturing context) discussed in the following subsection.

6.1.1 Ideation

Manufacturing is no longer solely revolving around offering physical products. The "changes in consumer demand, the nature of products, the economics of production, and the economics of the supply chain have led to a fundamental shift in the way companies do business. Customers demand personalization and customization as the line between consumer and creator continues to blur" (Deloitte, 2022). Undoubtedly, the market volatility has worrying effects on MSMEs, which necessitates directing ample attention to the potential advancements of the new product development (NPD) process. In brief, NPD is the schema a business follows to employ its resources and competences to create a new product or add value to an existing one (Ozer, 1999). NPD is arguably one of the most critical processes as it should be present during multiple stages of SMEs' lifecycle, which agrees with (Ali, et al., 2004), as it branched the NPD process into two stages including Pre-development stages and NPD Execution stages as elaborated below in Figure 57.

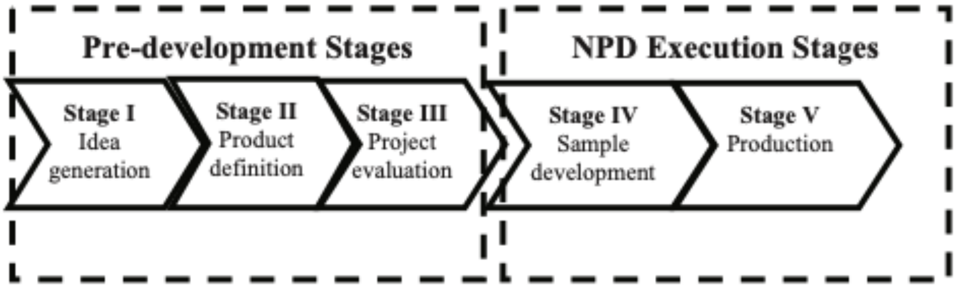


Figure 60 NPD Process (Ali, et al., 2004)

According to (Patel, 2015), "around the globe, small and medium scale product manufacturers are struggling to cope up with the digital transformation. Fueling innovation in product development and manufacturing processes is critical today for any manufacturer, irrespective of size and capacity. New companies, even with small scale facilities are increasingly bringing new competitive products to disrupt the conventional market through innovation". Thus, a surviving MSME should continually release a valuable stream of new products, which would guarantee a sustainable growth and market share. Usually, NPD is seen as enhancing existing products, and trying to catch up with competitors. However, NPD should be seen as "breaking the clutter and differentiating your product from others. Today customer demands keep evolving continuously, compressing product lifecycles. Product development is not an easy process. The success rate ranges between 45 and 62%" (Dhargalkar, et al., 2016). Hence, unsuccessful development of a product capable of attracting new customers and retaining past customers can endanger the survival of manufacturing businesses in general, knowing that "SMEs in manufacturing are faced with numerous constraints in order to achieve high performance in the pre-development process due to limitation on finance, workforce, skill, knowledge, and raw materials " (March-Chordà, et al., 2002). Therefore, a robust, speedy, and reliable NPD process is the "bloodline" of companies of small and medium sizes (Abu, et al., 2014).

Creativity and innovation have been "diagnosed" as remedies for sustained growth in an increasingly competitive and globalized market. Industrial design is a field that may facilitate and guide creative processes ranging from idea generation to the materialization of new products to enhance competitiveness. Indeed, "the application of creativity in the product development context is what in industry usually is agreed upon as the origin of innovation – by large the determining factor for the survival of companies in the today's highly competitive environment" (Brockhus, et al., 2014). Meeting the continuously changing customer demands has become a major obstacle with respect to MSMEs. According to (Kumar, et al., 2016), "Manufacturers are finding themselves stuck in 'better–faster–cheaper' triangle with the ever-growing prevalence of 'we can have it all' mindset of customers". According to (Yan, et al., 2006), "In developing a new product, for time- and cost-efficiency, it is imperative to place more effort on product conceptualization so as to reduce the number of design iterations. Compared with the later stages of NPD, it is well-known that product conceptualization commits more than 70% of total cost incurred during the product life cycle". On the same line, (Backman, et al., 2007) agreed that success or failure of the NPD process heavy relies upon the performance in the pre-development process.

(Muller & Ulrich, 2013) directed the attention to a fact that "In today's hypercompetitive environment in which markets change rapidly and competitive advantages are difficult to sustain, companies are forced to innovate and identify new business opportunities. However, innovation requires ingenuity and creativity. Product and service development depends on the creativity of employees, but harvesting and bringing novel ideas to fruition is often a chaotic process", which presents a gap that goes beyond the "systematicness" of the process, as "Small- and medium-sized enterprises (SMEs) largely depend on proficient idea generation activities to improve their front-end innovation performance, yet the liabilities of newness and smallness often hamper SMEs' ability to benefit from systematic idea generation" (Gama, et al., 2019). Moreover, the digital era has added additional power to the consumer's side, including more choice and on-demand access to information. Supported by social networks and their digital devices, consumers are increasingly requesting a more personalized experience to be capable of shaping the products and services they pay for. So, this stage does not solely revolve around the discovery of a winning business idea that could take advantage of an existent market opportunity. However, the ideation teams should be capable of developing various ideas in a relatively shorter length of time. Also, the ideation process should be supported by convenient data and technologies to predict the success or lifetime of its product. For example, according to (Chen, 2020), "a company that manufactures a product related to urban life might want to envision what cities around the world will look like in 2030. A manufacturer of products for children might want to construct a vision of what play will consist of in 2025". Ideally, to avoid waste of materials, a team should ensure that the proposed idea could satisfy both the current and future customer's meaningful requirements through its innovative solutions. Only then, the potential entrepreneur should initiate the identification of the key resources and their availability. Nevertheless, the business owners need technical resources, that could adequately analyse and identify the idea viability in light of uncertain conditions. The key actors in this stage include "higher education systems, startup competitions, and local governmental agencies as principal providers of knowledge and supports" (Passaro, et al., 2020). In fact, there are various traditional human-centered methods for collaborative intelligence brainstorming and generating creative ideas, which are provided in brief below:

Free-flowing ideas

A traditional strategy to stimulate CI is to assign to participants different tasks to deviate their minds away from the meeting's objective to inspire their creative brainstorming relying upon their own experiences and hobbies instead of their daily routine (Dhull & Beniwal, 2018). Later on, the meeting facilitator should converge the participants back to the product in hand and the relevant features that could apply, but this time they are expected to come back with ideas out of the box.

The Mastermind

Another strategy is based on asking each participant to spend some time being the focal point of the meeting by explaining their goals, struggles, methodology and progress. In return, other participants share ideas to help each other change their approach solving their problems through a different angle and a new perspective (MYCTOfriend,2020).

Invite the client

Another way to stimulate innovation is based on inviting clients to a session to make them share their ideas and express their opinions, thus ensure the alignment of both the business and clients' path and vision in real-time (Tomlinson, 1992).

Classic session

Another commonly used strategy is the preparation of a classic session. Such sessions usually kick start with a short norming period between participants to get everyone on board. Then comes the collaborative task as each participant is provided with a sticky note to write down his thoughts and collect as much ideas as possible. After collecting the sticky notes and hinging them to the wall to be seen by everyone, participants start categorizing their ideas with respect to business, client, accompanied challenges, etc. Finally, the group should start prioritizing ideas, assessing them regarding implementation time and estimated investment to formulate a road map and settle on a strategy to move forward (Mcguinness, 2009).

Clearly, as mentioned earlier, humanity has always believed in the productivity of CI in the creative tasks. However, it has always been about human brainstormers collaborating to complete a task. As it stands, the deployment of Artificial CI would support the human being towards a more efficient collaborative definition of the value proposition and analysis of the surrounding conditions based on real-time data incoming from different smart entities alongside insightful analytics offered by intelligent agents, which would skyrocket the chances of identifying a winning business idea and maintaining a sustainable growth of the project.

Recently, research efforts have been directed towards the development of AI-powered virtual assistants capable of augmenting the humans' abilities of generating ideas.

6.1.1.1 brAInstorm: Intelligent Assistance in Group Idea Generation

Computer technologies that enable on-line, real-time collaboration can revolutionize the process of idea generation (Gera, 2013), as team members have become capable of working together remotely with no constraints regarding their location (Gumienny, et al., 2012). In addition to the techniques provided above, brainstorming is widely used as a creativity technique that stimulates the generation of many ideas within a working group (Byron, 2012). In face-to-face brainstorming sessions, a moderator is responsible for encouraging participation, catalysing the generation of innovative ideas, and ensuring the session's abidance by the set rules (J. Kramer, et al., 2001). So, a moderator should possess specific skills and knowledge, which stands out as an obstacle hindering the effectiveness of the 'Electronic Brainstorming' (EBS). To address this issue, (Strohmann, et al., 2017) proposes an AI-powered moderator, who can resiliently "facilitate an EBS session by both, organizing a session and providing creativity stimulating content". By the way, an agent-based brainstorming support system was previously introduced by (Wang, et al., 2011). However, (Strohmann, et al., 2017) witnesses the introduction of AI technologies to augment human's ideas generation capabilities for the first time. Inspired by the Design Science Research Methodology introduced by (R. Hevner, et al., 2004) and (Gregor & Hevner, 2013), (Strohmann, et al., 2017) designed and implemented a "novel artifact" in order to innovatively fill the gap highlighted earlier. In fact, (A. Boden, 1998) is considered one of the earliest scientific resources that spotted the light on a potential link between AI and creativity, which paved the way for the introduction of "computational creativity" by (Colton & Wiggings, 2012). According to (R. Besold, et al., 2015), "the target of computational creativity is to model, simulate or replicate creativity to achieve one of the following ends: (1) create a program or computer capable of human-level creativity, (2) help to understand human creativity or (3) construct a program enhancing human creativity without necessarily being creative itself".

Accordingly, (Strohmann, et al., 2017) developed an AI-powered virtual assistant to stimulate human creativity without necessarily possessing the human's intelligence and creativeness. "brAInstorm" is a web-based tool for collaborative EBS, augmented with an AI-based Moderator (IMO), who intelligently completes different tasks on behalf of a Brainstorming human moderator and provides solutions for a number of current issues in EBS. A virtual AI moderator simultaneously provides individual team members real-time feedback and stimulates their input content, thus enabling the conduction of different brainstorming sessions at the same instant regardless of the ability of different human facilitators.

The design of 'brAInstorm' necessitated the incorporation of different AI-powered user interface applications based on NLP, ML, and reasoning. For example, to facilitate the communication of ideas between team members, (Strohmann, et al., 2017) employed the open-source chat platform Rocket.Chat. For the core Brainstorming activities like the individual idea generation and the collaborative idea assessment, the author equips the IMO with an open-source chatbot (Hubot) to help it facilitate and organize the session. Additionally, in an attempt to enhance the IMO's artificial emotional intelligence and enhance the session's efficiency, the authors equipped the IMO's Hubot with wit.ai Bot Engine to occasionally intervene in case of noticing the participants' deviation from the assigned task. Although Hubot has hearing and responding capabilities (text/voice input and output), it cannot deal with context understanding. Consequently, as pointed above, Hubot is supported with wit.ai's Bot Engine, which is simply an open-source and extensible natural language platform, providing different functionalities for developing applications to which a user can text or talk. Simply, wit.ai transforms team members' unstructured input text/voice into structured data. Then, a bot engine performs ML to react according to a set rule-based behaviour. In other words, relying upon wit.ai's predictions, Hubot can execute an action at the needed points in the session. Figure 58 summarizes the adopted AI-augmented Brainstorming process within the proposed model and the underlying technology behind each function.

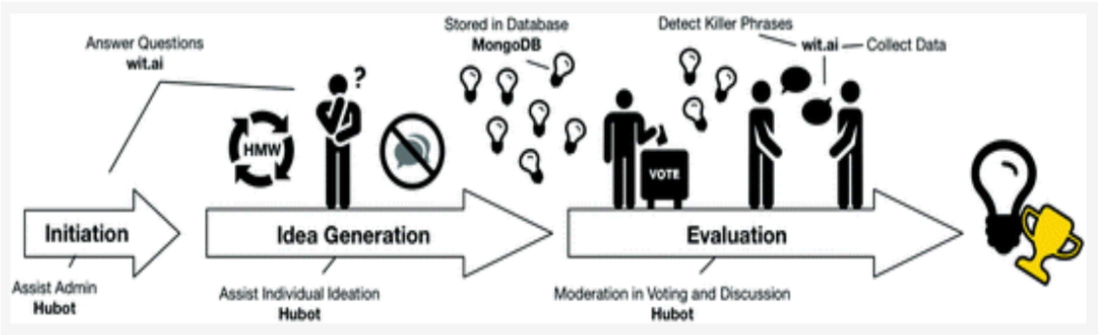


Figure 61 brAInstorm: Intelligent Assistance in Group Idea Generation (Strohmann, et al., 2017)

6.1.1.2 An Intelligent Evaluation Approach For NPD Projects

As pointed earlier, efficient and effective NPD necessitates a proactive management of all uncertainty causes. Over the past years, different tools have been coming to light aiming to improve the decision-making processes. The developed technologies include: probabilistic models, options pricing theory, scoring models and checklists, behavioral approaches, analytical hierarchy process, sensitivity analysis, scenario analysis and intelligent techniques. Among the various technologies developed over the past years, AI technologies could provide a valuable assistance to decision makers under dynamic market environments.

Relevantly, aiming to analyse the new product evaluation project, (Feyzioğlu & Büyüközkan, 2007) proposed an AI-powered decision-making system based on ANNs, fuzzy logic and Choquet integral. This system is especially applicable to the cases involving numerous new ideas generating sources, which complicates the decision maker's mission to rate the related products in terms of time and precision. In other words, it enables decision makers to 'roughly' and 'quickly' filter 'good' and 'bad' product ideas by making use of previous experiences, and then to analyze in detail a more shortened list. This thesis focuses on the former step (The Rough Evaluation Phase) as it highlights the use of AI technologies, while the latter step (The Exact Evaluation Phase) relies upon an optimization algorithm (Choque Integral) to determine the most appropriate NPD project implementation.

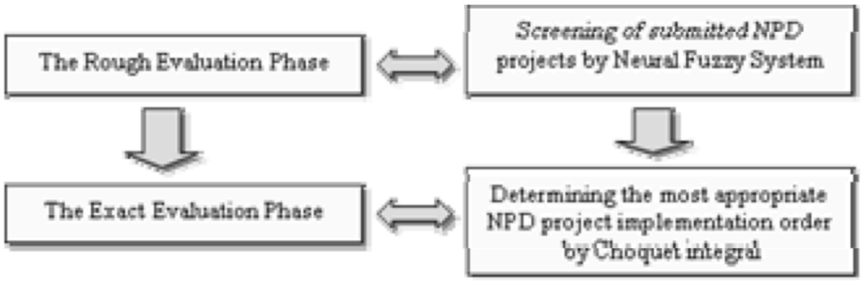


Figure 62 Intellligent Decision-making Framework (Feyzioğlu & Büyüközkan, 2007)

6.1.1.2.1The Rough Evaluation Phase

This phase represents an approach that merges neural networks and fuzzy logic. ANN imitate the way that the human brain learns and works, as it simply "possess the ability to learn from examples, have the ability to manage systems from their observed behavior, have the capacity to treat large amount of data and capturing complex interactions among the input variables" (Lin & Lee, 1996). On the other side, fuzzy logic is employed to manage unclear linguistic concepts or fuzzy terms, which facilitates reliable decision making in an unstable environment without missing the human's verbal judgment. Thus, NPD project selection could see significant advancements by integrating ANNs and fuzzy set theory.

First, the mentioned approach collects new product ideas generated by company designers, product managers, employees and customers via a formal web-based system. Then, an intelligent neuro-fuzzy inference system pre-processes the gathered ideas. Regarding the screening phase, good ideas are decided according to a scoring system with a pre-set evaluation criteria. Therefore, an input data base is built through converting these scores to 'eligibility percentages'. Accordingly, the incorporated fuzzy inference system (FIS) "maps the input space consisting of the information provided by past evaluations to the output space formed by the status of the ideas" (Feyzioğlu & Büyüközkan, 2007). The system is supported with a built-in AI technology that can depict the perspective of the company upper management towards products by learning the rules extracted from the companies' business plan. It also collaboratively eliminates the human's decision-making effort when the number of ideas/projects is large.

ANN algoritms support the fuzzy modeling framework to learn provided historical information and compute the membership function parameters that best enable the associated FIS to track the fed input/output data. ANFIS (adaptive network-based fuzzy inference system) is simply "a class of adaptive networks that are functionally equivalent to FIS" (Jang, 1993). Using a given input/output data set, ANFIS constructs a FIS whose membership function parameters are adjusted using either a back propagation algorithm or a hybrid-learning algorithm. Hence, using ANFIS, fuzzy systems can learn from the modeling data.

As pointed above, the main goal is classifying ideas as "good" or "bad". Thus, two ANFIS models (referred to as many ANFIS or MANFIS) are developed to figure out the corresponding idea status. One ANFIS model was trained to yield a value close to 1 if the idea is good, meanwhile the other model will perform the same for a bad idea. The classification procedure is performed by feeding the features of the idea to be classified to each of the two ANFIS models. The output is in the form of two non equivalent responses and a voting scheme is applied to decide the class to which the idea belongs. Obviously, only good ideas are saved for further analysis after the discrimination of bad ideas.

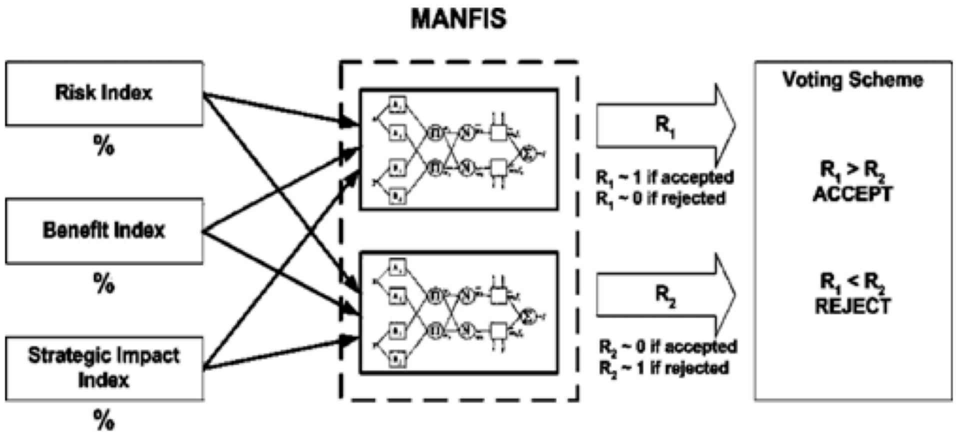


Figure 63 Discrimination of Ideas using MANFIS (Jang, 1993)

6.1.2 Intention

This stage focuses mainly on the possibility of transforming the idea resulted from the prior stage into a business that could both attract the interest of customers and seize a market opportunity. The major milestone of this phase revolves around completing the NPD process by developing a prototype. In brief, prototyping is an "iterative process in which prototypes are developed and tested in order to get fast feedback" (Kelley, 2001). Additionally, prototyping is an integral block of product development in ventures, and yet it is one of the least explored areas of design practice (Lauff, et al., 2018). In fact, completing a prototype is considered of utter importance to a successful future of MSMEs. To demonstrate, according to (Chou & Austin-Breneman, 2018), "prototyping is integral to the design process for all projects, but particularly for small and medium-sized enterprises (SMEs), [as] in resource-constrained contexts, designers must operate under unique constraints and opportunities".

Completing a prototype is also critical to avoid rushing to mass production without including customer's feedback early in the product development phase. To illustrate, according to (Brown, 2018), "prototyping is a vital part of the design and implementation process for all successful businesses in manufacturing. The days of blindly producing large batches of an unproven, untested product are long gone".

Hopefully, advancements in AI technologies could open up new opportunities with respect to augmenting the human's capabilities throughout the prototyping procedures. Thus, this work reviews the recent research efforts directed towards the deployment of human-AI collaboration to facilitate the final steps of NPD.

6.1.2.1 Generative Design (GD) Applications in Manufacturing

Generative Design (GD) is a technology that promotes automatic generation of "a large number of designs via an iterative algorithmic framework while respecting user-defined criteria and limitations" (A.Kallioras & Lagaros, 2020). It is mainly employed to assist designers throughout the development of prototypes in various sectors including: furniture manufacturing, aerospace industry and apparel industry. In the 1960s, the pioneering Hungarian computer artist Vera Molnár worked in the early programming language Fortran to "generate images examining theme, variation, automated generation, and display of options in her work" (Follett, 2020). Also, NASA incorporated an AI-driven generative design to examine "millions of potential antenna designs before settling on a final one. We told the computer program what performance the antenna should have, and the computer simulated evolution, keeping the best antenna designs that approached what we asked for. Eventually, it zeroed in on something that met the desired specifications for the mission" (Bluck, 2006).

Autodesk is considered among the leading companies when it comes to directing investments towards the integration of GD tools with AI technologies and CAD packages through the development of the program, Dreamcatcher (Buonamici, et al., 2020).

Figure 64 An application of Dreamcatcher Software (Hyunjin, 2020)

Using Dreamcatcher's software program limits the human's role to inputting basic forms and variables. On the other side, AI outputs a product that accounts for different factors including functionality, economy, structure, and appearance. Thus, further developments of AI technologies would significantly complement the human's role in the creative processes. In particular, a "generative design system will bring about great variation in the manufacturing process" (Hyunjin, 2020).

In essence, GD has recently "gained much attention due to its integration with artificial intelligence (AI) technologies" (Jang & Kang, 2020). Thus, this thesis spots the light on the researched changes in manufacturing due to the development of a generative design system. In particular, this technology is considered an opportunity to save a lot in time and effort, which can benefit many businesses, particularly MSMEs.

Relevantly, (Bentley & Wakefield, 1995) proposed a prototype design system which incorporates a genetic algorithm (GA) to generate new conceptual designs without being fed preliminary designs. In brief, the generative design system provides new designs and iteratively settles on the best option using a GA. GAs are built upon "the principles of evolution found in nature" (Ejigu & Lacquet, 2010) to first generate a population of solutions, and then "reproduce" the "fittest"' solutions. To enable the GA to pick 'fit' solutions from the reproduced solutions of every iteration, an assessment of designs is performed by an evaluation software. Hence, the proposed system saves the human developer a lot of time by avoiding the judgement of dozens of generated potential designs. By using software to evaluate designs, a human designer is saved the task of laboriously judging thousands of evolving candidate designs. Although the developed system was deployed to create designs for deceptive problems and complex shapes (prisms), the results were all satisfactory.

Also, (Hyunjin, 2020) provided a theoretical basis for the application of the GD system to portray the potential future changes in the manufacturing design process in the age of AI. Briefly, the traditional product manufacturing process is composed of five milestones: Propose, Plan, Design, Development, Evaluate, and Production.

First, Propose is the process of identifying the requirements of a project to develop a product. The next process is the Plan. Planning simply revolves around investigating and analysing differently-sourced data to prepare for the design phase. Following the prepared plan, the designer starts product design. Product Design is branched into conceptual design, basic design, detailed design, and production design. The Product Design phase ends whenever the designer settles on both the structure and shape of the product. The next step is to Develop, which takes the Product Design block's output as an input to refine it using 3D programs such as sketch-ups and 3D MAX. Then, the product is modelled, tested and assessed to validate its functionality and conformance to specifications. Finally, based on a successful evaluation step, a company approves the production and release of products on a large scale.

According to (Hyunjin, 2020), introducing a GD system will lead to a 'big change' in the manufacturing cycle. First, the designer feeds the system an approximate conceptual design. In return, the GD System provides a group of generated basic designs. Accordingly, designers pick the convenient design from the provided options to enable AI computing an 'optimal material proposal' taking functional and economical aspects into account. Important to mention, the system supports iterative reviewing of the proposal to receive the designer's approval before providing its final proposal. And the designer reviews this alternative. After the designer's review, the computer comes up with a final proposal.

Figure 65 A manufacturing process using a Generative Design System (Hyunjin, 2020)

As mentioned before, most of the generated designs are performed by collaboration between AI technologies and the human factor in what is called "hybrid design" (Young, 2018). Expectedly, a digital platform will be available via the Internet to take advantage of the advancing computing power and AI technologies to utilize accumulated data to make new forms of design (Young, 2018).

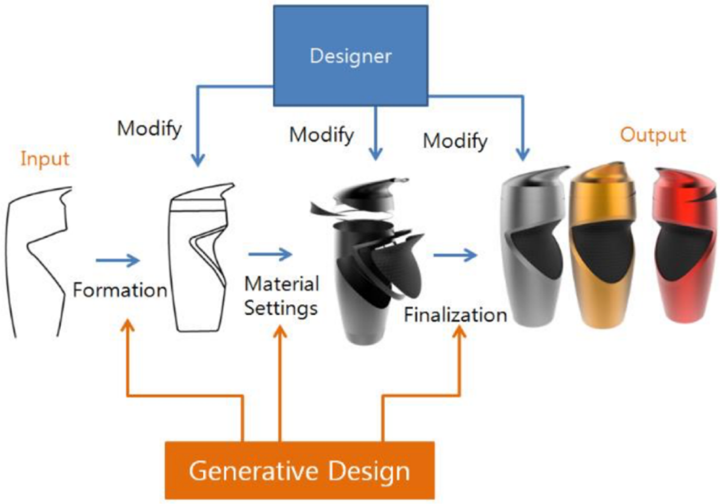


Figure 66 A Hybrid Design (Young, 2018)

6.1.2.2 Data-Driven Design

The concept development is the phase revolving around identifying the customer's needs, setting target markets, generating and evaluating different product ideas and taking decisions to pick one or more concepts for further development (T. Ulrich & D. Eppinger, 1995). The recent availability of vast amounts of data has encouraged researchers to direct their efforts towards studying its potential impact upon product design. Nowadays, insightful data could be collected by an enterprise both internally through customer relationship management systems (CRMs) and externally via the internet. Also, the deployment of "advanced information technologies such as the Internet of Things and edge computing in manufacturing industry" has accumulated a vast amount of "valuable data" (Georgakopoulos, et al., 2016). Additionally, throughout the "interaction between the product and the outside world (such as users and environment), a large amount of data can be produced, which represent the characteristics of the product's connection with the outside world" (Chang, et al., 2006). Thus, "the logical starting point of data-driven product design is to connect the virtual digital world and the real physical world" (Tao, et al., 2018).

The product design process refers to "the activity in which ideas and needs are given physical form, initially as solution concepts and then as a specific configuration or arrangement of elements, materials and components" (Walsh, et al., 1992). According to (Murray, 2005), product design represents "the creative process in researching markets, innovations and needs, then transforming ideas into products for particular markets". Thus, with the availability of ample product data, a designer should be capable of making reliable decisions to transform 'a set of functional requirements' into 'a specific implementation structure'. Additionally, data-driven design serves the entire product life cycle, which "covers the entire process including product requirement analysis, design, manufacturing, sales, after-sales service, and recycle" (Ryan & E. Riggs, 1996). Thus, (Feng, et al., 2020) aims to review the available research of data-driven design method applied in customer requirement analysis, conceptual design, and detailed design. However, the latter is considered out of this thesis scope due to the absence of AI technologies in its framework.

Requirement analysis: According to (Feng, et al., 2020), the recent technological advancements of BD technology facilitate an efficient collection and analysis of both the key preferences of customers and market data, which could be reliably transformed into market-fit product specifications in an intelligent and time-saving manner. Thus, this stage revolves around an effective 'capturing' and 'screening' of customer preference data to be capable of 'identifying' and 'forecasting' product features. (Chong & Chen, 2010) incorporated an artificial immune system (AIS) supported with an ANN to develop a customer requirements analysis and forecast (CRAF) system. The proposed system aims to analyze and predict the dynamic customer requirement data to diminish the risks of developing products for rapidly varying markets.

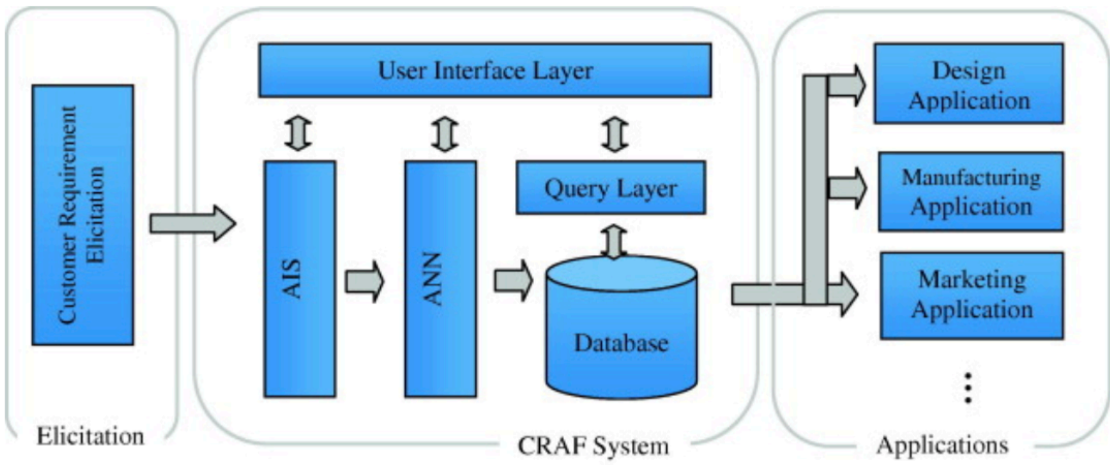


Figure 67 CRAF system framework in a manufacturing context (Chong & Chen, 2010)

On the same line, (Jin, et al., 2016) proposed a framework to manage consumer BD for customer requirements (CRs) understanding. Briefly, the authors identified product features and emotional polarity from big consumer opinion data using supervised learning approach and then employed a Kalman filter method to predict the trends of customer requirements and provide market-driven product designs.

Conceptual design: Product conceptual design is commonly known as a “series of iterative and complex engineering processes oriented to design requirements” (Feng, et al., 2020). Expectedly, “the design and decision made at the conceptual design stage have a significant influence on the success of the product development” (Cao, et al., 2013). As well, according to (Wynne & Mey-yen, 1998), “decisions made at the conceptual design stage have significant influence on factors such as costs, performance, reliability, safety and environmental impact of a product”. Unfortunately, because of operating in a volatile market, knowledge of all the design requirements and constraints during such an early phase of a product's life cycle is usually either inaccurate or ambiguous. At the same time, companies should constantly introduce new products that satisfy the customer’s demand for personalization and customization without inflating either the production expenses or the product development time frame.

In light of the BD era, “the requirements of most consumer groups can be determined from a large number of product data, thus reducing the ambiguity of conceptual design as product data contain rich design knowledge that can improve the efficiency of conceptual design and the innovation of design solutions” (Feng, et al., 2020). Relevantly, (Huang, et al., 2006) developed a computational intelligence approach for a better management of product conceptual generation and evaluation. Briefly, a set of satisfactory concepts (most-likely-to-succeed concepts) was generated by using GAs following the incorporation of information from a knowledge data. Then, a fuzzy neural network was then employed to implement concept evaluation and decision-making to achieve the optimal concept.

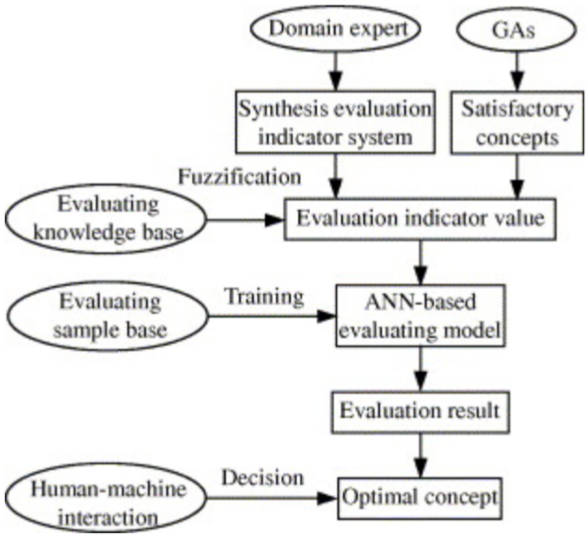


Figure 68 GA-NN-based evaluation process (Huang, et al., 2006)

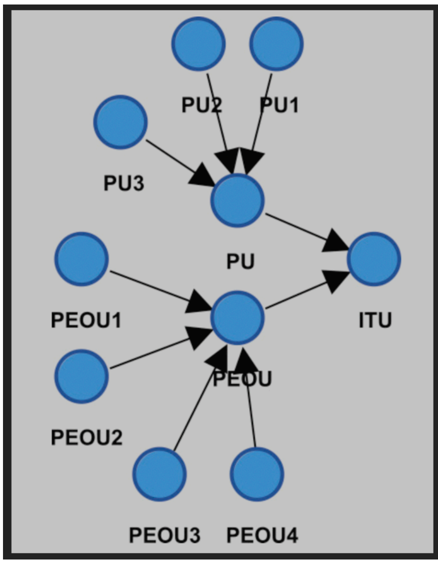
6.1.2.3 Evaluation of New Product Development Projects using Artificial Intelligence and Machine Learning

NPD has attracted researchers' interest given that markets are generally seen to be demanding higher quality and higher performing products, in shorter and more predictable development cycle-times and at lower cost (Maffin, 2001). Also, NPD decisions might be negatively affected by uncertainty causing events, which deviate the decision-maker from achieving the set target. The uncertainty arises from various sources including technical, management and commercial issues, both internal and external to the project. New product idea selection and evaluation are integral blocks of the new product management that companies need to avoid pursuing an unsuccessful project launch and encountering financial burdens. According to (Teel, 2021), "Many entrepreneurs think if only I had more money I could quickly and easily launch my product. There's no doubt about it, money is a huge obstacle for most new businesses, especially those developing new hardware products. Most reasons for failure eventually lead to running out of money. Perhaps you develop the wrong product that no one wants, and you don't have enough money to create the product people actually want". Unsuccessful NPD could lead to both "investment losses" and "missed investment opportunities" (Lestari, 2014). In the presence of a successful human-centred management system augmented with AI-powered tools, a MSME "will be able to determine right products or features to be developed, the right time to develop and launch and the right amount of investments" (Feyzioğlu & Büyüközkan, 2007).

An AI-powered evaluation of ideas/products necessitates the collection of ample data. In the era of BD and IoT, insightful information can be affordably extracted from data concerning the product's lifetime, customer's demands, suppliers' networks and logistics (Papadopoulos, et al., 2016). Analyzing this data may provide various benefits. However, a human-based analysis of data is both time consuming and prone to errors. Thus, few researchers have applied AI and ML technologies to augment the human's skills to analyze data collected in general about product development.

Briefly, Industrial design is "the process of designing products that are mass-produced in factories such as smartphones, computers, cars and bags" (Tjalve, 2015). The process of industrial design is critical to both the profitability of products and business sustainability as it plays an important role towards the avoidance of negative customers' reviews, insufficient sales and costive product recalls. Thus, (Viger, et al., 2022) provides a detailed survey of recent studies related to the incorporation of ML in industrial design. In fact, applying AI technologies in industrial design could cover a wide range of functions ranging from the design of a product to its mass manufacturing. In this lifecycle stage, we focus on the recent publications regarding the application of AI technologies to product acceptability estimation and product development failure prediction, as illustrated by (Viger, et al., 2022).

Product acceptability estimation refers to the estimation of the probability of success of products ideas. Assuming the presence of a preliminary prototype of the proposed idea/product, (Garces, et al., 2016) developed a ML model to forecast a product's success within customers during the early stages of the product development. To collect the required data for training the model, the authors prepared a questionnaire including all the product-related criteria identified in relevance to both the user (i.e ease of use) and the usage context (i.e social influence). Then, participants are requested to fill the questionnaire by evaluating the proposed product with respect to each factor according to a numerical scale (-5 to +7). Followingly, the data collected was used to build a Bayesian network. Based on the success applying the approach on a real design case of a communicating pen as elaborated in Figure 69, the built model can forecast the acceptability of the proposed product based on its features and characteristics. However, (Garces, et al., 2016) lacks a formal evaluation to determine the helpfulness of the model to designers.



Code	Factor description
PU	**Perceived utility**
PU1	The device functions as intended
PU2	The device helps to gain time during the procedures
PU3	The transmitted messages are of good quality
PEOU	**Perceived ease of use**
PEOU1	The device is easy to use
PEOU2	The forms are easy to fill out
PEOU3	The device ergonomics are appropriate
PEOU4	The forms are adapted to required usage
ITU	**Intention towards use**

Figure 69 Acceptability Model for a Communicating Pen (Garces, et al., 2016)

6.1.2.4 Product Development Failure Prediction

Understanding and modelling product design and development processes have attracted research interest over the past years. However, due to "the inherent intangibility and uncertainty of product design and development, there have been many limitations and difficulties in representing product development processes" (Duffy & J. O'donnell, 2005). Thus, in an attempt to efficiently understand and assess product development processes, few research efforts have developed an AI-assisted data analysis technique that evaluates and analyses product data. Briefly, (Do, et al., 2015) incorporates On-line Analytical Mining (OLAM) as the main tool for a convenient data analysis approach to enable analysts to understand and assess intangible and unstructured product development processes. Simply, OLAM is an integration between On-line Analytical Processing (OLAP) and data mining. OLAP is widely accepted as a "revolutionary technology that provides adequate analytic solutions for decision support" (Boutkhoum & Hanine, 2014). In earlier research, (Do, 2014) developed an architecture and prototype that can implement OLAP to evaluate product development performance. On the other side, data mining necessitates the deployment of ML to develop knowledge models capable of detecting hidden patterns from vast amounts of operational data. To sum up, OLAM facilitates viewing "product data from different angles using flexible and interactive OLAP queries and operations, and also prepare input data required for various data mining models" (Do, et al., 2015). Additionally, this approach also employs a Product Data Management (PDM) database as its major operational database. PDM database is mostly used by manufacturers to manage product data and development processes consistently, as (Kropsu-Vehkapera, et al., 2009) states "Product data management (PDM) has become one of the most important considerations for companies, especially in engineering and manufacturing industries".

To gather data logs required for analysis, (Do, et al., 2015) requested 20 students to deliver their work on product development over three months via a website. Students had to upload different documents related to product development including: product configurations (3D models in CAD format), assembly structures, engineering changes made to prototypes and product views. Then, the collected data was used to train a Naive Bayes Classifier model to determine the most significant reasons behind failures. The study's results proved that "the identified pattern can be used to proactively manage in-progress projects to prevent failure. For example, if managers identify a pattern where CAD creation time is taking longer than the average time for similar previous product development projects, they may start an investigation and manage them to avoid the coming failure". (Do, et al., 2015)

Recently, ML has also been incorporated to predict product defects through social media unstructured data and online reviews, respectively. Briefly, (Liu, et al., 2018) incorporates the features derived from replies and employs a multi-view ensemble learning method specifically tailored to the problem on hand as elaborated in Figure 70. Beside the benefits the NPD process would see, (Zhang, et al., 2016) states that applying ML techniques to develop automated product defect identification models could help manufacturers see an impactful reduction of labor costs.

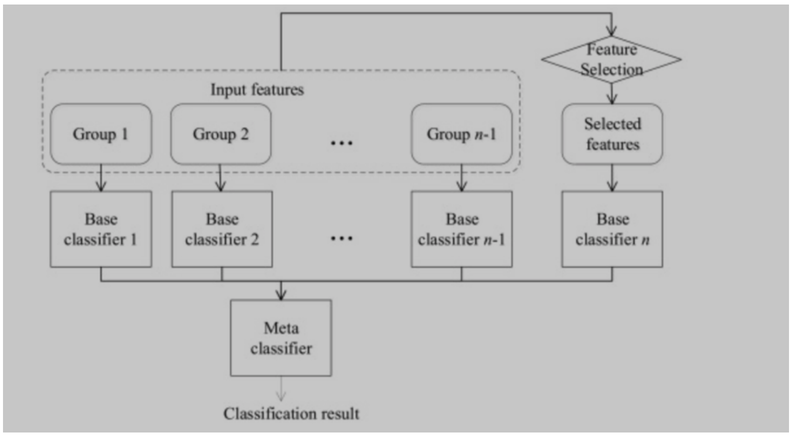


Figure 70 Multi-view Ensemble Learning Method for Product Defect Identification (Liu, et al., 2018)

6.1.3 Start-up

Reaching to this stage signifies the maturity of the newly launched business in terms of NPD. The startup phase necessitates the presence of "technological and commercial development and formal business planning, as well as the searching for additional and more considerable funding resources" (Passaro, et al., 2020). Accordingly, SMEs can request financial help from traditional sources (financial institutions, capital ventures) and crowdfunding platforms. This was verified by the study conducted on 50 MSMEs in Sri Lanka, as "The findings revealed that when the SMEs are identifying their business opportunities, they closely link with their families and friends. In the start up phase, SME owners gain encouragement, influence and initial capital through the social networks" (Thrikawala, 2011). Most importantly, the phase's major milestone is 'industrialization'. According to (Strautmane & Satrevics, 2015), industrialisation is "the totality of relations involving workers, employers and society as they develop to make use of the new machines, processes and services that modern technology has made possible". Hence, in this stage, great attention should be directed to maintaining relationships with other SMEs to gain access to further managerial, technical, and physical resources., which directs a MSME's attention towards acquiring the required skills to deal properly with the various operations associated with the industrialization phase. However, "manufacturing industry as a whole is struggling to recruit and maintain skilled laborers. Manufacturing SMEs may feel this reality even more acutely, as large companies often have more resources to attract the best candidates" (Hoffmeister, 2021). Referred to as the manufacturing skills gap, this dilemma "revolves around the labor market being unable to find workers who have the manual, operational, and highly technical skills, knowledge, or expertise to take the open positions. The manufacturing skills gap is not simply a buzzword within the industry. Instead, it's the reality that many manufacturers are facing right now. There are more open job positions than there are workers ready to fill them" (Zini, 2021). Thus, this work reviews the potential applications of augmenting the new manufacturing businesses with AI technologies to fill the so-called 'skill gap'.

6.1.3.1 AI-Enabled Training in Manufacturing Workforce Development

The rapid technological advancements indicate that "the future of work, especially in manufacturing, will require a different skills profile than what we have today" (Nguyen, 2020). Explaining further, as soon as technical skills will vary in response to the constant emergence of new technologies, employees need the ability to regularly upskill. For instance, in the near future, the computer interfaces used to control and monitor machines and devices in the IoT ecosystem are leading to an apparent skills gaps between the current workforce and requirements of future jobs. Workforce upskilling is also hindered due to "the aging and gradual retirement of baby boomers" (P. Dowell, 2020). According to (Sinha, 2021), "There is a much greater need today for the human-machine collaboration, even though automation has happened". Accordingly, the manufacturing sector should see an increase in demand for behavioural, and cognitive skills such as crisis management, resilience, quick decision making, critical thinking, basic computer interface skills and the ability to collaborate with AI-powered systems. According to (Deloitte, 2018), "a skill gap will result in an estimated 2.4 million jobs left unfilled between 2018 and 2028". Hence, workforce upskilling has become of crucial importance to the manufacturing society.

Relevantly, (Woolf, et al., 2020) proposed an AI-powered tutoring system to address the skill gap concerns in a manufacturing context. The proposed approach is divided into three steps: Identifying workers' needs, providing continuous skill development, and recommending a career path according to possessed competences. Briefly, the first step revolves around conducting one-on-one interviews with various stakeholders, operators, and unemployed personnel to determine the industry's requirements, pain points, and opinions. Interestingly, all the interviewees were adamant that the new waves of manufacturing automation are of great importance and that the currently provided training levels are not up to the level.

By the completion of the first step, (Woolf, et al., 2020) developed a software (DIRECT) to provide continuous assessment of skills and provide adequate training for upskilling the manufacturing workers. Additionally, through the analysis of data collected from online job postings, the developed software tool will intelligently facilitate the job selection process and skills development throughout the manufacturers' entire career path.

The developed software consists of three interlinked components: (i) a skill level diagnosis and assessment component that incorporates cognitive models to evaluate worker skill levels from on-job data, (ii) a training experience development component that employs intelligent tutoring concepts to assist workers develop new skills and (iii) a skill gap identification component that uses labor market analysis to identify high-demand jobs and the skill gaps between a worker and their desirable job.

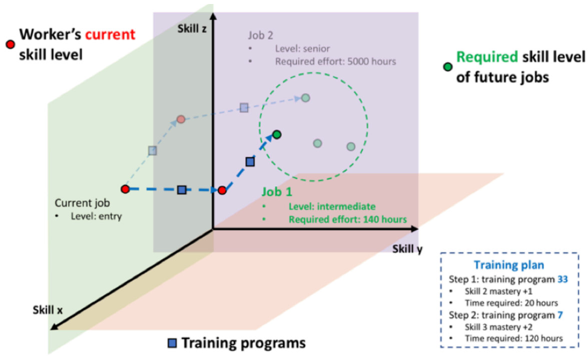


Figure 71 AI-enabled Skill Evaluation and Training Program (Woolf, et al., 2020)

The third component of DIRECT software employs predictive AI algorithms to connect manufacturers to potential jobs and choose training programs to develop the required skills. To illustrate, the system uses a fully connected neural network as a "career move prediction model", which processes the worker's skill levels and job title to predict the likelihood of success of the corresponding career move. By the way, the software is developed to enable interactive collaboration with the workers. To elaborate, in case of a user ignores the system's training recommendations and takes his own path, DIRECT will select training programs to efficiently complete the rest of the pathway. As well, the system uses a long short-term memory network (LSTM) developed by (Hochreiter & Schmidhuber, 1997) as a state transition model to update the skill levels of each worker over time as they engage with the training recommendations. From the employer's perspective, the proposed system predicts the probability that the applicant will successfully fit the job after being fed the worker's current skill levels as an input. Also, the system provides personalized pathways embodying a series of training programs for applicants to develop the necessary skills along with the estimated upskilling effort for each training program. Furthermore, to avoid defecting both the worker's productivity and work-life balance, the authors suggested the development of smart intelligent tutors to track the worker's learning during on-job training and provide manageable upskilling experiences.

6.1.3.2 AI-Assisted Smart Training Platform for Future Manufacturing Workforce

The pacing deployment of I4.0 has arguably changed the way operators interact with machines on the shop floor. For example, different manufacturing ventures have been developing AR based systems to augment human operators and enhance their efficiency in locating objects and repairing production faults (Karamalegos, 2018).

Despite the apparent extensive research towards the deployment of smart manufacturing techniques, the design of convenient training platforms is still comparably insufficient. The noticed imbalance was confirmed by (Deloitte, 2018), as it stated that "despite manufacturers focus on internal training programs, the pace of change still exceeds the extent and capacity of the training programs".

In response to the highlighted gap, (Wang, et al., 2020) proposed an AI-assisted training platform for manufacturing workforce to harness the potential of collaboration between human's intelligence and AI. Unlike the previous research dedicated to deploying AR to train assembling tasks, the proposed platform evaluates the performance of a worker during all phases of a manufacturing task.

Briefly, the developed platform will employ various types of non-intrusive sensing devices to facilitate gathering and analysing rich data (both macro and micro movement) regarding the interactions between operator-machine, operator-product, and operator-operator. In return, without interrupting his job, the AI learning algorithm provides the operator with the possible training procedures through mixed reality equipment. Similar to DIRECT software, the developed platform accepts being fed with an operator's input to support a collaborative improvement of the learning algorithm's intelligence.

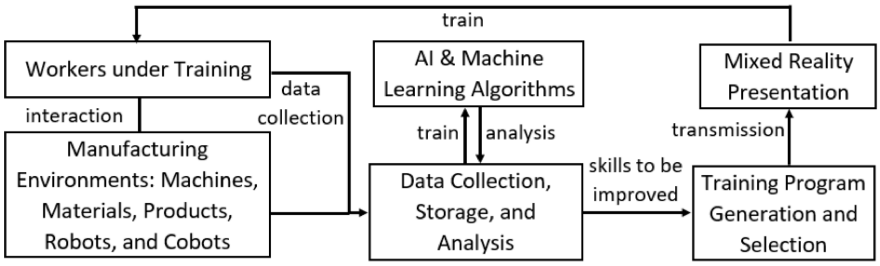


Figure 72 An AI-assisted Training Platform for Manufacturing Workforce (Wang, et al., 2020)

As shown in the figure above, the proposed platform is composed of multiple blocks. Anyway, this thesis spots the light on the role that AI can play in the different components of the system.

6.1.3.2.1 Artificial Intelligence and Machine Learning for Manufacturing

The future manufacturing paradigm urges demanding different applications of AI than those applied in smart manufacturing ventures. To illustrate, the autonomously guided vehicles (AGVs) on shop floors rely upon image processing to scan its path and avoid collision. Instead, the system proposed by (Wang, et al., 2020) supports CI between operators and AGVs instead of enhancing their guidance algorithms. As well, the developed system would enable the operators to upskill their programming capabilities (ex: 3D printer). In brief, an AI algorithm is developed to analyse previously compiled programs by different operators. Through the deployment of ML, the system could identify the operator's programming faults and suggest amendments.

6.1.3.2.2 AI for Human/Machine Interaction

This part focuses on the training activities for an operator's handling of a machine/product. Through the deployment of non-intrusive sensors, the system could gather data of both the operator's motion/actions and the machine's various parameters such as vibration and power consumption to feed the trained AI and ML algorithms that can derive out deviations from the expected operations. Briefly, assuming a machine's parameter follow a non-linear time series, the platform utilizes ANNs and RNNs with a Gated Recurrent Unit (GRU) to model the machine's state. Taking the variety of manufacturing tasks performed by a machine, the platform breaks a task into a combination of basic operations. In other words, the learning algorithm is trained to model the basic operations of a machine. The human operator is then responsible for dealing with a manufacturing task as a combination of the modelled basic operations.

On the other side, the classification and modelling of human actions is more challenging due to the variance between a human and another. Even a single operator may execute the same movement slightly different each time. Thus, the developed platform utilizes a CNN to model different human behaviours after learning from the data collected by sensors. Once the actions are identified, the platform points out any recommendations in case of meeting any deviations from the actions executed by an experienced operator.

6.1.3.2.3 AI for Human/Robot Interaction

The authors tried to address the challenge of modelling interactions between a human and a robot. The challenge emerges due to the need to model the interaction between two sides who are moving and possess intelligence. Consequently, similar to the communicative collaboration between two human beings, a human trainee should be capable of adapting to the 'intellectual level' and 'behaviour' of the robot and vice versa. Thus, instead of solely working on improving a robotic arm's smartness, the AI algorithms built in this component focuses on the design and improvement to the training programs for the engineers. In brief, the AI algorithm assesses and enhances communication between human operator and robot. To do so, the authors adopted the the teaching-learning-prediction (TLP) model with extreme learning machine developed by (Wang, et al., 2018) to enable the robot to predict a user's intention.

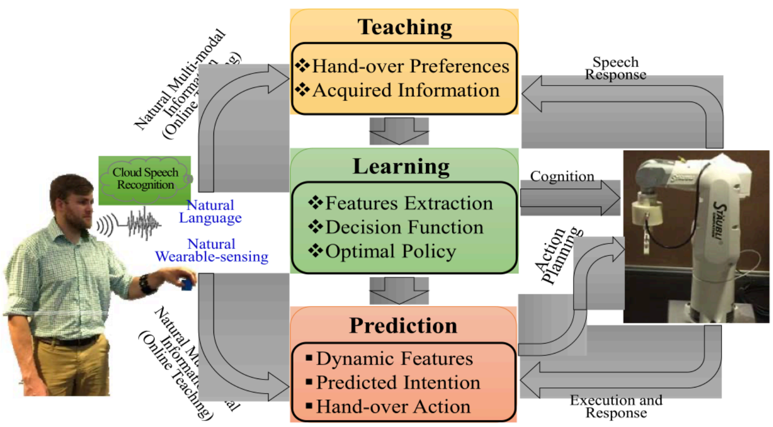


Figure 73 TLP Framework (Wang, et al., 2018)

The proposed platform builds on the efficiency of the TLP model through the adoption of AR and VR, as it provides a more effective technology to communicate the intent of a robot to the operator. As well, the robot is developed to track the operator's gaze to accurately predict his intention.

Additionally, the AI algorithms will help improving the human/robot collaboration by recommending the convenient training activities. Throughout the collaboration procedures, the developed platform will track and analyze both the successful and failing jobs to make recommendations. Briefly, the CNN algorithm merges feature learning and defect diagnosis to derive out the different types of collaboration mistakes from the correction efforts and provide a model that identifies the common factors of failure. By the way, an auto encoder can be incorporated for unsupervised feature learning, and the learned features will be input to the platform for model training and classification.

6.1.4 Expansion

According to the adopted model, by putting a foot into this stage, a MSME has to look up to upscaling its operations and handling a higher turnover. According to the British Manufacturer's organisation, "the scale-up challenge for UK manufacturers [SMEs] is different from the average business due to the cost of heavy-duty equipment and industrial real estate". Thus, this thesis reviews the potential application of CI to help optimize a manufacturing SME's assets.

6.1.4.1 Predictive Manufacturing

The globalization of the world's economies is a huge concern to local industry and it is pushing the manufacturing sector to improve its competitiveness. Also, some MSMEs have "lost its place in manufacturing industry because of globalization and fast change in global market" (Han & Chi, 2016). Despite the tendency to apply continuous improvement methodologies (ex: Lean Manufacturing), the manufacturing companies still encounter both internal and external uncertainties. Most interestingly, the internal uncertainties include unexpected failure events due to the degradation of machines and processes. Leveraging the emerging technologies, such as IoT, advanced analytics and AI has opened a door for further improvement of efficiency and productivity. Hence, "in order to achieve transparency, the manufacturing industry has to transform itself into predictive manufacturing" (Lee, et al., 2013) to "early-predict equipment condition and make optimized recommendations for adjustments and maintenance to ensure normal operations (Stojanovic, 2019).

Thus, over the past years, noticeable interest of researchers has been directed towards the deployment of AI technologies and BD analytics to "create manufacturing environment that enables the implementation of all new technologies based on capabilities such as "self-awareness", "self-predicting", "self-maintaining" and "self-learning"" (Nikolic, et al., 2017). Relevantly, (Ademujimi, et al., 2017) reviewed the literature on how ML techniques were used in manufacturing predictive fault diagnosis with a focus on ANN algorithm. To demonstrate, (Zhang, et al., 2013) developed an AI-based classification method to predict the degradation (Remaining Useful Life) and anticipate the failure of the components and machines. Briefly, the developed system is based on collecting vibration signals from the sensors mounted on the machines for critical components monitoring. Followingly, the gathered data and features extracted are employed to train the ANN as shown in Figure 74.

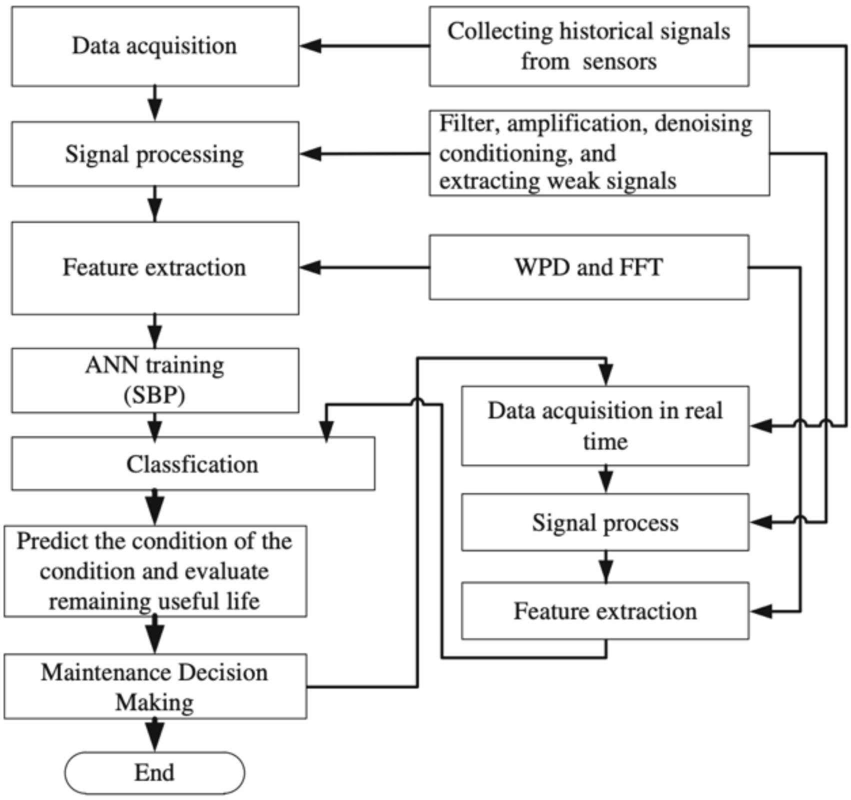


Figure 74 AI-based Diagnosis and Prognosis Framework (Zhang, et al., 2013)

On the same line, (Han & Chi, 2016) developed an AI-based system to predict a CNC tool wear compensation offset value (to maintain product quality) by employing the support vector regression (SVR) alongwith various combinations of data pre-processing methods. Furthermore, (Khan, et al., 2022) recently proposed a manufacturing analytics model to predict failures in the production process in heterogeneous streams of data. The comparison with other classification methods, such as SVM, KNN, ANN, on real data showed that the proposed approach can predict product failure with reasonable accuracy.

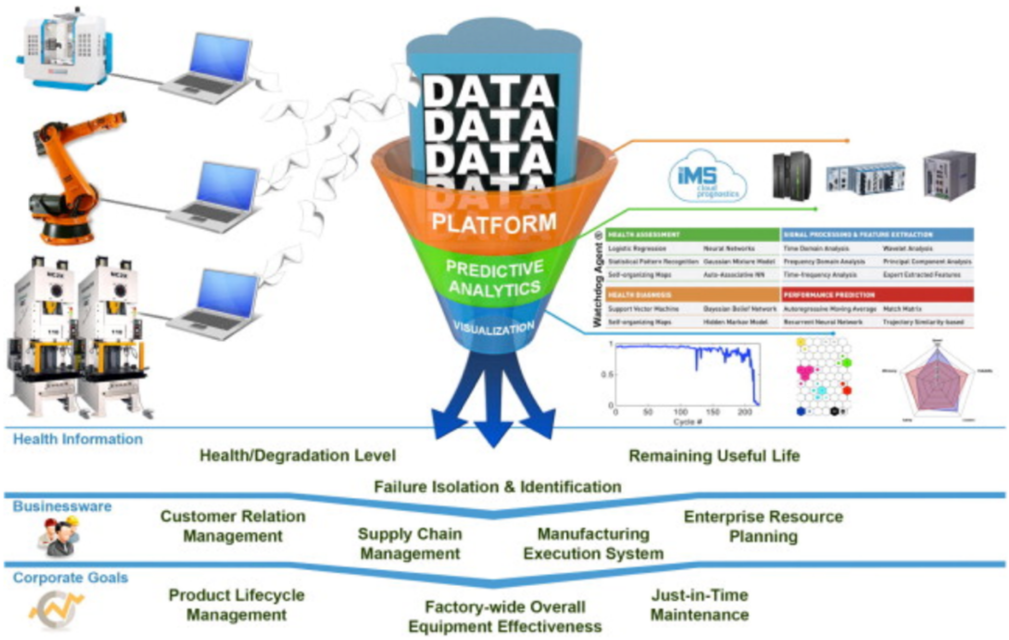


Figure 75 Predictive Manufacturing Analytics Framework (Lee, et al., 2013)

Another aspect that might benefit from the human-AI collaboration is inventory management. Likely, "small and medium scale manufacturing industries are in most cases faced with the problems of inadequate inventory of raw materials and spare parts. These shortages often lead to breaks in production schedule, machine breakdown and low capacity utilisation and thus constituted a barrier to their effective growth" (Monisola, 2013) . Also, "Inventory is the life-blood of every organization and mandates efficient management, especially for startups which have significant cash constraints" (Murthy, 2016). Thus, this thesis focuses on the potential applications of CI in effective inventory management.

6.1.4.2 A Decision Support System (DSS) for Inventory Management and Supplier Selection

Unlike LEs, manufacturing SMEs lack the tools and knowledge to utilize data to support their decision-making process. To elaborate, SMEs have a common problem of effectively taking advantage of the availability of data due to the deficiency of resources, and consequently the absence of data analytics (Coleman, et al., 2016). As a result, the majority of SMEs' decision-making processes "have relied on intuition combined with entrepreneurial experience and knowledge" (Musso & Francioni, 2012). The application of DSSs in the areas of inventory management has been proposed in several studies. This thesis focuses on the development of a DSS for sourcing and inventory management in MSMEs that have limited resources and knowledge in utilizing data to support their decision-making.

Inventory management revolves around inventory replenishment, inventory optimization, and inventory control (Jalali & Van Nieuwenhuyse, 2015). In an attempt to encounter the uprising market dynamism, researchers have been proposing various models taking into account the various sources of uncertainties. To illustrate, (Nakandala, et al., 2018) proposed an Integer Programming optimization model for inventories to determine both the optimum size and cost of orders from reliable suppliers. Despite being easily adopted by MSMEs, but this model might not be reliable enough as it restricts its input to data associated with reliable suppliers, which might not be the case for many firms. In response, researchers have started employing AI technologies to meet the businesses' needs. For example, through the integration of ANN and FIS, (Deb, et al., 2017) proposed an adaptive neuro-fuzzy inference system (ANFIS) to work as DSS for uncertain inventory management. Briefly, the system is fed demand as input and outputs optimized procurement, ordering and holding cost to control production and supply. The system relies upon learning the changes in demand of certain goods and establishing their association with the related costs observed in the data set used for training the algorithm.

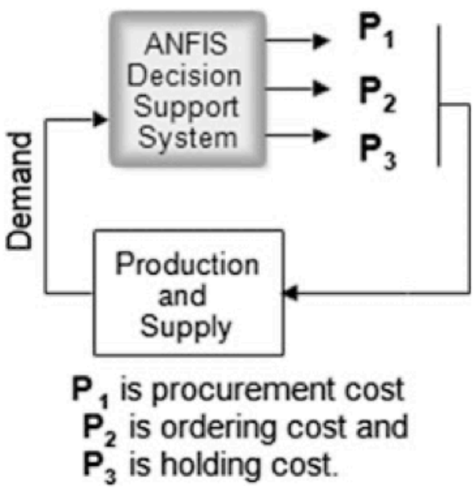


Figure 76 ANFIS DSS Framework (Deb, et al., 2017)

Moreover, (Teerasoponpong & Sopadang, 2022) proposed a DSS to "minimize the total purchased cost of raw materials based on the company's behavioral preferences in supply and inventory management". Therefore, through the integration of ANN (for learning unusual patterns) and GA (for exploring many parameters in each iteration), the proposed DSS utilizes a simulation-optimization approach to augment the human's intelligence through the inventory management process. Technically, the DSS receives uncertain raw data from both the internal operations and the volatile external business sphere.

In the proposed system, the human's role follows the completion of data processing, system training, and parameter optimization, as he verifies and validates the generated optimization to be used for augmenting his decision-making process. The optimized iterations generated by the system consists of five key parameters: total cost of purchased raw materials, optimal order quantity, order quantity from each supplier, safety stock, and reorder point. In case of generating a non-feasible solution, the system enables the human supervisor to re-adjust the input data. Followingly, the GA would take the re-adjusted parameters and re-iterate the optimization process to propose a feasible solution.

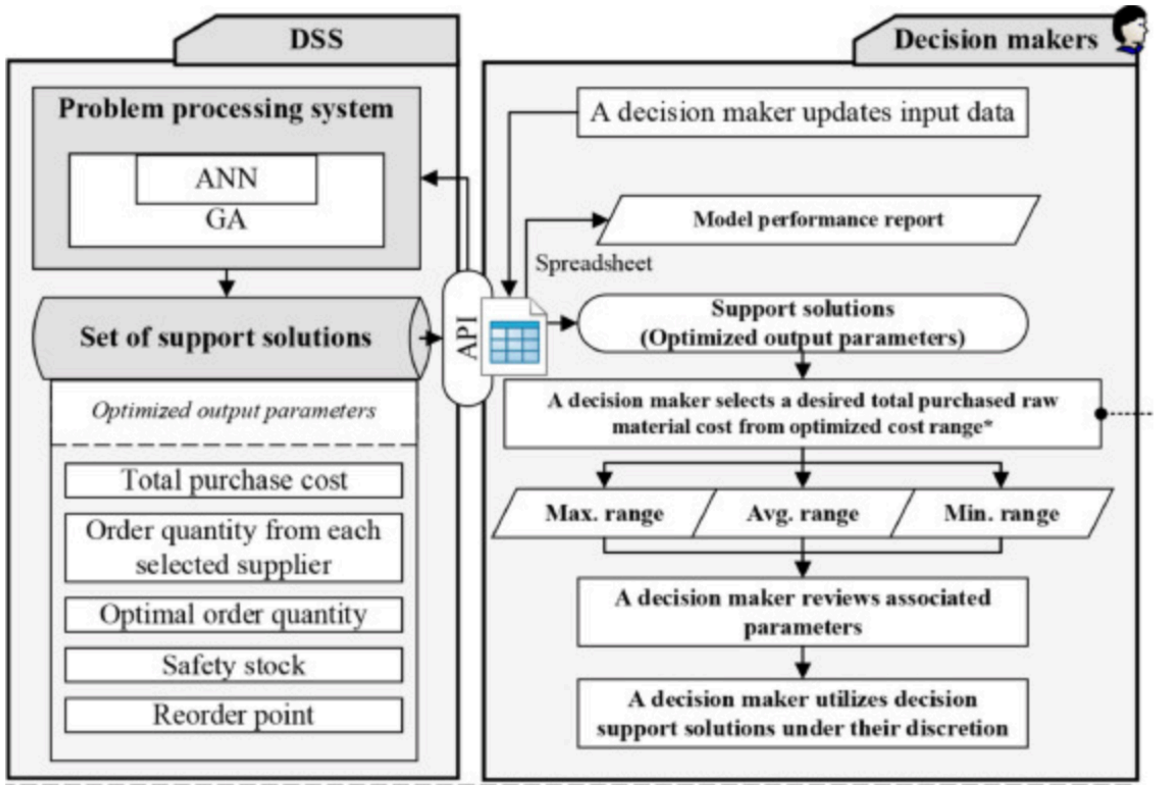


Figure 77 ANN-GN Simulation-Optimization DSS Framework (Teerasoponpong & Sopadang, 2022)

Technologies Involved \ Applications	brAInstorm: Intelligent Assistance in Group Idea Generation	An Intelligent Evaluation Approach For NPD Projects	Product Development Failure Prediction	Evaluation of New Product Development Projects using Artificial Intelligence and Machine Learning	Generative Design
Smart IoT Devices					
Wearable Devices					
Smart Sensors					
AI/ML Algorithms					
Spatio-temporal Markov Chains/Hidden Markov Models					
Learning from Demonstration (LfD)					
Ensemble model /Reinforcement learning/ Continual Learning	✓	✓	✓		
Image/Pattern Recognition					
ANN/Classifiers/CNN/ DNN/ Bayesian/GA/Kalman Filter/FIS		✓	✓	✓	✓
NLP/NLU	✓				
STT/TTS	✓				
DBPS					
In-house Computing		✓	✓	✓	✓
Cloud Computing	✓	✓	✓	✓	✓
Edge Computing					
Communication Networks					
4G					
5G					
WiFi/Bluetooth	✓	✓	✓	✓	✓
DT/AR/VR/MR					

Table 12 An Analysis of the Technological Requirements of the Potential CI Applications in Manufacturing SMEs (1/2) (According to the author's Findings)

Applications / Technologies Involved	**Data-Driven Design**	**AI-Enabled Training in Manufacturing Workforce Development**	**AI-Assisted Smart Training Platform for Future Manufacturing Workforce**	**Predictive Manufacturing**	**A Decision Support System (DSS) for Inventory Management and Supplier Selection**
Smart IoT Devices					
Wearable Devices			✓		
Smart Sensors			✓	✓	
AI/ML Algorithms					
Spatio-temporal Markov Chains/Hidden Markov Models				✓	
Learning from Demonstration (LfD)					
Ensemble model /Reinforcement learning/ Continual Learning			✓		
Image/Pattern Recognition			✓		
ANN/Classifiers/CNN/ DNN/ Bayesian/GA/Kalman Filter/FIS	✓	✓	✓	✓	✓
NLP/NLU			✓		
STT/TTS			✓		
DBPS					
In-house Computing		✓			
Cloud Computing	✓	✓	✓	✓	✓
Edge Computing	✓		✓		
Communication Networks					
4G	✓		✓	✓	✓
5G			✓		
WiFi/Bluetooth	✓	✓			✓
DT/AR/VR/MR			✓		

Table 13 An Analysis of the Technological Requirements of the Potential CI Applications in Manufacturing SMEs (2/2) (According to the author's Findings)

6.2 A Qualitative Analysis of the Usability and Maturity of the Researched CI Technologies in MSMEs

Application	Usability	Maturity
Ideation		
brAInstorm: Intelligent Assistance in Group Idea Generation	HIGH	HIGH
An Intelligent Evaluation Approach For NPD Projects	HIGH	HIGH
Intention		
Product Development Failure Prediction	HIGH	MEDIUM
Evaluation of New Product Development Projects using Artificial Intelligence and Machine Learning	HIGH	MEDIUM
Generative Design	HIGH	HIGH
Data-Driven Design	HIGH	HIGH
Start-up		
AI-Enabled Training in Manufacturing Workforce Development	HIGH	MEDIUM
AI-Assisted Smart Training Platform for Future Manufacturing Workforce	HIGH	MEDIUM
Expansion		
Predictive Manufacturing	HIGH	MEDIUM
A Decision Support System (DSS) for Inventory Management and Supplier Selection	HIGH	MEDIUM

HIGH MEDIUM LOW

Table 14 An Analysis of the Applicability, Usability and Maturity of the Different Technologies in Manufacturing Small and Medium Enterprises (From the author's perspective)

6.3 A Qualitative Analysis of the Human Intelligence and Artificial Intelligence Contribution

Application	Human Intelligence	Artificial Intelligence	Collaborative Intelligence
Ideation			
brAInstorm: Intelligent Assistance in Group Idea Generation	MEDIUM	HIGH	HIGH
Evaluation of New Product Development Projects using Artificial Intelligence and Machine Learning	MEDIUM	HIGH	HIGH
Intention			
Product Development Failure Prediction	MEDIUM	HIGH	HIGH
Generative Design	MEDIUM	HIGH	HIGH
Data-Driven Design	MEDIUM	HIGH	HIGH
Start-up			
AI-Enabled Training in Manufacturing Workforce Development	MEDIUM	MEDIUM	HIGH
AI-Assisted Smart Training Platform for Future Manufacturing Workforce	MEDIUM	MEDIUM	HIGH
Expansion			
Predictive Manufacturing	MEDIUM	MEDIUM	HIGH
A Decision Support System (DSS) for Inventory Management and Supplier Selection	MEDIUM	MEDIUM	HIGH

HIGH MEDIUM LOW

Table 15 Analysis of the Contribution of Human Intelligence and Artificial Intelligence in the Different Technologies In Small and Medium Enterprises (From the author's perspective)

7. Collaborative Intelligence Challenges

7.1 Social challenges

7.1.1 Technology acceptance and trust

The adoption degree of intelligent human-centric manufacturing systems hugely depends on the human's trust in intelligent technologies. Technologies must be reliable, intelligent, entertainable, and value privacy of data. This alarms a challenging objective of developing empathic machines to build a trust-based collaborative relationship between the two entities, which necessitate significant advances in "cognitive science" and "unbiased intelligence" in intelligent machine agents (Lu, et al., 2022) .

7.1.2 Change of team dynamics

Undoubtedly, collaborative work set-ups embracing intelligent machines will force changes to the team dynamics in a work environment. Human operators need to adjust the way they deal with intelligent machines, as such entities would expectedly be heavily involved in a human operator's physical, cognitive, and decision-making performance (Lu, et al., 2020)

7.1.3 Continuous learning

The development of technologies to understand humans must be met with effective training of human operators to enrich the necessary skills for an adequate utilization of the developed technologies and support a productive human-machine teamwork, which would reflect on a better overall system's performance.

7.2 Technical challenges

7.2.1 Data integration

Differently sourced data is the core of an efficient collaborative intelligence framework, which remarks data integration as a critical research topic. Simply, data integration architecture aims to "combine the data residing at different sources and to tie these different sources controlled by different owners under a common schema". Undoubtedly, taking the IIoT-oriented environment into consideration, the biggest dilemma in the way of an efficient data integration is developing an automatic scheme that provides a "correct logical sequence" with respect to the real processes on the industrial production ground (Chen, et al., 2016).

7.2.2 Personalized Human-centric AI

To foster the human-centricity in the future factories, empathic machines would essentially be collaborative, understanding, proactive, and personalized. Such harmonized relationship would be the key to harness the potential of CI instead of threatening human's jobs for compromised productivity.

7.2.3 Transparency and Explain-ability

For a trust based and bi-directional HRC, human operators should be aware of the way AI technologies arrive to its conclusions and decisions (Lu, et al., 2022). Unfortunately, the current DL-based systems are not up to the required level referring to this issue (Hagras, 2018). Therefore, tangible advancements are necessary to make AI explainable.

7.2.4 Manufacturing systems research

The shift from system-centric manufacturing to human-centric manufacturing complicates the current manufacturing strategies research. To elaborate, the higher degree of freedom granted to human workers urges amendments to the current manufacturing strategies research in order to be prepared to make for the human factor's contingencies before defecting the overall system's productivity.

7.2.5 Trusted and privacy-protected model design

The privacy of data and knowledge is an utter necessity for both data owners and consumers in a CI architecture. Regarding a collaborative intelligence mode, it is unnegotiable to study and design a privacy-secured data model for data processing, data analysis, knowledge discovery and knowledge exploitation. Although data privacy concept is regarded with a high importance within the CI value chain, but yet there is no available unified standard model that satisfies such necessity due to the unlike requirement of data owners and consumers. Normally, developing empathic machines would urge the researchers to develop a reinforced "universally accepted ethical system" to keep the "disruptive" potentials of new AI technologies under societal control (Hagendorff, 2020). For example, assuming being aware of the consequences, workers should be granted the authority to control the flow of their personal data to smart devices.

8. Future Research Opportunities

The evolution from the Operator 4.0 vision towards Operator 5.0 prioritizes establishing trusting relationships between humans and machines, paving the way for “smart resilient manufacturing systems to capitalize not only on smart machines’ strengths and capabilities, but also to empower their smart operators with new skills and gadgets for the new working paradigm” (MOURTZIS, et al., 2022). Expectedly, alongside the evolution of the new generation of operators, operator 5.0, Industry 5.0 will stimulate the creation of new job roles. For example, the CI-based work environment will necessitate the presence of a Chief Robotics Officer (CRO), who possesses the knowledge about robots and the human-machine relationships (MOURTZIS, et al., 2022). This role could be integral to the manufacturing system’s efficiency, as the CRO would lead the decision-making concerning the addition/removal of particular robots from the working environment. Therefore, bearing the operator 4.0 vision in mind, the time has clearly come to direct the focus to determining the required skills to be present in the operator 5.0. Also, we should start identifying the possible new job roles and the necessary skills to support a smooth shift from I4.0 to I5.0.

Figure 78 Preliminary Skills and Attributes of the Industrial Operator 5.0 (MOURTZIS, et al., 2022)

9. Conclusion

The rapid, continuous technological advancements have encouraged researchers to direct their attention to the potential impact of the collaboration between human intelligence and machine intelligence upon the various fields. In fact, the term "Collaborative Intelligence" has been attracting the research attention since 1999, which resulted in the development of various crowd-based collaborative platforms such as Wikipedia. However, artificial intelligence has not been called to action until 2015, a few years after the emergence of the industry 4.0 initiative. Actually, the terms "collaborative intelligence" and "artificial intelligence" have started showing an increasing trend of being mentioned together by the introduction of Industry 5.0 in 2015. Industry 5.0 aims to harness the potential of augmenting the human factor with artificial intelligence technologies to bring back the human's touch to prepare the manufacturing sector for the future's competitive differential, mass personalization. According to a qualitative analysis, in the short term, the manufacturing sector would benefit from the Human-Centric Collaborative Intelligence in terms of collaborative sensing technologies, AI-powered decision-making system, Pi-mind technology, augmented analytics in quality control, shared workplaces between humans and collaborative robots and intelligent virtual technical assistants (Chatbots). However, such technologies necessitate the presence of other technologies including Edge computing, cloud technologies, AR/VR, and Digital twins, which makes it difficult to be adopted by manufacturing SMEs compared to Large Enterprises (except small-scale Cobots and chatbots).

Manufacturing SMEs are relatively more prone to failure than other sectors for various reasons including lack of labour skills, higher initial investments, changing customer demands, difficulties of prototype/product development and lack of real-time data-driven decision support systems. According to literature, augmenting the human's capabilities with affordable artificial intelligence and other enabling technologies would offer many solutions to the problems highlighted above, which would facilitate the manufacturing SME's way to ramp-up processes and help diminishing the failure rate. According to a qualitative analysis, manufacturing SMEs are comfortably ready to apply CI technologies to new product development, prototyping, up-skilling workforce and inventory management.

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APPENDIX A

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
1	A critical review of symbiosis approaches in the context of Industry 4.0	8	*Journal of Computational Design and Engineering*	2020
2	Technology enablers for the implementation of Industry 4.0 to traditional manufacturing sectors: A review	15	*Computers in Industry*	2021
3	Industry 5.0: A survey on enabling technologies and potential applications	28	Journal of Industrial Information Integration	2021
4	Humans Are Not Machines—Anthropocentric Human–Machine Symbiosis for Ultra-Flexible Smart Manufacturing	4	Engineering Journal	2021
5	Perspectives on Manufacturing Automation Under the Digital and Cyber Convergence	0	European Business Review Journal	2020
6	User-Friendly MES Interfaces: Recommendations for an AI-Based Chatbot Assistance in Industry 4.0 Shop Floors	4	Asian Conference on Intelligent Information and Database Systems	2020
7	Patented intelligence: Cloning human decision models for Industry 4.0	58	Journal of Manufacturing Systems	2018
8	Human-AI Collaboration in Quality Control with Augmented Manufacturing Analytics	1200 downloads	IFIP International Conference on Advances in Production Management Systems	2021
9	A human cyber physical system framework for operator 4.0 – artificial intelligence symbiosis	21	Manufacturing Letters	2021
10	An Artificial Intelligence-Based Collaboration Approach in Industrial IoT Manufacturing: Key Concepts, Architectural Extensions and Potential Applications	19	*Sensors* 2020	2020

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
11	A futuristic perspective on human-centric assembly	1	Journal of Manufacturing Systems	2020
12	Bridging human and machine learning for the needs of collective intelligence development	5	Procedia Manufacturing	2020
13	Collaborative Robots: Frontiers of Current Literature	17	Journal of Intelligent Systems: Theory and Applications	2021
14	Fifth revolution: Applied AI & human intelligence with cyber physical systems	19	International Journal of Engineering and Advanced Technology (IJEAT)	2021
15	An alliance of humans and machines for machine learning: Hybrid intelligent systems and their design principles	4	Technology in Society	2021
16	Knowledge Project - Concept, Methodology and Innovations for Artificial Intelligence in Industry 4.0	1	IEEE International Conference on Industrial Informatics (INDIN)	2021
17	Trust in artificial intelligence within production management–an exploration of antecedents	0	Ergonomics	2021
18	A survey on evolutionary machine learning	72	Journal of the Royal Society of New Zealand	2019
19	Industry 5.0: The Convergence of AI and HI (Human Intelligence)	1	Research Paper: COLLEGE OF ENGINEERING, PUNE (COEP) - MAHA	2021
20	A Study on the System for Controlling Factory Safety based on Unity 3D	NIN	Journal of Korea Game Society	2020

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
21	The Digital Shipyard Opportunities and Challenges	0	Australian Industrial Transformation Institute	2021
22	Systematic literature review on augmented reality in smart manufacturing: Collaboration between human and computational intelligence	28	Journal of Manufacturing Systems	2021
23	Hybrid big data analytics and Industry 4.0 approach to projecting cycle time ranges	9	*The International Journal of Advanced Manufacturing Technology*	2022
24	Sustainable Operations Management for Industry 4.0 and its Social Return	11	IFAC-PapersOnLine	2019
25	Digital Manufacturing as a basis for the development of the Industry 4.0 model	NIN	Procedia CIRP	2021
26	What to Expect From Artificial Intelligence in Business: How Wise Board Members Can and Should Facilitate Human-AI Collaboration	NIN	Challenges and Opportunities of Corporate Governance Transformation in the Digital Era Book	2020
27	Cognitive Digital Twins for Smart Manufacturing	412 downloads-4 citations	*IEEE Intelligent Systems*	2021
28	A Mapping Analysis of Maintenance in Industry 4.0	NIN	*Journal of Applied Research and Technology*	2021
29	A human cyber physical system framework for operator 4.0 – artificial intelligence symbiosis	21	Manufacturing Letters	2021
30	An Artificial Intelligence-Based Collaboration Approach in Industrial IoT Manufacturing: Key Concepts, Architectural Extensions and Potential Applications	19	*Sensors* 2020	2020

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
31	Soft Computing in Smart Manufacturing: Solutions toward Industry 5.0	NIN	Book:	2021
32	Impact of artificial intelligence on employees working in industry 4.0 led organizations	5 (1012 downloads)	*International Journal of ManPower*	2021
33	Design choices for next-generation IIoT-connected MES/MOM: An empirical study on smart factories	2	Robotics and Computer-Integrated Manufacturing Journal	2022
34	AI for Improving the Overall Equipment Efficiency in Manufacturing Industry	5	Book: New Trends in the Use of Artificial Intelligence for the Industry 4.0	2020
35	The Digitization of Design and Manufacturing: A State-of-the-Art Report on the Transition from Strategic Vision to Implementation in Industry	6	Procedia CIRP	2020
36	Skill transfer support model based on deep learning	12	*Journal of Intelligent Manufacturing*	2021
37	Assessment of Implicit and Explicit Measures of Mental Workload in Working Situations: Implications for Industry 4.0	4	Applied Sciences Journal	2020
38	From Artificial Intelligence to eXplainable Artificial Intelligence in Industry 4.0: A survey on What, How, and Where	11 views	IEEE Transactions on Industrial Informatics	2022
39	Outlook on human-centric manufacturing towards Industry 5.0	416 views	Journal of Manufacturing Systems	2022
40	Towards proactive human–robot collaboration: A foreseeable cognitive manufacturing paradigm	7	Journal of Manufacturing Systems	2021

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
41	Future Research Directions on Human–Robot Collaboration	614 Downloads	Book :Advanced Human-Robot Collaboration in Manufacturing	2021
42	The evolution of AI and the human-machine interface as a manager in Industry 4.0	1	Strategy, Leadership, and AI in the Cyber Ecosystem	2021
43	Collaborating AI and human experts in the maintenance domain	3	AI & SOCIETY Journal	2021
44	Narrative-based human–artificial collaboration. A reflection on narratives as a framework for enhancing human–machine social relations.	NIN	Research Paper : Politecnico di Milano	2022
45	Smart and Sustainable Collaborative Networks 4.0	NIN	Working Conference on Virtual Enterprises	2021
46	Adapting Autonomy and Personalisation in Collaborative Human–Robot Systems	156 Downloads	Book: Intelligent Systems, Control and Automation: Science and Engineering	2021
47	Self-organizing manufacturing network: A paradigm towards smart manufacturing in mass personalization	6	Journal of Manufacturing Systems	2021
48	HOW DIGITALIZATION CAN ENHANCE THE EFFICIENCY OF THE PROJECT SUPPLY CHAIN	NIN	Dissertation	2021
49	Artificial Intelligence and Business Value: a Literature Review	2 (3698 Downloads)	I*nformation Systems Frontiers*	2021
50	The Rise of Automation and Robotics in Warehouse Management	NIN	Book: Transforming Management Using Artificial Intelligence Techniques	2021

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
51	Facing Disruptive Challenges in Supply Chain 4.0	7 (1899 downloads)	Research Paper: The University of Queensland	2020
52	Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments	2	*Annals of Operations Research*	2021
53	IndustEdge: A Time-Sensitive Networking Enabled Edge-Cloud Collaborative Intelligent Platform for Smart Industry	1	IEEE Transactions on Industrial Informatics Journal	2022
54	A study on manufacturing facility safety system using multimedia tools for cyber physical systems	0	Multimedia Tools and Applications	2021
55	Towards a Reference Software Architecture for Human-AI Teaming in Smart Manufacturing	NIN	The 44th International Conference on Software Engineering	2022
56	Adequate Research Directions for Smart Factory: A literature survey	1 citations (170 views)	Conference Paper	2011
57	Artificial Intelligence and its added value in Manufacturing Environments: A model for AI- based human augmentation	NIN	Master thesis	2021
58	The role of big data for Supply Chain 4.0 in manufacturing organisations of developing countries	428 downloads	Journal of Enterprise Information Management	2021
59	Human in the AI Loop in Production Environments	1200 downloads	IFIP International Conference on Advances in Production Management Systems	2021
60	Participatory Design for Digital Transformation of Manufacturing Enterprises	1	MIT Work of the Future Working Paper	2020

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
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65	AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework	NIN	Journal of Business Research	2022
66	Collaborative Industrial Internet of Things for Noise Mapping: Prospects and Research Opportunities	1	IEEE Industrial Electronics Magazine	2021
67	Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges	6	Journal of Building Engineering	2021
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Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
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72	Implementing challenges of artificial intelligence: Evidence from public manufacturing sector of an emerging economy	4	Government Information Quarterly Journal	2021
73	Towards augmenting cyber-physical-human collaborative cognition for human-automation interaction in complex manufacturing and operational environments	21	International Journal of Production Research	2020
74	Human-robot collaboration empowered by hidden semi-Markov model for operator behaviour prediction in a smart assembly system	NIN	Journal of Manufacturing Systems	2022
75	Managing production systems with machine learning: a case analysis of Suzhou GCL photovoltaic technology	177 views	1. Production Planning & Control Journal	2020
76	Collaborative Machine Learning for Energy-Efficient Edge Networks in 6G	97 views	IEEE Network Journal	2021
77	Advances in Production Management Systems: Issues, Trends, and Vision Towards 2030	7 (375 downloads)	Advancing Research in Information and Communication Technology	2021
78	A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective	2	Human Resource Management Review Journal	2021
79	Innovation and production management in the process industries— An extended editorial viewpoint and a way forward for future research	NIN	Journal of Business Chemistry	2020
80	The Role of the Artificial Intelligence in the Labour Law Relations in European and Asian Aspect	NIN	NIN	2021

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83	An integrated human-AI Framework towards organizational agility and sustainable performance	24 views	International Conference on Digital Age & Technological Advances for Sustainable Development	2021
84	Industrial and Artificial Internet of Things with Augmented Reality	3	Convergence of Artificial Intelligence and the Internet of Things Journal	2020
85	Cloud intelligence in manufacturing	5	*Journal of Intelligent Manufacturing*	2015
86	Digital technologies and social interaction	87	Book: The Culture of AI Everyday Life and the Digital Revolution	2019
87	Artificial Intelligence Trends: Insights for Digital Economy Policymakers	1	Information and Knowledge in Internet of Things	2021
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Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
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92	IMPROVING IT-BASED USER ASSISTANCE FOR EARLY PRODUCT-COST OPTIMIZATION: EVALUATION OF A SOLUTION DESIGN	NIN	Proceedings of the workshop on designing user assistance in Intelligent Systems	2019
93	Artificial intelligence in supply chain management: A systematic literature review	74	Journal of Business Research	2021
94	Artificial intelligence in operations management and supply chain management: an exploratory case study	11724	Special Issue Article: Industry Experiences of Artificial Intelligence: Benefits and Challenges in Operations and Supply Chain Management	2021
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98	Employees' Trust in Artificial Intelligence in Companies: The Case of Energy and Chemical Industries in Poland	1	*Energies Journal*	2021
99	Understanding artificial intelligence adoption in operations management: insights from the review of academic literature and social media discussions	52	*Annals of Operations Research* Journal	2020
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Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
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106	Digital Twin: Visualization- Assisted Corrective Maintenance	1 (170 views)	Conference Paper	2011
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APPENDIX B

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2	Sustainable Operations Management for Industry 4.0 and its Social Return	12	IFAC-PapersOnLine	2019
3	Artificial intelligence and internet of things in small and medium-sized enterprises: A survey	66	Journal of Manufacturing Systems	2021
4	How to survive in the age of artificial intelligence? Exploring the intelligent transformations of SMEs in central China	166 Downloads	International Journal of Emerging Markets	2021
5	THE DIGITAL INNOVATION POLICY LANDSCAPE IN 2019	18	OECD SCIENCE, TECHNOLOGY AND INNOVATION POLICY PAPERS	2019
6	Supporting Technology Commercialization for SMEs: A New Service Model to Support Idea Generation in the Product Development Process	111	Journal of Advanced Management Science	2016
7	The Digital Shipyard Opportunities and Challenges	2	VINE Journal of Information and Knowledge Management Systems	2020
8	Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs	5	Cambridge Journal of Regions, Economy and Society	2020
9	Competitive advantage during industry 4.0: The case for South African Manufacturing SMEs	2	School of Mechanical, Industrial & Aeronautical Engineering University of the Witwatersrand	2018
10	Manufacturing upgrading in industry 4.0 era	9	Systems Research and Behavioral Science	2020

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11	Implementing Machine Learning in Small and Medium-Sized Manufacturing Enterprises	1067 views	Proceedings of the Changeable, Agile, Reconfigurable and Virtual Production Conference and the World Mass Customization & Personalization Conference	2021
12	Digital twin-enabled smart industrial systems: recent developments and future perspectives	2	International Journal of Computer Integrated Manufacturing	2021
13	A Fuzzy Evaluation of Projects for Business Processes' Quality Improvement	4	Book: Intelligent Techniques in Engineering Management	2015
14	A Qualitative Study into the Supplier Selection Decision-Making Process in the Malaysian SME Manufacturing Industry	3	Dissertation	2017
15	An effective adaptive customization framework for small manufacturing plants using extreme gradient boosting-XGBoost and random forest ensemble learning algorithms in an Industry 4.0 environment	13	Machine Learning with Applications Journal	2021
16	Design of multi-agent based cloud integrated manufacturing system (CIMS) for new product development	NIN	Book	2015
17	Application of Modern Digital Systems and Approaches to Business Process Management	NIN	Sustainability Journal	2022
18	Development of an Internet-based intelligent design support system for rolling element bearings	7	International Journal of Systems Science	2002
19	Decision Support for SME Owners-Managers: A Performance Evaluation Benchmarking Tool	4	The 2004 IFIP International Conference on Decision Support System	2004
20	Impact of Industry 4.0 on Quality Management: identification of main challenget towards a Quality 4.0 approach	153 Views	IEEE International Conference on Engineering, Technology and Innovation	2021

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21	Decision support system for adaptive sourcing and inventory management in small- and medium-sized enterprises	3	Robotics and Computer-Integrated Manufacturing Journal	2022
22	Collaborative Softbots: Enhancing Operational Excellence in Systems of Cyber-Physical Systems	5	Working Conference on Virtual Enterprises	2019
23	Trends of digitalization and adoption of big data & analytics among UK SMEs: Analysis and lessons drawn from a case study of 53 SMEs	314 views	IEEE International Conference on Engineering, Technology and Innovation	2020
24	Sustainable Industrial Value Creation in SMEs: A Comparison between Industry 4.0 and Made in China 2025	116	International Journal of Precision Engineering and Manufacturing-Green Technology	2018
25	From Industry 4.0 to Industry 5.0—An Overview of European Union Enterprises	1	Book: Sustainability and Innovation in Manufacturing Enterprises	2022
26	Consideration of manufacturing data to apply machine learning methods for predictive manufacturing	5	Eighth International Conference on Ubiquitous and Future Networks	2016
27	Fuzzy multi-criteria analysis for machine tool selection and optimal machine loading in flexible manufacturing cell	NIN	Dissertation	2016
28	ROBO-PARTNER: Seamless Human-Robot Cooperation for Intelligent, Flexible and Safe Operations in the Assembly Factories of the Future	162	Procedia CIRP	2014
29	Beyond the Hype: Smart Manufacturing and Sustainable Excellence for SMEs	19 views	Book: Sustainable Excellence in Small and Medium Sized Enterprises	2022
30	Enhancing SMEs’ resilience through digitalisation	NIN	OECD SME and Entrepreneurship Papers	2021

Index	Document Title	Number of Citations (or downloads)	Journal Name	Release date
31	Enhancing SMEs' resilience through digitalisation	NIN	OECD SME and Entrepreneurship Papers	2021
32	Trends for Low-Cost and Open-Source IoT Solutions Development for Industry 4.0	NIN	Procedia Manufacturing Journal	2021
33	Artificial Intelligence and Analytics for Better Decision-Making and Strategy Management	0	Decision Intelligence Analytics and the Implementation of Strategic Business Management book	2022
34	Wind Turbine Blades Defect Detection Based on Acoustical Features and Small Sample	13	NIN	2022
35	Chapter 15 - Application of Internet of Things-aided simulation and digital twin technology in smart manufacturing	4	Book: Advances in Mathematics for Industry 4.0	2021
36	Exploring heterogeneous Digital Innovation Hubs in their context	NIN	Project: Smart Specialisation Platform	2019
37	Cooperation of start-ups and SMEs in Germany: Chances, challenges and recommendations	1	NIN	2020
38	Industry 4.0 in SMEs Across the Globe: Drivers, Barriers, and Opportunities	NIN	Book: Industry 4.0 in SMEs Across the Globe: Drivers, Barriers, and Opportunities	2022
39	The SMEs Innovation in Europe	142 views	Proceedings of the 3rd International Conference on Finance, Economics, Management and IT Business	2021
40	Small and Medium-Sized Enterprises (SMEs): Towards a New Paradigm	0	European Journal of Business and Management	2021

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41	The impact of technology, entrepreneurship and consumer attitudes on firm performance	1	Polish Journal of Management Studies	2021
42	Digital transformation: A systematic literature review	NIN	Computers & Industrial Engineering Journal	2021
43	Big data driven innovation for sustaining SME supply chain operation in post COVID-19 scenario: Moderating role of SME technology leadership	0	Computers & Industrial Engineering Journal	2022
44	Development of fuzzy based ergonomic-value stream mapping (E-VSM) tool: a case study in Indian glass artware industry	128 views	Production Planning & Control Journal	2022
45	Industry 4.0 technologies adoption: evidences from Italian SMEs in the manufacturing sector	NIN	Dissertation	2019
46	Industry 4.0 and Marketing: Towards an Integrated Future Research Agenda	0	NIN	2022
47	Analysis of the status-quo of industrial 4.0 in the SMMEs: a critical review	NIN	Proceedings of the International Conference on Industrial Engineering and Operations Management	2006
48	Development of an agent-based Virtual CIM architecture for small to medium manufacturers	76	Robotics and Computer-Integrated Manufacturing Journal	2007
49	Estimation of Machining Sustainability Using Fuzzy Rule-Based System	NIN	Materials Journal	2021
50	DESIGNING AND OPTIMIZING PRODUCTION IN A HIGH VARIETY / LOW VOLUME ENVIRONMENT THROUGH DATA-DRIVEN SIMULATIO	NIN	ECMS Conference Proceedings	2021

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53	An optimized model for open innovation success in manufacturing SMES	1	NIN	2021
54	Strategic Roadmapping Towards Industry 4.0 for Manufacturing SMEs	NIN	Book: Advances in Production Management Systems	2021
55	Appropriate Smart Factory for SMEs: Concept, Application and Perspective	17	International Journal of Precision Engineering and Manufacturing	2021
56	Artificial intelligence and internet of things in small and medium-sized enterprises: A survey	66	Journal of Manufacturing Systems	2021
57	Intelligent process quality management for supporting collaboration of mold manufacturing SMEs	2	Procedia Manufacturing	2020
58	Adoption of digital technologies of smart manufacturing in SMEs	64	Journal of Industrial Information Integration	2019
59	The implications of Artificial Intelligence on Soweto furniture manufacturing SMEs	2	Proceedings of the International Conference on Industrial Engineering and Operations Managemen	2018
60	Ambient intelligence technologies for industrial working environments in manufacturing SMEs	5	IEEE International Technology Management Conference	2016
61	DIGITAL INNOVATION: CROSS-SECTORAL DYNAMICS AND POLICY IMPLICATIONS	1	Book: The Digitalisation of Science, Technology and Innovation	2020
62	Look Who's Talking: Interpretable Machine Learning for Assessing Italian SMEs Credit Default	NIN	NIN	2021