Laurea Magistrale in Ingegneria Gestionale

Impacts of Industry 5.0 target dimensions on the performance of intra-logistics systems: a proposed assessment framework

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LIST OF ACRONYMS

I5.0 Industry 5.0

DRM Design Research Methodology

IoT Internet of Things

CPS Cyber-Physical System

AM Additive Manufacturing

AMRs Autonomous Mobile Robots

SKU Stock Keeping Units

VLM Vertical Lift Module

ARSGs Augmented reality smart glasses

AGV Automated Guided Vehicle

SLR Systematic Literature Review

HRC Hand-guiding Human Robot Collaboration

NTaaS Navigation/Tracking-as-a-Service

AI Artifical Intelligence

CI Computational Intelligence

CFE Cloud–Fog–Edge

VR Virtual Reality

VR HMDs Virtual Reality Head-Mounted Displays

CS Collaborative robots cobots

HRC Human robot collaboration

ISWs Industrial Smart Wearables

AR HMDs Augmented Reality (AR) Head-Mounted Displays (HMDs)

CCPSS Cognitive and Cyber–Physical–Social Systems

HIRT Human interaction and recognition technologies

NLP Natural Language Processing

NUIs Natural user interfaces

IoE Internet of Everything

IIoT Industrial Internet of Things

IEMS Intelligent energy management systems

DSDT Dinamic simulation and digital twin

IoP^2 Internet of personalized products

CI Computational Intelligence

DMMs Domain Mapping Matrices

INTRODUCTION

The aim of this work is to develop a framework to assess the impacts of Industry 5.0 target dimensions, human centricity, sustainability and resilience, on the performance of Internal Logistics Systems by following the steps of the Design Research Methodology (DRM) (Blessing L., Chakrabarti A., 2009). It is important to research these topics because together they can bring innovation and benefits to the manufacturing industry. In fact Industry 5.0 represents the paradigm that the industry is moving towards, after having experienced Industry 4.0 up until now. Being such a new topic it is crucial to not only understand it on its own, but also in conjuction with aspects of the industry, such as Internal Logistics Systems. For example Shah Z. and others (2023) explore the three I5.0 target dimensions in logistics, without giving a framework that evaluates the impact that they have on the Internal Logisitic Systems.

To do so, after a brief description of what Industry is, its evolution over the years into Industry 5.0 and the Internal Logistics Systems, the first step of the first stage Criteria Definition defined in the DRM was to conduct a Systematic Literature Review to understand how the three Industry 5.0 target dimension may be applied to industrial systems. This led to the second stage of the DRM, the Descriptive Study I and the first step was to draw a list of approaches and technologies for each Industry 5.0 target dimension that best describes how to implement them in practice. Once this list was obtained it was necessary to design a questionnaire to submit to experts in the manufacturing and logistics fields in order to validate it and obtain a final list of the most important approaches and technologies for each target dimension to use for the second step of the research.

The next step of this work was to analyze the Internal Logistics Systems, with a focus on the automated ones, specifically material handling, storage and picking systems, and derive the performance parameters associated with them firstly by consulting professional literature and then consolidating the list of such parameters through scientific literature. These results will be put into Domain Mapping Matrices which are matrices that allow to determine a relationship between two domains, the ones entered in the rows and those entered in the columns, in this case approaches and technologies for each Industry 5.0 target dimension and the performance parameters for the Internal Logistics Systems in order to confront them and be able to assess the degree of the impact that the firsts have on the seconds, completing the second stage of the DRM.

As a future step of the research, a Delphi Study, as part of the application of the third stage of the DRM will be carried out. These matrices will be compiled by experts from companies manufacturing material handling, storage, and picking systems and university, using a Likert scale that indicates the impact that the Industry 5.0 target dimensions have on the Internal Logistics Systems, which can be a significant decrease, a decrease, no increase or decrease, an increase or a significant increase in the performance parameters.

Ultimately the assessment of the matrices will be analysed and the result will be the determination of which I5.0 approaches and technologies have the greatest impact (both positive and negative) on the performance of which Internal Logistics Systems. This will serve to establish guidelines on how intra-logistics system developers can integrate Industry 5.0 into their systems in order to increase their performances, in order to complete the third stage of the DRM.

1. THEORETICAL BACKGROUND

The present chapter explains what the term Industry means and the role that it had over the years, together with its evolution into Industry 4.0 and now Industry 5.0. This can be viewed as an introduction to Industry 5.0, understanding where the term comes from and its background. Such a knowledge is crucial to understand the research work.

1.1. WHAT IS INDUSTRY

The European economy is significantly impacted by the industry, as it creates employment opportunities and contributes to prosperity throughout the continent. From 2009 to 2019, the industrial sector consistently accounted for over 20% of the EU's GDP, with manufacturing contributing around 14.5% of value to the EU economy. Despite its strength, the European industry encounters persistent challenges due to fierce competition in an increasingly intricate multinational economy.

To sustain Europe's prosperity, the industry must continually adjust to new challenges, necessitating ongoing innovation. Innovation can enhance efficiency at various stages of the value chain, make production systems more resilient to meet the evolving needs of global customers, and maintain Europe's position as a global leader in quality. Advanced digital technologies, such as sensor technologies, big data, and artificial intelligence (AI), will play a crucial role in driving innovation. This innovation will continue to accelerate as these technologies progressively automate, connect, and optimize a wide range of industrial processes (Breque M., De Nul L., Petridis A., 2021).

1.2. INDUSTRY 4.0

The current fourth industrial revolution, referred to as Industry 4.0 or 4IR, is rooted in the third industrial revolution, which relied on transistors, sensors, and microelectronics to generate data. The term Industry 4.0 was coined by German professor Wolfgang Wahlster at the Hannover Fair in 2011. It encompasses the computerization of production, integrating advanced digital technologies with industrial machines and processes.

By interconnecting these technologies with utmost operational efficiency, productivity, and automation, an intelligent, connected, and data-driven manufacturing ecosystem is formed.

Industry 4.0 is based on digital and computing technologies interconnected with physical systems. Core computing technologies include artificial intelligence, machine learning, big data, cloud computing, and cybersecurity, while physical technologies encompass automation, robotics, IoT, CPS, and AM. These technologies enable agile, flexible, on-demand manufacturing, a vital element of smart manufacturing or factories, delivering the benefits of Industry 4.0 systems and enhancing operational efficiency.

In the foreseeable future, European industry can anticipate a solid ambition and sound guiding principles for innovation and technological progress through Industry 4.0, which describes how technology will be utilized to adapt to a changing global environment and economy.

The traditional cycle of education, work, and retirement for industrial workers is being challenged by profound changes in the workforce organization. Increased automation may undermine the societal role of industry as an employer and driver of prosperity.

Broader societal changes and transitions will also significantly impact industry. The current political priorities at the European level have a profound impact on industry. The Green Deal emphasizes a transition to a more circular economy and increased reliance on sustainable resources, including energy. "Europe Fit for the Digital Age" prioritizes digitalization for Europe, offering significant innovation potential. Research and innovation in Europe will be connected and boosted by the re-energized European Research Area (ERA), while Europe's new Industrial Strategy and Skills Agenda aims to address skills shortages.

The Covid-19 crisis has underscored the need to reconsider existing ways of working and approaches. It has highlighted the vulnerabilities of industries, such as weak strategic value chains, and emphasized the need to find flexible and robust innovations to address these weaknesses.

Industry 4.0 was conceived as a futuristic project and part of the nation's high-tech strategy, expected to be widely accepted by business, science, and decision-makers. Its aim was to meet not only the economic requirements of "green production" for a carbon-neutral and energy-efficient industry, but also the special ecological requirements.

In 2013, the German Academy of Engineering Sciences (Acatech), prompted by the Federal Ministry of Research (BMBF), published a research agenda and implementation recommendations based on the "National Roadmap for Embedded Systems". This paper discusses the impact of the Internet of Things (IoT) on production organization, leading to new interactions between humans and machines and a new wave of digital applications in manufacturing. Deutsche Bank (2014) suggested that the adoption of Industry 4.0 was to position itself as the “factory outfitter of the world”.

The term has significant influence globally and is used in various ways by think tanks, business leaders, international organizations, and policymakers. Advanced and manufacturing-intensive economies such as China have determined how it would be implemented in their own setting. The government initiative "Made in China 2025" is directly inspired by "Industry 4.0" and focuses on revitalizing the Chinese manufacturing industry and achieving steady change.

In the decade since its inception, Industry 4.0 has shifted its focus from social fairness and sustainability to digitalization and AI-driven technologies to enhance production efficiency and flexibility. Industry 5.0 introduces a new perspective and emphasizes the importance of researching and innovating to support industry in its sustained service to humanity within planetary boundaries. It is essential to stress that Industry 5.0 should not be considered a chronological continuation or a replacement for the current Industry 4.0 paradigm. It is the result of a forward-looking process aiming to define how European industry and emerging societal trends and needs will intertwine. It emphasizes aspects that will be decisive in determining the positioning of industry in future European society; these factors are not only economic or technological but also have significant environmental and social implications (Breque M., De Nul L., Petridis A., 2021) (Gródek-Szostak, Z., et al.., 2023).

1.3. INDUSTRY 5.0

While the world of science and practice is still trying to adjust and harness the potency of Industry 4.0, policymakers, industrialists, and scholars are beginning to discuss the upcoming industrial revolution: Industry 5.0. If Industry 4.0 involves digitally connecting machines to enable a continuous flow of data and achieve optimal efficiency, Industry 5.0 is said to reintegrate people for collaboration and involve them in manufactured products, with a focus on sustainable production.

The European Commission emphasizes three crucial factors for the new Industry 5.0 industrial paradigm:

1. A human-centric approach that prioritizes human needs in the production process, considering how technology can benefit workers and be practical.

2. Sustainability, which emphasizes reusing, repurposing, and recycling natural resources, as well as reducing waste and environmental impact.

3. Resilience, which involves enhancing the robustness of industrial production through flexible processes and resilient production capacity, especially during crises.

The European Commission views Industry 5.0 as a necessary progression from Industry 4.0, as the latter is not suitable for achieving Europe's 2030 goals due to the technological dominance and significant wealth disparity in the current digital economy.

Furthermore, Industry 5.0 does not represent a technological advancement, but rather a broader examination of the Industry 4.0 approach, aiming to provide a regenerative purpose and focus on the technological transformation of industrial production for the benefit of people, the planet, and prosperity. Industry 5.0 is a transformative model that reflects the evolution of our thinking after the COVID-19 pandemic, with a focus on designing a more resilient industrial system that truly integrates social and environmental principles.

The European Commission took a stance against Industry 4.0 in early 2022, asserting that this paradigm is not a suitable framework for addressing the current climate crisis and social tensions. According to their position, Industry 5.0 represents a fresh approach to the industry, reimagining the role and functionality of value chains, business models, and digital transformation in a highly interconnected business environment. Studies have shown that Industry 5.0 differs from Industry 4.0 by prioritizing both performance-based competitiveness and sustainability, strengthening the human workforce through a human-centered approach to technological development, and innovating in environmental sustainability, such as smart renewable systems.

Industry 5.0 also promotes stakeholder primacy in technology management, innovation growth, and sustainable performance management, and it encompasses specific technologies and functional principles to expand the scope of corporate responsibility throughout the entire value chain.

The consensus in the literature is that Industry 5.0 deviates from previous industrial revolutions by presenting a stakeholder-driven socio-technological event that consistently shifts traditional profit- and consumption-driven economic models to circular economy, sustainability, sustainable development, and economic value creation models (Breque M., De Nul L., Petridis A., 2021) (Ródek-Szostak, Z., et al.., 2023).

1.4. INTERNAL LOGISTICS SYSTEMS

The selected Internal Logistics Systems for this work are automated material handling systems, automated storage systems and automated picking systems: the preference for the automated ones is due to the fact that this study is focused on Industry 5.0.

The key components of a material handling system encompass various technologies and processes designed to enhance efficiency and safety. These components work together to streamline the movement, storage, and retrieval of materials, ultimately impacting overall warehouse performance (Pat R. M., Haslebacher K.A., 2001).

Automated storage systems significantly enhance warehouse efficiency and productivity by streamlining operations, reducing human error, and optimizing inventory management. These systems leverage advanced technologies to automate various processes, leading to improved performance across multiple dimensions (Madhu Vamsi A., et al.., 2020).

Picking refers to the process of selecting and retrieving items from a storage area, often in the context of order fulfillment in various industries. This process can involve both manual and automated systems, each designed to enhance efficiency and accuracy in inventory management. Automated picking systems utilize technology to optimize the retrieval process. For instance, systems can plan picking paths based on the loading device's position and capacity, ensuring efficient operations (Komatsu Seigo, 2007).

1.4.1 AUTOMATED MATERIAL HANDLING SYSTEMS

This section illustrates some examples of automated material handling systems that will also constitute a reference for the present work.

Automated Guided Vehicle (AGV) refers to self-navigating vehicles guided by a pre-established navigation system, which can be implemented using wires or magnets embedded in the floor, magnetic strips, or visual signals. Among AGVs, Laser Guided Vehicles (LGVs) utilize advanced navigation technologies like lasers and/or cameras to move independently along predetermined routes without requiring human intervention, distinguishing them in the market (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 1).

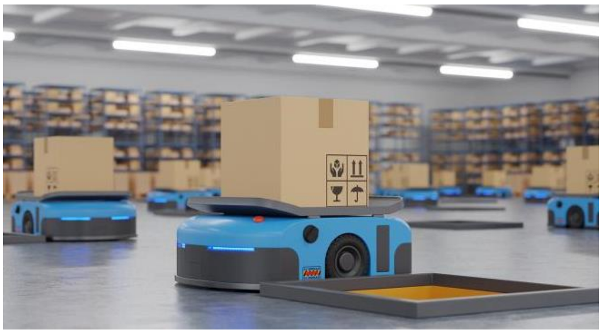

Figure 1 Automated Guided Vehicles, Source: [11]

Autonomous Mobile Robots (AMRs) are autonomous vehicles equipped with intelligent systems that enable them to recognize their own position within a previously stored warehouse layout. They utilize a combination of technologies, including lasers, radio frequency, and QR codes installed on the ground to guide and navigate themselves within the warehouse environment (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 2).

Figure 2 Autonomous Mobile Robots, Source: [12]

The **Open Shuttle** autonomous mobile robot is able to to interconnect different areas of the warehouse while delivering the correct quantity of goods at the exact location at the accurate time. It has an intelligent software to securely execute transport orders independently, navigating warehouse space freely while detecting and staving off obstacles. This means it can be integrated in existing warehouse environments with no extra infrastructure needed. It also offers maximum flexibility while growing productivity and relieving human resources for value-generating tasks [2].

Automated Forklifts can be utilized in various transportation applications in factories, warehouses, and distribution and fulfillment centers. These vehicles, also known as AGV or AMR forklifts, are specialized in lifting and moving heavy objects or materials without human guidance. They are equipped with sensors and a guidance system to ensure precise movements and eliminate the need for manual labor. These machines can be programmed to move in any direction, operate at different speeds, and adjust their route based on the environment. By automating repetitive tasks, they can significantly improve efficiency and reduce costs. They typically consist of a frame, electric motors, sensors, wheels, and onboard computing power. The sensors allow the vehicle to detect obstacles and alter its course as needed. Navigating busy factories while avoiding obstructions is essential for safety. The automated forklift also features computer-controlled navigation systems that enable operators to choose destinations for the vehicle's journey. Once programmed, the vehicle will embark on its journey without any assistance, accurately following specified routes, turns, and curved paths while avoiding obstacles [3] (figure 3).

Figure 3 Forklift AGV, Source: [9]

The **Open Shuttle Fork** features integrated 3D obstacle detection and can classify obstacles as either static or mobile. Based on this information, it makes decisions and plans where it goes. Another unique feature is the fully electric lifter – completely different from a scissor lift. This is why the Open Shuttle Fork can be used with pallets in all industries and can transfer them to existing conveyor systems. The Open Shuttle Fork can move in every direction, also turning on its own axis. This means the Open Shuttle Fork can move at a 90-degree angle from its usual alignment and can, for example, pick up pallets that may have been manually placed less precisely on a position. This also means it can move about in tighter spaces, saving space and serving a more compact layout with narrower aisles [2].

Cobots: collaborative robots equipped with advanced grippers, computer vision, and machine-learning systems are capable of handling a wide range of objects, even in unstructured environments such as bins or totes. They can easily incorporate SKU scanning and pick up pouches or items of almost any size or shape, making e-commerce, fulfillment, warehousing, logistics, and supply chain operations more efficient and faster. Collaborative robots streamline material handling, packaging, palletizing, bin picking, labeling, and kitting operations. By automating material handling tasks with lightweight collaborative robot arms, workers can be relieved from repetitive work and heavy lifting. Automation helps offset the increasing costs of new product packaging and shortened product life cycles, and enables businesses to cope with seasonal peaks despite labor shortages. In case of workflow changes, the material handling cobot can be quickly and easily redeployed in new setups [4]. By handling hazardous overhead tasks, repetitive and monotonous operations, or extremely small tasks, cobots reduce the workload on staff while consistently delivering high quality (Javaid M., et al.., 2022).

A **sorter** is an automated system for sorting orders by destination, consisting of pre-sorting accumulation area, material insertion bays, sorting system, accumulation channels, and potential picking bays. Using barcodes, the sorter scans and identifies all added items, directing them to different exits corresponding to specific delivery points. The size of the accumulation area depends on the synchronization between the picking and sorting activities. Sorters can be linear or ring sorters, with the ring sorter allowing for recirculation of goods in case of sorting failure, which is not possible in the linear system (Dallari F., Bianco D., Corti A., Farioli M., 2023).

The **linear sorter** is a system that moves pieces along a single conveyor line and directs them to different exits using directional diverters.

The **ring sorter** transports parts on a ring or loop and sorts them using directional diverters placed along the route. One of the benefits of the loop system is the recirculation of goods in the event of sorting failure, which is not possible in the linear system. Additionally, there are various types of direction diverters used to dispatch material into the accumulation channels, which can be categorized into two main groups: active systems and passive systems. Active direction diverters are equipped with motorized or electronically controlled mechanisms that enable the active change of the direction of material flow. Passive direction diverters use gravity to route the material to the desired accumulation channel, without the need for motorized components. Sorters require coordinated implementation with upstream picking systems, as the former focuses on sorting and selecting items, while the latter is responsible for picking and preparing them for shipment or delivery (Dallari F., Bianco D., Corti A., Farioli M., 2023).

There are different types of sorter that are classified this way:

Bomb Bay: it is used to quickly sort non-fragile, lightweight, and unstable items. This system allows for the arrangement of items in baskets or totes that are linked to particular orders or destinations. The conveyors move the items over the fixed

Figure 4 Bomb Bay, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

positions of the destination baskets or crates and release them by using a tilting tray or a pusher. This type of system is referred to as a Push Tray Sorter in this case (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 4).

Cross Belt: this sorting system consists of multiple belt conveyor modules arranged perpendicular to the direction of travel in the loop. Each module has a conveyor system to discharge products into the appropriate channel. The high throughput (up to 20,000 handling units/hour) and the ability to handle a wide range of objects make this system excellent for order generation. Its flexibility allows it to handle both single pieces and packages, including small outputs. Additionally, connections can be established between different areas of the facility (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 5).

Figure 5 Cross Belt, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

Tilt Tray: this system contains several modules (trays) where the products to be sorted are placed. However, sorting is achieved by deflecting the tray towards the side where the container for the newly sorted goods is located, making it more suitable for handling heavy and sturdy objects (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 6).

Figure 6 Tilt Tray, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

Shoe Sorter: An automatic sorting system that utilizes a surface made of connected laths similar to a belt. Along one side of the laths, there are diverters that move laterally independently. This enables the routing of loads to different discharge lanes. The diverters are controlled sequentially to move from one side of the conveyor to the other, making contact with the loads and directing them to the corresponding unloading lanes. Unloading lanes can be fed by chutes for continuous flow of loads. This system is typically used for sorting packages and has a throughput of about 9,000 SKU/h (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 7).

Figure 7 Shoe Sorter, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

Pouch Sorter: This overhead sorting system utilizes pockets, pouches, or bags to store and transport individual pieces and packages. The building's ceiling is equipped with a system of carts or rails that allows for the utilization of previously unused space. This overhead conveying system is both space-saving and versatile, enabling the processing of multiple sales channels simultaneously. By utilizing the space below the ceiling, it allows for the transportation of goods without using floor space. One load carrier can transport, buffer, sort, and sequence both flat and hanging goods in one system, achieving high throughput. By hanging individual pockets or pouches from this rail system, they can be moved independently, allowing for precise sequencing of outbound picking or sorting. Unlike the previously mentioned systems, it also functions as a buffer. Products are taken out and placed into pouches for further picking and packing. Pouch sorters are commonly used in e-commerce order fulfillment and returns handling to increase sorting capacity at about 7000-10000 pockets/h per module (Dallari F., Bianco D., Corti A., Farioli M., 2023) [5] (figure 8).

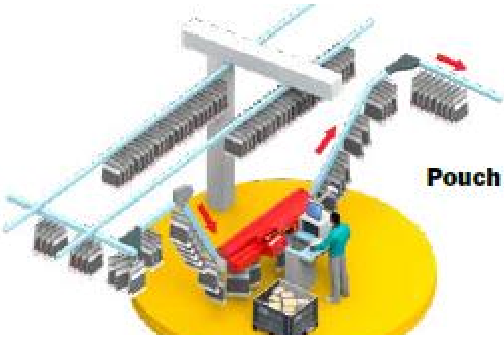

Figure 8 Pouch Sorter, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

1.4.2 AUTOMATED STORAGE SYSTEMS

The chosen automated storage systems for this work are:

Miniload: a miniload is an automated storage and retrieval system designed for small or medium-sized load units, such as boxes, cartons, or trays. They consist of aisles with single- or double-deep racking, and automated machines that can move horizontally and vertically (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 9).

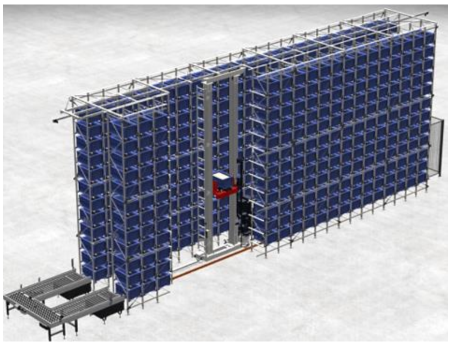

Figure 9 Miniload, Source: [17]

Shuttle based: The shuttle system is a solution for automated storage and retrieval of totes, cartons, or trays. It consists of a series of aisles with single- or double-deep racking. Shuttles at each aisle move independently along the X axis and use telescopic arms with fingers to make picks from the racks left and right along the Z axis. If each level of the rack has a shuttle, it's called a 'full shuttle' system. In a 'roaming shuttle' system, robots are dedicated to multiple levels and require lifts to move the shuttles between levels. Unlike 'multilevel shuttle' or 'miniload' systems, the shuttles in this system operate at a fixed height without a lift along the Y-axis, so lifts are installed at the end of the corridors. These shuttles offer high throughput levels among all automated storage systems, making them suitable for dynamic applications with high volume handling (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 10).

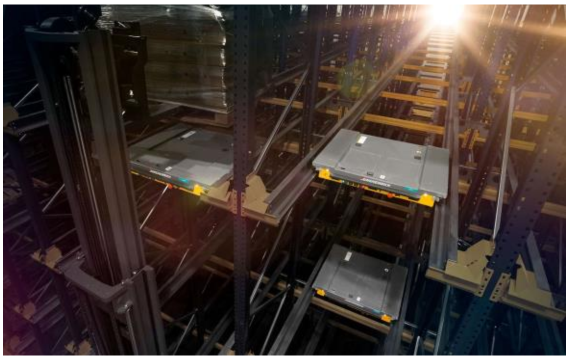

Figure 10 Shuttle, Source: [18]

AMR based: AMRs (Autonomous Mobile Robots) are vehicles that can drive on their own using autonomous intelligence and can recognize their own position in a warehouse layout that has been previously stored. They use various technologies like lasers, radio frequency, and QR codes on the floor to orient themselves and move within the warehouse environment (Dallari F., Bianco D., Corti A., Farioli M., 2023).

Figure 12 Shel-to-picker, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

The AMR system, called **Shelf-to-Picker**, consists of three main parts: the robot, the transported pod, and a workstation (an ergonomically designed area for workers to perform picking and replenishment operations). When an order is received, the software assigns the requested item first to a workstation where an operator is active, and then to an available robot. The robot leaves its dwell station (where the battery is charged) using a barcode grid on the floor to fetch the load unit with the ordered products. After delivering the pod to the designated location, the robot enters a buffer area and waits for the operator to retrieve or replenish an item, either manually or through automation for better performance. Once the operator completes their task, the robot returns the pod to the specified storage location based on the remaining items (figure 12). AMR solutions that aid in the transportation of individual containers (also known as "**Bin-To-Pickers**") come in different designs and functionalities. Lastly, there are AMR vehicles designed to assist human operators in retrieving necessary items from shelves or storage areas with efficiency and accuracy. These vehicles, also known as **Picker-To-Good**, can follow the assigned picking route

Figure 11 Picker-to-good, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

and provide support during the picking and packing process (figure 11) (Dallari F., Bianco D., Corti A., Farioli M., 2023).

Compact storage: Compact storage is an automated storage system that is small and uses robots to pick or place totes on columns on either the top or bottom grid surface. The system comprises four primary components: the robots, the aluminum structure, the totes, and the operator station (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 13).

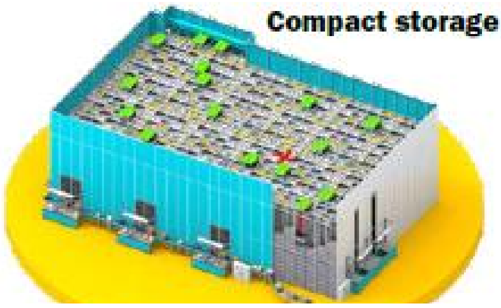

Figure 13 Compact storage, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

Dispenser: VLMs are a subtype of vertical carousels that use a miniload-like system for translations that are based on two Cartesian axes (single-column) or three Cartesian axes (multi-column) instead of a chain device inside the structure and handles trays through a single-column or multi-column system (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 14).

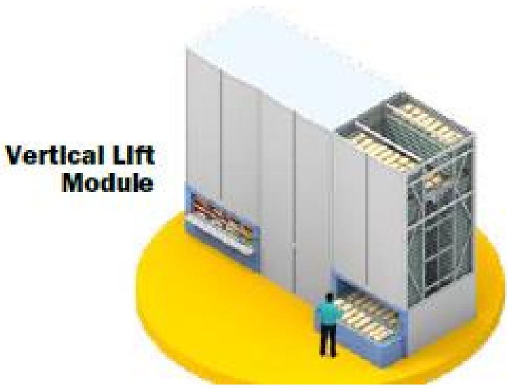

Figure 14 Vertical Lift Module, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

Horizontal Carousels function in a manner similar to traditional carousels. They consist of a series of shelves or drawers that rotate horizontally. A computerized system controls the sequential stopping of the shelves or drawers for picking when an order number

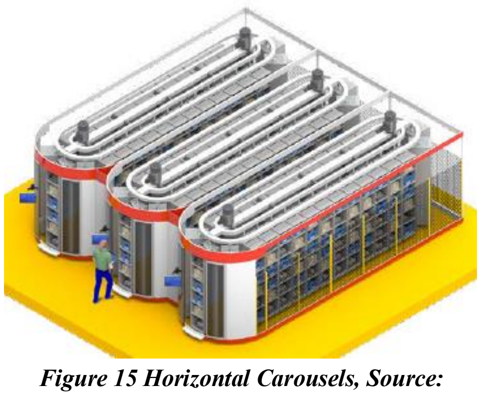

Figure 15 Horizontal Carousels, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

is input. Typically, carousels are arranged in an oval shape and feature one or more central pick stations (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 15).

The **A-frame dispenser** has a frame that looks like the letter 'A' from the side. The frame contains two picking faces with slanted channels, each intended for a specific type of item (Dallari F., Bianco D., Corti A., Farioli M., 2023) (figure 16).

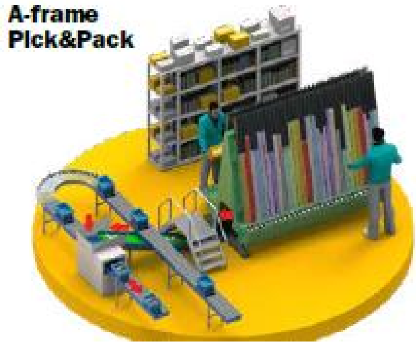

Figure 16 A-frame Pick&Pack, Source: Dalari F., Bianco D., Corti A., Farioli M., 2023

The **AutoStore** system, shown in figure 17, is an efficient, adaptable robotic storage and piece picking system that maximizes storage density and allows for four times the inventory in the same space as conventional storage systems and twice that of other automated systems. Order fulfillment with AutoStore is based on the goods-to-person (GTP) principle, eliminating worker travel time to pick locations and supporting high picking productivity, the removal of dedicated pick faces, excellent product security/inventory accuracy, increased order processing speed, and improved order accuracy. AutoStore's flexibility and adaptability allow for simple performance enhancement by adding additional robots, increasing storage locations, or adding new workstations. Moreover AutoStore's compact design prevents stock loss by storing products securely and keeping them inaccessible until an order is started (Dallari F., Bianco D., Corti A., Farioli M., 2023) [6]. AutoStore is a specialized system for automated storage and retrieval that uses a grid of bins and robots to efficiently store and retrieve items. It utilizes roller pallets and channels to dynamically manage inventory, enabling high-density storage and quick access to various

Figure 17 Autostore, Source: [10]

materials (Heinrich E., 2003). In contrast, Compact storage systems concentrate on maximizing space efficiency through methods such as data compaction and automated management of storage resources. For example, a compact storage apparatus can independently manage data, optimizing capacity and performance by migrating and compacting data as necessary (Choi I.S., et al., 2015). While both systems aim to improve storage efficiency, compact storage emphasizes data management within devices, while AutoStore focuses on automating physical item retrieval and storage. This underscores the different approaches to optimizing storage solutions in various contexts.

1.4.3 AUTOMATED PICKING SYSTEMS

The chosen automated picking systems for this work are:

Pick to voice or voice picking is a technology that, by taking advantage of text-to-speech devices, is able to send simple and clear voice commands to the picker, indicating the route for staff to follow and the tasks to be performed. The voice picking system supports and enables the optimization of logistical operations of picking and order preparation. The operation of voice picking depends directly on computer terminals. These are equipped with synthesizers and voice recognition systems. Being able to recognize the human voice, the device gives and receives instructions, establishing a “two-way communication” with the picker. It should be noted, in fact, that voice picking can receive responses from an operator thanks to the multi-modal feedback system, thus increasing flexibility in carrying out picking activities [7].

Pick To Light devices, are installed directly on the items by illuminating their position and showing the quantity required. Models equipped with sensors for processes that require maximum reliability can detect if the selected item is the right one and alert the operator if there is an error. Pick To Light systems are especially advantageous for sites where items are high-end and/or subject to significant stock rotation. Additionally, they are also useful at sites with medium and low stock rotation, where solutions with higher possibilities can be set up or in conjunction with radio frequency systems [8].

Put To Light solutions are the best choice for small item order preparation Put to Light systems offer a quick, intuitive, scalable, and error-free process for sorting processes that are commonly used in e-commerce. The operator is visually guided to the containers where they should deposit (put) the items from each order by means of displays. Each location or container assigned to an order is associated with a light display. Upon identification of the item, the displays visually indicate the locations where it should be deposited and the quantity required for each order. Put-to-light solutions are employed to assign items to designated locations, such as from transported containers (Project-to-Person principle), from previously selected containers (Batch Picking or two-step picking processes), or from picking carts with distinct orders [8].

The picking method **Pick by scan** involves workers using a mobile barcode scanner with a screen that shows them the storage location of an item [8].

Augmented reality smart glasses (ARSGs) enhance the efficiency of order-picking tasks by increasing speed and reducing error rates. Compared to traditional support tools, the use of ARSGs directly improves workers' well-being perceptions. Workers use ARSGs to automatically show relevant information within their line of sight, eliminating the need for constant head movements to access desired information, simplifying operations and reducing completion time. The information can be displayed anywhere, allowing workers to utilize ARSGs' capabilities as needed, significantly boosting flexibility. The potential of ARSGs to enhance the order-picking process is evident in their features and hands-free nature, enabling workers to complete tasks faster and without interruptions. Additionally, ARSGs can prevent picking errors compared to traditional picking support tools. This is due to the prominent display of instructions, reducing the reliance on memory and ad-hoc decision making, leading to increased task reliability even in the event of interruptions (Windhausen A., et al.., 2024).

Exoskeletons help workers by providing support for monotonous or stressful postures and more even load distribution when lifting, moving and handling heavy objects. They also reduce safety risks through a mix of function and protection (e.g. through certain surfaces) and vibrations which, if sustained, increase the risk of musculoskeletal disorders (MSDs). In short, an exoskeleton increases workplace safety, reduces the wear and tear of many individual work steps and at the same time increases efficiency in the relevant sub-segment (Drees T., et al.., 2021).

Collaborative robots minimize the need for extensive travel between functional areas at each stage of the picking process, thereby reducing unnecessary movement within the warehouse. They do so by assisting employees in managing the workload and by guiding them through tedious order-picking activities and relocating orders to the appropriate areas once picking is completed (Javaid M., et al.., 2022). For instance, the picking robot is a collaborative robot designed to automate the process of picking. It selects items from one storage container and transfers them to another without human intervention. With the help of advanced vision software based on deep learning and a highly adaptable gripping device, the robot can handle a wide range of items with utmost accuracy, regardless of their shapes, sizes, or finishes. Robotic picking provides the ultimate solution for boosting productivity, cutting operating costs, and optimizing order fulfillment efficiency in various industries, including e-commerce, pharmaceuticals, textiles, and food [13].

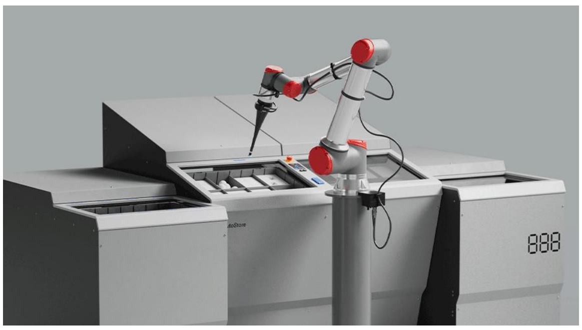

Figure 18 Cobot installed on Autostore, Source: [14]

Robots specialized in picking individual items can also be combined with oicking bays to handle tasks involving picking and placing items. These robots can assemble orders for future processing. When there are two workstations available, the robotic arm can extract products from Bins containing items and put them into empty Bins or totes, which will serve as prepared Bins. Once the prepared Bins are ready, they are returned to the storage system. By working together with an automated packing system and a takeaway conveyor positioned on or next to the AutoStore Port, piece picking robots can manage both picking and packing duties. The robots pick products from an AutoStore Bin presented at the workstation, scan the picked item(s) using automated scanning, and place the item(s) into a carton presented on the conveyor. Subsequently, a conveyor moves it to an automated packing station, where the carton can be sealed and labeled. The robotic arm can be utilized for batch picking when it picks from AutoStore to multiple destinations, for example, multiple totes or various compartments on a putwall. This approach is especially effective in settings with high order volumes and similar item requirements across orders [14] (figure 18).

1.5. DESIGN RESEARCH METHODOLOGY

After a brief description of what Industry is, its evolution over the years into Industry 5.0, and discussing the Internal Logistics Systems, this section illustrates the methodology used for this thesis work: the Design Research Methodology.

The goals of Design Research involve creating and confirming models and theories related to the concept of design, as well as creating and confirming knowledge, techniques, and resources, based on these theories, to enhance the design process. Design research must systematically create and confirm knowledge, which necessitates a research methodology (Blessing L., Chakrabarti A., 2009).

The primary objective of engineering design research is to assist the industry by enhancing our comprehension of engineering design. This involves creating knowledge in the shape of guidelines, methods, and tools that can enhance the likelihood of creating a successful product.

Another fundamental characteristic of design research is that of duality: it aims not only to understand the phenomenon of design but to use this gained understanding for the sake of stimulating changes in existing practices. This involves not only a model describing the present situation but also one of the wanted future situation and a roadmap leading through the process of transformation. In this respect, design research also involves both research components, the improvement of knowledge, and development components, creating norms and strategies, which require various methodologies and approaches.

The nature of design research is such that it seeks to comprehend the phenomenon of design and to apply this comprehension to bring about a change in the current state. Achieving the latter involves more than just a representation (or theory) of what currently exists; it also necessitates a representation of what would be preferable and how the current situation could transition into the preferred state. As a result, design research also involves both research components, the improvement of knowledge, and development components, the development of guidelines and methods, each of which demands distinct methodologies and approaches.

The DRM was introduced by Blessing and Chakrabarti (Blessing L., Chakrabarti A., 2009) and comprises four key stages: Research Clarification (RC), Descriptive Study I (DSI), Prescriptive Study (PS), and Descriptive Study II (PS-II). According to the authors, the RC stage serves to clarify the current understanding and the overall research objective, establish a research plan, and provide a focal point for the subsequent stages. The goal of the DS-I stage is to enhance comprehension of design and the factors influencing its success through an examination of the design phenomenon, in order to inform the development of support. In this context, "support" encompasses potential methods, aids, and measures for improving the current situation and facilitating the evaluation of the researcher's core contribution (a guiding manual for this paper). The PS stage aims to systematically develop support, taking into consideration the findings of

DS-I. Lastly, the DS-II stage concentrates on assessing the usability and applicability of the actual support and its effectiveness (Blessing L., Chakrabarti A., 2009) (Calderon M.L, 2010).

1.6. GENERAL RESEARCH APPROACH

The DRM was chosen because the ultimate goal of the research in which this thesis is embedded is to define guidelines for the design and development of internal handling systems. As explained in Section 1.5 its primary is to assist the industry by enhancing our comprehension of engineering design. In this case, this involves creating knowledge in the shape of guidelines, methods, and tools that can improve the design of future Internal Logistics Systems.

This section describes each of the stages and steps of the DRM applied in this work.

In the first stage of the DRM, the Criteria Definition, through a literature review it was set the main research question of the present study, namely

How the impacts of Industry 5.0 on the performance of intra-logistics systems, and in particular material handling, storage, and picking systems, can be assessed in a comprehensive way?

Where comprehensive means considering all the three I5.0 target dimensions and the main Internal Logistics Systems in the same framework.

This laid the path of the research which led to the second stage of the DRM, the Descriptive Study I, here a Systematic Literature Review was developed for gathering information on how to implement Industry 5.0 target dimensions in practice by developing the two concepts of approach and technology. After drawing a list of these approaches and technologies for each Industry 5.0 target dimension, this step then required the experts' knowledge in order to validate the list and obtain a final list of the most important I5.0 approaches and technologies. The experts' knowledge was obtained through the submission of a questionnaire on approaches and technologies of each I5.0 target dimension to professors from both Politecnico di Torino and Technical University of Munich (TUM) experts in logistics and manufacturing topics. The analysis of the answers given on the questionnaire provided a list of the most important and relevant approaches and techologies. The following step consisted of a research on the performance parameters of the Internal Logistics Systems, namely material handling, storage and picking systems. At first this research was done by consulting professional magazines, the information gathered from there was then consolidated by scientific literature. This was done by searching on Scopus the performance parameters founded, to double check that they were also debated in the scientific literature by experts in the field as well. In particular, for each performance parameter selected from professional literature, the number of papers that included it as an author-keyword was looked for. The performance parameters that did not have a number of papers greater than 10 were excluded from the list.

The research on the performance parameters of the Internal Logisitic Systems was crucial for the development of the Domain Mapping Matrices, final step of the application of DS I stage. The DDM were chosen as a framework to put together the results found on both Industry 5.0 approaches and technologies and the Internal Logistics Systems performance parameters, because they allow to gather the experts' opinions on the degree of the impact of the approaches and technologies for each Industry 5.0 target dimension on the Internal Logistics Systems. So the main reason why they were chosen for this work is because they are particular matrices that enable to include not just one domain at a time but allow to determine a relationship between two domains, the ones entered in the rows and those entered in the columns [15] (figure 19).

Table 1 illustrates a summary of the adopted research approach.

DRM STAGE	METHODS	RESULTS
CRITERIA DEFINITION (RESEARCH CLARIFICATION)	LITERATURE REVIEW	RESEARCH OBJECTIVE: assessing how I5.0 influences the performance of Internal Logistics Systems (material handling, storage, and picking systems).
DESCRIPTIVE STUDY I	LITERATURE REVIEW	APPROACHES AND TECHNOLOGIES FOR EACH I5.0 TARGET DIMENSION.
	EXPERTS KNOWLEDGE (QUESTIONNAIRE)	PERFORMANCE PARAMETERS FOR MATERIAL HANDLING, STORAGE, AND PICKING SYSTEMS.
		DEVELOPMENT OF DOMAIN MAPPING MATRICES (DMM).

Table 1 Design Research Methodology

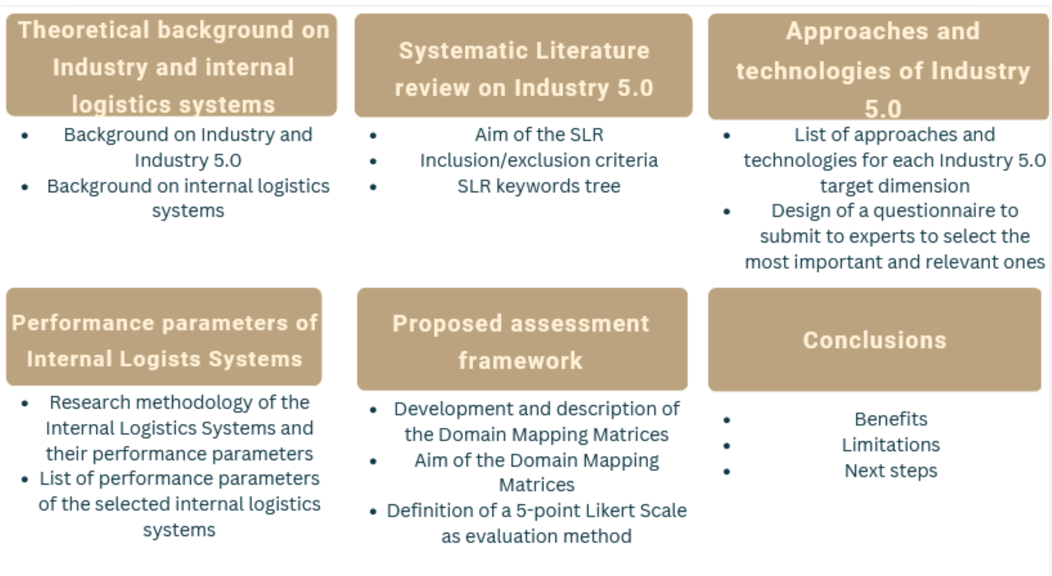

Figure 19 Resume of the content of each chapter of this thesis

2. SYSTEMATIC LITERATURE REVIEW

This is the chapter about the Systematic Literature Review (SLR), which is one of the research methods used for the present work. It was the best option to research such an innovative theme because it allowed to gather much information founded by other experts in the field and reported in their papers. Moreover this method was also chosen because it is able to synthesize information from multiple studies and arrive at a comprehensive view of the topic of interest, in this case Industry 5.0 and how it can be applied, as it is stated in Section 2.1.

2.1. METHODOLOGY

The final aim of this research is assess how Industry 5.0 influences the performance of intra-logistics systems. So, it is necessary to understand how Industry 5.0 and its target dimensions can be implemented in these systems. For such a reason it is necessary to know how the Industry 5.0 notion can be practically applied. As a consequence the reasearch question of the present SLR was *"how to implement in practice each of the three Industry 5.0 target dimensions?"*

Following the guidelines provided in the paper "A systematic literature review of innovative technologies adopted in logistics management" (Lagorio A., et al.., 2020), the first step was to define the inclusion/exclusion criteria and then a list of keywords for the research were listed. After that, the papers founded were filtered by first reading the title, then the abstract and lastly their content.

After reviewing the results of the SLR, a way of defining the ways to apply Industry 5.0 in practice, thus answering to the research question above, was to divide them into approaches and technologies an approach can be defined as *"a strategic direction or a specific way to implement Industry 5.0 target dimensions (Matt C., Hess T., Benlian A., 2015)"* a technology can be defined as *"innovations, machinery and equipment that utilize scientific knowledge to support operations effectively and efficiently in order to achieve Industry 5.0 target dimensions* (*Tiwari S., Bahuguna P.C., Walker J., 2022)".*

2.2. INCLUSION/EXCLUSION CRITERIA AND KEYWORDS

The chosen multidisciplinary database was Scopus at international level. The queries for conducting the research on Scopus contained the selected keywords along with Boolean logical operators ("AND" and "OR"). The queries were usually formulated as "Keyword A AND Keyword B OR Keyword C". Only the articles with Open Access for PoliTo Students have been considered (figure 20). At the start, the search strings were "Industry 5.0 overview", "Industry 5.0 AND sustainability OR ecological", "Industry 5.0 AND human centricity", "Industry 5.0 AND resilience". Following the results founded with these queries, the search string became "Approach A AND industry 5.0", "Technology B AND industry 5.0". In the end 2343 papers were analised and 24 were kept in the corpus (Table 2).

The publishing year, the document type and the English language have been considered as inclusion criteria. More specifically the publishing time interval is set between 2019 and 2024 because the concept of industry 5.0 hadn't been brought up by researchers and experts in the field previously, in fact before 2019 there are many papers about industry 4.0 and fewer on industry 5.0 which are not as relevant for this study (Table 2).

The second admission criterion, the document type, was limited "Journal Papers", "Conference Papers", "Book Chapter" and "Review" in order to maintain homogeneity among the definitions of the different contributions, enhancing consistency across the themes (Table 2).

The third criterion, the English language, was obliged, due to the fact that the author knows in a professional way only English and Italian and the work thesis is written in English to let the thesis be globally comprehensible (Table 2).

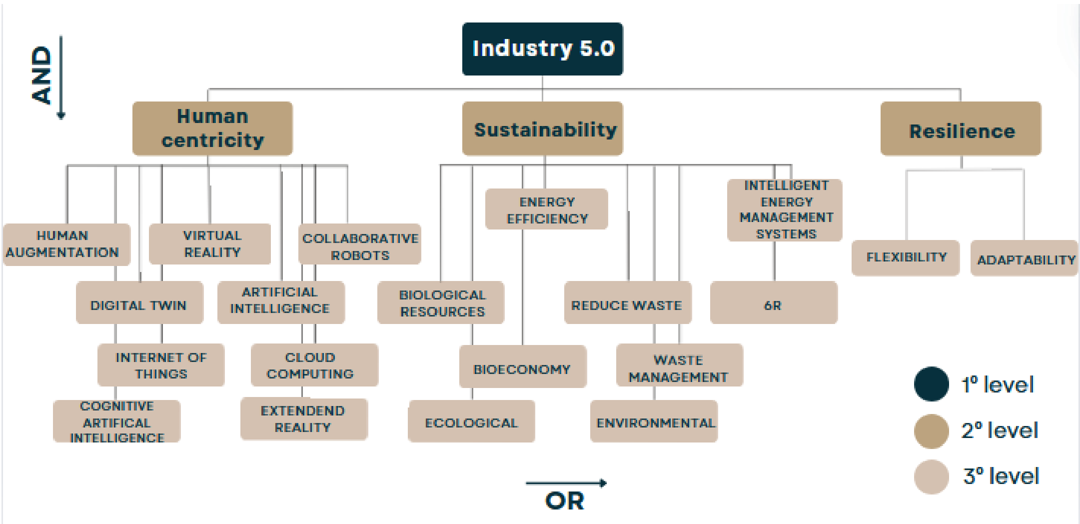

Figure 20 Keywords tree

Inclusion criteria	
Pubilishing year	from 2019 to 2024
Document type	Journal Papers, Conference Papers, Book Chapter and Review
Language	English
Database	Scopus

Table 2 Inclusion criteria

2.3. PAPER ANALYSIS

The selected papers in the corpus are 24 and they are distributed in the chosen time interval as shown in figure 21.

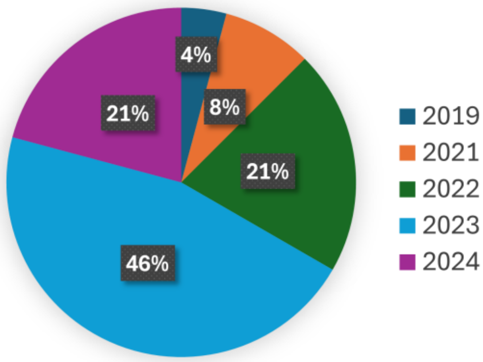

Figure 21 Papers distribution per year

Almost half of the papers belong to the year 2023 contribuing with 46%, then for both year 2022 and 2024 there are 5 papers, which consist in 21% each. Finally for the year 2019 and 2021 the are respectively 2 and 1 papers which fill out the remanaing 8% and 4%.

All the relevant approaches and technologies cited in the papers analised have been listed in the table included in Appendix 1 in this thesis work, the next chapter delves deeper into this topic. The table shows the approaches and technologies in the columns, divided by the three target dimensions in which they're mentioned by the papers which are included in the rows of the table. The first thing that comes up is that some approaches and technologies are mentioned in two or all three target dimensions, meaning that they can bring a positive outcome in implementing, possibly, all the industry 5.0 principles. Every approach and technology is mentioned on average 2 times with a minimum of 1 and a maximum of 6 times by all the considered papers. Each target dimension contains almost the same total amount of citations, more specifically 41 for human centricity, 30 for sustainability and 32 for resilience. This is also highlighted in figure 22 which shows the percentage of the numbers above. It is again reflected in the fact that the number of approaches and technologies for each target dimension is almost the same.

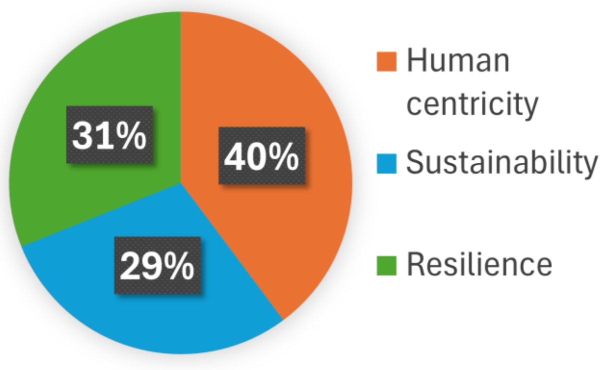

Figure 22 Papers numerosity per target dimension

Finally in figure 23 is shown the number of citations for the approaches and technologies in percentage to the total amount of citations per target dimension. What's common in all three graphs is the fact that technologies are more popular than the approaches.

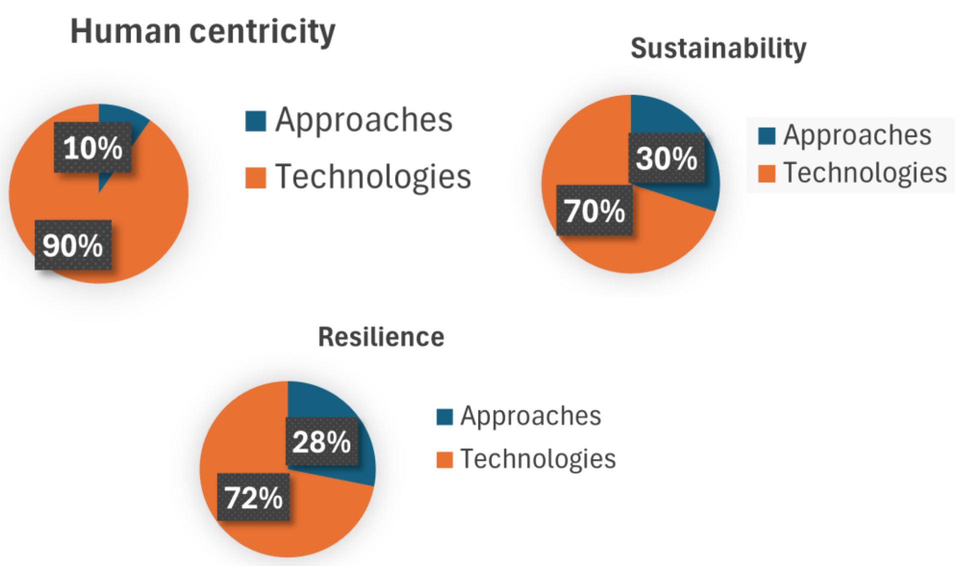

Figure 23 Papers distribution per target dimension

3. APPROACHES AND TECHNOLOGIES TO IMPLEMENT INDUSTRY 5.0 TARGET DIMENSIONS

Industry 5. 0 is described as an expanded and rejuvenated sense of purpose that goes beyond simply making goods and services for profit. Key elements include resilience, sustainability and human centricity. (Breque M., De Nul L., Petridis A., 2021)

A **human-centered** approach in Industry 5. 0 places human needs and interests at the core of the production process, rather than starting with new technology and assessing its potential for improving efficiency. Instead of asking what we can do with new technology, we ask what the technology can do for us. The objective is to utilize technology to guide and train industry workers, while adapting the production process to their requirements, rather than expecting them to adapt their skills to keep up with rapidly evolving technology. It also ensures that new technologies do not infringe upon workers' basic rights, such as privacy, autonomy, and human dignity.

To protect the planet, industries must embrace sustainable practices. This involves establishing circular systems that reuse, repurpose, and recycle natural resources, while minimizing waste and environmental impact. **Sustainability** entails reducing energy consumption and greenhouse gas emissions to prevent the depletion and degradation of our natural resources. Technologies such as AI and additive manufacturing can make a significant contribution by enhancing resource efficiency and reducing waste.

Resilience refers to the necessity of creating greater strength in industrial production, enabling it to better withstand disruptions and ensuring it can maintain and support essential infrastructure during crises. Geopolitical shifts and natural disasters, like the Covid-19 pandemic, highlight the vulnerability of our current global production model. This should be counterbalanced by establishing sufficiently resilient strategic value chains, adaptable production capabilities, and flexible business operations, especially in sectors that address fundamental human needs, such as healthcare and security (Breque M., De Nul L., Petridis A., 2021).

3.1. HUMAN CENTRICITY

The results of the Systematic Literature Review led to a list of approaches and technologies that best fit the aim of the target dimension Human Centricity, below there's a list and description of all of them.

3.1.1 APPROACHES

Decentralized decision-making which is when top managers delegate some decision-making processes to lower level managers and sometimes blue collar workers. This gives more importance to people aided by new technologies (e.g. Internet of things) in taking decisions. This leads to a quicker or real time decision making (Zizic M.C., et al.., 2022).

Human-robot collaboration in the workplace involves humans focusing on tasks that require creativity, while robots handle other tasks. This collaboration enables human workers and robots to complete tasks that would be challenging or impossible to do alone, leading to increased innovation and competitiveness in the industry (Demir K.A., Döven G., Sezen B., 2019) (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024). **Hand-guiding Human Robot Collaboration (HRC)** is a form of interaction where the human operator physically guides the robot's movements within the workspace. It is used in various industrial and manufacturing applications to assist robots in performing complex tasks or to train them for new activities. **Speed and Separation Monitoring HRC** involves the use of advanced monitoring systems to ensure safe interactions in industrial and manufacturing environments. These systems monitor the speed and distance between the human operator and the robot to prevent accidents and ensure the operator's safety. They utilize sensors and cameras to identify the presence of a human operator in the workspace. **Power and Force Limiting HRC** restricts the power and force exerted by robots to prevent accidents and ensure the safety of human operators in industrial and manufacturing environments. These systems monitor the interaction between the human operator and the robot and adjust the robot's power and force in real time using sensors and algorithms (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Navigation/Tracking-as-a-Service (NTaaS), when combined with cloud-based infrastructure, offers on-demand localization services to a variety of industries, including retail, manufacturing, supply chain, transportation, healthcare, and logistics. These services include navigational tracking in machine cells, real-time location information maintenance, and factory asset management for industrial cobots, AGVs, isochronous factory operations, environmental sensing (Shah Z., et al.., 2023).

3.1.2 TECHNOLOGIES

Artifical Intelligence can enhance worker happiness by freeing up workers' time for more complex and creative work by automating monotonous and repetitive jobs. AI systems' real-time insights may help improve overall job satisfaction and work-life balance (Valeriya, G., et al.., 2024). Moreover applying AI frees up time, creativity and human capital, making worker's tasks less repetitive (Giugliano G., et al.., 2023). AI also allows people to manage massive datasets, automate tasks, gather insights, and increase the overall efficiency and effectiveness of engineering methods within the field of digital transformation. In this context, AI-enabled tools capable of extracting information help to streamline the flow of information, knowledge transfer, and interaction between humans and various lifecycle stages of processes, systems, and machines. By utilizing AI-based machine learning, cognitive abilities are harnessed to generate nearly optimal plans (Alimam H., et al..,2023). Other AI declinations are **Humancentered AI** and **Edge AI**. The former concentrates on ongoing advancements through human input, provides explainable AI models, and enables humans and cobots to work together effectively. For instance, AI-powered informed algorithms, like data-driven physics-informed models, can learn from incoming data and embedded mathematical physics models. They mimic human brain learning, even in unclear, high-dimensional, and undefined settings. The latter involves a blend of Computational Intelligence (CI) and Cloud-Fog-Edge (CFE) computing, which can enhance human-machine collaboration by understanding action perception more deeply (Shah Z., et al.., 2023). The concept of the digital triplet advocates for seamless integration and collaboration among humans, machines, and artificial intelligence. Its primary objective is to facilitate smooth interaction and synergy among these entities, thereby improving productivity, decision-making, and problem-solving capabilities (Alimam H., et al.., 2023).

Virtual Reality (VR) provides an immersive virtual environment which users can experience, observe, and interact with virtual objects to perceive the real environment (Krupas M., et al.., 2024). Industry 5.0 integrates virtual reality for human-robot collaboration enhancing safety and efficiency in interactions between humans and robots (Marinelli M., 2023). **Virtual Reality Head-Mounted Displays (VR HMDs)** are used to offer the human operator an interactive virtual world. In HRC, VR HMDs can be used to provide the operator with a sense of presence and improve their capacity to collaborate with the robot (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Collaborative robots can be employed for repetitive activities and labor-intensive work, while humans handle personalization and critical thinking duties (Pizoń J., et al.., 2022). Their implementation prioritizes the well-being of workers (Calzavara M., Faccio M., Granata I., 2023). Cobots also create a balanced mix of human intelligence and cognitive computing that promises mass personalization representing high-value-generating products resulting in higher sustainability (Aheleroff S., et al.., 2022). Cobots can ultimately reduce the volume of tedious, repetitive, and exhausting work, thereby alleviating individuals from the strain that could potentially result in work-related illnesses. The integration of collaborative robots and safety-focused technology establishes a robust framework for maintaining a secure working environment (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Applying exoskeletons and wearable technologies supports workers’ physical activities and improves health through monitoring physiological conditions (Giugliano G., et al.., 2023). **Exoskeletons** enhance the abilities, strength, productivity, and stability of industrial workers. Meanwhile, **exosuits** are wearable robots that offer mechanical support to the user. They are often used in HRC to supplement human strength and stamina, assisting the human operator in completing tasks that may otherwise be too physically demanding.

Wearable technology, such as wristwatches, headsets, or glasses, is an emerging technology that provides more immersive experiences when interacting with humans. Wearable technology is increasingly utilized in HRC to enhance the interaction between individuals and robots. **Head-worn industrial smart wearables (ISWs)** enhance the navigation and information-sharing capabilities of human operators. **Clothing industrial smart wearables (ISWs)** utilize conductive or optical sensors to monitor and track workers' vital signs. **Embedded tracking industrial smart wearables (ISWs)** track workers' mental and physical strain and stress (Ghobakhloo M., et al.., 2023) (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Augmented Reality can boost human and robot cognitive capacities by integrating humans into production processes in real-time and dynamically (Alves J., Lima T., Gaspar P., 2023). It also improves our sensory perception by letting us engage with data (Humayun M., 2021). Augmented reality can be applied to transmit knowledge and better cognitive abilities (Giugliano G., et al.., 2023).

Moreover, Augmented Reality Technologies merge virtual information with the real world, providing computer-generated perceptual information (Shah Z., et al.., 2023). Augmented reality applications are most commonly utilised on mobile devices such as phones, tablets, and glasses. Its capacity to overlay digital information makes it a useful tool for improving worker safety, efficiency, and trust of technologies (Krupas M., et al..,2024). **Augmented Reality (AR) Head-Mounted Displays (HMDs) (AR HMDs)** are utilized to present information and visuals within the user's line of sight. In HRC, AR HMDs can be used to provide the human operator with information about the task, such as instructions and real-time feedback, as well as to enhance their ability to collaborate with the robot (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024, Langås).

Cognitive and Cyber-Physical-Social Systems (CCPSS) is a rapidly evolving interdisciplinary technology that integrates cognitive computing architecture at the intersection of three crucial machine/cobot spaces to deliver intelligent solutions. These three critical cobot environments include cyber, physical, and counterpart social (human) components that enable human-machine interaction (Shah Z., et al.., 2023). People no longer interact and operate with a single machine, but rather a network of cyber-physical systems. These systems integrate robots and people, defining them as cyber-physical-social (Giugliano G., et al..,2023). Human Cyber Physical Systems have a significant application in utilizing augmented reality (AR) and virtual reality (VR) technologies to develop human-machine interfaces that are more immersive and interactive. This can improve humans' ability to collaborate effectively with machines, allowing them to understand and control the manufacturing process (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Human interaction and recognition technologies (HIRT) is the most effective way to interconnect and integrate humans with machines leading to safer, more efficient, and more enjoyable physical and cognitive tasks. Examples of emerging HIRT are: vision-guided robotics, short-wave infrared technology, sensor fusion, sensor data triangulation, embedded vision systems, adaptable human intention and trajectory prediction, and multi-lingual speech and gesture recognition

(Ghobakhloo M., et al.., 2023). Human Machine Interaction in Human Machine Collaboration can be achieved by using depth RGB cameras, like Microsoft Kinect, which are commonly used to visualize the human body and workspace for safety and ergonomics in applications (Krupas M., et al.., 2024).

Brain-Computer Interface (BCI): BCI combines machine intelligence and human cognitive processes. It surpasses existing forms of human-machine interaction by seamlessly fusing the two extending the limits of human intelligence and interactions in real-world settings. Various creative applications in the Metaverse can be made possible by BCI technologies. These uses include interacting with people keeping an eye on their cognitive states and managing virtual avatars in cyberspace. By eschewing traditional input devices like keyboards and joysticks BCI also provides a more straightforward and intuitive method of human–machine interaction. Users can now manipulate and have an impact on the virtual representation with their thoughts and intentions enabling a smooth and intuitive control over the digital twin. With the help of brain activity monitoring and analysis of cognitive states attention spans and emotional reactions BCI can give users real-time feedback. By using this feedback the digital twins behavior can be optimized and adjusted to better suit the goals and preferences of the user. Digital Triplet systems will be able to dynamically modify their behavior in response to mental or physical states of the user thanks to BCI. For example in order to preserve system performance and user safety the associated digital twin may automatically adjust its operations or offer extra support if a user shows signs of fatigue or distraction. Ultimately digital twins and BCI combined offer strong training and skill-enhancement resources. With the use of cutting-edge immersive interfaces like virtual reality (VR) and augmented reality (AR) users can practice and hone their skills while getting real-time feedback from the digital twin system (Alimam H., et al.., 2023).

The real-time monitoring of workers and equipment made possible by **edge computing** can be leveraged to enhance worker safety. Sensors can be used for instance to keep an eye on employees whereabouts movements and vital signs as well as to identify potentially dangerous circumstances like the presence of dangerous gases or overheating machinery (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

The **digital twin**'s use includes comparing different control algorithms and interaction strategies to find the best approach for HRC. This can enhance the efficiency and effectiveness of the collaboration while decreasing the risk of accidents. Digital twins in HRC can anticipate and address potential safety issues. For instance, by simulating a robot's behavior in hazardous environments and evaluating its potential impact on human collaborators. Moreover, digital twins facilitate communication and coordination between human and robot collaborators by offering a shared visual representation of the physical system. Additionally, digital twins can help improve decision-making accuracy and reduce misunderstandings between human and robot collaborators (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024). Together with IoT, the cognitive digital twin analyzes data from connected sensors and provides valuable insights to aid human decision-making. This integrated approach leads to a human-centered cognitive cycle involving human integration, machine, and cyberspace (Alimam H., et al.., 2023).

The technology enabling human operators to communicate with robots using natural language, such as speech or text, is called **Natural Language Processing (NLP)**. This allows them to interact with the robot more intuitively and user-friendly (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Gesture-tracking devices, such as gloves and hand-held controllers, are used to identify the movements and gestures of the human operator. This allows the robot to respond to their actions and work with them, enabling communication between humans and robots (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Wearable sensors such as gyroscopes and accelerometers are utilized to track the movements and position of the human operator. These sensors provide the robot with movement data about the operator, enabling it to react to their actions and work alongside them. **Force/torque sensors** are used to measure the force and torque that the robot applies, allowing it to respond to changes in its surroundings and avoid potential dangers. **Vision sensors** like lidars and cameras provide the robot with a visual picture of its surroundings and enable it to perform activities that require visual recognition, track human operators, and detect obstacles. **Proximity sensors**, including infrared and ultrasonic sensors, can identify the presence of objects and humans in the vicinity of the robot, contributing to the safety of the human operator. **Tactile sensors**, or touch sensors, detect physical contact between objects and humans, enabling the robot to respond to physical interactions and perform delicate tasks. They also serve as a method for the robot to communicate its status and information to the human operator. **Motion sensors**, such as accelerometers and gyroscopes, are used to detect the motion of the robot and its surroundings, providing information on its orientation and movements, and helping it respond to changes in its environment and maintain its stability (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024). Additionally, various **biological sensors** are being used to track human behavior during human-robot cooperation by measuring physiological data from humans. These include the Electrooculogram (EOG), Electrocardiogram (ECG), Electroencephalogram (EEG), Magnetoencephalogram (MEG), and Electromyography (EMG). In HRC systems, these signals are widely used to anticipate human operators' intentions (Asad U. along with others, 2023).

Natural user interfaces (NUIs) are user interface designs that focus on utilizing natural human behaviors and actions for interaction, rather than requiring the user to adapt to the technology. Examples of NUIs include voice assistants and touch interfaces (Krupas M., et al.., 2024).

Industrial Internet of Things (IIoT) engage and collaborate with other technologies such as 3D printers, adaptive-collaborative bots, and autonomous vehicles in order to ease human robot collaboration (Ghobakhloo M., et al.., 2023). Indoor localization services can be enhanced by offering various methods, wireless technologies, and approaches using IoT and widespread connectivity, which can include WiFi, radio frequency identification (RFID) devices, Ultra-Wideband (UWB), or Bluetooth Low Energy (BLE) (Krupas M., et al.., 2024).

The Internet of Everything (IoE) has the potential to enhance worker safety by monitoring work environment conditions and alerting workers to potential hazards (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Drones enhance human abilities by linking up to high-speed 5G networks, enabling them to communicate efficiently with their operator from anywhere with signal coverage. Human drone interface (HDI) research has resulted in new natural user interfaces like gesture-based control, brain-computer interfaces, speech recognition, touch, and a combination of multiple modes (Taj, I., Jhanjhi, N.Z., 2022).

3.2. SUSTAINABILITY

The results of the Systematic Literature Review led to a list of approaches and technologies that best fit the aim of the target dimension Sustainability, below there’s a list and description of all of them.

3.2.1 APPROACHES

The human factor regains its rightful place at the centre of the production process, this transformation is intended to influence the **reduction of climate change** and environmental degradation and thus improve the quality of life for present and future generations (Gródek-Szostak Z., et al..,2023).

The production of renewable biological resources in **bioeconomy** includes utilizing starch-based, sugar-based, lignocellulose, algal biomass, and waste-derived feedstocks to create biofuels, polymers, and other products, as well as transforming these resources and waste streams into valuable products such as food, feed, bio-based products, and bioenergy. This process is referred to as biologization (Demir K.A., Döven G., Sezen B., 2019).

In industry 5.0 sustainability is based on the principle of industrial recycling, i.e., the **6R's policy**: Recognize, Reconsider, Realize, Reduce, Reuse, and Recycle, so that it is possible to prevent waste and, at the same time, create/produce customized products with high quality (Alves J., Lima T., Gaspar P., 2023).

Adoption of **circular processes** that enable the reuse and recycling of natural resources, reducing waste and environmental damage (Baig M.,Yadegaridehkordi E., 2024).

Predictive maintenance uses data analytics and machine learning to monitor equipment and identify maintenance needs before issues occur, enabling proactivity and waste reduction (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Remanufacturing involves refurbishing products at the end of their lifespan to a like-new state by replacing worn components and thoroughly cleaning them. This process increases the value of the products and reduces costs compared to using new materials and manufacturing (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

The integration of the internet of things contributes to social sustainability by enhancing customer satisfaction and loyalty, and by providing **customised experiences** based on the data collected. Employing technology in everyday business operations to address environmental issues and improve social and governance practices contributes to digital sustainability, making it a valuable asset in the battle against climate change. Economic sustainability can be achieved through the digitization of manufacturing processes and the advancement of networks, resulting in reduced travel expenses, optimized energy usage, and empowering producers to implement automation. The use of digitalization, intelligent technologies, and paperless processes enhances human productivity and supports environmental sustainability (Baig M.,Yadegaridehkordi E., 2024 M.).

Utilizing **renewable sources**, reusing energy, and reducing energy wastage are methods to enhance sustainability. For instance, renewable energy sources such as solar, wind, hydro, and bioenergy offer a sustainable alternative to fossil fuels, significantly reducing greenhouse gas emissions. This transition not only mitigates environmental impact but also improves public health by enhancing air quality (Giugliano G., et al.., 2023).

3.2.2 TECHNOLOGIES

AI can increase environmental sustainability by adaptating to changing circumstances in real-time using machine learning algorithms, which optimize energy use and minimize emissions. Additionally, data driven AI can contribute to waste reduction, which leads to resource efficiency (Valeriya, G., et al.., 2024). Artificial intelligence can also be used to minimize waste by making detailed and low-error forecasts of product demand (Mesjasz-Lech A., 2024). Furthermore, AI-driven quality control methods guided by Big Data analytics contribute to enhancing product quality. These methods maintain consistency, streamline inspections, and detect defects, leading to decreased waste and rework, as well as improved final product quality. AI-powered quality control ensures consistent product quality, resulting in higher customer satisfaction and reduced waste (Vatin N.I., et al.., 2024).

Bio-inspired protective gears improve industrial workers' capabilities, strength, productivity, and stability (Ghobakhloo M., et al.., 2023).

Intelligent energy management systems (IEMS) aims to promote energy efficiency by monitoring and controling energy systems, improving the technical and commercial efficiency of energy production, assessing energy quality, and enhancing the reliability of energy systems. IEMS and complementary technologies like cloud demand also complement each other (Ghobakhloo M., et al.., 2023).

Dinamic simulation and digital twin DSDT is crucial to Industry 5.0's sustainability objectives because it enables businesses to model and forecast the digital socio-environmental impact of their products and services throughout the design, prototyping, development, end-user consumption, and end-of-liferecovery stages (Ghobakhloo M., et al.., 2023)

Cobots can help manufacturers become more sustainable, by assisting in the devolpment of mass personalisation. This creates more value from resources and reduces waste (Aheleroff S., et al.., 2022).

The **Internet of Personalized Products (IoP^2)** merges IoT and human creativity to create customized products. It involves sharing exclusive data over the internet to produce a wide range of scalable and cost-effective personalized products. IoP^2 differs from IoT as it takes a service-oriented approach, considering customer data and requirements to deliver services using essential technologies. IoP^2 facilitates enhanced personalization, encompassing unique appearances, materials, and features to provide an affordable and distinctive customer experience. It promotes a human-centered model to purposefully engage and deliver value with sustainability (Aheleroff S., et al.., 2022).

Big data and **machine learning** can play a crucial role in advancing environmental sustainability by enhancing our global comprehension of the needs for food, energy, and water (Baig M.,Yadegaridehkordi E., 2024 M.). Furthermore, AI and big data contribute to sustainable practices, reducing resource consumption and minimizing environmental impact by offering real-time data analysis and predictive capabilities to support sustainability efforts. They are utilized to monitor energy usage patterns, predict consumption, and optimize processes for reduced energy usage. This not only helps in achieving environmental goals but also leads to cost savings (Vatin N.I., et al.., 2024).

The use of **machine learning** and deep learning technologies has a significant impact on optimizing energy consumption, predicting energy demand, and managing renewable energy resources. Additionally, they enable more accurate environmental monitoring, leading to pollution control and sustainability initiatives (Amr A., 2023).

Sustainable manufacturing can benefit from the integration of sensors and devices in the manufacturing process through the **Internet of Things (IoT)**. Manufacturers can collect real-time data on energy consumption, water usage, and other sustainability metrics, enabling them to pinpoint areas of inefficiency and waste and make informed decisions to optimize resource utilization (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024). The use of Internet of Things to reduce wastage in the supply chain, maximizes production processes and aids waste management (Mesjasz-Lech A., 2023). Furthermore, architectures based on Edge AI and green IoT can effectively assess energy efficiency, demonstrating the potential of this combination in reducing carbon emissions. Additionally, 3D virtual simulations of implemented systems can be conducted to evaluate their environmental and social impacts, aiding in the redesign and redeployment of systems to adhere to green production policies (Shah Z., et al.., 2023).

Robust biosensors represent novel analytical tools that integrate both physiochemical and biological sensing components to facilitate detection using analytes. These biosensors are utilized in environmental monitoring and the identification of toxins (Shah Z., et al.., 2023).

Cyber Physical Systems (CPSs) play a role in enhancing energy management efficiency, optimizing energy usage, and reducing greenhouse gas emissions. Additionally, they enable predictive infrastructure maintenance, thereby extending the lifespan of utilities and ensuring sustainable resource management (Amr A., 2023). Industry 5.0 necessitates efficient information transmission for tasks within the production system and improved interaction to support better decision-making processes across the entire supply chain. These characteristics drive the need for enhanced data and information exchange among various stakeholders, predominantly impacting the agility and intelligence of a smart logistics system. This objective can be achieved through a network of data interoperability, where sensors exchange and process information within a big data environment. In the context of Industry 5.0, a Smart Cyber-Physical System (SCPS) can be implemented to facilitate data transmission and bolster the sustainability of production and logistics systems. However, this digital transformation must prioritize energy efficiency by incorporating green practices such as green production, green recycling/disposal, and green IoT (G-IoT) to support a lean circular economy (CE) (Jafari N., Azarian M., Yu H., 2022).

Using **Computational Intelligence (CI)** and edge computing to move towards green computation and circular economy that could help in reducing the carbon emissions (Shah Z., et al.., 2023).

Using **Blockchain** technology and data science to control processes related to energy conservation and responsible resource consumption based on key performance indicators (Mesjasz-Lech, A., 2023).

3.3. RESILIENCE

The results of the Systematic Literature Review led to a list of approaches and technologies that best fit the aim of the target dimension Sustainability, below there's a list and description of all of them.

3.3.1 APPROACHES

Organizational resilience means understanding and adapting to new situations, and managing the organizational vulnerabilities. New technologies allow to track information that supports organizational resilience (Zizic M.C., et al.., 2022).

Safety strategies need to be adopted to achieve higher degrees of reliability and production flexibility in the human-robot interaction through dynamic and synergistic measures (from both human and robotic perspectives) (Alves J., Lima T., Gaspar P., 2023).

Human-assisted learning strategies can be applied to monitor and control automated additive manufacturing systems, as well as manufacturing error detection systems (Alves J., Lima T., Gaspar P., 2023).

Biological resilience refers to the ability of an operator to keep industrial hygiene in terms of occupational health and safety, which can be aided by the use of smart personal protective equipment (Romero, D., Stahre, J. 2021).

Physical resilience refers to the ability of an operator to maintain stamina and strength in face of demands, which can be aided by exoskeletons technology providing that extra needed musclepower, protection, and endurance (Romero, D., Stahre, J. 2021).

Cognitive resilience refers to the ability of an operator to maintain mental ability under stress and avoid human-error, which can be aided by augmented reality technology acting as a digital assistance system (Romero, D., Stahre, J. 2021).

Psychological resilience refers to the ability of an operator to emotionally cope with a crisis, which can be aided by virtual reality technology offering a safe (virtual) environment for training for risk and crisis management (Romero, D., Stahre, J. 2021).

Human-machine systems resilience refers to the ability of human and machine systems to display adaptive autonomy by adjusting their own autonomy and exchanging control to sustain the operational performance of the cooperative system at an optimal balance between convenience, comfort, and continuity. When humans delegate some control to the machine, they become more responsive to unexpected events (Romero, D., Stahre, J. 2021).

The integration of **renewable energy** contributes to energy security, resilience, and economic growth. Embracing renewable energy reduces reliance on external energy sources, leading to increased energy self-sufficiency (Amr A., 2023).

3.3.2 TECHNOLOGIES

The **AI**-based innovative system is designed to intelligently handle unexpected critical events autonomous and without the need for human intervention (Shah Z., et al.., 2023) Furthermore, AI can also increase economic resilience by reducing costs through increased efficiency (Valeriya G., et al.., 2024).

Cobots can speed up some processes and adapt to unique circumstances, which can enhance output (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024). Implementing collaborative robots which are not specialized for a single product variant, like traditional robots, but they can be easily adapted to different products (Calzavara M., Faccio M., Granata I., 2023). Developing industrial contexts increasingly robust and adaptive to new needs through the use of new technologies such as **VR**, cobots and **wereable technologies** (Giugliano G., et al.., 2023).

Intelligent adaptive robots are an evolution of traditional and collaborative robots, and they are highly productive robots that can adapt to complicated environments and novel situations while compliting a more comprehansive set of complex tasks (Ghobakhloo M., et al.., 2023).

Drones play a crucial role in providing quick assistance during natural disasters, fires, or medical emergencies, reducing response times and enhancing safety. They are utilized for monitoring and maintenance in hard-to-reach or hazardous areas such as power lines, bridges, or tall buildings. The aerial data and imagery collected by drones aid in making better decisions and planning strategically. Unmanned Aerial Vehicles (UAVs) also contribute to surveillance and security, offering a cost-effective and versatile solution for public safety monitoring. In the realm of transportation and logistics, UAVs support the rapid and efficient delivery of goods, thereby improving supply chain operations (Amr A., 2023).

Digital Twin represents the comprehensive system consisting of deployed industrial assets, enabling them to communicate and interact intelligently to optimize the overall production process. Interconnected Digital Twin systems combined with augmented technologies can effectively leverage human intelligence for management and control purposes. Through collaboration with Industrial Internet-of-Things (IIoT) and Cyber–Physical Systems, Digital Twin can facilitate genuine digital hyperconnectivity in future factories, including remote maintenance and predictive maintenance within the factory ecosystems (Shah Z., et al.., 2022). Digital Twin also assists Industry 5.0 by identifying technical issues earlier, customizing components, generating more accurate estimates, predicting future failures, and preventing substantial financial losses. By doing so it allows to adapt to unexpected changes (Humayun M., 2021).

NextG wireless networks (NGWNs) enhance manufacturing processes by making them more efficient, adaptable to changes in market demand, and capable of accommodating product/service customization and innovation requirements in Industry 5.0. Integrated network softwarization which combines Software-defined Networking (SDN), Network Functions Virtualization (NFV), and microservices architectures, leads to a more agile and adaptable network infrastructure. This enables organizations to respond to changing demands and requirements more efficiently, thereby enhancing their overall competitiveness (Shah Z., et al.., 2023).

In the field of computational intelligence (CI) **supervised learning** is the most frequently used learning method that requires the labeled data to learn the patterns or trends to perform various tasks, including prediction, forecasting, classification, detection and segmentation (Shah Z., et al.., 2023).

Machine learning and deep learning technologies play an important role strengthening safety and security (Amr A., 2023).

Big Data Analytics can better understand customer behaviour to optimize product pricing, improve manufacturing efficiency, and lower overhead expenses. By doing so it allows to adapt to unexpected changes. To enhance predictability and explore new possibilities, Big Data analytics approaches are utilized to identify and eliminate non-essentials (Humayun M., 2021).

Cloud Computing is a concept enabling the immediate rental of computer resources with minimal interaction with the provider. Cloud computing simplifies operations by eliminating the need for precise resource planning and allowing flexible usage without prior commitment. It facilitates adaptation to unforeseen changes (Humayun M., 2021). Cloud manufacturing refers to the utilization of cloud computing technologies in the manufacturing process. This can optimize production processes, reduce costs, and enhance product quality. It also enables businesses to efficiently share resources and collaborate. It allows for quick response to unexpected events (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

Edge computing is a distributed computing model involving processing and analyzing data closer to the source, rather than relying solely on centralized cloud servers. This technology is crucial for Industry 5.0 as it improves response time and reduces latency. For example, it can be used to collect and process data from sensors and devices on the factory floor, which can then be used to optimize production, minimize downtime, and enhance product quality. The edge computing-based framework reduces computation and communication bottlenecks, as well as latency, and facilitates the shift from a centralized to a distributed industrial process paradigm (Shah Z., et al.., 2023).

IoE technology can optimize the production process, reduce downtime, and improve quality control. It aids operators in quickly identifying and resolving issues by connecting multiple machines and sensors to provide real-time performance data. Intelligent decision-making is facilitated by IoE technology. It also integrates various data sources to provide a comprehensive view of the supply chain or manufacturing process. This data can be used to identify patterns and trends, informing decisions to enhance productivity, reduce expenses, and improve overall customer satisfaction. IoE technology also provides real-time information on the location, status, and condition of goods through the connection of various sensors, RFID tags, and other devices, enabling the identification and resolution of potential issues before they escalate into major problems. It allows for quick responses to unexpected events (Zafar, M.H., Langås, E.F., Sanfilippo, F., 2024).

3.4. QUESTIONNAIRE TO IDENTIFY THE MAIN INDUSTRY 5.0 APPROACHES AND TECHNOLOGIES

After reviewing the results of the Systematic Literature Review on Industry 5.0's approaches and technologies, the next step was to select the most important ones. In order to do so, a questionnaire was submitted to professors from both Politecnico di Torino and Technical University of Munich (TUM) experts of the Logistics and the Manufacturing subjects. More specifically the people involved were 8 in total, 4 from Politecnico di Torino and 4 from Technical University of Munich.

The questionnaire was designed in three sections, one for each I5.0 target dimension: each of them contained all the relative approaches and technologies with a brief description. The questions asked were the same for all three target dimensions: "*In your opinion, how important are the following approaches for the implementing the Human Centricity/Sustainability/Resilience dimension of Industry 5.0?",* while each approach and technology had a Likert scale structured as follows:

Very unimportant	Unimportant	Neutral	Important	Very important
1	2	3	4	5

Table 3 Likert scale for the questionnaire

The motive behind the choice of the Likert Scale that contains the neutral item as an evaluation method was dictated by the fact that some approaches and technologies are relatively new, they might be lesser know to each expert involved, so this it was useful to them to give a neutral response that doesn't include any bias errors into the evaluation (Table 3)..

Every responder had to choose the value that in his opinion best fit the question above for the approach or technology in question. All the answers were collected through a Google Form and then analysed as explained in the following section.

3.5. ANALYSIS OF THE QUESTIONNAIRE OUTCOMES

The chosen way to analyse the answers of the questionnaire was to calculate the median. The motive behind this choice is the fact that calculating the median allowed for a selection of the most relevant approaches and technologies based on the majority of the answers given by the experts. In fact the median is a calculation method supported by the Likert scale. In addition, the median works by arranging the data points associated with each value of the Likert scale from smallest to largest and then it selects the central one [16].

The median score was set at more or equal to 3.5 as the selection criterion. The reason was due to the fact that this score allowed for a selection was neither too strict or too lenient, because, with the Likert scale used, a median of 3.5 corresponds to a response that is not quite neutral, but tends towards the important.

In the end the final selection of approaches and tehcnologies for the human centricity target dimension are shown in Table 4 and Table 5:

HUMAN CENTRICITY	
APPROACHES	*MEDIAN SCORE*
Decentralized decision making	4,00
Human-robot co-working	3,50
Tracking-as-a-Service (NTaaS)	3,50

Table 4 Human centricity selected approaches

HUMAN CENTRICITY	
TECHNOLOGIES	*MEDIAN SCORE*
AI	5,00
Natural language processing for interacting with robots	5,00
Intelligent smart wearables (ISWs) and exoskeletons	4,50
Cobots	4,50
Natural user interfaces (NUIs)	4,00
Human interaction and recognition technologies (HIRT)	4,00
Gesture-tracking devices	4,00
Augmented reality	4,00
Sensors	4,00
Internet of Everything (IoE)	4,00
Clothing industrial smart wearables	4,00
Internet of Things	3,50
Edge computing	3,50
Cyber-physical systems	3,00
Digital twin	3,00
Virtual Reality	3,00
Drones	2,50
Brain computer interface (BCI)	2,00

Table 5 Human centricity selected technologies

The final selection of approaches and technologies for the sustainability target dimension are shown in Tble 6 and Table 7:

SUSTAINABILITY	
APPROACHES	*MEDIAN SCORE*
Circular processes	5,00
Reduction of climate change	5,00
Renewable sources	5,00
Remanufacturing	4,50
6Rs policy	4,00
Predictive maintenance	4,00
Bioeconomy	4,00
Customized experiences	3,00

Table 6 Sustainability selected approaches

SUSTAINABILITY	
TECHNOLOGIES	*MEDIAN SCORE*
Machine learning	5,00
Intelligent energy management systems (IEMS)	4,00
Big data	4,00
AI	4,00
Computational Intelligence (CI)	4,00
Internet of Things	3,50
Internet of personalized products (IoP^2)	3,50
Bio-inspired protective gears	3,00
Digital twin	3,00
Cyber-physical systems	3,00
Cobots	3,00
Biosensors	3,00
Blockchain	2,00

Table 7 Sustainability selected technologies

The final selection of approaches and tehcnologies for the resilience target dimension are shown in Table 8 and Table 9:

RESILIENCE	
APPROACHES	*MEDIAN SCORE*
Organizational resilience	5,00
Cognitive resilience	4,00
Psycological resilience	4,00
Operator safety strategies	4,00
Biological resilience	4,00
Human-machine systems resilience	4,00
Renewable sources	4,00
Physical resilience	3,50
Human-assisted learning strategies	3,00

Table 8 Resilience selected approaches

RESILIENCE	
TECHNOLOGIES	*MEDIAN SCORE*
Big data	4,50
Machine learning	4,00
AI	4,00
Internet of Things	4,00
Cyber-physical systems	4,00
NextG wireless networks (NGWNs)	4,00
Cloud computing	3,50
Internet of Everything (IoE)	3,50
Intelligent adaptive robots	3,00
Intelligent smart wearables (ISWs) and exoskeletons	3,00
Digital twin	3,00
Augmented reality	3,00
Drones	3,00
Cobots	2,50
Virtual reality	2,00

Table 9 Resilience selected technologies

4. PERFORMANCE PARAMETERS OF INTERNAL LOGISTICS SYSTEMS

This is the chapter where the chosen performance parameters for the Internal Logistics Systems, focus of the present research, and the methodology used for their selection, are discussed. This is the second step of the Descriptive Study I of the Design Research Methodology and it is crucial for the development of the Domain Mapping Matrices part of the proposed assessment framework, final step of the Descriptive Study I.

4.1. METHODOLOGY

The performance parameters for the Internal Logistics Systems were chosen in two steps: at first a research was conducted on professional literature (i.e. professional magazines) such as (Dallari F., Bianco D., Corti A., Farioli M. (2023) “Dossier Logistica”, “Logistica management”, 2024, n°342) and (Logistica Management, March 2024, n°342), to gather information about the different types of Internal Logistics Systems, namely material handling, storage and picking systems, and possible performance parameters and their characteristics such as cycle time, system lifetime and so on.

After, the research proceeded on Scopus, where the performance parameters founded from professional literature were searched on the multidisciplinary database to double check that they were also debated in the scientific literature by experts in the field as well. In particular, for each performance parameter selected from professional literature the number of papers that included it as an author-keyword was looked for. The performance parameters that did not have a number of papers greater than 10 were initially excluded from the list. The chosen timeline for the search was 2010-2024 to have knowledge of these systems that is coherent with the new findings on Industry 4.0 and Industry 5.0.

Some examples of queries were:

PICKING SYSTEMS:
warehouse AND "picking line"
warehouse AND picking AND productivity
warehouse AND "picking cycle time"
warehouse AND picking AND accuracy
warehouse AND picking AND efficiency
warehouse AND picking AND "mean time to repair"
warehouse AND picking AND mttr
warehouse AND picking AND automation
warehouse AND picking AND worker AND movement
warehouse AND picking AND scalability

STORAGE SYSTEMS:
warehouse AND "storage depth"
warehouse AND storage AND "single-deep"
warehouse AND storage AND height
"storage system" AND "picking productivity"
storage AND "picking productivity"
storage AND shuttle AND speed
warehouse AND selectivity
warehouse AND accessibility

MATERIAL HANDLING SYSTEMS:
"material handling" OR "internal transportation" AND "load capacity"
"material handling" OR "internal transportation" AND "energy consumption"
"material handling" OR "internal transportation" AND "battery" AND "logistics"
"material handling" OR "internal transportation" AND "speed"
"material handling" OR "internal transportation" AND "cycle time"
"material handling" OR "internal transportation" AND "reliability"
"material handling" OR "internal transportation" AND "human interaction"

4.2. AUTOMATED MATERIAL HANDLING SYSTEMS AND THEIR PERFORMANCE PARAMETERS

After the process described in Section 4.1, the list of performance parameters for material handling systems resulting from the scientific literature search through Scopus was checked by the author of this thesis and her two supervisors. They noticed that some performance parameters indicated as pretty important by professional literature, such as the ones associated with reliability, are either not touched or poorly debated by scientific literature. So, they decided to include them in the final list of performance parameters for material handling systems.

Therefore, the chosen performance parameters for the automated material handling systems are:

Load capacity [kg]: Maximum weight that the material handling system is able to handle. It is measured in kg.

Level of energy consumption: degree of energy consumption.

Battery autonomy: time between battery recharges.

Speed: it is measured in meter per second.

Cycle time: time needed to complete one picking operation**.**

Reliability involves **Mean time to repair**, which is calculated by dividing the time spent repairing the asset by the total number of repairs performed**. Mean time between failures** is determined by the ratio of the difference between down time and up time to the number of failures. **Mean time to failure** is calculated by dividing the total time of operation by the number of failures.

Degree of interaction with humans: ability of a system to cooperate with the human operator.

Obstacle detection ability: Minimum time and space required for the system to detect the presence of obstacles (objects or people) in its proximity.

Investement cost: the cost of building a new storage system.

Operation costs: it includes the energy cost, personnel costs and cleaning costs.

Precision in handling: degree of precision in handling.

Utilisation rate: ratio of actual employment time to available work time.

Level of automation: : it can be defined by evaluating several factors that reflect how much human intervention is required, the complexity of tasks the system can perform autonomously, and the technologies integrated into the system.

Scalability/Flexibility: advanced material handling systems have the ability to adjust more readily to fluctuations in order volume and product variety, simplifying the process of scaling warehouse operations up or down as required.

4.3. AUTOMATED STORAGE SYSTEMS AND THEIR PERFORMANCE PARAMETERS

After the process described in Section 4.1, the list of performance parameters for storage systems resulting from the scientific literature search through Scopus was checked by the author of this thesis and her two supervisors. They noticed that some performance parameters indicated as pretty important by professional literature, such as the ones associated with reliability, are either not touched or poorly debated by scientific literature. So, they decided to include them in the final list of performance parameters for storage systems.

Therefore, the chosen performance parameters for the automated storage systems are:

Storage capacity [kg]: Maximum weight that the storage system is able to handle. It is measured in kg.

Storage depth: it can be single, double, triple or multi deep. Single storage depth means that the storage system has one rack and it is able to store one item, same goes for double and triple with two racks and two items and three racks and three items. Whereas multi deep means that the storage system has multiple racks and can store multiple items simultaneously.

Storage height [m]: it refers to the height of the the storage system. It is measured in meters.

N order lines/h: it identifes with the productivity of the strorage system by calculating the completion picking operations time.

Speed [m/s]: it is measured in meter per second.

Storage density: it is calculated by dividing the cubic meters of gross stowable goods by the square meters of the area occupied by automation alone.

Selectivity: it refers to the direct access items.

Accessibility: accessibility to the items in case of failure of the storage system.

Modularity: it refers to having the possibility to expand the existing storage system for exmple by making the racks longer or by increasing the number of aisles if there's enough physical space to do so.

Scalability/Flexibility: it is the ability that a technology has to handle an increase in work or worloads in an effective and efficient way.

Redundancy: it refers to the ability of the system, in which are present different resources, to ensure that the operations can progress despite unexpected events or technical problems.

Cycle time: time needed to complete one picking operation.

Reliability involves **Mean time to repair**, which is calculated by dividing the time spent repairing the asset by the total number of repairs performed**. Mean time between failures** is determined by the ratio of the difference between down time and up time to the number of failures. **Mean time to failure** is calculated by dividing the total time of operation by the number of failures.

Storage system capacity: number of SKU storable in a warehouse, it is an indicator that shows the size of the warehouse and it is measured in loading units.

Investement cost: the cost of building a new storage system.

Operating costs: it includes the energy cost, personnel costs and cleaning costs.

Maintenance cost: it includes the cost of the preventive maintenance of the storage system.

System lifetime: total time that the storage system is able to function.

Utilisation rate: ratio of actual employment time to available work time.

Level of automation: the extent to which automation technologies, such as conveyor systems, robotics, and Warehouse Management Systems (WMSs), are utilized to enhance the speed of operations within storage systems.

4.4. AUTOMATED PICKING SYSTEMS AND THEIR PERFORMANCE PARAMETERS

After the process described in Section 4.1, the list of performance parameters for picking systems resulting from the scientific literature search through Scopus was checked by the author of this thesis and her two supervisors. They noticed that some performance parameters indicated as pretty important by professional literature, such as the ones associated with reliability, are either not touched or poorly debated by scientific literature. So, they decided to include them in the final list of performance parameters for material handling systems.

Therefore, the chosen performance parameters for the automated picking systems are:

Picking lines/h: it identifes with the productivity of the picking system by calculating the completion picking operations time per hour.

Cycle time: time needed to complete one picking operation.

Efficiency and accuracy: it is the ability of the picking system to get the right product in the right quantity.

Reliability: it comprehends **Mean time to repair** which the time obtained by dividing the time spent repairing the asset by the total number of repairs performed. **Mean time between failures** the time obtained from the ratio of the difference between down time and up time to number of failures. **Mean time to failure** the time obtained from the ratio of the total time of operation to number of failures.

Level of automation: : it can be defined by evaluating several factors that reflect how much human intervention is required, the complexity of tasks the system can perform autonomously, and the technologies integrated into the system.

Ability to reduce unnecessary worker movement: reducing worker movement in between operations.

Level of physical strain required: automated picking systems decrease the physical strain on employees, resulting in fewer injuries and promoting a healthier workforce.

Investement cost: the cost of building a new picking system.

Operating costs: it includes the energy cost, personnel costs and cleaning costs.

Maintenance cost: it includes the cost of the preventive maintenance of the storage system.

5. PROPOSED ASSESSMENT FRAMEWORK

This is the chapter dedicated to the development and description of the Domain Mapping Matrices, final step of the Descriptive Study I of the Design Research Methodology. The framework proposed is one made with Domain Mapping Matrices, in order to put together the results found on both Industry 5.0 approaches and technologies and the Internal Logistics Systems performance parameters.

Together with a 5-point Likert scale, Domain Mapping Matrices allow to gather the experts' opinions on the degree of the impact of the approaches and technologies for each Industry 5.0 target dimension on the performance of Internal Logistics Systems. So the main reason why they were chosen for this work is because they are particular matrices that enable the methodology to include not just one domain at a time but allow to determine a relationship between two domains, the ones entered in the rows and those entered in the columns. Meanwhile, the motive behind the choice of the following 5-point Likert Scale as an evaluation method was dictated by the fact that it contains the neutral item, since some approaches and technologies might have no effect on the performance parameters of some Internal Logistics Systems (Table 10).

5-point Likert evaluation scale				
1	2	3	4	5
Significant decrease	Decrease	No change	Increase	Significant increase

Table 10 Likert scale for the Domain Mapping Matrices

Below, from Table 11 to Table 28, there are these matrices for each Industry 5.0 target dimension and type of Internal Logistics Systems.

			MATERIAL HANDLING SYSTEMS																
								Reliability											
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Human centricity	Approaches	Decentralized decision making																	
		Human-robot co-working																	
		Tracking-as-a-Service (NTaaS)																	

Table 11 Domain Mapping Matrix between human centricity approaches and the performance parameters of material handling systems

			MATERIAL HANDLING SYSTEMS																
								Reliability											
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Human centricity	Technologies	Artificial Intelligence (AI)																	
		Natural language processing for interacting with robots																	
		Intelligent smart wearables (ISWs) and exoskeletons																	
		Cobots																	
		Natural user interfaces (NUIs)																	
		Human interaction and recognition technologies (HIRT)																	
		Gesture-tracking devices																	
		Augmented Reality (AR)																	
		Sensors																	
		Internet of Everything (IoE)																	
		Clothing industrial smart wearables																	
		Internet of Things (IoT)																	
		Edge computing																	

Table 12 Domain Mapping Matrix between human centricity technologies and the performance parameters of material handling systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investement costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Human centricity	Approaches	Decentralized decision making																				
		Human-robot co-working																				
		Tracking-as-a-Service (NTaaS)																				

Table 13 Domain Mapping Matrix between human centricity approaches and the performance parameters of storage systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investement costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Human centricity	Technologies	Artificial Intelligence (AI)																				
		Natural language processing for interacting with robots																				
		Intelligent smart wearables (ISWs) and exoskeletons																				
		Cobots																				
		Natural user interfaces (NUIs)																				
		Human interaction and recognition technologies (HIRT)																				
		Gesture-tracking devices																				
		Augmented Reality (AR)																				
		Sensors																				
		Internet of Everything (IoE)																				
		Clothing industrial smart wearables																				
		Internet of Things (IoT)																				
		Edge computing																				

Table 14 Domain Mapping Matrix between human centricity technologies and the performance parameters of storage systems

			PICKING SYSTEMS										
						Reliability							
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making											
		Human-robot co-working											
		Tracking-as-a-Service (NTaaS)											

Table 15 Domain Mapping Matrix between human centricity approaches and the performance parameters of picking systems

			PICKING SYSTEMS										
						Reliability							
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)											
		Natural language processing for interacting with robots											
		Intelligent smart wearables (ISWs) and exoskeletons											
		Cobots											
		Natural user interfaces (NUIs)											
		Human interaction and recognition technologies (HIRT)											
		Gesture-tracking devices											
		Augmented Reality (AR)											
		Sensors											
		Internet of Everything (IoE)											
		Clothing industrial smart wearables											
		Internet of Things (IoT)											
		Edge computing											

Table 16 Domain Mapping Matrix between human centricity technologies and the performance parameters of picking systems

			MATERIAL HANDLING SYSTEMS																
								Reliability											
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Sustainability	Approaches	Circular processes																	
		Reduction of climate change																	
		Renewable sources																	
		Remanufacturing																	
		6Rs policy																	
		Predictive maintenance																	
		Bioeconomy																	

Table 17 Domain Mapping Matrix between sustainability approaches and the performance parameters of material handling systems

			MATERIAL HANDLING SYSTEMS																
								Reliability											
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Sustainability	Technologies	Machine Learning																	
		Intelligent Energy Management Systems (IEMS)																	
		Big Data																	
		Artificial Intelligence (AI)																	
		Computational Intelligence (CI)																	
		Internet of Things (IoT)																	
		Internet of Personalized Products (IoP^2)																	

Table 18 Domain Mapping Matrix between sustainability technologies and the performance parameters of material handling systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investment costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Sustainability	Approaches	Circular processes																				
		Reduction of climate change																				
		Renewable sources																				
		Remanufacturing																				
		6Rs policy																				
		Predictive maintenance																				
		Bioeconomy																				

Table 19 Domain Mapping Matrix between sustainability approaches and the performance parameters of storage systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investment costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Sustainability	Technologies	Machine Learning																				
		Intelligent Energy Management Systems (IEMS)																				
		Big Data																				
		Artificial Intelligence (AI)																				
		Computational Intelligence (CI)																				
		Internet of Things (IoT)																				
		Internet of Personalized Products (IoP^2)																				

Table 20 Domain Mapping Matrix between sustainability technologies and the performance parameters of storage systems

			PICKING SYSTEMS										
						Reliability							
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Sustainability	Approaches	Circular processes											
		Reduction of climate change											
		Renewable sources											
		Remanufacturing											
		6Rs policy											
		Predictive maintenance											
		Bioeconomy											

Table 21 Domain Mapping Matrix between sustainability approaches and the performance parameters of picking systems

			PICKING SYSTEMS										
						Reliability							
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning											
		Intelligent Energy Management Systems (IEMS)											
		Big Data											
		Artificial Intelligence (AI)											
		Computational Intelligence (CI)											
		Internet of Things (IoT)											
		Internet of Personalized Products (IoP^2)											

Table 22 Domain Mapping Matrix between sustainability technologies and the performance parameters of picking systems

			MATERIAL HANDLING SYSTEMS														
								Reliability									
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Resilience	Approaches	Organizational resilience																	
		Cognitive resilience																	
		Psycological resilience																	
		Operator safety strategies																	
		Biological resilience																	
		Human-machine systems resilience																	
		Renewable sources																	
		Physical resilience																	

Table 23 Domain Mapping Matrix between resilience approaches and the performance parameters of material handling systems

			MATERIAL HANDLING SYSTEMS														
								Reliability									
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Degree of interaction with humans	Obstacle detection ability	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Maintenance costs	Utilization rate	Level of automation	Scalability (Flexibility)
Resilience	Technologies	Big Data																	
		Machine Learning																	
		Artificial Intelligence (AI)																	
		Internet of Things (IoT)																	
		Cyber-physical systems																	
		NextG wireless networks (NGWNs)																	
		Cloud computing																	
		Internet of Everything (IoE)																	

Table 24 Domain Mapping Matrix between resilience technologies and the performance parameters of material handling systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investement costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Resilience	Approaches	Organizational resilience																				
		Cognitive resilience																				
		Psycological resilience																				
		Operator safety strategies																				
		Biological resilience																				
		Human-machine systems resilience																				
		Renewable sources																				
		Physical resilience																				

Table 25 Domain Mapping Matrix between resilience approaches and the performance parameters of storage systems

			STORAGE SYSTEMS																			
													Reliability									
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Accessibility	Selectivity (direct access to items)	Modularity	Scalability (Flexibility)	Redundancy	Mean Time to Repair	Mean Time Between Failures	Mean Time to Failure	Storage capacity	Investement costs	Operating costs	Maintenance costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Resilience	Technologies	Big Data																				
		Machine Learning																				
		Artificial Intelligence (AI)																				
		Internet of Things (IoT)																				
		Cyber-physical systems																				
		Next G wireless networks (NGWNs)																				
		Cloud computing																				
		Internet of Everything (IoE)																				

Table 26 Domain Mapping Matrix between resilience technologies and the performance parameters of material handling systems

			PICKING SYSTEMS										
						Reliability							
			Picking lines/h (N. picking productivity)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience											
		Cognitive resilience											
		Psycological resilience											
		Operator safety strategies											
		Biological resilience											
		Human-machine systems resilience											
		Renewable sources											
		Physical resilience											

Table 27 Domain Mapping Matrix between resilience approaches and the performance parameters of picking systems

			PICKING SYSTEMS										
						Reliability							
			Picking lines/h (N. picking productivity)	Cycle time for picking operation (picking time)	Picking accuracy	Mean Time to Repair	Mean Time Between Failure	Mean Time to Failure	Level of automation	Ability to reduce unnecessary worker movement	Level of physical strain required	Investment costs	Operating costs
Resilience	Technologies	Big Data											
		Machine Learning											
		Artificial Intelligence (AI)											
		Internet of Things (IoT)											
		Cyber-physical systems											
		Next G wireless networks (NGWNs)											
		Cloud computing											
		Internet of Everything (IoE)											

Table 28 Domain Mapping Matrix between resilience technologies and the performance parameters of picking systems

6. CONCLUSIONS

This final chapter presents the benefits and limitations of this work, together with the future steps of this research which will be focused on the third stage of the DRM, the Prescriptive Study, that will take place starting from this thesis results.

6.1. BENEFITS

The benefits of this work can be found in the fact that in literature are present only researches on Industry 5.0 or Internal Logistics Systems alone: for example (Romero, D., Stahre, J., 2021), (Vatin N.I., et al.., 2024) and (Krupas M., et al.., 2024) only focuses on one target dimension of Industry 5.0, whereas (Ghobakhloo M et al.., 2023), (Shah Z., et al.., 2023) focues on all the I5.0 target dimension but does not mention the Internal Logistics Systems. So putting them together in this work has the potential to be a good addition to the literature already present nowadays. This thesis can also give a methodology on how to measure the impact of Industry 5.0 on the performance of Internal Logistics Systems and what characteristics the latter should have to implement Industry 5.0 target dimensions. It can also stimulate the definition of guidelines for designing future Internal Logistics Systems based on how Industry 5.0 can improve their performances.

6.2. LIMITS

The limits of this work are firstly the fact that it hasn't been completed yet, which makes it useful in theory but not in practice. This limitation will be overcome once the second part of the research is complete.

Another limit is due to the number and type of Internal Logistics Systems considered: since this research is aimed at analysing some Automated Internal Logistics Systems, while in reality there are industries that do not only use Automatic Internal Logisitcs Systems but also other manual ones, it becomes difficult to apply this work to all manufacturing companies.

While the concept of Industry 5.0 is still being studied, this work is focused only on the information on I5.0 available today, meaning that with more knowledge on the topic of Industry 5.0 and future Internal Logistics Systems, in the near term the outcomes of this thesis might be result uncomplete.

6.3. NEXT STEPS

As mentioned at the beginning of this chapter, the next stage of the Design Research Methodology that will be applied in the present research is the Prescriptive Study. It will be implemented by conducting a Delphi Study which is made up of two steps: the first being the selection of experts from companies manufacturing material handling, storage, and picking systems and university. They'll independently assess, through the developed DMMs, how each I5.0 approach and technology influences the performance parameters of the Internal Logistics Systems using the 5-point numerical Likert Scale defined in Chapter 5. Then the experts' input will be summarised and the resulting summary will be sent again to the experts involved in the study.

The second consists of, again, experts independently assess the influences of I5.0 approaches and technologies on performance parameters through DMMs using the same approach as in the first stage: review if experts change their assessment after reviewing the summary results from the first stage of the Delphi Study.

Finally the results of the Delphi Study will be analised and the result of this analysis will be clustering of DMM values to determine which I5.0 approaches and technologies have the greatest impact (both positive and negative) on the performance of which Internal Logistics Systems.

Eventually since it is such a new topic, future research can take into consideration aspects of Industry 5.0 that haven't been discovered or talked about to this day, making the work even more complete and thefore helpfull if applied in real life contexts.

REFERENCES

Aheleroff S., Huang H., Xu X., Zhong R. (2022) "Toward sustainability and resilience with Industry 4.0 and Industry 5.0", *Food Industry 4.0 Emerging Trends and Technologies in Sustainable Food Production and Consumption Developments in Food Quality and Safety*, Sustainable AgriFoodtech Innovation & Research (SAFIR), Arras, France, pp. 283-290

Alimam H., Mazzuto G., Tozzi N., Emanuele Ciarapica F., Bevilacqua M. (2023) "The resurrection of digital triplet: A cognitive pillar of human-machine integration at the dawn of industry 5.0", *Journal of King Saud University - Computer and Information Sciences*, Vol.35 No.10, pp. 1-30 https://doi.org/10.1016/j.jksuci.2023.101846

Alves J., Lima T., Gaspar P. (2023) "Is Industry 5.0 a Human-Centred Approach? A Systematic Review", *Processes* 2023, Vol.11 No.1, pp. 1-15 https://doi.org/10.3390/pr11010193

Amr A. (2023) "Unlocking the Future: Fostering Human–Machine Collaboration and Driving Intelligent Automation through Industry 5.0 in Smart Cities", S*mart Cities*, Vol.6 No.5, pp. 1-41 https://doi.org/10.3390/smartcities6050124

Asad U., Khan M., Khalid A., Lughmani W.A. (2023) "Human-Centric Digital Twins in Industry: A Comprehensive Review of Enabling Technologies and Implementation Strategies", *Sensors*, Vol. 23 No.8, pp. 1-27 https://doi.org/10.3390/s23083938

Baig M.,Yadegaridehkordi E. (2024) "Industry 5.0 applications for sustainability: A systematic review and future research directions", *Sustainable Development*, Vol. 32 No.1, pp. 662-681 https://doi-org.ezproxy.biblio.polito.it/10.1002/sd.2699

Blessing L., Chakrabarti A. (2009) “DRM: a design research methodology”, *DRM, a Design Research Methodology*, pp. 1–15

Breque M., De Nul L., Petridis A. (2021) “Industry 5.0 Towards a sustainable, human-centric and resilient European industry”, Luxembourg, LU: European Commission, Directorate-General for Research and Innovation, 46.

Calderon M.L. (2010) “The Design Research Methodology as a framework for the development of a tool for engineering design education”, *DS 62: Proceedings of E and PDE 2010, the 12th International Conference on Engineering and Product Design Education - When Design Education and Design Research Meet*, pp. 298–303

Calzavara M., Faccio M., Granata I. (2023) “Multi-objective task allocation for collaborative robot systems with an Industry 5.0 human-centered perspective”, *the International Journal of Advanced Manufacturing Technology*, Volume 128, pp. 297-314, https://doi.org/10.1007/s00170-023-11673-x

Choi I. S., Ki Y. S., Qiu S. (2015) “Storage apparatus and method for autonomous space compaction”, U.S. Patent No. 11,042,328. 22 Jun. 2021.

Dallari F., Bianco D., Corti A., Farioli M. (2023) “Dossier Logistica”, “Logistica management”, 2024, n°342

Demir K.A., Döven G., Sezen B. (2019) “Industry 5.0 and Human-Robot Co-working”, *Procedia Computer Science Volume 158*, pp. 688–695 https://doi.org/10.1016/j.procs.2019.09.104

Drees T., Kunnen S., Pluhnau R., Nagarajah A. (2021) “Methodology for a task-specific and personalized development of an initial exoskeleton design”, *Proceedings of the Design Society*, Volume 1, pp. 2077–2086 https://doi.org/10.1017/pds.2021.469

Giugliano G., Laudante E., Formati F., Buono M. (2023) "Approaches and Technologies for the Human-Centered Industry 5.0", *Advanced Engineering Informatics*, Vol.62, pp. 1-17 https://doi.org/10.25267/P56-IDJ.2023.i3.05

Ghobakhloo M., Iranmanesh M., Tseng M., Grybauskas A.,Stefanini A., Amran A. (2023) "Behind the definition of Industry 5.0: a systematic review of technologies, principles, components, and values", Hassoun A., *Journal of Industrial and Production Engineering,* Vol. 40 No.6, pp. 432–447 https://doi.org/10.1080/21681015.2023.2216701

Gródek-Szostak, Z., Szeląg-Sikora, A., Siguencia, L.O., Nieczyk, A. (2023) "From Industry 4.0 Paradigm Towards Industry 5.0", *Environment. Technology. Resources. Proceedings of the 14th International Scientific and Practical Conference. Volume 2, 2023*, pp. 46-49 https://doi.org/10.17770/etr2023vol2.7192

Heinrich E. (2003) "Method for storing materials in automatic compact warehouse uses roller pallets in channels on different levels which hold different materials replaced from separate storage magazine when removed for delivery". Patent

Humayun M. (2021) "Industrial Revolution 5.0 and the Role of Cutting Edge Technologies", *International Journal of Advanced Computer Science and Applications*, Vol.12 No.12, pp. 605–615 https://thesai.org/Publications/ViewPaper?Volume=12&Issue=12&Code=IJACSA&SerialNo=76

Jafari N., Azarian M., Yu H. (2022) "Moving from Industry 4.0 to Industry 5.0: What Are the Implications for Smart Logistics?", *Logistics*, Vol.6 No.2, pp. 1-27 https://doi.org/10.3390/logistics6020026

Javaid M., Haleem A., Singh R.P., Rab S., Suman R. (2022) "Significant applications of Cobots in the field of manufacturing", *Cognitive Robotics*, Voume 2, pp. 222–233 https://doi.org/10.1016/j.cogr.2022.10.001

Krupas M., Kajati E., Liu C., Zolotova I. (2024) "Towards a Human-Centric Digital Twin for Human–Machine Collaboration: A Review on Enabling Technologies and Methods", *Sensors*, Vol.24 No.7, pp. 1-20 https://doi.org/10.3390/s24072232

Marinelli M (2023) "From Industry 4.0 to Construction 5.0: Exploring the Path towards Human–Robot Collaboration in Construction", *Systems,* Vol.11 No.3, pp. 1-23 https://doi.org/10.3390/systems11030152

Mesjasz-Lech A. (2023) "Can Industry 5.0 be seen as a remedy for the problem of waste in industrial companies?", *Procedia Computer Science*, Volume 225, pp. 1816-1825, https://doi.org/10.1016/j.procs.2023.10.171

Pizoń J., Cioch M., Kański L., García L. S. (2022) "Cobots Implementation in the Era of Industry 5.0 Using Modern Business and Management Solutions", *Advances in Science and Technology Research,* Volume 16 No. 6, pp. 166-178, https://doi.org/10.12913/22998624/156222

Romero D., Stahre J. (2021) "Towards The Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems", *Procedia CIRP*, Volume 104, pp. 1089-1094

Shah Z., Aamir M., Sunder A. K., Kapal D., Syed A. H., Mikael G., Bellavista P. (2023) "Towards defining industry 5.0 vision with intelligent and softwarized wireless network architectures and services: A survey", *Journal of Network and Computer Applications*, Vol.223, pp. 1-42 https://doi.org/10.1016/j.jnca.2023.103796

Taj I., Jhanjhi N.Z. (2022) "Towards Industrial Revolution 5.0 and Explainable Artificial Intelligence: Challenges and Opportunities", *International Journal of Computing and Digital Systems*, Vol.12 No.1, pp. 285–310 https://dx.doi.org/10.12785/ijcds/120124

Vatin N.I., Negi G.S., Yellanki V.S., Mohan C., Singla N. (2024) “Sustainability Measures: An Experimental Analysis of AI and Big Data Insights in Industry 5.0”, *BIO Web of Conferences*, Volume 86, pp. 1-11 https://doi.org/10.1051/bioconf/20248601072

Valeriya G., Kirola M., Gupta M., Acharya P., Sharma R. (2024) “Evaluating the Impact of AI-Based Sustainability Measures in Industry 5.0: A Longitudinal Study”, *BIO Web of Conferences,* Volume 86, pp. 1-13 https://doi.org/10.1051/bioconf/20248601058

Zafar M.H., Langås E.F., Sanfilippo F. (2024) “Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review”, *Robotics and Computer-Integrated Manufacturing*, Volume 89, pp. 1-29 https://doi.org/10.1016/j.rcim.2024.102769

Zizic M.C. , Mladineo M. , Gjeldum N. , Celent L. (2022) “From Industry 4.0 towards Industry 5.0: A Review and Analysis of Paradigm Shift for the People, Organization and Technology”, *Energies*, Vol.15 No.14, pp. 1-20 https://doi.org/10.3390/en15145221

Windhausen A., Heller J., Hilken T., Mahr D., Di Palma R., Quintens L. (2024) “Exploring the impact of augmented reality smart glasses on worker well-being in warehouse order picking”, in *Computers in Human Behavior,* Volume 155, pp. 1-13 https://doi.org/10.1016/j.chb.2024.108153

LIST OF VISITED WEBSITES

[1] https://limblecmms.com/metrics/mean-time-to-failure/#process

[2] https://www.knapp.com/

[3] https://www.vecnarobotics.com/

[4] https://www.universal-robots.com/

[5] https://www.ssischaefer.com/

[6] https://www.dematic.com/

[7] https://www.mecalux.it/

[8] https://www.picktolightsystems.com

[9] https://www.ams-fa.com/product/forklift-agv/

[10] https://www.autostoresystem.com/it

[11] https://www.therobotreport.com/the-future-is-agv/

[12] https://warehouseoptimizers.com/pallet-racking/amr-warehouse-robots-the-labor-shortage-solution/

[13] https://www.mecalux.com/warehouse-automation/picking-robot

[14] https://www.autostoresystem.com/insights/piece-picking-robots-in-the-warehousing-industry

[15] https://dsmweb.org/domain-mapping-matrix-dmm/

[16] https://community.tableau.com/s/question/0D54T00000C5dwESAR/calculating-the-median-of-likert-scale-data-that-assumes-that-the-5-point-scale-represents-a-continuous-random-variable

[17] https://www.daifuku.com/solution/intralogistics/products/automated-warehouse/miniload-asrs/

[18] https://www.jungheinrich.co.uk/automation/storage-systems/shuttle-compact-storage-system-108364

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APPENDIX 1

			Human centricity																				
			Approach			Technologies																	
	Title	Citation	Decentralized decision making	Human-robot co-working	Navigation/Tracking-as-a-Service (NTaaS)	AI	Virtual reality	Cobots	Intelligent smart wearables (ISWs) and exoskeletons	Augmented reality	Cyber-physical systems	Human interaction and recognition technologies (HIRT)	Clothing industrial smart wearables (ISWs)	Brain computer interface (BCI)	Edge computing	Digital twin	Natural language processing for enteracting with robots	Gesture-tracking devices	Sensors	Natural user interfaces (NUIs)	Internet of everything (IoE)	Internet of things (IoT)	Drones
1	From Industry 4.0 towards Industry 5.0: A Review and Analysis of Paradigm Shift for the People, Organization and Technology	[85]	X																				
2	From Industry 4.0 Paradigm Towards Industry 5.0	[0]																					
3	Evaluating the Impact of AI-Based Sustainability Measures in Industry 5.0: A Longitudinal Study	[0]				X																	
4	Industry 5.0 and Human-Robot Co-working	[307]		X																			
5	From Industry 4.0 to Construction 5.0: Exploring the Path towards Human–Robot Collaboration in Construction	[9]					X																
6	Multi-objective task allocation for collaborative robot systems with an Industry 5.0 human-centered perspective	[3]						X															
7	Cobots Implementation in the Era of Industry 5.0 Using Modern Business and Management Solutions	[9]						X															
8	Approaches and Technologies for the Human-Centered Industry 5.0.	[38]				X			X	X	X												
9	Behind the definition of Industry 5.0: a systematic review of technologies, principles, components, and values	[2]							X			X	X									X	
10	Towards Industrial Revolution 5.0 and Explainable Artificial Intelligence: Challenges and Opportunities	[18]																					X
11	Toward sustainability and resilience with Industry 4.0 and Industry 5.0	[8]						X															
12	Is Industry 5.0 a Human-Centred Approach? A Systematic Review	[7]								X													
13	Industry 5.0 applications for sustainability: A systematic review and future research directions	[0]																					
14	Unlocking the Future: Fostering Human–Machine Collaboration and Driving Intelligent Automation through Industry 5.0 in Smart Cities	[3]																					
15	Can Industry 5.0 be seen as a remedy for the problem of waste in industrial companies?	[0]																					
16	The resurrection of digital triplet: A cognitive pillar of human-machine integration at the dawn of industry 5.0	[1]				X								X		X							
17	Towards defining industry 5.0 vision with intelligent and softwarized wireless network architectures and services: A survey	[1]			X	X				X	X												
18	Industrial Revolution 5.0 and the Role of Cutting Edge Technologies	[35]								X													
19	Towards The Resilient Operator 5.0: The Future of Work in Smart Resilient Manufacturing Systems	[129]																					
20	Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review	[0]		X			X	X	X	X	X				X	X	X	X	X		X		
21	Human-Centric Digital Twins in Industry: A Comprehensive Review of Enabling Technologies and Implementation Strategies	[12]																	X				
22	Moving from Industry 4.0 to Industry 5.0: What Are the Implications for Smart Logistics?	[59]																					
23	Sustainability Measures: An Experimental Analysis of AI and Big Data Insights in Industry 5.0	[8]																					
24	Towards a Human-Centric Digital Twin for Human–Machine Collaboration: A Review on Enabling Technologies and Methods	[0]					X			X		X								X		X	
	COLUMN TOTAL		1	2	1	4	3	4	3	6	3	2	1	1	1	2	1	1	2	1	1	2	1
	TOTAL PER I5.0 TARGET DIMENSION		43																				

	Sustainability																				
	Approach								Technologies												
	Reduction of climate change	Bioeconomy	6R	Circular processes	Predictive maintenance	Remanufacturing	Customized experiences	Renewable sources	AI	Bio-inspired protective gears	Intelligent energy management systems IEMS	Digital twin	Cobots	Internet of personalized products (IoP^2)	Big data	Machine learning	Internet of things IoT	Biosensors	Cyber Physical Systems (CPSs)	Computational Intelligence CI	Blockchain
1																					
2	X																				
3									X												
4		X																			
5																					
6																					
7																					
8								X													
9										X	X	X									
10																					
11													X	X							
12			X																		
13				X			X								X	X					
14								X								X			X		
15									X								X				X
16																					
17									X								X	X		X	
18																					
19																					
20					X	X											X				
21																					
22																			X		
23									X						X						
24																					
COLUMN TOTAL	1	1	1	1	1	1	1	2	4	1	1	1	1	1	2	2	3	1	2	1	1
TOTAL PER I5.0 TARGET DIMENSION	30																				

	Resilience																							
	Approach									Technologies														
	Organizational resilience	Operator safety strategies	Biological resilience	Physical resilience	Cognitive resilience	Psycological resilience	Human-machine systems resilience	Renewable sources	Human-assisted learning strategies	AI	Cobots	Virtual reality	ISW Wearable technologies and exoscekeletons	Intelligent adaptive robots	Drones	Digital twin	Internet of things IoT	Cyber Physical Systems (CPSs)	Augmented reality	Big Data	Cloud computing	Internet of everything (IoE)	NextG wireless networks (NGWNs)	Machine learning
1	X																							
2																								
3										X														
4																								
5																								
6											X													
7																								
8											X	X	X											
9														X										
10																								
11																								
12		X							X															
13																								
14								X							X	X								X
15																								
16																								
17										X						X	X	X	X				X	X
18																X				X	X			
19			X	X	X	X	X																	
20											X										X	X		
21																								
22																								
23																								
24																								
COLUMN TOTAL	1	1	1	1	1	1	1	1	1	2	3	1	1	1	1	3	1	1	1	1	2	1	1	2
TOTAL PER I5.0 TARGET DIMENSION	31																							