



Cattedra

RELATORE

CANDIDATO

Anno Accademico

Table of Contents

Foreword: Motivation and Objectives

Structure of the Thesis

Introduction

Literature Review

1. Logistics Digital Transformation

- 1.1 Digital Transformation and its Role in Modern Logistics
- 1.2 Industry 4.0: Definition and Key Technologies
- 1.3 From Traditional Logistics to Logistics 4.0

2. Artificial Intelligence in Logistics 4.0

- 2.1 Definition and Key Features
- 2.2 Artificial Intelligence (AI) in Logistics
 - 2.2.1 Fields of applications
 - 2.2.1.1 Demand Forecasting
 - 2.2.1.2 Route Optimization
 - 2.2.1.3 Robotics
 - 2.2.1.4 Computer Vision
 - 2.2.1.5 Gen AI

3. Internet of Things in Logistics 4.0

- 3.1 Definition and Key Features
- 3.2 Internet of Things (IoT) in Logistics
 - 3.2.1 Fields of applications
 - 3.2.1.1 Smart transportation
 - 3.2.1.2 Smart warehousing
 - 3.2.1.3 Smart delivery

4. The Convergence of AI and IoT in Logistics 4.0

- 4.1 AI-IoT Integration: Enabling Smart and Adaptive Logistics
 - 4.1.1 Digital twins for real-time simulation and optimization
 - 4.1.2 AIoT-driven Robotics
- 4.2 Challenges in AI and IoT Integration
 - 4.2.1 Data privacy, security, and ethical concerns
 - 4.2.2 Technological and infrastructural barriers

4.2.3 Workforce transition and reskilling

4.3 Cross-cutting applications of the AIoT approach beyond logistics

4.3.1 Energy sector

4.3.2 Residential context

4.3.3 Healthcare sector

4.3.4 Smart city context

Conclusion

Foreword: Motivation and Objectives

In recent years, logistics has become a privileged laboratory for experimentation with Industry 4.0 technologies: the competitive pressure to guarantee reduced delivery times, end-to-end visibility and lower emissions has met the maturation of Artificial Intelligence (AI) systems and Internet of Things (IoT) networks capable of transforming dispersed data into real-time operational decisions. Literature attests that machine-learning algorithms applied to forecasting, computer vision and reinforcement learning can reduce logistics costs, contain inventories and increase service levels. At the same time, RFID sensors, wearable devices and LPWAN networks allow to monitor containers, warehouses and vehicles, cutting waste and delays along the supply chain. Despite these results, research shows a notable fragmentation: studies on AI and IoT often proceed on parallel tracks, while the convergence of the two domains remains hindered by problems of data quality, interoperability, cybersecurity and skills gaps. It is within this cognitive fracture that the motivation for this investigation lies. Understanding in depth the specific contributions of AI and IoT, before evaluating their synergy, is a necessary condition to avoid easy technological generalizations and to offer companies and policy-makers truly applicable indications.

The thesis therefore aims to:

- (1) critically reconstruct the evolution of AI and IoT in the context of Logistics 4.0, clarifying their areas of effectiveness and infrastructural constraints;
- (2) identify, through a systematic and interdisciplinary review of the scientific and professional literature, the points of intersection between the two technologies that already generate value today or that show the greatest potential in terms of scalability;
- (3) mapping the main technical, organizational and regulatory barriers that hinder integrated adoption.

The choice of a theoretical-analytical approach, based on a broad review of academic sources, white papers and industry reports, allows to fill a double gap: on the one hand, providing an organic and comparative framework of the two technologies considered individually; on the other, clearly defining the perimeter within which their convergence can translate into a smarter, more transparent and sustainable logistics ecosystem. Thus outlined, the research aims to offer an original contribution to the scientific discussion.

Structure of the Thesis

The thesis opens with an Introduction that presents digital transformation as a driving force capable of reshaping industrial models and rewriting the interaction between companies, customers and citizens. In this scenario, the perimeters of the research are carefully defined, offering the reader a clear and coherent reading grid that guides the development of the subsequent chapters.

This premise is followed by a central body consisting of four chapters, conceived as a single extensive literature review organized with a logical progression.

The first chapter reconstructs the digital transformation of logistics, relating the drivers of speed, transparency and sustainability with the evolution of Industry 4.0 technologies and showing how these drivers have reconfigured processes, business models and skill needs.

The second chapter focuses the analysis on AI: after having traced its evolution, it illustrates the main application lines clarifying the benefits, limits and infrastructural requirements highlighted by the most recent studies.

The third chapter is dedicated to IoT and delves into sensors, LPWAN/5G networks and edge-cloud platforms that allow obtaining end-to-end visibility on physical flows, discussing use cases in smart transportation, smart warehousing and smart delivery and focusing on interoperability and security issues.

The fourth chapter represents the point of convergence of the previous two: taking up the results on AI and IoT, it defines the AIoT paradigm as the “digital nervous system” of the supply chain, analyses the areas in which this synergy generates value and identifies the main barriers to adoption, from data governance to the lack of specialist skills.

At the end of the path, the Conclusions section summarizes the original contributions of the work, highlights its methodological limitations and suggests directions for future research. In this way, the thesis accompanies the reader from the general framework of the transformations in progress, through the in-depth analysis of the two leading technologies and their integration, up to the practical implications and development prospects.

Introduction

Digital transformation has redefined the way we live and work, reshaping traditional industrial structures and reinterpreting what it means to be a customer and a citizen (Berman et al., 2016). Digital transformation is often defined by scholars as “the use of new digital technologies (..) to enable major business improvements” (Fitzgerald et al., 2014, p. 1). This process is not based on a single technology, rather, it involves significant changes driven by a “combination of information, computing, communication, and connectivity technologies” (Bharadwaj et al., 2013, p. 471), i.e. “a fusion of advanced technologies” that are integrating physical and digital systems (EC, 2018). At its core, digital transformation has the ultimate aim to create value, by driving operational efficiency, improving customer experience, enhancing business models, enabling strategic differentiation, ultimately leading to improved stakeholder relationships, costs reduction and stronger competitive advantage (Morakanyane et al., 2017).

The last decade, characterized as “the digital age” (Hirt and Willmott, 2014), has fundamentally changed the dynamics within industries. This evolution is largely driven by Industry 4.0, also known as the Fourth Industrial Revolution, whose emergence triggered radical changes in the global economic landscape, characterised by a deep integration of cutting-edge technologies, especially in manufacturing and logistics. (Lu 2017; Ghobakhloo et al. 2021; Meindl et al. 2021; Zhang et al. 2021). As explained by Abdirad and Krishnan (2020), this phenomenon involves the extensive introduction of ICT and its seamless connection with the Internet of Things (IoT), services and data to enable real-time production. This evolution has resulted in traditional machine-dominated manufacturing being replaced by digital manufacturing, in which cyber-physical systems, AI and data analysis converge to create smart factories and interconnected systems that improve automation and decision-making (Donald, 2024 et. al).

In this context of change, the concept of Industry 4.0 has been extended to the field of logistics and supply chain management (LSCM) (Abdirad and Krishnan 2020; Kucukaltan et al. 2022; Barata 2021) giving rise to the so-called *Logistics 4.0* (or Smart Logistics). Logistics 4.0 introduces a radical change in how items are delivered, stored and transported (Khan et al. 2022; Derakhti et al., 2023; Rosário and Dias 2023; Da Silva et al. 2023). Through the use of digital technologies such as advanced analytics, automated processes, robotics, IoT, AI and cloud computing, LSCMs can potentially improve their operations in terms of efficiency, visibility and responsiveness to better meet their customers’ needs. Successful Resource Planning, Warehouse Management Systems, Transportation Management Systems, Intelligent

Transportation Systems, and Information Safety applications are required to operate logistics 4.0 in an effective and strong manner (Barreto et al. 2017).

The recent turning point in the digitisation of logistics operations stems more from the real-time connectivity of assets: machines, vehicles and devices can now be monitored via sensor technologies that capture all kinds of data in real time. In addition, operators can also provide feedback information through mobile and wearable devices. This broad connectivity provides (near) real-time visibility of all work activities. It all adds up to a kind of ‘digital control tower’, analogous to the airport control tower, providing visual alerts that warn of stock shortages or process bottlenecks before they occur. Using simple control algorithms, a course can be corrected before potential problems even become real. Furthermore, being able to collect a vast amount of data, the resulting high availability of historical data leads to the creation of increasingly sophisticated algorithms that add further intelligence to the control rules. Indeed, predictive analyses learn from historical data uncovering patterns and correlations that are not obviously detectable by humans. Moreover, with a digital twin of physical logistics operations, real-time analysis and optimisation can even prescribe decision-making, where users make decisions based on what intelligent agents recommend (Merkert & Hoberg, 2023).

Based on the above, it is clear that IoT and AI are the two most influential technologies when it comes to Logistics 4.0. IoT plays a crucial role by enabling sensor-based real-time tracking, facilitating seamless connectivity between assets, warehouses, and transportation systems (Roshid et al., 2024). These connected devices continuously collect vast amounts of data, forming the foundation for AI-driven predictive analytics, which allows for anticipatory decision-making and automated optimization of logistics flows (Ilin et al., 2019). Thus, the integration of AI algorithms with IoT sensor networks empowers logistics providers to enhance operational visibility, automate workflow adjustments, and implement digital twins that simulate real-world scenarios for more accurate forecasting and process improvement (Kocaoglu, 2024).

In light of this context, this thesis will focus primarily on exploring the synergy between AI and IoT. By examining how these technologies interconnect to support real-time monitoring, predictive analysis and decision-making processes, the aim of this thesis is to shed light on their central role in driving the next wave of digital transformation in logistics.

Literature Review

1. Logistics Digital Transformation

1.1 Digital Transformation and its Role in Modern Logistics

Digital technologies are significantly transforming the functioning and organisation of businesses. Organisations are constantly reformulating their business models in numerous ways, mainly by exploiting the so-called “SMACIT”, which stands for Social media, Mobility, Analytics, Cloud and Internet of Things (Ross et al., 2016). As a result, the role of digital technologies and their applications is growing to the point where they are progressively impacting organisational products, business processes, and even the personal dimension. Companies that fail to integrate into a digital environment inevitably end up succumbing to so-called “digital Darwinism”, in which only those who adapt quickly to technological trends survive in the marketplace (Schwartz, 2001). Consequently, it is imperative to constantly innovate in order to stay abreast of current potentials and trends, a process commonly referred to as Digital Transformation (DT). A notable gap in the existing literature is the absence of a commonly accepted definition of this concept. As Table 1 illustrates, various scholars have formulated different conceptualisations, reflecting the multiple perspectives of this phenomenon.

Author	Definition
Vial, G. (2019)	A process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies.
Van Veldhoven, Z., & Vanthienen, J. (2021)	The continuously increasing interaction between digital technologies. business, and society.
Fitzgerald, M. (2013)	The use of new age digital technologies to enable major business improvements (such as enhancing customer experience, streamlining operations or creating new business models).
Kraus et al. (2022)	Digital transformation can be defined as integrating digital technology into all aspects and operations of an organization, which leads to infrastructural changes in how the organization is operated and delivers value to its customers.
Hess et al. (2016)	Digital transformation is concerned with the changes that digital technologies can bring about in a company's business model, products, processes and organizational structure.
While Schilirò (2022)	Digital transformation implies a profound change, particularly a structural change, i.e., changes in organizations, processes, and business models in the firms, and changes in consumer behavior, not just a digitalization of business processes.
Boulton (2021)	Digital transformation means a rethinking of how an organization uses technology, people, and techniques in pursuit of new business models and additional revenue streams, driven by changes in customer expectations around products and services.

Table 1 - Digital Transformation definitions

Source: Author's personal elaboration

In this thesis, we will mainly refer to the definition proposed by Saldanha (2019), who describes Digital Transformation, also called “Digital Transformation 2.0”, as the strategic integration of emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT). Through this integration, it is possible to simplify operations, extract useful insights from data, and develop creative business models. Thus, the current digital transformation pertains to the Fourth Industrial Revolution. Unlike previous phases of digital transformation, which focused primarily on harnessing technology to achieve specific goals, Digital Transformation 2.0 represents a more holistic change: it aligns technology with an organisation’s core strategy and culture. Digital transformation, indeed, profoundly affects the foundations of a company, starting with its organisational structure, which becomes more agile and responsive (Lee & Edmondson, 2017). The aim is to reduce hierarchical rigidity and internal divisions, favouring a more open model in which information and services can flow freely within the organisation. Besides redefining the corporate structure, digitisation leads to the emergence of new strategic roles, which stimulate innovation and facilitate change (Singh et al., 2020). This process also has an impact on corporate culture, fostering a more risk-oriented, collaborative and experimental mindset (Kane, 2019). Value creation processes also change, with increasing integration of services into traditional business models (servitization), a key element for competitive advantage in the long run (Kryvinska & Bickel, 2020; Linde et al., 2021). Another central aspect concerns the use of business data, which becomes a strategic asset for generating business value (Barrett et al., 2015). Finally, one of the most noticeable effects of digital transformation is the change in the relationship between customers and the company: interaction with services increasingly takes place through digital channels, redefining the user experience and how products and information are accessed (Curi & Casquino, 2022; Mangalaraj et al., 2021).

Despite the increasing focus on digital transformation, there is often confusion between related terms with different meanings. Indeed, in academic literature and common language, the terms *Digitisation*, *Digitalisation* and *Digital Transformation* are often used interchangeably, generating ambiguity. However, each has a specific meaning and refers to different stages in the process of adopting and integrating digital technologies within a company. *Digitisation* refers to the conversion of analogue information into digital format (sequences of 0s and 1s), thus making it processable, storable and transmittable by computers (Maltaverne, 2017). *Digitalisation*, on the other hand, concerns the use of digital technologies to modify and optimise existing business processes (Unruh & Kiron, 2017). Finally, Digital Transformation represents the broadest and most profound phase of change, in which digital technologies do

more than simply enhance processes, as they lead to the development of new business models. As described by Maltaverne (2017), it is the design of “new ways of doing things that generate new sources of value”.

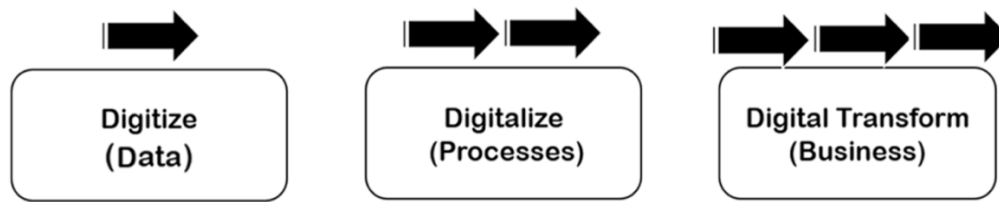


Figure 1 - Phases of Change

Source: Adapted from Kocaoglu, B. (2024). *Logistics Information Systems: Digital Transformation and Supply Chain Applications in the 4.0 Era*. Springer, p. 37.

Over the past decade, this huge phenomenon has substantially altered the competitive landscape of numerous industries, including that of logistics services. As defined by The Economic Times (2024) “logistics involves the systematic management of acquiring, storing, and transporting resources to their intended destinations”. In this industry, ensuring effective operations management is crucial, especially in today's highly competitive global environment. Moreover, with the advent of globalisation, the logistics industry has begun to face significant challenges as demand is outstripping forecasts, driven by emerging technologies disrupting the market (Muango et al., 2021). In order to remain competitive and foster growth, logistics service providers are therefore challenged to redefine their value proposition for shippers and customers by increasing operational efficiency, solving critical industry issues and delivering an increasingly intelligent, fast and sustainable experience (DP-DHL, 2018; Gruchmann and Seuring, 2018; Daugherty et al., 2019). From this perspective, technology assumes a decisive role in distinguishing the value of logistics (Gunasekaran et al., 2017), as it is able to promote innovations (Mathauer and Hofmann, 2019) capable of further raising efficiency and responsiveness (Gunasekaran et al., 2017).

Digital transformation is redefining the transport and logistics (T&L) industry globally. It is one of the main drivers of change, along with service excellence in B2B and B2C markets, decarbonisation of operations according to ESG targets, and the need for constant growth in a changing competitive environment. Traditionally perceived as a labour-intensive industry, T&L is achieving significant improvements in productivity, efficiency and scalability through the adoption of digital technologies (PwC, 2024). Digital transformation in this area is a complex process, involving technological innovation, customer focus, operational efficiency, regulatory compliance and cultural change as Fig.2 illustrates.

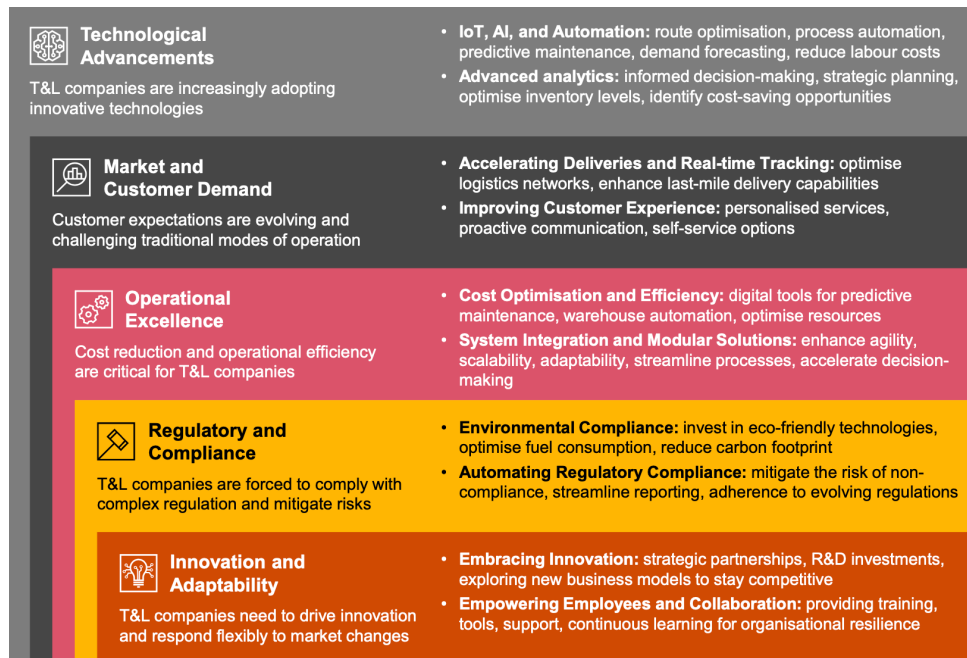


Figure 2 - Key drivers for transformation

Source: PwC, 2024

Companies that strategically integrate these elements will not only successfully meet the challenges but will also be able to seize new opportunities for growth and competitive differentiation.

Logistics has always had customer satisfaction as its main objective and the profound changes taking place are largely the result of the evolution of customer expectations, which continue to transform, redefining the standards of the industry. As customers' needs and wants evolve, the industry must adapt and find ever more efficient and effective ways of operating. What consumers prefer nowadays are convenience, control, automation, transparency and above all a personalised experience. Technology has certainly influenced people's new inclinations, having significantly simplified our lives. It is now commonplace to browse online shops and social media, as well as to use digital banking and video on demand. This is also evidenced by generational differences. Note for instance generations Y and Z, located in the 1990s and later, have grown up with a superior digital experience and in fact behave differently. Consequently, in their professional life they expect to be offered the same things that they have come to appreciate in their private life, which is why expectations regarding the customer experience and professional tools must change accordingly (Wurst & Graf, 2021).

Digitalisation is transforming logistics and supply chain management, reducing costs, and errors through automation. This approach consists of reproducing the physical world in digital form, using tools such as optical character recognition (OCR) and the Internet of Things (IoT).

The so-called digital twins, integrated with tangible reality, push forward the boundary of automation, requiring the conversion of products and services into data, rules and algorithms. Robotic process automation (RPA), artificial intelligence (AI), blockchain technologies and smart contracts are the main enablers of this evolution. In the Fourth Industrial Revolution, these innovations do not operate in isolation but are integrated into digital platforms. These platforms act as ecosystems which aggregate information on digital identities, prices, services, shipping locations and data generated by IoT devices. Consequently, this leads to creating vast volumes of data that require artificial intelligence tools for analysis and value extraction. The new digital realities are gaining market share, threatening traditional suppliers who, if they do not adapt, risk an increase in customer churn rate and a reduction in margins, which is particularly critical in the SME segment. In parallel, companies from other sectors are entering logistics, as shown by Amazon and Alibaba, which have progressively internalised the management of shipments, developing their own logistics infrastructure, from warehouses to transport and delivery networks. In some markets, these platforms already offer excess logistics capacity to third parties, consolidating their role in the sector. The logistics landscape is therefore evolving rapidly. Traditional carriers are focusing on direct sales and customer contact, while shippers are adopting digital tools to become logistics operators. Start-ups are introducing new business models, technology companies are establishing themselves as logistics intermediaries and some operators are specialising in providing software solutions (SaaS) or data analytics (AaaS). This transformation is redefining the business models and competitive dynamics of the entire industry (Wurst & Graf, 2021).

1.2 Industry 4.0: Definition and Key Technologies

Industrialisation was the main force behind the changes in world history that began in the 19th and 20th centuries and continue to shape the 21st century and our lives.

Industrial revolutions, from past to present, have been the result of the emergence of human needs. Indeed, so far, man-made innovations have generated profound transformations that have primarily impacted the functioning of the economy. From the invention of the steam engine to digitally automated production, the First Industrial Revolution and subsequent revolutions led to significant changes in the production process. As a result, increasingly complex, automated and sustainable production systems have emerged (Paksoy et al., 2021). It was the Frenchman Louis Guillaume Otto who first mentioned the concept of the “industrial revolution” in a letter of 1799. Today, by this term we mainly refer to “a radical change in the production activities, methods and presentations used to transform raw materials, manufactured

goods and semi-finished products into the final commodity”, as Sözen and Mescio˘ (2019) define it.

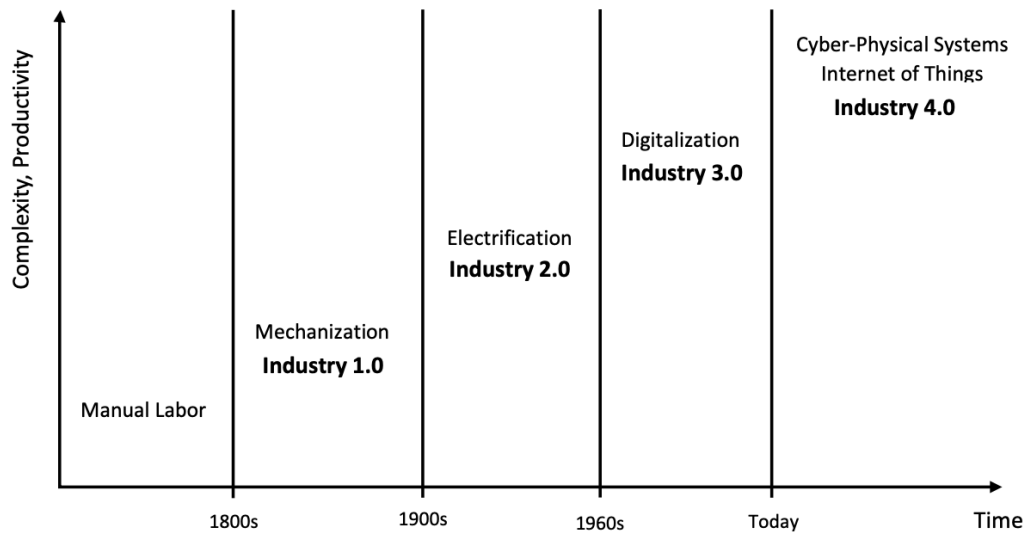


Figure 3 - An Overview of the Four Industrial Revolutions

Source: Paksoy, T., Koçhan, Ç., & Ali, S. S. (Eds.). (2021). Logistics 4.0: Digital Transformation of Supply Chain Management. CRC Press, p. 3.

The industrial revolutions developed in three waves. The first originated in Great Britain in the 1870s, later spreading to Western Europe and the United States. The second affected Russia, Japan, parts of Eastern and Southern Europe, as well as Canada and Australia from the 1880s onwards. The last wave began in the 1960s in the Pacific Rim, reaching Turkey, India, Brazil and other parts of Latin America two decades later. Each phase of industrialisation rapidly involved countries that were not yet industrialised, transforming their basic social and economic structures.

The first three industrial revolutions took place over a period of almost 200 years. Industry 1.0 was initiated with the introduction of mechanical production facilities through the invention of water and steam machines. In fact, starting with mechanical looms powered by the steam engine in the late 1700s, textile production shifted from private homes to central factories, leading to a sharp increase in productivity. Almost 100 years later, Ohio marked the beginning of the second industrial revolution by using conveyor belts in the Cincinnati slaughterhouses. This revolution was characterised by the introduction of mass production, induced by electrification and the division of labour (Taylorism), i.e. the use of machinery powered by electric and combustion engines, as well as the first examples of assembly lines (Paksoy et al., 2021). The Third Industrial Revolution, also called digital revolution, then began to take shape in the 1970s as a result of improvements in information technology and advanced electronics

that enabled the automation of the industrial processes (Hermann et al. 2016). Modicon's introduction of the first programmable logic controller in 1969 was the turning point that made digital programming in automation systems possible. This paradigm still holds the reins of modern automation systems engineering, leading to highly flexible and efficient automation systems (Drath and Horch 2014). Finally, Industry 4.0 has emerged. Industry 4.0 refers to the integration of digital technologies into production processes, leading to smart factories and interconnected systems. This paradigm exploits the use of cyber-physical systems (CPS), the Internet of Things (IoT), Artificial Intelligence (AI) and data analytics to automate processes and support decision-making (Donald et al., 2024). This is done through the extensive use of information and communication technologies (ICT) linked to an environment of objects, services and data, thus enabling real-time production. Increasing digitisation involves products, value chains and business models, helping to improve operational efficiency, reduce costs and increase productivity (Abdirad and Krishnan, 2020). Figure 4 shows how, in the context of Industry 4.0, the integration of physical and digital systems can foster the creation of smart factories.

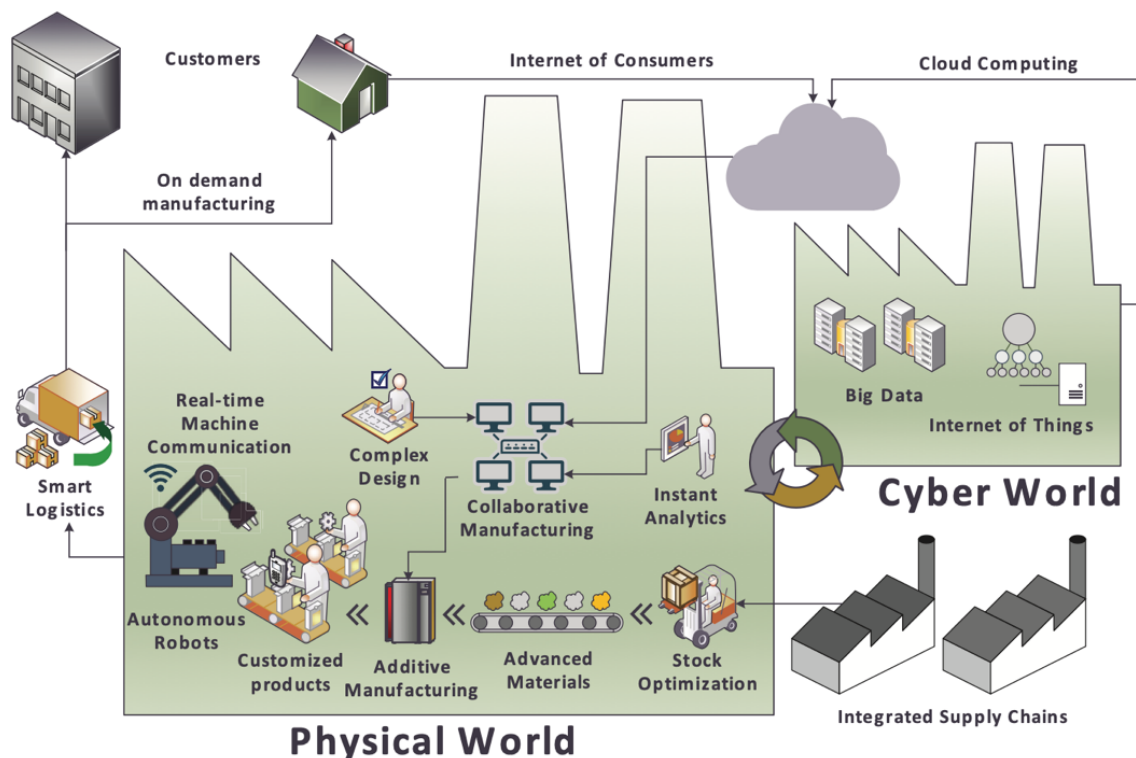


Figure 4 - Schematic of smart factories with general properties required in Industry 4.0.

Source: Ugur M. Dilberoglu et al. / *Procedia Manufacturing* 11 (2017) 545 – 554

Industry 4.0 is a revolutionary advancement fuelled by nine technological pillars (See Fig. 5).

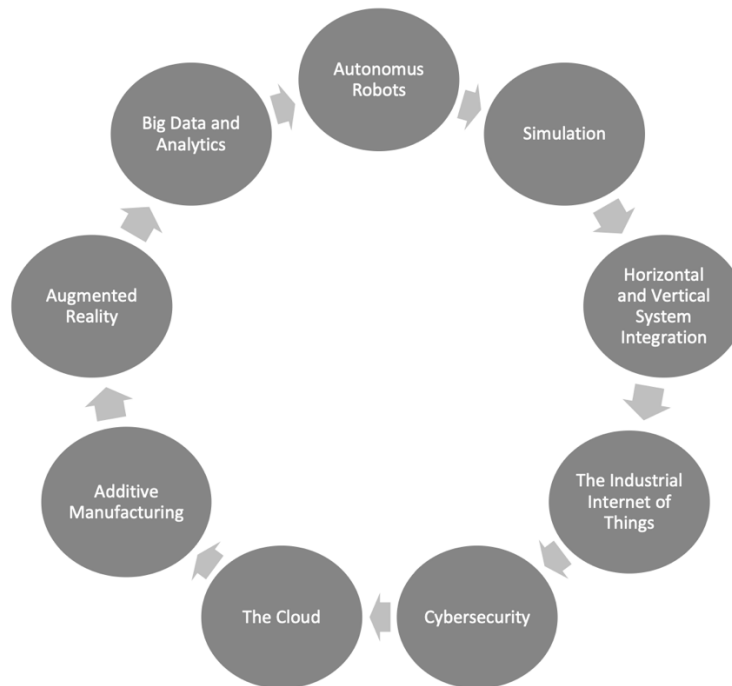


Figure 5 - Fundamental Technologies of Industry 4.0

Source: Rüßmann et al. 2015

Autonomous Robots

The use of industrial robots is not new and has existed for several decades. In the past, robots used in industry were configured to perform repetitive and monotonous tasks, executing a series of movements within pre-defined programmes. These robots were therefore not very sophisticated: apart from safety functions, they did not have any intelligence systems. In other words, these robots were only equipped with specific systems that locked the robot to avoid incidents (The Boston Consulting Group, 2015). The latest generation of robots, defined ‘intelligent collaborative robots,’ rely on sensors and artificial intelligence to provide flexible and contextual responses, adapting to different situations and needs. Unlike traditional robots, these robots possess a cognitive capacity that enables them to think and act autonomously, learning from mistakes and minimising possible inaccuracies. (Lima et al., 2019). Moreover, these robots redefine industrial automation through human-machine collaboration. This is not a simple replacement of human labour, but a change in the skills required: less skilled operators will be progressively replaced by augmented operators, capable of interacting with machines. These robots integrate cutting-edge technologies (e.g. computer vision, geo-localisation, haptic sensors, mechatronics, cloud robotics and artificial intelligence) which allow them to automate physically demanding tasks such as lifting heavy loads, precision positioning and visual quality

control, reducing effort and risks for workers (Ammari et al., 2018). This opens up an area of cooperation between man and machine, where the role of the general worker is replaced by that of a highly skilled operator, responsible for higher value-added tasks (Confartigianato, 2017).

Simulation

With the help of simulation software, a virtual representation of a physical object can be created in order to comprehend its behaviour, forecast its performance, compare options, and ultimately select the best one. By altering its variables, the virtual model can be used to simulate a series of operations and determine how those changes will affect the system as a whole. In a warehouse, for example, simulation allows the operational capacity of machines and the flow of resources from inventory to be kept under control, facilitating more efficient utilisation and encouraging the introduction of just-in-time systems. (CFI, 2015).

Horizontal and vertical system integration

Industry 4.0 requires deep integration of data and systems along the entire value chain, thus enabling the transformation of companies into cohesive and automated entities (Bartodziej, 2017). We can distinguish between horizontal and vertical integration. Horizontal integration concerns the coordinated management of the production chain, which facilitates the sharing of information and resources between decentralised production sites and promotes global value networks (Grosvenor, Liu & Qin, 2016). This approach improves competitiveness and flexibility through collaboration between companies (Li et al., 2016). On the other hand, vertical integration concerns product lifecycle management, linking hierarchical levels for a continuous flow of information between production and management processes (Chukalov, 2017). Essential for smart factories based on cyber-physical systems and IoT technologies, it enables the dynamic reconfiguration of processes (Ayala et al., 2018). The convergence of these integrations is crucial for smart factories, as it supports coordinated production management through advanced value networks and improves market adaptability and responsiveness (Ganzarain, Ibarra & Igartua, 2018). The adoption of integrated strategies increases productivity, resource efficiency and opens up new business models (Adamik, 2019).

Industrial Internet of Things

Underlying the development of Industry 4.0 is an intensive use of the Internet, which serves as a central tool for information management. The very idea of the fourth industrial revolution is based on the creation of an online communication channel capable of ensuring a continuous two-way flow of data between humans and machines, but also between machines themselves (Cooper & James, 2009). The term Internet of Things (IoT) refers to the network of physical devices ('things') equipped with sensors, software and digital technologies, capable of

connecting and communicating with each other using the Internet (Partners et al., 2015). When the ‘things’ that are connected are industrial devices or systems used to support industrial operations, then we are referring to the Industrial Internet of Things (IIoT). Examples of IIoT can be industrial operations such as manufacturing, quality control, supply chain and logistics (Arnold & Kiel, 2016). IIoT integrates information and communication technologies (ICT) within the production environment, connecting various types of devices through the use of sensors, so that they communicate with each other and with a centralised control unit. Indeed, the very nature of this approach requires that data is first monitored and administered on an IIoT platform and then flowed to a cloud server that represents the central brain of the system. In a production system, the data that can be collected from these sensors can be for example heat, temperature, pressure, moisture level, vibration, friction and motion. Through the continuous acquisition of this data in real time, statistical correlations with product performance are established, providing a comprehensive view of every single aspect of the system. IoT has a huge potential in smart factories, leading to reduced production costs, enabling preventive maintenance and creating a safer working environment (Anastasiadis, Lampropoulos & Siakas, 2019).

Cybersecurity

As products and production processes become increasingly connected and distributed, they generate an ever-increasing flow of information that consequently exposes the company to the risk of cyber attacks (The Boston Consulting Group, 2015). For this reason, it is essential to ensure confidentiality, authenticity, integrity and privacy. Cybersecurity is an instrument that provides protection from potential damage to hardware and software components and from data breaches (Adamik, 2019). Therefore, it is crucial to create a reliable data management infrastructure in order to ensure an optimal level of security and reliability of IT platforms. The main goal of any cybersecurity-related operation is to safeguard data and strengthen the security system (Buliga, Müller, & Voigt, 2018). After that, such measures need to be shared with institutions which establish security rules, and with final customers who must be informed about potential risks and make sure their privacy is protected (Broberg et al., 2019). Protection relies on encryption to authenticate information and secure transmission to guard against eavesdropping. Cybersecurity includes threat detection, infrastructure protection, vulnerability identification, real-time low-impact recovery, and the protection is done at three different levels: user, cloud and production (Csik et al., 2016). Integrated measures consolidate corporate security in a more robust manner, while partnerships with third parties and sharing of best practices establish uniformity of standards.

Cloud

As already mentioned several times, everything in Industry 4.0 is data-driven. Inevitably, this requires the need for large channel capacities to process and store this data. In this sense, cloud computing is crucial (Siagri, 2021). It is a virtualized platform that provides computing, networking, storage and analysis capacity over the Internet for more efficiency, versatility and capacity for scaling. Cloud computing is a mechanism for sharing and storing information. This technology is characterised by the speed with which it operates, allowing administrators to save data in the cloud and set up digital systems for process monitoring and control (Juan-Verdejo and Surajbali 2016). It is composed of three elements: front-end that encompasses user access; back-end that is exemplified by infrastructure of the provider; and network that ties all these players together. There are three fundamental services that the user has access to: Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). In the context of manufacture, Cloud Manufacturing shows us a new paradigm of production management in which digital and physical assets get pooled in the cloud to maximise the supply chain. IoT technology makes smart resource allocation possible and automatic process control easy to implement (Martinelli et al., 2021). Costs get minimized, infrastructure is simplified, and ease of access to real-time information increases. Moreover, cloud computing facilitates easy management of Big Data to manage large quantities of structured as well as unstructured data. Indeed, it can be asserted that cloud computing and data analytics have become indispensable tools to foster innovation and productivity in Industry 4.0 (Nuñez et al., 2017).

Additive Manufacturing

Conventional production techniques must be rethought in light of Industry 4.0's requirement for mass customisation. Because of this, Additive Manufacturing (AM) is an essential element in this scenario. Unlike traditional manufacturing processes like milling and turning, which produce products by removing material, or injection moulding, which produces products by injecting materials into a mould (Rutkofsky & Banu, 2018), AM creates three-dimensional solid objects by building a layer of materials on top of each other (Padmakumar, 2022). Industrial companies are increasingly using this technology to move away from mass production of standardised products towards smaller batches of customised and sophisticated products with advanced attributes. (Dilberoglu et al, 2017).

Augmented Reality

Augmented reality (AR) is a technology that integrates digital information into the real environment to enhance the user experience by projecting virtual objects into the physical world (Paelke, 2014). AR enhances perception of the real world without intending to replace

it, in contrast to Virtual Reality (VR), which creates an entirely artificial environment. An AR system is characterised by three essential factors: integration between real and virtual objects, real-time interactivity, and consistent alignment between the two (Azuma et al., 2001). AR is widely used in the workplace, especially in human-machine cooperation, where it improves integration in cyber-physical systems (Lee et al., 2015) by enabling animations and simulations of products and processes. AR transforms workers into intelligent operators who can make strategic decisions and solve problems more effectively, supporting vertical integration in factories (Posada et al., 2015) and facilitating the transition to Industry 4.0 through the use of visual computing (Sudharshan, 2020). According to Jung and Tom Dieck (2017), AR plays a crucial role in this context, enabling employees to access company databases, providing relevant information instantly and improving flexibility and operational efficiency.

Big Data and Analytics

Big data analysis is the collection, processing and interpretation of large volumes of data to generate useful information to support business decision-making. This approach transforms intangible resources into tangible value, making decisions more objective and based on data rather than intuition or opinion. The data-driven decision-making process consists of three main phases: data collection and observation (from internal and external sources), processing and contextualisation to extract meaningful information, and application of the information to generate strategic knowledge. The evolution of big data is closely linked to other pillars of Industry 4.0, such as the Internet of Things (IoT), robotics and cloud computing. The generation and structured organisation of data in the production environment makes it possible to optimise processes, improve quality and increase service efficiency (Bagnoli et al., 2022). The integration of data into decision-making is essential, as every piece of data generated affects business activities, contributing to knowledge creation and strategy formulation (Chen et al., 2015). In the new industrial environment, data analysis enables quick and efficient responses to market fluctuations, improving the adaptability of companies. Without careful analysis, decisions would result in longer response times and reduced effectiveness (Esmaeilian et al., 2016). Consequently, strategic data management becomes a key element in creating value and optimising production processes (Kagermann, 2015).

1.3 From Traditional Logistics to Logistics 4.0

The term logistics is derived from the Greek «λογικὸς», meaning “which makes logical sense”. Logistics has played a fundamental role in the expansion of empires and in the management of supplies throughout human history. An example may be the figure of the logistician instituted

by Julius Caesar, or the creation of special military departments due to the vital importance of supply management during the First and Second World Wars. Only after the Second World War did logistics become the subject of in-depth study and research, in order to affit mathematically robust analytical and solution structures to logical principles. It was only after World War II that logistics became the subject of in-depth study and research, in order to affit mathematically robust analytical and solution structures to logical principles (Casadio Strozzi & Sala, 2024). The pillars of logistics (transport, inventory management and storage) have long been essential elements of industrial and economic activity. However, due to its fragmented nature, consisting of numerous sub-functions and subsystems that are often managed separately, it is only in the last 20-30 years that logistics has been recognised as an autonomous function. Today, both academia and business realise the importance of taking a more integrated and holistic approach to coordinating these different operations, to take into account their interrelationships and interactions and to ensure the optimisation of the overall operation (Rushton, Croucher, & Baker, 2022). The Chartered Institute of Logistics & Transport UK (2019) defines logistics as “getting the Right product, in the Right quantity, in the Right condition, at the Right place, at the Right time, to the Right customer, at the Right price”, that is commonly known as “The Seven R’s of Logistics”. Another important definition of logistics is the one given by the Council of Logistics Management, which defined logistics as “the part of the supply chain process that plans, implements, and controls the efficient, effective flow and storage of goods, services and related information from point of origin to point of consumption in order to meet customers’ requirements”.

Logistics, according to the SCOR (Supply Chain Operation Reference) model, developed over time by the Supply-Chain Council (a non-profit organisation founded in 1996), is represented through a linear system involving the supplier-company-customer triad . This approach then extends to suppliers of suppliers and customers of customers, providing a general reference for the management of logistics activities (Figure 6) (Casadio Strozzi & Sala, 2024).

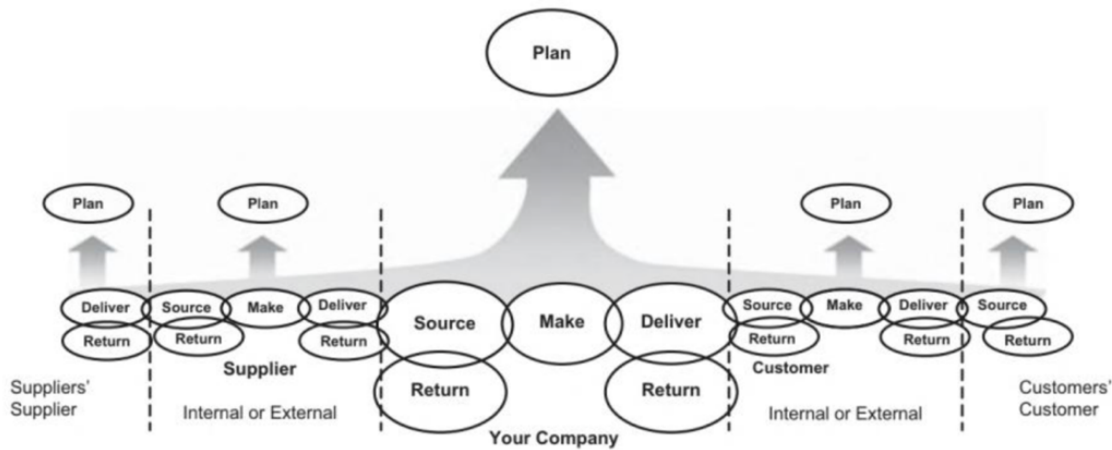


Figure 6 - SCOR Model

Source: Supply Chain Council, 2008

In this scheme, each link in the chain (supplier, company, customer) is responsible for the same types of activities, which are, however, managed in different ways and with different horizons depending on the level of planning required and the actual role of each actor. Consequently, suppliers and customers must be clear about their areas of intervention, albeit with a different scope of governance. In particular:

- **Procurement processes (source):** they define the rules of engagement with suppliers (quantity, frequency of deliveries, prices, payment methods, penalties, performance indicators, etc.), as well as how goods are transferred, received, checked and stored. This portion of the model can be referred to as *inbound logistics*.
- **Production processes (make):** these concern production planning, the realisation of the product/service involved in the chain and, consequently, monitoring and evaluation activities.
- **Distribution processes (deliver):** the company selects and uses internal or external forwarding services to place the manufactured goods on the market, adopting an appropriate distribution scheme to reach the target market. This section of the model refers to *outbound logistics*.
- **Return management processes (return):** they have to be designed and managed with particular attention to their peculiarities (return procedures, inspection, repair or disposal), including support and follow-up activities, which need to be attended to punctually.

As the SCOR model makes clear, logistics is split into inbound and outbound logistics.

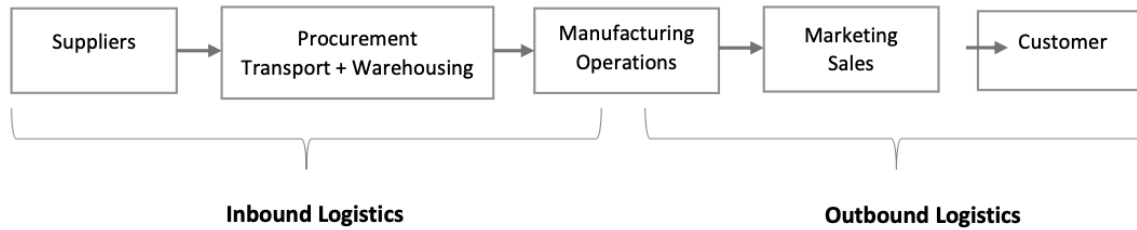


Figure 7 - Inbound and Outbound Logistics Activities

Source: Paksoy, T., Koçhan, Ç., & Ali, S. S. (Eds.). (2021). Logistics 4.0: Digital Transformation of Supply Chain Management. CRC Press, p. 17.

According to Porter (1985), inbound logistics refers to the relationship with suppliers and includes all the activities necessary to receive and store raw materials or goods arriving within the company e.g. consolidation of goods, choice of carrier and mode of transport, warehousing and backhaul management. Outbound logistics, on the other hand, includes all activities required to collect, store and distribute output from manufacturers to buyers, e.g. network planning and management, order processing, vehicle scheduling and routing, materials handling and warehousing of finished goods (Paksoy et al., 2021). Product characteristics are the criterion that differentiates inbound from outbound logistics. The materials handled in inbound logistics are raw materials or unfinished products, as opposed to outbound logistics which only handles finished goods. Furthermore, due to higher production values and strict customer satisfaction requirements, such as on-time delivery, outbound logistics requires more complex processes than inbound logistics. Physical distribution is the area of business management that deals with all material movements. It is usually associated with outbound product movements, but actually extends to inbound product movements as well (Ballou 2007). The activities that take place in a warehouse begin with **receiving**, where the unloading of goods, document control, quality control and the possible modification of loading units take place to make them suitable for storage. Next, we move on to **warehousing**, where the loading units are assigned their location and physically located. Once the goods are stored, they may need to be moved to the **picking area**. At this point, we proceed to **order filling**, which includes picking, packing, order consolidation, completeness, accuracy and quality checks, and the modification of loading units for shipment. Finally, we come to **shipment**, structured in the grouping of the loading units by carrier and the loading of the means of transport (Casadio Strozzi & Sala, 2024).

These are the basic characteristics of logistics. Over time, changing consumer preferences and expectations, increasing globalisation, advances in communication technologies, the expansion

of activities to be handled and the influence of digital innovations have radically altered the way in which logistics operates.

If we consider the different industrial revolutions in chronological order, it is evident that each evolution of the production sector has had parallel effects on logistics processes (Timm and Lorig, 2015). In other words, the development of logistics closely follows industrial development. It is no coincidence that the growth path of logistics (Figure 8) is divided into four phases, just like the evolutionary process of industry (Galindo, 2016).

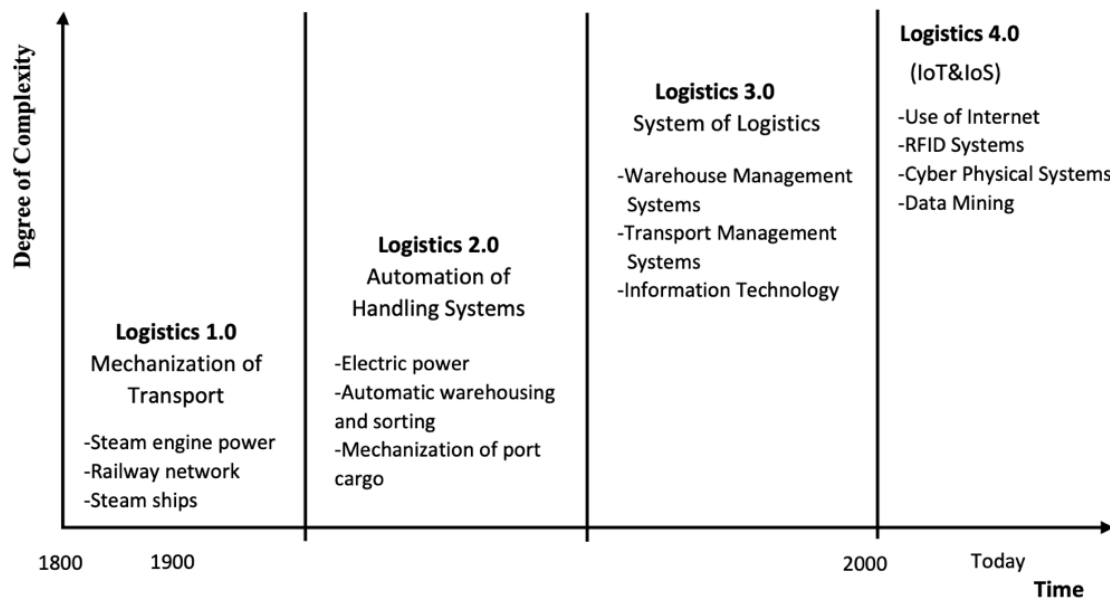


Figure 8 - Development Process of Logistics

Source: Paksoy, T., Koçhan, Ç., & Ali, S. S. (Eds.). (2021). Logistics 4.0: Digital Transformation of Supply Chain Management. CRC Press, p. 21.

The first phase (Logistics 1.0) was initiated by the mechanisation of transport in the late 19th and early 20th century. In fact, the first industrial revolution (Industry 1.0) characterised by the industrialisation of the steam engine occurred in parallel with this period. At the time, warehouses were conceived as rooms for finished products or raw materials, which were handled and transported manually by people (İyigün & Görçün, 2022). With these major changes, human and animal power were essentially replaced with distribution by sea or rail (Wang et al., 2016). Ships and trains equipped with steam engines became the main means of transport for the movement of goods and containers, leading to a significant growth in transport capacity, marking the beginning of the era of mass transport (Paksoy et al., 2021).

The second phase (Logistics 2.0) emerged in the 1960s with the automation of handling systems. During this period, the spread of electricity and the introduction of materials such as steel, copper and aluminium stimulated mass production techniques in the manufacturing

industry, while automated systems for loading, unloading, storage and sorting gradually replaced conventional warehouses. The presence of electricity in logistical processes made it possible to automatically place and retrieve products from the shelves, facilitating the replacement of manual forklifts with electric handling and transport vehicles (Wang et al. 2016). On the transport front, the advent of container ships redesigned cargo handling in ports, marking a further acceleration towards mechanisation and automation of logistics activities (Paksoy et al., 2021).

The third phase (Logistics 3.0) emerged in the 1980s with the spread of logistics management systems. In fact, the integration of computers and information technology (IT) initiated the third logistics evolution, leading to significant automation and systemisation of activities (Paksoy et al., 2021). In this context, software such as the WMS (Warehouse Management System) and the TMS (Transport Management System) have taken on a key role, capable of more accurately planning incoming processes, managing supplier demand and optimising the transport of the end product or raw materials (Galindo, 2016). In addition, this period is characterised by the use of automatic moving belts or electric forklifts in internal handling operations, while in some companies we find advanced robots that transport materials on predetermined routes (İyigün & Görçün, 2022).

The digital transformation of logistics processes, commonly referred to as ‘Logistics 4.0’, marks a crucial shift away from the traditional, ‘hardware-oriented’ approach towards an integrated, automated model based on IT platforms that exploit cyber-physical systems (CPS), Internet of Things (IoT), Data Mining (DM), RFID, sensors, GPS and cloud computing. This paradigm does not only innovate the technological infrastructure, but invests the entire organisational and management structure of the supply chain, from goods transportation to storage, distribution to packaging, and real-time tracking (Yilmaz and Duman, 2019; Timm and Lorig, 2015). In parallel, the prospect of intensive use of connectivity and Industry 4.0 principles, such as interoperability, information transparency, technical assistance and autonomous decision-making capacity (Horenberg, 2017), makes possible highly automated and coordinated workflows, capable of adapting quickly to changing market needs. From this perspective, the development of logistics 4.0 platforms offers a structured and ‘global’ response to the growing complexity of goods and information flows (Fernández-Villacañás, 2019a). New-generation logistics centres, known as ‘4.0 platforms’, take the form of intermodal hubs in which the integration of different modes of transport (road, rail, maritime, air) takes place in real time, exploiting advanced digital technologies and coordination based on shared data. This perspective is part of the broader context of the so-called ‘Global Sustainable Logistics’, which

aims to reconcile competitiveness and environmental, social and economic sustainability, in line with the sustainable development objectives defined by the main international organisations (Carter and Rogers 2008). Indeed, the wide spread of e-commerce and the need to reduce costs, errors and environmental impact drive towards distributed, flexible and connected value chains in open digital networks (Montreuil et al. 2010; Hofmann and Rüsch 2017). Newly designed logistics platforms perform the function of operational centres where transport, storage, distribution and ancillary services activities are concentrated, generating competitive advantages for companies and surrounding territories (Fernández-Villacañas 2018; Gajšek and Grzybowska 2016). Thanks to the sharing of technologies and infrastructures, such hubs enable optimisation of physical and information flows, reduce handling costs and create synergies between public and private operators. Their effectiveness is particularly evident in supporting omnichannel and synchromodality strategies (Payne et al. 2017), where the choice of the most efficient transport mode (road, rail or sea) is defined in real time, based on up-to-date information on traffic, demand and environmental constraints. Moreover, the lean and agile approach that characterises the most advanced supply chains is reinforced by the use of Data Mining and AI techniques, which are crucial to forecast demand, plan inventories, and coordinate production and distribution in order to reduce delays and inefficiencies (Çağlar 2014). In many cases, the evolution towards ‘Logistics Platforms 4.0’ grafts onto existing infrastructural nodes - e.g. ports, freight villages and airports - gradually transforming them into multifunctional hubs with high technological content (Mladenow et al. 2016). Particularly relevant is the concept of the ‘aerotropolis’, i.e. a new model of urban development in which the airport becomes the hub of an integrated system of logistical, technological and commercial services, capillary connected to the surrounding economic fabric and international traffic corridors (Fernández-Villacañas 2019b; Kasarda 2019). By facilitating the rapid exchange of people and goods, the aerotropolis is a candidate as a nerve centre for logistics 4.0 platforms, thanks to the possibility of integrating air transport services with road and rail modes, reducing delivery times and improving access to global markets. A further building block of this transformation is ‘urban logistics’ (Boudoin et al. 2014; Rodrigue and Dablanc 2020), which has the task of harmonising the distribution of loads in metropolitan contexts: on the one hand, the growing demand for fast and personalised deliveries fuels urban traffic, on the other hand, municipalities must protect the liveability of cities, reducing congestion, pollution and inefficiencies (Lagorio et al. 2016). The realisation of urban sorting hubs (city hubs) - related to 4.0 platforms - makes it possible to consolidate shipments and rationalise delivery routes, perhaps using electric or environmentally friendly vehicles. Joint planning, based on advanced

information systems and predictive algorithms, proves essential to balance the needs of users and logistics companies (Fernández-Villacañas 2019a; Stindt 2017). In this perspective, logistics 4.0 platforms fully fit into the framework of smart cities and sustainable development initiatives (Szymańska et al. 2017). The constant interconnection between devices and systems - made possible by IoT and CPS - enables smart urban services (such as real-time traffic management), while the massive generation and analysis of data (big data) support faster and more accurate decisions. At the same time, the standardisation of communication protocols and the sharing of information between public and private actors foster an intermodal ecosystem, in which logistics nodes, transport means and infrastructures talk to each other, ensuring the synchronisation of processes and a holistic view of the value chain (Fernández-Villacañas 2019b). In the future, a further evolution of this model could take the form of the ‘Physical Internet’ (Montreuil et al. 2010), which prefigures an open and global logistics system, based on standardised packaging formats and communication protocols, with the aim of minimising inefficiencies and maximising sustainability. Ultimately, the emergence of Logistics 4.0 and new logistics platforms, integrated with Industry 4.0, represents a coherent response to the challenges of an increasingly competitive, variable and environmentally and socially sensitive market (Hofmann and Rüsch 2017). The adoption of cyber-physical systems, the use of artificial intelligence algorithms and the synchronised planning of transport networks form the basis for automated, high-precision decision-making processes (Timm and Lorig, 2015). The ability to reduce costs and emissions while ensuring high standards of service becomes a key factor for the competitiveness of companies and the sustainable development of territories. These dynamics, enhanced by constant research and innovation, are already profoundly transforming both business models and organisational culture, pushing towards a ‘software-oriented’ logistics paradigm that, by combining operational efficiency and strategic vision, responds in an integrated way to the needs of the supply chain and the community (Göçmen and Erol 2018).

2. Artificial Intelligence in Logistics 4.0

Artificial Intelligence (AI) is now the center of gravity of Logistics 4.0. What was once a substantially reactive supply chain becomes a proactive system, capable of anticipating peaks in demand, dynamically orchestrating fleets and warehouses, identifying anomalies before they result in failures and modulating flows in order to reduce energy consumption and emissions. The most recent literature shows that, by integrating supervised machine learning for forecasting, deep learning for computer vision and reinforcement learning for sequential

resource management, companies can reduce forecasting errors, significantly improve punctuality indicators, improve logistics costs by 15%, inventory levels by 35%, and service levels by 65% (McKinsey, 2021). While AI enables hyper-performing logistics, it requires clean data infrastructures, advanced analytical skills and governance models that balance transparency, privacy and mitigation of decision-making biases. The challenges are clear: the quality of data often fragmented between partners, the need for explainability of models to comply with the new EU Regulation on AI, integration with legacy systems and, last but not least, the retraining of workforce skills towards roles of interpretation and algorithmic supervision. Yet the benefits far outweigh the initial costs: recent studies indicate that, thanks to digital twins and edge-AI platforms capable of processing information directly on board vehicles or sensors, it is possible to maintain operational continuity even in the absence of stable connectivity and drastically reduce decision-making latencies. An era of autonomous supply chains is thus emerging, in which logistics ecosystems do not simply react to events, but predict and model them, integrating considerations of economic efficiency with long-term ESG objectives. Starting from these premises, this chapter delves into the theoretical-methodological framework of AI applied to logistics, analyses the main empirical evidence and outlines the strategic implications for companies that intend to translate the predictive and prescriptive power of data into a lasting, sustainable and measurable competitive advantage.

2.1 Definition and Key Features

AI is a branch of computer science that aims to create intelligent machines capable of simulating human-like intelligence (Tang & Hai, 2021). It encompasses a diverse range of techniques and approaches that enable machines to perceive, learn, reason, and make decisions. It is a rather intangible and very complex concept. Broadly speaking, it can be conceived as a scientific discipline that deals with a range of information technologies derived from the processes by which humans perceive, process information and act on the outside world using the human nervous system and body (Przegalińska, 2019). AI uses information derived from various fields, such as biology, computer science, philosophy, logic and psychology, and has already found application in several areas, such as natural language processing, speech recognition, intelligent robots, automated demonstration of theorems and image processing (Zhang & Lu, 2021). Its methodology makes it possible to transfer aspects of human behaviour to machines and supports new forms of knowledge representation and systems capable of handling information in a structured and efficient form. Being inherently multidisciplinary, AI seeks to understand and perhaps replicate the enormous range of functions associated with the

human intellect, thus moving towards an ever more advanced technology (Brachman & Henig, 1988).

Historical evolution:

- **Phase 1 (1950-2010): The era of algorithmic innovations**

In the first phase, from the early 1950s to the early 2000s, the limits and progress of AI were strongly linked to innovation in algorithms (Wu et al., 2025). The theoretical roots go back to the work of Turing (1950) and the Dartmouth Conference (1956), which defined the goal of replicating human reasoning ability in machines. At the time, the lack of large data sets and considerable computing power relegated AI systems to projects focused on symbolic reasoning (e.g., expert systems such as DENDRAL or MYCIN) or early neural networks (Hopfield 1982; Rumelhart et al. 1986). Despite interest in ‘connectionism’, many initiatives stalled due to technical limitations - including unspecialised hardware and small data sets - until work such as LeCun’s on convolutional networks for digit recognition (LeCun et al. 1989) paved the way for ‘deep learning’.

- **Phase 2 (2010-2024): Computing revolution and ‘renaissance’ of deep learning**

Around 2012, AI underwent a major breakthrough when the availability of GPUs (Graphics Processing Units) became the main driver of results (Wu et al., 2025). AlexNet¹ (Krizhevsky et al. 2012) demonstrated how parallel GPU training of a deep network could far surpass previous computer vision methods. This period was characterised by the idea that ‘bigger is better’, as the growth of parameters in models and the extension of datasets dramatically improved performance. Deep neural networks conquered areas such as vision and natural language processing (Vaswani et al. 2017). The focus was on specialised hardware (GPUs, TPUs) and massive datasets. In the mid-2010s, the emergence of deep reinforcement learning made AI systems able to compete with humans in complex domains (Silver et al. 2016).

- **Phase 3 (2024 onwards): ‘data-centric’ paradigm**

Subsequently, the focus began to shift from mere computational advances to data quality and specialisation (Wu et al., 2025). The availability of clean, varied and contextual information became the real factor for improvement. The so-called ‘data-centric AI’ (Ng 2021) highlights the importance of refined processes for acquiring and curating datasets, reducing bias and expanding coverage. In parallel, reinforcement learning strategies have

¹ AlexNet, developed in 2012 by Alex Krizhevsky and Ilya Sutskever under the guidance of Geoffrey Hinton, was the breakthrough that popularized deep learning for computer vision: its paper, cited in over 130,000 publications as of 2023, decisively demonstrated the superiority of CNNs in automatic image analysis.

moved towards the management of more realistic environments (car racing simulators, self-driving simulators such as CARLA), while integration with robotics and control systems has paved the way for a deeper AI presence in physical contexts.

According to Wu et al., (2025) each of these phases is not completely separate from the others, but overlaps and complements each other, highlighting how the availability of algorithms, computational power and specific data has been the real driving factor from time to time. The shift from simple pattern recognisers to complex decision-making systems, up to autonomous robots and, perhaps in the future, intelligences capable of redefining their own goals, underlines the profound transformation taking place and opens up far-reaching ethical and regulatory questions (Wu et al., 2025).

The historical evolution of AI, from the earliest symbolic and connectionist studies to the current scenario dominated by deep learning, reinforcement learning and an increasing focus on data quality, has laid the foundations for four distinct generations of AI:

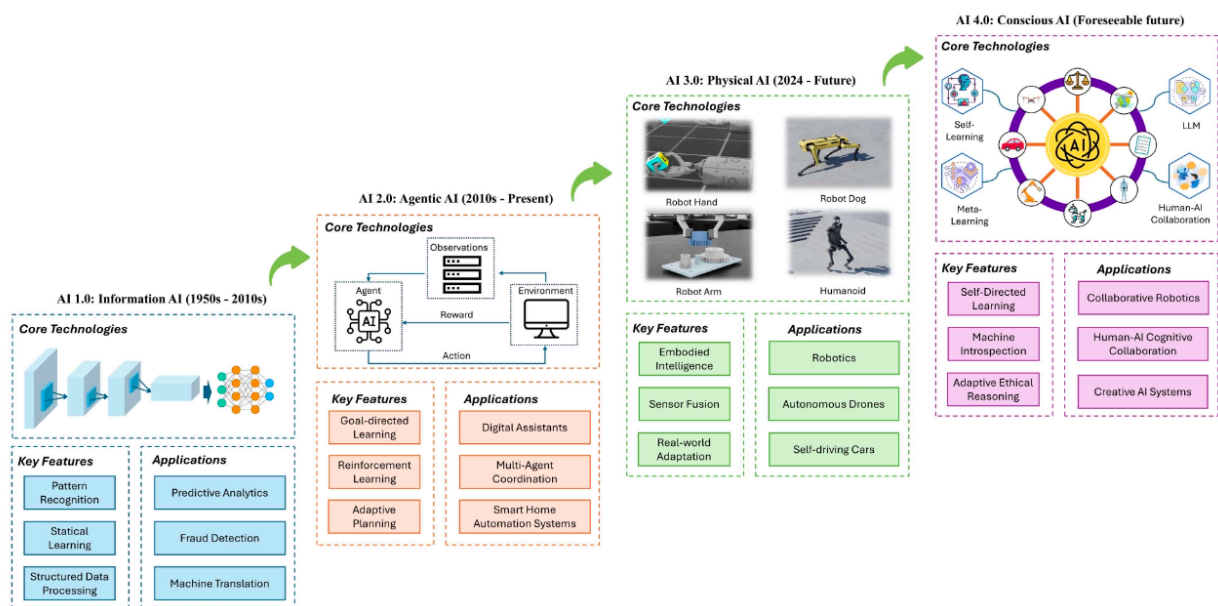


Figure 9 - The evolution of AI Generations from AI 1.0 to AI 4.0

Source: Wu, J., You, H., & Du, J. (2024). AI generations: From AI 1.0 to AI 4.0. University of Florida.

• AI 1.0: Information AI

‘Information AI’ includes systems that excel in pattern recognition and data analysis, such as computer vision methods (AlexNet) or language models based on relatively “superficial” architectures. These solutions, consolidated by decades of research on neural networks and statistical approaches (Wu et al., 2025), work well on static datasets, but lack true autonomy.

- **AI 2.0: Agentic AI**

The second generation, known as ‘Agentic AI’, emphasises the shift towards the ability to make decisions in dynamic environments, such as automatic trading software or real-time recommendation agents (Wu et al., 2025). Here, the impetus comes from reinforcement learning and autonomous planning: systems do not merely classify information, but interact with the (digital) environment and adapt their strategies. AlphaGo is an emblematic example of this (Silver et al. 2016).

- **AI 3.0: Physical AI**

‘Physical AI’ takes artificial intelligence beyond the purely virtual space by integrating it into robots, autonomous vehicles and physical devices (Wu et al., 2025). The acquisition of sensory data (cameras, LiDAR, proximity sensors) and the need to act promptly in the real world impose reliability and safety requirements. Examples include industrial assembly robots, autonomous drones and self-driving vehicles (Levine et al. 2018). Here the challenge lies in optimising computation and algorithms in the presence of noise, uncertainties, energy limitations and human interaction.

- **AI 4.0: Conscious AI**

The fourth generation, which to date is highly speculative, hypothesises systems with target self-management capabilities and, in an extreme form, even some form of ‘consciousness’ (Wu et al., 2025). Important topics include the necessity of strict “AI alignment” to guarantee that AI objectives and values continue to be consistent with human ones (Russell, 2019) and philosophical discussions over the nature of consciousness. Although the actualization of a “self-conscious” AI is yet hypothetical, the subject is pertinent to comprehend potential future ramifications with regard to governance, ethics, and accountability (Wu et al., 2025).

AI embraces many technologies, the two main ones being machine learning (ML) and deep learning (DL). Nowadays, intelligent systems offering AI capabilities often depend on ML. ML describes the ability of systems to obtain knowledge from training data of specific problems to simulate the analytical model building technique and associated problem solving (Kristian, 2018). AI and ML are becoming the main and best problem-solving methodologies in various fields of industry and research, particularly due to the recent triumph of DL (Jordan & Mitchell, 2015). DL is the subset of ML and ML is the subset of AI, as can be seen in Figure 10. If a higher level of detail is desired, have a look at Figure 11.

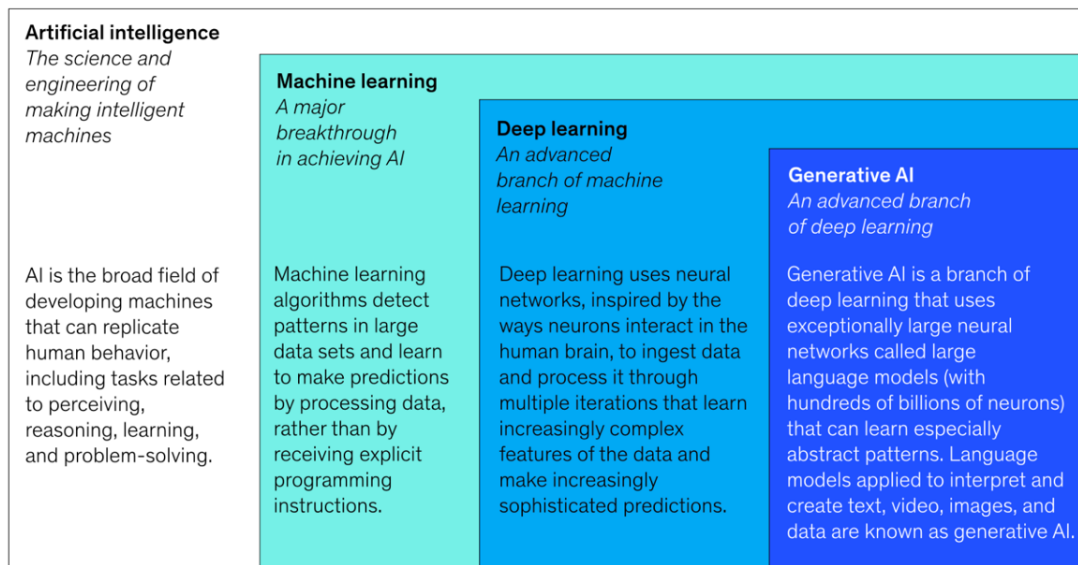


Figure 10 - AI components

Source: McKinsey & Company. (2024, April 3). What is AI (artificial intelligence)? [Illustration] (p.3).

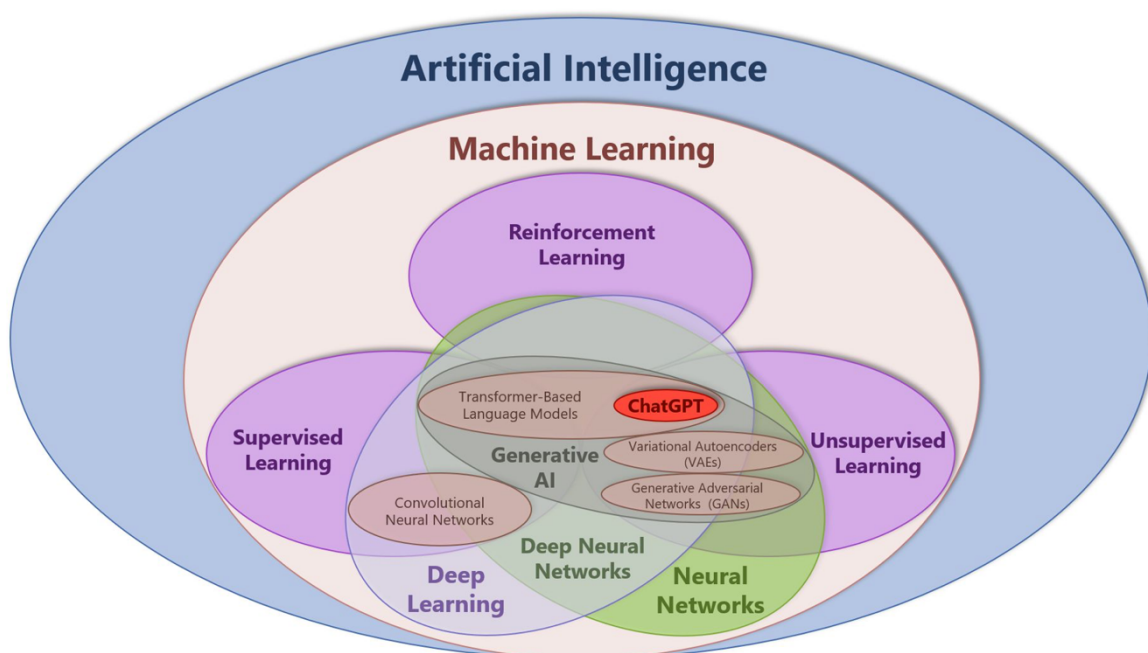


Figure 11 - Building blocks of AI

Source: Jeff Winter

Machine learning (ML) is the idea of developing computer systems that are capable of improving their performance autonomously through experience, ranking today as one of the fastest growing technologies at the intersection of statistics and computer science, and representing a central element of data science and AI. The extensive application of machine learning algorithms in data-intensive environments indicates their relevance in many different sectors, e.g., manufacturing, education, public safety, healthcare, marketing, and finance

(Dietterich, 1997). These techniques are also crucial for handling next-generation problems like natural language processing, robotic control, speech recognition, facial recognition, character understanding, database exploration, gaming, and medical data analysis (Raj & Kos, 2022).

Deep Learning (DL) is a sub-category of ML. It is a technique for instructing computers to do something that comes naturally to human beings, namely to understand by example. In DL, a computer model performs classification tasks directly from text, sound or images. DL models have the potential to sometimes even surpass human performance, being able to achieve greater accuracy. Computer vision, data mining, supercomputers, fraud detection, natural language processing, customer relationship management systems, human activity recognition and autonomous vehicles (Raj & Kos, 2022) are all possible fields of application for DL technology. Figure 12 presents the differences between the operating principles of ML and DL. It shows that feature extraction and classification are two different steps in ML, whereas in DL they occur together in one step.

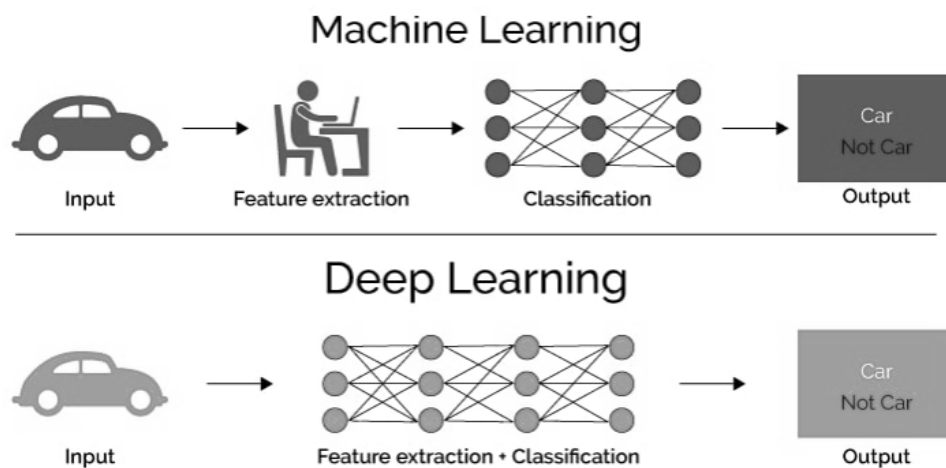


Figure 12 - Difference between machine learning and deep learning

Source: Oppermann, A. (2019). What is deep learning and how does it work. Towards Data Science.

Artificial Neural Networks (ANNs) represent the fundamental algorithmic structure on which deep learning is based. ANNs represent a set of learning models inspired by the functioning of the human brain, in which neurons (units) are interconnected by means of synaptic weights (Rathore, 2016). The basic structure of ANNs is in fact based on the idea of elementary units (neurons) organised into an input layer (input), one or more hidden layers and an output layer (output), as illustrated by various control architectures (Filho, Cabral, & Soares, 1998).

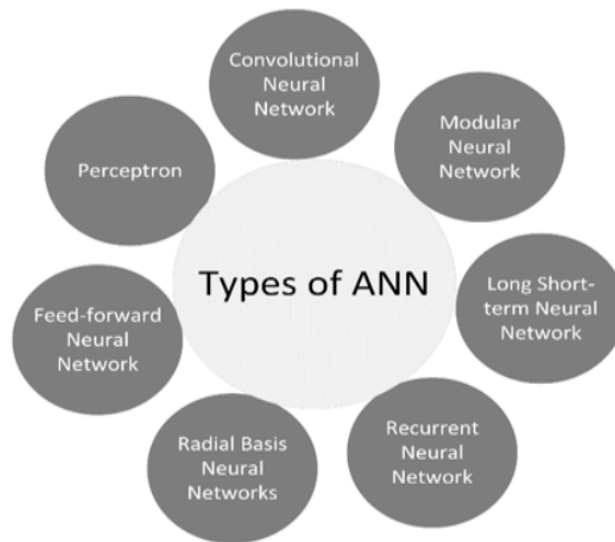


Figure 13 - Major classification of artificial neural networks

Source: Fernandez, C. M., Alves, J., Gaspar, P. D., Lima, T. M. & Silva, P. D. (2023). Innovative processes in smart packaging: A systematic review. *Journal of the Science of Food and Agriculture*, 103(3), 986–1003.

Of the various types of ANNs, Perceptrons constitute the simplest and most historically relevant form, having initiated the systematic study of artificial networks due to their inherent classification and learning properties (Singh & Banerjee, 2019). Multilayer Perceptrons (or ‘feed-forward neural networks’) are distinguished by the propagation of information through successive, loop-free layers; Recurrent Neural Networks (RNNs), on the other hand, include recurrent connections that make them particularly effective in modelling sequential data; Modular Neural Networks, which are rapidly expanding, adopt learning strategies and task decomposition through specialised modules. Convolutional neural networks (CNNs) are central to deep learning and are widely used in fields such as computer vision and natural language processing. We find its applications in areas such as autonomous vehicles or facial recognition systems (Li et al., 2021). Radial-based neural networks (RNNs), derived from function approximation, have an excellent capacity for fast training and local response (Dash et al., 2016). Finally, Long Short-Term Memory (LSTM), conceived as a variant of RNNs, possess cells with multiple memory states and are exploited for a wide range of recognition, prediction and sequence analysis tasks (Smagulova & James, 2019).

2.2 Artificial Intelligence (AI) in Logistics

Artificial Intelligence has become the reason for the revolution of many industries; among them, the leading position belongs to logistics. Logistics, in the modern business world, includes many activities and processes requiring urgent decisions and solving various problems right on the spot. AI can predict outcomes and then optimize the processes. This potentially

very powerful tool might be in the position to transform complex processes and standardize them. AI models can actually learn from data and hence adapting it to specific business needs becomes far easier for a company (Woschank, Rauch, & Zsifkovits, 2020).

In the rapidly evolving logistics landscape, AI plays a role as a process ‘transformer’, providing new levels of efficiency and resilience. The motivations behind the need for improvement are manifold:

I. Increasing global complexity

Modern supply chains often extend on a global scale, involving a great number of suppliers, distributors and customers. This makes flow management an extremely complex task. In this scenario, AI offers tools capable of integrating different variables (such as transport costs, delivery times and customs regulations) in real time to elaborate dynamic and flexible plans. Several studies (Ejjami & Boussalham, 2024) show how machine learning algorithms are able to integrate large volumes of data from the field (via Internet of Things, sensors, GPS, etc.) to adapt shipping plans in response to unexpected events or sudden changes in demand. Furthermore, some studies report that in case of extraordinary events, AI’s predictive ability allows for a very quick switch to alternative routes or secondary distribution centres, leading to an overall increase in system resilience (Boute & Udenio, 2021). This flexibility is crucial in a global marketplace characterised by volatility and uncertainty, as evidenced by the growth of geopolitical crises, extreme weather phenomena and the rise of e-commerce (Ejjami & Boussalham, 2024). In addition, AI models help to improve end-to-end traceability, a key factor in preventing counterfeiting and inefficiencies, and in providing greater transparency to consumers (Chen et al., 2021).

II. Increased competitive pressure and reduced margins

The exponential increase of online orders and the expectation of just-in-time deliveries squeeze the operating margins of logistics companies (Belhadi et al., 2024). In today’s environment, companies are faced with rising costs (fuel, maintenance) while having to offer competitive rates and innovative services (e.g. same-day delivery). Through the use of sophisticated predictive models applied to different time horizons, AI helps to reduce the tensions arising from market competition.

III. Need for greater reactivity and continuous adaptation

Demand volatility and sudden changes in trends (e.g. regulatory changes, health crises, sudden changes in consumer preferences) require responsive supply chains (Singh, 2023). In this context, AI is certainly a tool that helps companies in the logistics sector to increase

this responsiveness by enabling them to constantly process vast amounts of data (e.g. sales, inventory, traffic and weather data) in order to be able to redefine delivery plans in real time if necessary (Xia et al., 2020; Javaid et al., 2022).

2.2.1 Fields of application

The scientific and professional literature has highlighted how AI is successfully applied in many areas of logistics. In specialized literature, it is now common to distinguish four AI systems, each of which finds peculiar applications in the logistics field: supervised AI, unsupervised AI, machine learning-based AI and reinforcement-based AI. Supervised AI is based on labeled data and is particularly effective for predictive activities like demand estimation, distribution route optimization or dynamic calculation of delivery times. Unsupervised AI, on the contrary, operates on datasets without predefined labels and lends itself to the recognition of hidden patterns. Clustering and dimensionality reduction techniques are used, for example, to segment customers according to purchasing behavior or to identify anomalies in warehouse flows. In a context characterized by increasing demand volatility, these features allow to identify micro-trends that are difficult to detect with traditional methods, favoring the customization of services and the improvement of operational efficiency (Ramirez-Asis et al., 2022). Alongside these two paradigms, there is AI based on machine learning in the broad sense, which acts as a methodological “glue”: regression algorithms, classification, time series and ensemble methods are integrated into Warehouse Management Systems (WMS), fleet management platforms and management dashboards to support tactical and strategic decisions. Unlike classic deterministic models, machine learning is able to update itself incrementally as new IoT data flows into corporate data lakes, ensuring an always up-to-date view of the logistics network. Finally, reinforcement-based artificial intelligence stands out for its ability to “learn by doing”: an agent explores the logistics environment (physical or simulated) and receives rewards or penalties based on the results obtained (Ramirez-Asis et al., 2022). This logic finds application, among other things, in the real-time control of autonomous handling vehicles, in the dynamic definition of stock levels and in the multi-objective optimization of the transport budget. The continuous feedback element, characteristic of reinforcement learning, is valuable in complex scenarios where operating conditions change rapidly as in the case of e-commerce distribution centers during seasonal peaks. The main application areas of AI as a whole will be analyzed in detail later in the chapter. A detailed breakdown can be seen in Figure 14.

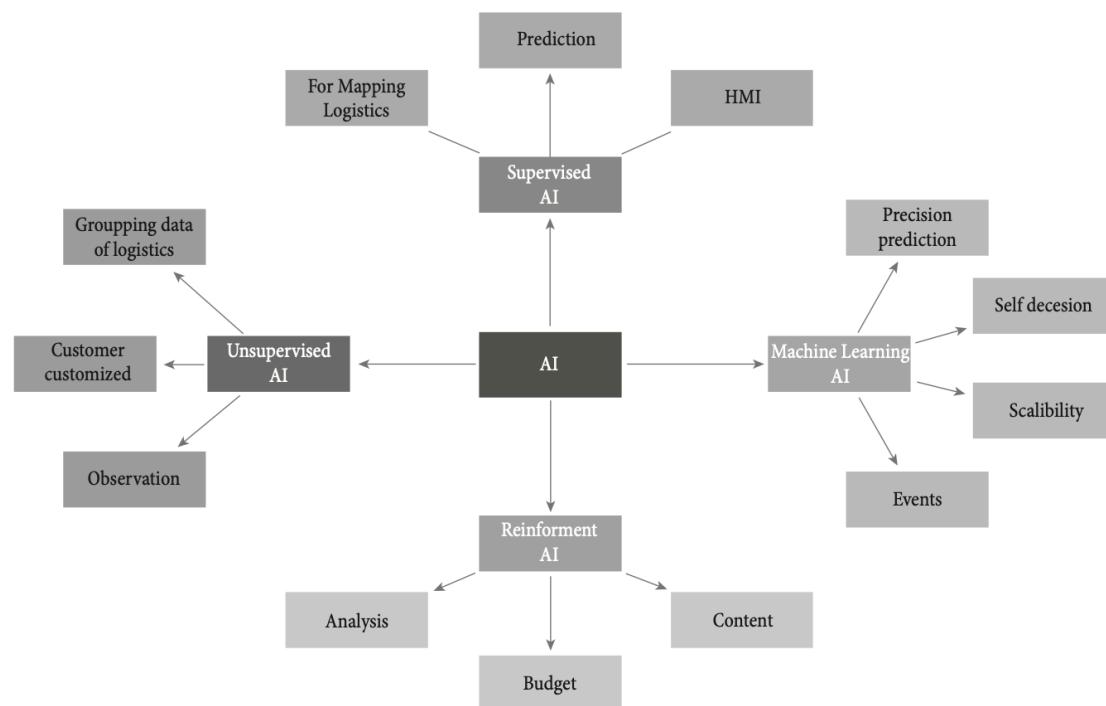


Figure 14 - Use of the AI system in different parts of logistics

Source: Boorová, B., Mijušković, V. M., Aćimović, S., & Đurđić, D. (2024). Application of artificial intelligence in Logistics 4.0: DHL case study analysis. *Economics of Enterprise*, 29, 292–304.

Below we delve into five key domains: Demand Forecasting, Route Optimization, Robotics, Computer Vision and Gen AI.

2.2.1.1 Demand Forecasting

Demand forecasting has always been one of the most critical activities for logistics management, because it directly affects procurement decisions, inventory allocation, production planning and transport choices. However, “classic” statistical methods, based on historical series and the assumption of relatively stable markets, are increasingly less effective in contexts characterized by short product life cycles, aggressive promotions and continuous exogenous shocks (Begum et al., 2024). The digitalization of the supply chain and the explosion of data from IoT sensors, e-commerce platforms and social media have therefore favored the adoption of AI techniques capable of learning in real time from heterogeneous sources and modeling highly non-linear relationships (Priore et al., 2018). Within the vast AI panorama, supervised learning algorithms are the first piece applied to logistics. They range from linear regression – which is still useful when the relationship between the independent and dependent variable is substantially linear (Ye et al., 2014) – to ensemble models such as Random Forest, which combine tens or hundreds of decision trees trained on different subsamples of the dataset to reduce variance and bias, returning robust forecasts even in the

presence of strong noise (Vairagade et al., 2019). Also boosting techniques, such as gradient boosting machine, further improve precision by iteratively correcting the errors of the previous model (Perera et al., 2019). Many case studies, particularly in retail and manufacturing, show consistent reductions in forecast errors compared to both traditional methods and single decision trees (Purnamasari et al., 2023). When seasonality is complex or demand is affected by long latency periods, deep learning algorithms offer even superior performance. Recurrent neural networks (RNN) and, above all, Long Short-Term Memory (LSTM) are able to “memorize” long-term temporal dependencies and adapt to multidimensional datasets that include meteorological variables, macroeconomic indicators and sentiment extracted from social media (Sukolkit et al., 2024). Combining LSTMs with statistical models such as ARIMA² resulted in the development and implementation of hybrid techniques. These techniques are capable of capturing both linear and nonlinear components of time series, significantly reducing the mean absolute percentage error (Perera et al., 2020). Along with predictive models, unsupervised learning approaches such as k-means clustering are beneficial for segmenting customers, channels, or product categories based on comparable demand patterns (Mani et al., 2017). The combined adoption of segmentation and forecasting allows to customize reordering parameters, improving the overall efficiency of the distribution network. In scenarios where labeled data is scarce (typical of new markets or newly launched products) semi-supervised approaches are gaining ground, exploiting a small subset of validated data to guide the discovery of patterns in the large volume of unlabeled data (Abolghasemi et al., 2015). Recent literature also emphasises the role of *fuzzy logic*³ as a technique for modelling uncertainty and common approximations in logistics processes (Chaowai & Chutima, 2024). The combination of fuzzy rules with AI models allows for the incorporation of specialised knowledge, while keeping the ability to learn from data. The result is a more flexible framework that takes into account quality defects, delivery delays and lead time variability, elements often overlooked by more “rigid” models. On the operational level, companies that have implemented AI solutions for demand forecasting report tangible benefits: reduced inventory levels, fewer stockouts, and more accurate planning of delivery routes (Diabat &

² ARIMA (AutoRegressive Integrated Moving Average) is a statistical model for time series that combines three components: autoregression (AR), which uses a finite number of past values; integration (I), which differencing the series to make it stationary; and moving average (MA), which models the error as a linear combination of past errors.

³ Fuzzy logic extends classical Boolean logic by replacing the “true/false” values with a continuous interval between 0 and 1, thus indicating the degree of truth of a statement. Through membership functions, linguistic rules of the type “IF ... THEN” and a subsequent “defuzzification”, it translates qualitative concepts (for example “high demand” or “long lead-time”) into numerical values that mathematical models can use to provide more realistic decisions that adhere to operational complexity.

Deskoore, 2016). Thanks to IoT connectivity, forecasts can be updated virtually in real time: sales data from cash registers, signals from beacons in the warehouse, or environmental parameters collected by sensors along the cold chain flow into the models, which re-optimize production and distribution logistics with very rapid feedback loops (Perera et al., 2019). However, significant challenges remain. Data quality which is often heterogeneous in format, frequency, and granularity, strongly affects model performance (Duan et al., 2019). The lack of transparency in deep learning architectures generates resistance in sectors subject to stringent auditability requirements, where the “black box” must be justified at a managerial and regulatory level (Raghupathi & Raghupathi, 2014). Added to this are the significant costs of hardware infrastructure, cloud, and specialized skills, which represent a particularly burdensome obstacle for SMEs (Albergaria & Jabbour, 2020). Finally, ethical issues such as bias in training data and privacy protection require adequate governance mechanisms (Zhang et al., 2020). Despite these critical issues, the evolution of AI towards increasingly scalable models leads to predict an expansion of their use in logistics. Integration with emerging technologies such as edge computing will reduce latencies, enabling “at-the-edge” forecasts and decisions directly on IoT devices. In parallel, the expansion of multi-modality datasets (text, images, process signals) will provide further fertile ground for advanced algorithms capable of capturing previously invisible nuances of demand. In this framework, AI does not replace the strategic role of the logistics planner, but amplifies their ability to interpret complex scenarios and act promptly across the entire supply network.

2.2.1.2 Route Optimization

Transportation route optimization is a strategic aspect in logistics management, as it heavily impacts both operating costs and the level of service offered to customers. In today’s context, characterized by continuous demand variability, unpredictable weather phenomena and increasing road congestion, traditional planning methods (such as deterministic approaches to the “Travelling Salesman Problem”⁴ and the “Vehicle Routing Problem”⁵) highlight strong limitations: in addition to requiring very high computation times, they are unable to dynamically update the solutions (Vaka, 2024). Faced with this growing complexity, the recent evolution of AI techniques, and in particular the use of large learning models (large AI models), offers innovative perspectives to make the routing process more flexible, adaptive and precise

⁴ TSP is a classic optimization challenge that seeks to find the shortest possible route that visits a set of locations exactly once and returns to the starting location.

⁵ VRP is a generic name given to a whole class of problems concerning the optimal design of routes to be used by a fleet of vehicles to serve a set of customers.

(Ping et al., 2024). Machine learning (ML) applications are now the cornerstone of predictive routing: algorithms such as gradient boosting, random forests and neural networks (including RNNs) learn from historical data – traffic patterns, delivery windows, road network morphology, weather variables – and anticipate bottlenecks before such events occur. A delivery company can then schedule shipments in less crowded time slots or preemptively change routes in the event of heavy rain, for example, resulting in improved punctuality and reduced emissions. Experiments by multinational operators such as DHL and FedEx have proved the practical success of this technology, having recorded significant reductions in delays and operating costs thanks to continuously self-learning ML systems (Li, Zhuang, Yang, Lu, & Xu, 2024). When environmental uncertainty increases, reinforcement learning (RL) models extend forecasting capabilities with an online adaptation component. In a classic *Markov Decision Process*⁶ scheme, the “state” includes the vehicle’s current position, completed stages, capacity constraints, and even traffic conditions or warehouse opening times (Yarlagadda, 2024). In order to choose the action, that is the next destination, the AI agent maximises a reward function that penalises wasted kilometres and delays and rewards fuel efficiency and punctuality (Ejjami & Boussalham, 2024). A good example is UPS with ORION. It is a platform which can learn from millions of simulations and update routes in near real time, saving millions of miles traveled each year. Adopting multi-agent RL models similar benefits can emerge. By coordinating entire fleets, these models ensure constrained time frames are met in areas with extremely high delivery density while also removing bottlenecks at sorting centres. When real-time data streams (such as those from IoT sensors) are included, the power of ML and RL is further enhanced as this data is immediately translated into route recalculations (Li, Zhuang, Yang, Lu, & Xu, 2024). Hybrid models – predictive in the long term and reactive in the short term – thus allow strategic planning and tactical adaptability to be combined, avoiding, for example, the simultaneous blocking of multiple vans in the same area at risk of congestion. The use of intelligent maps enriched with details on one-way streets, pedestrian zones or no-turn zones makes it easier to choose optimal loading zones and reduces the time drivers spend looking for parking, especially in high-density contexts. The use of AI in route optimisation goes beyond just figuring out the shortest path. In addition, it makes it

⁶ A Markov Decision Process (MDP), used in AI and reinforcement learning, describes the agent–environment interaction as a chain of states s , actions a , and rewards r : the agent, in state s_t , selects an action a_t , the environment returns a reward r_{t+1} and transitions to a new state s_{t+1} according to a probability distribution $P(s_{t+1} | s_t, a_t)$ that depends only on the current state (Markov property). The goal is to find a policy that maximizes the expected sum of future rewards, i.e., the overall return of the agent’s behaviour.

possible to assign drivers and vehicles in the most efficient manner, reducing wasted kilometres and matching loads to actual warehouse space availability. Moreover, there is a major environmental impact: cutting the route traveled lowers CO₂ emissions and fuel costs, supporting the sustainability and ESG goals that are becoming more and more important in corporate policies (Ejjami & Boussalham, 2024). Empirical analyses show drops of 10–15% in total transportation costs and decreases of around 15% in average delivery times (Ping et al., 2024). Anyway, this potential is not free from critical issues: the computational complexity and the need for a huge amount of “clean” and constantly updated data constitute non-trivial obstacles. Furthermore, the transparency of AI decisions and the management of possible biases (for example, in the preferential assignment of a certain sorting center) remain open questions. Nonetheless, the direction taken by the logistics industry is now clear: AI, integrated with IoT sensors and cloud data analytics platforms, represents the key to logistics 4.0. The result is a more resilient, sustainable logistics ecosystem that can meet increasingly stringent service standards (Li et al., 2024; Ping et al., 2024).

2.2.1.3 Robotics

The integration of robotics and Artificial Intelligence is generating a sea change in the industrial and manufacturing field, rewriting traditional definitions of operational efficiency, accuracy and safety (Khang, Hajimahmud et al., 2024). This is not just a technological advancement, but a true paradigm shift with implications ranging from risk management and complex decision-making processes to the automation of repetitive tasks. This transformation is particularly evident in the logistics sector, where AI-enabled robots are revolutionizing activities like order-picking, packaging, sorting and also last-mile delivery (Javaid et al., 2022). In parallel, the explosion of e-commerce has significantly increased the volume of goods transported on a daily basis, leading consumers to demand faster and more convenient deliveries (Simic et al., 2023). The adoption of intelligent robots marks a turning point in meeting the new challenging needs of customers. Indeed, it has been shown that autonomous electric vehicles, for example, are reducing the need for manpower, enabling a 25-35% increase in successfully completed daily deliveries alone, in the face of growing demand for advanced decision-making processes for robotic navigation (Wang et al., 2018). Thanks to these solutions, autonomous robots can predict delivery times of autonomous electric vehicles, thus drastically reducing errors and delays (Simic et al., 2023). These recent developments underscore the key role of AI in increasing trust in the use of robots, based on their ability to make systems safer, more reliable and able to handle the high level of complexity inherent in

operational environments (Kiangala & Wang, 2022). Traditionally, robots were considered as simple machines resulting from mechanical or electronic engineering, with a “bottom-up” approach that emphasised hardware and sensorimotor functions (Oloff et al., 2020). With the advent of artificial intelligence systems, we have witnessed an expansion of robotic capabilities. One example is the reduction of picking errors in warehouses, where the adoption of radio frequency identification (RFID) has had a considerable impact on the process (Ceyhun, 2020). RFID tag embed unique identities which are read and transmitted via radio to a nearby reader, enabling to localize and track with precision the movements of robots or the goods position (Confidex, 2023). One notable example is Confidex, a company that has developed chips that can resist to various chemicals, intense washing and high temperatures to make automation compatible with the entire product life cycle (Confidex, 2023). However, there are some critical issues. Tags can get damaged, and managing and updating search tables (containing coordinates, routes or geographical positions) can be challenging (Oloff et al., 2020). In the face of these limitations, computer vision (which will be discussed in detail below), emerges as a valuable alternative or complement, acting as the main system for navigation and cargo recognition (Dohrmann, Pitcher, & Kamdar, 2024). AI technologies that form the core of modern robotic systems include machine learning, computer vision, and natural language processing, each with its own strategic role. For what concerns machine learning, supervised learning methods improve the ability of robots to predict and optimize specific tasks, since training on labelled data allows them to provide precise indications on correct actions or configurations (Yadav B.R., 2024). Equally important is also the unsupervised learning, which allows to analyse large amounts of unlabelled data, identify unexpected patterns or anomalies, thus leading robots to become more adaptive in facing such unexpected circumstances (Dwivedi et al., 2019). Of particular significance is also the reinforcement learning, allowing autonomous systems to make decisions according to feedback from the environment, iteratively adjusting control strategy and playing a critical role for navigation, object manipulation and solving complex problems in real time (Cioffi et al., 2020). On the computer vision side, objects recognition and detection algorithms allow robots to identify specific elements, classify them with precision and manage procedures like assembly or sorting (Cioffi et al., 2020). Furthermore, pose estimation and tracking techniques allow to evaluate of the orientation and position of objects in space, favouring an accurate manipulation in sectors demanding high levels of accuracy. Because of these advances, applications of AI-powered robotics extend to multiple fields:

- In warehouses, these robots automate picking, packing and sorting operations, reducing the use of manpower and increasing efficiency at the same time;
- In the transport of materials, the use of autonomous mobile robots, capable of adapting their routes based on obstacles or changes, improves productivity in factories and warehouses;
- In delivery services, these devices can move in urban environments or in company complexes to distribute goods directly to recipients, optimizing the route and minimizing delays (Yadav B.R., 2024; Cioffi et al., 2020).

AI-driven control systems are the very basis of autonomous robots, as they enable them to tackle complex tasks and adapt to variable and unpredictable operating conditions (Yadav A.B., 2024). In defining such systems, a crucial aspect is represented by control architectures, which establish how robots process information, plan their actions and perform specific operations (Dwivedi et al., 2019). On the one hand, there are reactive approaches, which favour immediate responses to sensory stimuli and are based on machine learning algorithms capable of rapidly analysing previous experience, thus allowing them to react promptly to rapid changes in the environment (Yadav A.B., 2024). On the other hand, there are deliberative approaches, which involve more in-depth planning oriented towards the achievement of long-term goals, often supported by techniques such as the use of decision trees and models based on symbolic reasoning. In many cases, however, hybrid control structures are preferred, as they are capable of combining the decision-making speed typical of reactive approaches with the analytical capacity and long-term strategic projection typical of deliberative ones (Dwivedi et al., 2019). AI plays a key role in this context, integrating real-time sensor data with high-level planning, ensuring that the robotic agent can simultaneously handle both immediate contingency needs and more strategic challenges. In terms of actual algorithms, a very important aspect is represented by the methodologies designed to govern the physical movements of the robot and regulate its interaction with the surrounding environment. PID (Proportional-Integral-Derivative) controllers are a traditional solution, widely adopted for low-level control in tasks such as maintaining speed, position or orientation. Although they are known for their simplicity and effectiveness, they find a further evolution when they are combined with AI features that allow the dynamic optimization of the parameters, in order to make them more robust in the face of unexpected variations (Cioffi et al., 2020). A second important paradigm is represented by Model Predictive Control (MPC), based on the principle of predicting the future states of the system in a certain time horizon and deriving, for each interval, the optimal control action. This prediction is performed in real time, allowing to respect constraints and guarantee results

close to the optimal even in highly dynamic environments. The use of machine learning techniques, in the form of neural network models or other prediction tools, also allows to improve both the precision of the predictions and the speed with which the MPC solver is able to operate (Yadav B.R., 2024). A third fundamental axis in the construction of advanced control systems is Reinforcement Learning. With this technique, the robot does not simply follow instructions or execute decisions made by a central planner, but actively interacts with the environment, learning optimal control policies from feedback obtained in the form of rewards or penalties. Algorithms such as Q-learning or policy gradient methods allow defining lines of conduct that adapt to complex scenarios, including those characterized by uncertainty or sudden changes. With the advent of Deep Reinforcement Learning (DRL), made possible by deep neural networks, the ability to manage large state and action spaces has expanded, favoring applications in which the robot must perform complex evaluations, such as path planning in congested environments or the precise manipulation of objects with irregular edges (Yadav B.R., 2024). In practice, designing an AI-based control system requires addressing some cross-cutting challenges that affect the robustness and reliability of the robot (Dwivedi et al., 2019). Among these, the need to ensure real-time processing, so as to process sensor data, decide and act in a synchronized way even within very narrow time windows; to maintain stable and disturbance-tolerant behavior, so that the system continues to operate reliably even in the presence of noise, interference or imperfect data; and to be able to deal with unexpected or extreme situations, such as unmapped obstacles or component failures, thanks to techniques ranging from anomaly detection to online learning (Cioffi et al., 2020). The integration between AI control architectures and algorithms, therefore, allows to significantly increase the autonomy, precision and adaptability of robots, with important implications for their applicability in varied and turbulent contexts. Looking ahead, these advances push the boundaries of automation and robotic innovation, opening up scenarios where intelligent, adaptive machines can work alongside humans with unprecedented levels of efficiency and reliability (Yadav A. B., 2024).

2.2.1.4 Computer Vision

Nowadays, thanks to technological advances in 3D reconstruction, depth perception, and the interpretation of dark and blurry images, computer vision offers a wide range of new supply chain opportunities.

AI provides computers with the capability of “thinking”, while computer vision allows them to “observe and understand”. Computer vision uses cameras to capture images or videos and

then applies AI algorithms to analyse the data extracted from these digital contents. Rudimentary visual AI systems are trained to simply distinguish one object from another. More advanced versions of these systems, on the other hand, are able to track objects from multiple viewpoints, learn autonomously and, in recent upgrades, make predictions through pattern recognition. Computer vision trend developed in conjunction with advances in deep machine learning, taking advantage of the increasing quality and decreasing cost of recording devices. There are several factors driving the adoption of computer vision technology, including the growing need for workflow automation and optimisation in several sectors (Dohrmann, Pitcher, & Kamdar, 2024).

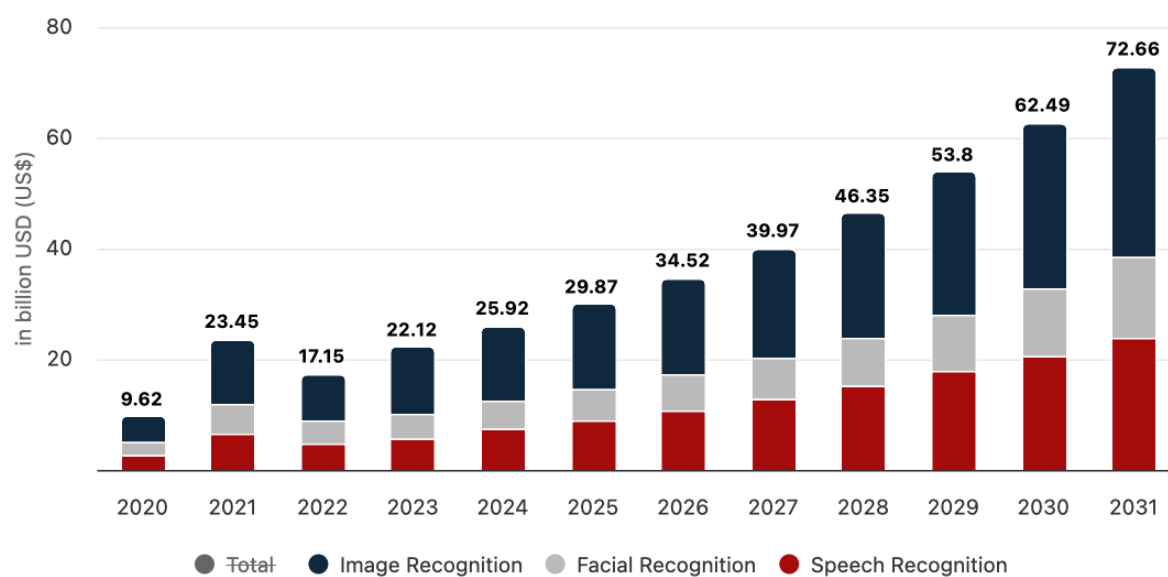
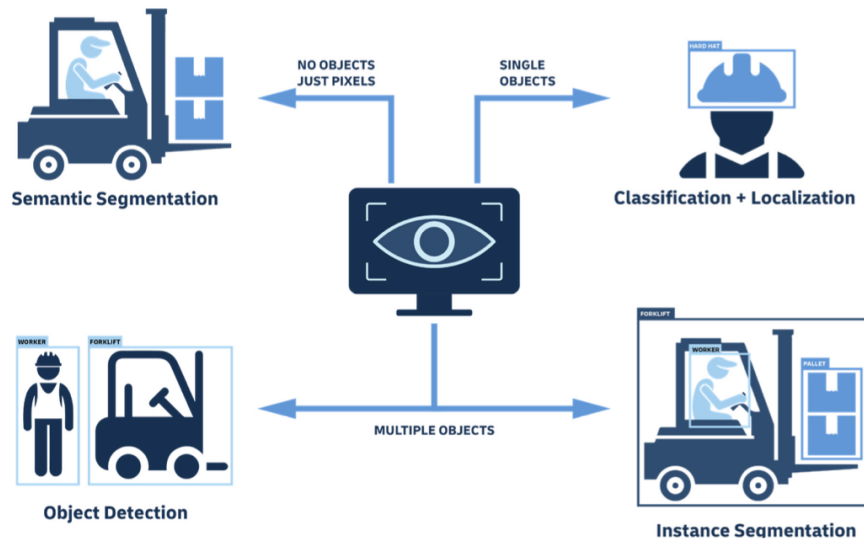


Figure 15 - Computer Vision Market Size Worldwide (in billion USD(US\$))

Source: Statista. (2024). Computer Vision – Worldwide Market Outlook. Statista Market Insights.

In 2024, the global computer vision market was valued at over US\$ 25.92 billion and is projected to expand at a compound yearly growth rate of 15,96% by 2031, driven by ongoing advancements in AI, vision systems, and computer processing (Statista, 2024). Computer vision accuracy rates for identifying and classifying objects increased from 50% to 99% in less than a decade. Moreover, further integration of AI, automated machine learning, edge computing, Internet of Things, and other technologies will propel future adoption. Within the next five years, computer vision will be widely used in logistics operations, and a lot of new applications are probably going to appear. By enabling safer, more sustainable operations and more automated, efficient procedures, this technology will support and promote future logistics success (Dohrmann, Pitcher, & Kamdar, 2024).



Graphic source: **Packt Publishing (2021): Computer Vision**

Figure 16 - Classification & segmentation of Computer Vision

Source: DHL. (2024). *Logistics trend radar 7.0: Your guide to innovation in logistics.*

Computer vision systems develop their capabilities repeatedly analysing wide range of high quality visual data. Through this iterative process, they learn to identify different images and distinguish even the smallest variations. To this end, two different technologies are adopted: deep learning and convolutional neural network. Deep learning uses algorithms and artificial neural networks able to improve themselves to continuously extract new information from visual input. On the other hand, convolutional neural network decomposes images into labelled segments and applies mathematical operations to these segments to refine the accuracy of the prediction over several iterations. In logistics contexts, these segmentation approaches can be extended to instance-level techniques that differentiate one parcel or pallet from another, even if they belong to the same category (Naumann et al., 2020).

Today computer vision systems are used in different ways. The most common application is image classification: the system sees an image and predicts that it belongs to a certain class. Another well-known application is object detection, also known as machine vision: the system not only classifies an image but also takes note of its aspect (tabulation). Once an object has been identified, it can be tracked: object tracking is often done through the use of sequential images and videos. Yet another application of computer vision systems is content-based image recovery to increase the precision of digital image search and recovery (Dohrmann, Pitcher, & Kamdar, 2024). Figure 17 shows the various processes that computer vision images undergo.

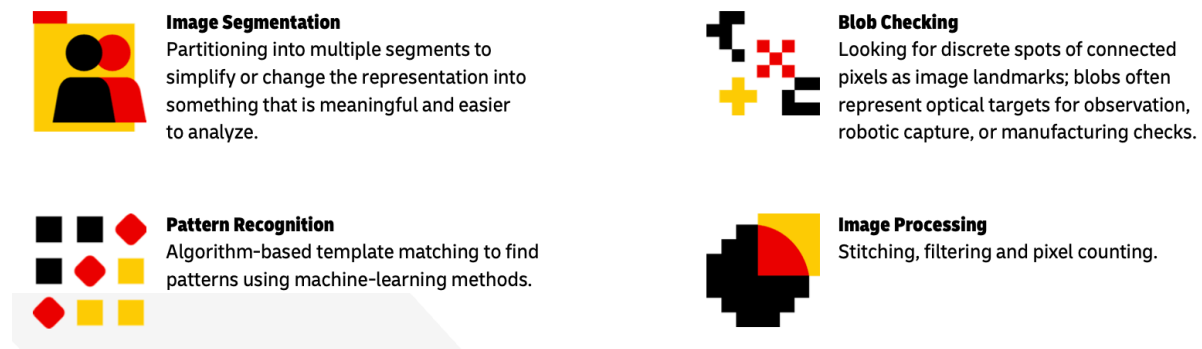


Figure 17 - Image Processing Stages in Computer Vision

Source: DHL Trend Research. AI-driven computer vision: A DHL perspective on the impact of computer vision in logistics.

Already today, computer vision is proving its worth in a vast range of applications that transform everyday logistics operations:

- Health and Safety Applications
- People and Operations Applications
- Maintenance Applications
- Asset Management Applications
- Dimensioning Application
- Compliance Applications
- Shipment Localization: Automatic Sorting

Health and Safety Applications

Accident Prevention

Busy logistics facilities like warehouses, yards, and depots pose a serious risk to employees' health and safety. Computer vision and AI technologies represent a valuable support tool for reinforcing safety and security, as they allow the movements of people and vehicles to be observed and analysed in real time. Speeding, moving in the wrong direction, parking in the incorrect spot, and other violations can be detected by a computer vision system. In an attempt to minimise risk and hazardous behaviour, it can also detect non-compliance in real time (e.g., when workers are not using walkways), and it can send out safety alerts for timely intervention. This monitoring encourages proactive safety decisions, improves operational coordination and enables timely corrective actions to reduce risks, creating a more protected workplace. A significant example is the project launched by DHL: thanks to the AI-based solution for detecting risk events, developed by the startup Protex AI, a proof-of-concept was created that enables EHS (Environment, Health and Safety) teams to proactively intervene on safety. This

initiative made it possible to transform the information obtained into concrete actions, with the aim of reviewing work flows, raising operational safety standards and introducing targeted corrective interventions (Dohrmann, Pitcher, & Kamdar, 2024).

Ergonomic Pose Improvement

Human Pose Estimation (HPE) is a technology that exploits computer vision to identify and classify joints in the human body. It collects a series of coordinates for each joint, forming a skeletal representation that describes a person's posture and movements. This information is essential for ergonomics, the discipline that studies the efficiency of people in the workplace. For example, leaning forward can increase the risk of back injury. Likewise, twisting or turning movements, improper lifting, and carrying excessive loads pose significant risks. An interesting case is the one of TuMeke, a tech company that developed an AI ergonomic risk assessment platform using computer vision to detect incorrect postures: by recording and analysing video potentially dangerous movements can be detected (such as lifting boxes) and injuries prevented (Dohrmann, Pitcher, & Kamdar, 2024).

Protective Personal Equipment (PPE)

Employers are responsible for supplying Personal Protective Equipment (PPE) and ensuring its proper use in the workplace. For example, safety helmets, eye protection, and specialized clothing are common forms of PPE. However, simply wearing the correct equipment is not enough: it must be used correctly. Using computer vision, AI systems can verify adherence to safety procedures and even identify the reasons for non-compliance. These systems can be trained to recognize various types of PPE in real time by analyzing video streams from strategically positioned cameras, confirming that workers are both equipped with the appropriate PPE and using it correctly. Additionally, they can detect defective or damaged PPE, which represents a significant safety hazard. All this helps ensure compliance with safety protocols and avoid accidents (Dohrmann, Pitcher, & Kamdar, 2024).

Driver Support

Computer vision can also be used to detect signs of fatigue in drivers of heavy goods vehicles on long journeys. For example, thanks to cameras and machine learning algorithms, facial recognition technology can detect lowered eyelids and changes in expression, signs that indicate fatigue. In such cases, the system can suggest the driver to stop to have a break, and, if necessary, it can also activate an alarm to warn other road users of a possible hazardous situation. This technology is also able to check whether the seat belt is being worn correctly, plus whether unauthorized accesses inside the vehicle are occurring. The latest and most advanced computer vision systems can perform multiple tasks simultaneously. An example of

this multitasking ability can be found in autonomous vehicles: the system identifies and classifies more elements (e.g., pedestrians, other vehicles or obstacles) at the same time, tracks their movements and makes decisions based on this information allowing for safe travel throughout the entire journey (Dohrmann, Pitcher, & Kamdar, 2024).

People and Operations Applications

Heatmaps

Computer vision-based heat maps enable to accurately identify bottlenecks and areas of high activity within the warehouse, using contactless and non-invasive methods both inside and outside the facility. The analysis of video streams from surveillance cameras allows to measure the frequency and duration of movements of people and vehicles, applying a color-coded overlay. For example, a certain shade of red indicates high activity, while white signals a lack of movement. This data helps managers to identify inefficiencies like overcrowded or, at the opposite, underutilized sections, so as to optimize inventory and placement, increasing the efficiency of operations overall. To assess the impact of the modifications, it is also possible to compare heatmaps over time (Dohrmann, Pitcher, & Kamdar, 2024).

Head Counting

Warehouse managers must guarantee an adequate staffing to complete planned activities. Few employees can cause delays, while having too many can lead to unnecessary costs. Moreover, it is essential to respect the safety limits concerning the maximum permitted capacity. Manually counting people in a defined area is tedious, repetitive, and a waste of time. For this reason, computer vision systems are adopted to count both people and vehicles within logistics facilities 24/7. This visual information allows managers to analyze the collected data and determine the optimal number of operators needed to perform specific activities, always ensuring safety requirements are met (Dohrmann, Pitcher, & Kamdar, 2024). In this regard, it is worth mentioning AVID, a startup which created an AI software using surveillance cameras that provides automatic detection and counting solutions. The software is also enriched by demographic information like age and gender, useful to provide operational insights and patterns for businesses.

Pick Path Optimization

It is essential that products in the warehouse are picked quickly, accurately and efficiently. In fact, pickers must follow the best routes during their shift, since this activity represents a relevant part of the overall operations. Thus, improving picking paths results in tangible operational savings plus an increased customer satisfaction. While algorithms alone cannot

guarantee success in every situation, adopting computer vision increases the likelihood of optimizing the route. Cameras video streams feed machine learning algorithms which identify patterns and trends in the data, suggesting changes to the workflow. They can recommend to repositioning equipment or supplies to reduce distance travelled, without compromising picking efficiency for example. Moreover, this data may highlight the benefits of changing the order of execution of certain activities: if a heatmap reveals a high intensity activity in a specific warehouse area, this allows to analyse workflow in that area and intervene to eliminate any potential bottleneck (Dohrmann, Pitcher, & Kamdar, 2024).

Access Control

In traditional camera surveillance, analyzing large volumes of footage requires human intervention, while an intelligent surveillance system uses sophisticated algorithms for real-time monitoring, analysis, and detection. Back-end AI systems process video very quickly, providing detailed information that can improve security and reduce the possibility of theft. In addition to serving as a basic visualization platform, a computer vision system can identify unauthorized access or intrusions into restricted areas. By analyzing video streams, the system can detect when someone enters a restricted area or crosses a virtual boundary. As a consequence, the system immediately triggers an alarm to allow security personnel to take timely action. In addition, another ability of the system is to detect patterns of routine activities, thus facilitating the identification of anomalies like suspicious behavior or strange movements in areas of interest (Dohrmann, Pitcher, & Kamdar, 2024).

Maintenance Applications

Predictive Maintenance

Computer vision technology allows to conduct a constant and accurate monitoring of logistics assets, alerting the maintenance team before problems arise. Thanks to the analysis of data collected from various types of equipment, it can predict when critical assets will require intervention. In this way, managers can plan maintenance and repairs, thereby prolonging the life of the assets and reducing the risk of damage (Dohrmann, Pitcher, & Kamdar, 2024).

Quality Inspection and Defect Identification

When a site moves thousands of items of various types, sizes and shapes every day, it becomes difficult to spot a damaged package. However, if a box is wet, torn or deformed and the contents are damaged, it affects brand image and customer satisfaction. When it comes to quality inspection of shipments, it is essential to detect any damage as soon as possible (Dohrmann, Pitcher, & Kamdar, 2024). Before the diffusion of computer vision technology, identifying defects was a very demanding manual process that was subject to human error and required

personnel to be constantly available. Today, computer vision can automatically identify potential imperfections, errors, color inconsistencies, deformations, anomalies, malfunctions and even signs of tampering with over 90% accuracy by comparing an object's current shape to its expected geometry (Noceti et al., 2018). This technology is a valuable support for Gemba Walks in warehouses, allowing real-time monitoring of the condition of machinery and structures during inspections, collecting and analysing data. It also allows for calculating repair and damage costs, simplifying maintenance procedures thanks to integration with asset management systems.

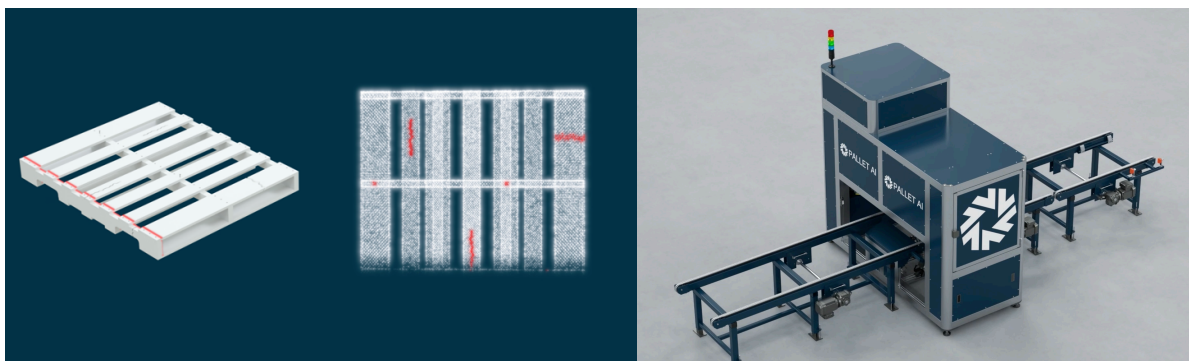


Figure 18 - Pallet AI: Defect Detection System for High-Speed Pallet Inspection

Source: IVISYS. (2024). PalletAI – Automated pallet inspection system.

For instance, Ivisys, a cutting-edge startup, has developed Pallet AI, an innovative solution for identifying defects, specifically designed for rapid pallet inspection. Thanks to an advanced neural network, the system uses pattern recognition techniques to process footage from multiple cameras, detecting anomalies on 250-450 pallets per hour and thus boosting both productivity and worker safety (IVISYS, 2024).

Asset Management Applications

Utilization & Capacity Assessment

Computer vision is extremely useful in capacity planning, as it can rapidly estimate how much space is being utilized, reducing the guesswork often associated with human observation.

The technology can assess the overall volume inside trucks and containers and calculate the available space before loading. For instance, by counting the number of items or verifying whether a forklift's load area is occupied, systems can immediately detect underfilled or overflowing transportation containers (Özgür et al., 2016). With this data, the system can determine the ideal placement of products to minimise wasted space. Furthermore, measurements can be taken throughout the entire loading process, enabling real-time decisions based on concrete data. Some approaches monitor how many parcels remain on a pallet,

ensuring that resources are fully utilized and preventing partial shipments from leaving the facility (Dörr et al., 2020). This results in time savings, greater efficiency, lower environmental impact and reduced costs. Computer vision also supports the analysis of pallets and cages' dimensions and orientation, ensuring proper positioning to optimize weight distribution and increase efficiency (Dohrmann, Pitcher, & Kamdar, 2024). A good case to bring to attention is that of a Danish start-up called Sentsipsec. It uses this technology to monitor every stage of interaction with inventory, both in and out of the warehouse.

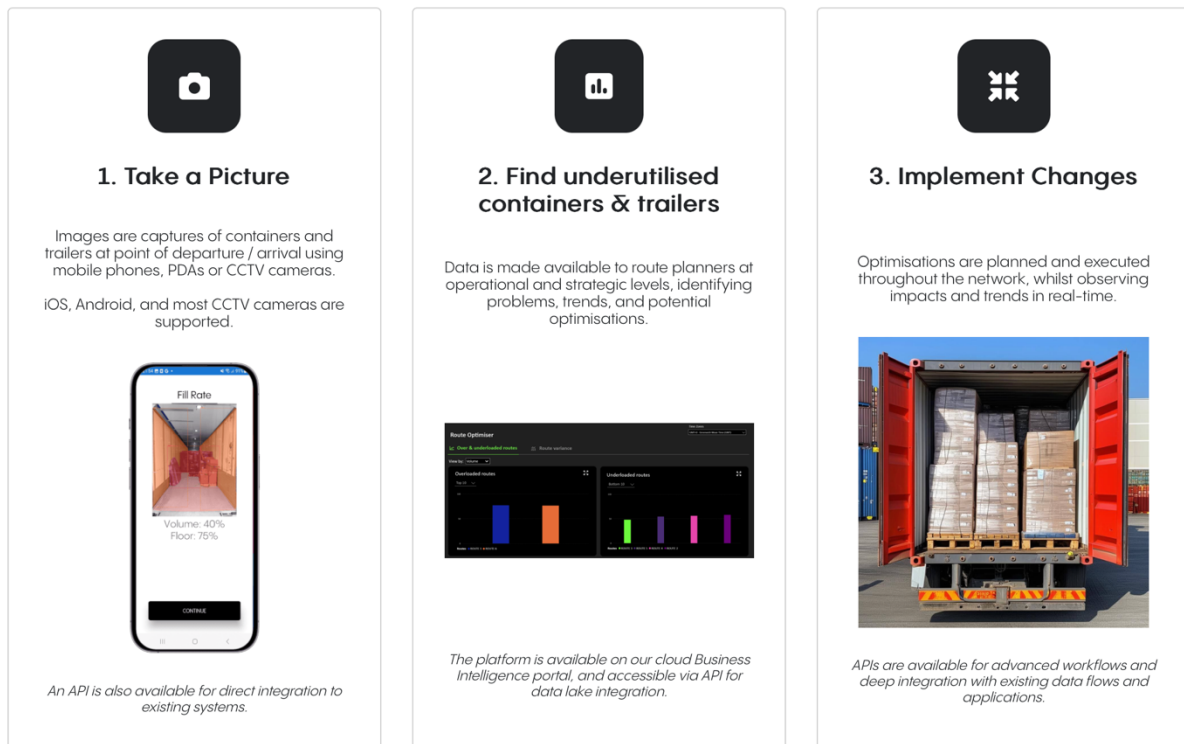


Figure 19 - Sentsipsec Load Optimization Workflow

Source: Sentsipsec. (2024). Smart logistics solutions powered by AI and computer vision.

Instead of allowing partially filled trucks and containers to exit the facility, Sentsipsec Inspector records fill levels daily, allowing the planning department to maximize overall loading (Sentsipsec, 2024).

Asset Counting and Localization

Losing pallets, crates, carts, and other assets is a common problem in warehouses, and it costs time and money to find, return, or replace them. By leveraging computer vision systems that can automatically recognize and localize pallets, for instance via stereo cameras or RGB-D sensors (Varga et al., 2015; Xiao et al., 2017), managers can count and track these resources in real time, even in areas of the warehouse where the signal is weak and tracking sensors are not working properly. Modern approaches frequently combine plane fitting, region-growing, and

feature-based classification to isolate each asset from the warehouse floor (Molter & Fottner, 2018). Deep learning algorithms, such as those employing Faster R-CNN⁷ or Kalman filtering⁸ for temporal tracking, count objects detecting and classifying them in an image or video stream. They identify key points and then repeat the analysis to count all occurrences of a given object, further boosting accuracy by matching each detected object to an existing model and continually updating its position (Mohamed et al., 2020; Molter & Fottner, 2019). Assets can be recognized by type (roller crate, shelf, forklift) or by a unique identification code, valid for both a single asset and multiple assets captured by the same camera. For localization, a multi-target tracking system (multi-camera or multi-sensor setups) that uses the so-called “handshake method” is particularly effective: when an asset leaves the field of view of one camera and reappears in that of another, a backend algorithm analyzes these transitions to reconstruct its path within the warehouse. This thus providing the basis for real-time, centimeter-level georeferencing throughout the warehouse (Haanpaa et al., 2016). The computer vision platform of Kibsi, a startup in the sector, is based precisely on the networks of cameras already present to monitor assets and activity in the warehouse.

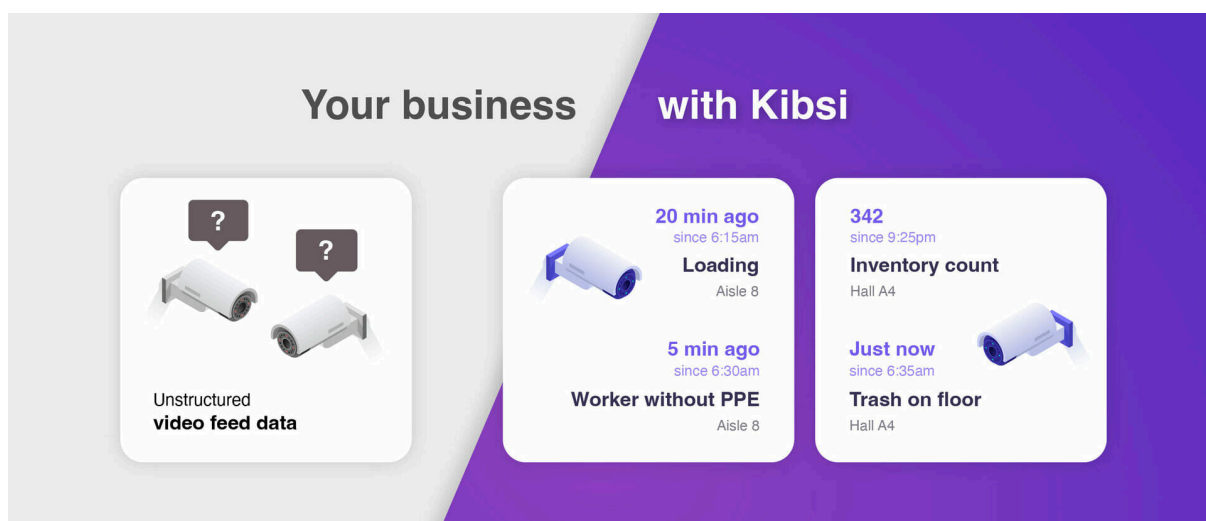


Figure 20 - From Raw Footage to Real Insights With Kibsi

Source: Kibsi. (2024). Computer vision solutions for smart operations. Kibsi.

The assets can be georeferenced on a virtual map, allowing operators to locate them with an accuracy of the order of a few centimetres (Kibsi, 2024).

⁷ Faster R-CNN (region-based convolutional neural network) is an object detection model that identifies objects in an image and draws bounding boxes around them, while also classifying what those objects are.

⁸ The Kalman filter fuses a system model with noisy measurements (assumed to be Gaussian noise) to give, at each new reading, the most probable estimate of its hidden state. It is used to estimate quantities that are not directly measurable, to strengthen controllers and to identify model parameters.

Fleet Management

Goods outside the warehouse can be monitored 24/7 by an integrated system that combines computer vision with video surveillance. To allow only authorized vehicles to access the yard, cameras recognize each truck and record the time of entry, exit, and number of daily trips. The system also analyses vehicle usage, including periods of inactivity, helping to optimize fleet management (Dohrmann, Pitcher, & Kamdar, 2024).

Dimensioning Application

Measuring the area or volume of an object before shipping is essential for optimally managing storage capacity, handling, load utilization and freight transportation, as well as for correct invoicing. This process also supports the updating of data that warehouse management systems (WMS) rely on (Kucuk et al., 2019). Time is a crucial factor in dimensioning. Considering, for example, the huge amount of packages of various sizes that DHL handles every day, often at high speeds on conveyor belts: even a short delay in measuring can significantly slow down the process. In addition, recognizing irregularly shaped packages is not only a matter of speed, but also of more efficient use of materials and appropriate packaging. Thus, handling irregularly shaped items adds complexity and calls for robust computer vision or sensor-fusion strategies (Brylka et al., 2021). The dimensioning process automated using computer vision lends itself to various solutions. For instance, DHL pioneered a gate-based scanning solution using dual MS Kinect sensors, discretizing height maps to quickly compute total volume with an error margin in the millimeter range (Kückelhaus, 2013). Laotrakunchai et al. (2013), instead, developed a smartphone-based method that merges accelerometer readings with feature-matching on a pair of images to derive parcel dimensions, making the process more portable. Likewise, fixed systems such as MetriXFreight from the German company Metrilus, constantly monitors a predefined measurement area and detects the dimensions of an object if it remains within that area for a certain period of time. Alternatively, the Californian company Qboid offers a mobile dimensioning system based on portable terminals, equipped with 3D color sensors and integrated software. This approach allows to automate the estimation of shape and dimensions in a wider number of contexts than traditional systems (Sun et al., 2020).

Compliance Applications

Label Detection and Alignment

In the logistics context, computer vision plays a key role in the automation of Label Detection and Alignment activities, enabling systematic and scalable control of packages along the entire

supply chain. Transport labels act as “unique identifiers” of the shipment and, consequently, are essential for the orderly management of goods flows and for compliance with safety and traceability requirements (Mishra et al., 2019). In the case of food, beverage or pharmaceutical products, any labelling errors (illegible expiration dates, missing ingredients, undeclared allergens) generate additional costs and can lead to legal disputes. An artificial vision system, integrated with IoT sensors present in sorting centers, acquires images of the front and back of the products before shipping, comparing each label with a reference model and verifying, when necessary, the expiration date. If inconsistencies are detected (for example faded ink, misplaced labels, falsified codes or incorrectly labeled items) the algorithm reports the anomaly in real time: the package is isolated, relabeled and quickly reintroduced into the distribution flow, reducing delays and minimizing damage to the company’s image (Dohrmann, Pitcher, & Kamdar, 2024).

Barcode Scanning and OCR Capture

Automatic product identification is now based on a synergy between computer vision, barcode reading and OCR, capable of replacing manual typing at critical points in the supply chain. Traditional linear barcodes introduced in the 1980s have evolved into 2D symbologies, while OCR converts printed or photographed texts into data that can be processed by management systems. Research has shown that object detection models trained on synthetic datasets (Dörr et al., 2019) or designed for unfavorable environmental conditions (Brylka et al., 2020) reach levels of precision that are now compatible with warehouse operations. Lightweight architectures⁹ such as those tested by Kamnardsiri et al. (2022) also guarantee low latencies, an essential requirement on high-speed belts. This scientific evidence is confirmed in concrete industrial applications. PepsiCo has adopted KoiReader’s AI platform, which can read labels and barcodes at line pace even when they are partially covered, damaged or tilted. Similar solutions are proposed by Banner, whose sensors decode poor-quality barcodes on reflective surfaces, and by Belgian Zetes, which integrates gates equipped with cameras to photograph complete pallets, simultaneously decode multiple labels and compare the data with shipping orders. In case of missing or illegible codes, the system blocks the package and notifies the operator in real time. Each operation is documented with dated images as an objective proof for audit purposes (Dohrmann, Pitcher, & Kamdar, 2024). In short, the combination of academic progress and market solutions demonstrates that automatic label reading is no longer

⁹ “Lightweight architectures” are neural networks that have few layers and a small number of parameters to calculate. In practice, they “weigh” less on the processor and therefore produce a very fast response (latency of a few milliseconds).

a frontier innovation, but a mature technology that reduces errors, accelerates flows and generates valuable data for continuous optimization of the logistics chain.

Shipment Localization

Automatic Sorting

Before being sorted by type and delivery destination, packages must be identified. This visual classification step can be too slow and tiring for staff, creating potential bottlenecks, which is why automating these tasks is essential. Through artificial intelligence and machine learning, it is possible to acquire images and positions of packages, envelopes, bags and other formats, in order to precisely determine the orientation and positioning of each item. To speed up these operations, automated camera-based sorting systems are adopted, which achieve the best results when using high-quality 3D data. These systems recognize the unique characteristics of each object, allowing automatic picking and vertical alignment. As the products flow on the conveyor belt, they are uniformly separated, aligned and singulated (a process known as “singulation”). The cameras acquire images of each item, which are then processed by AI-based technologies. Once identified, the object is sent to the appropriate bin or directed to another conveyor for further sorting. This computer vision system associates the captured image with the sorting decision in real time, breaking down the process into three main stages: converting the shot into a binary image, separating the object from the background, and finally, recognition (Dohrmann, Pitcher, & Kamdar, 2024).

2.2.1.5 Gen AI

A Generative Artificial Intelligence (Gen AI) model is a particular machine learning architecture capable of creating new data (text, images, audio or video) by drawing inspiration from the patterns learned during the training phase, without limiting itself to copying the original examples. These models, although having a highly expressive basic structure, generally require a fine-tuning phase to be adapted to specific application domains, as occurs, for example, in solutions dedicated to logistics. Deep neural networks are particularly suitable for this purpose because, thanks to the flexibility of their architectures, they are able to model different types of data – sequential, spatial or multimodal – with high effectiveness (Janiesch et al. 2021; Kraus et al. 2020). Among the most widespread generative paradigms today, on the one hand, we can distinguish Generative Adversarial Networks (GANs), which produce visual and multimedia content through the competition between two adversarial networks, and, on the other, transformer-based models, capable of exploiting large amounts of information

found online to generate coherent texts. The latter family includes Generative Pre-trained Transformers (GPT), which became known thanks to conversational applications such as ChatGPT. Refinement with Reinforcement Learning from Human Feedback (RLHF) techniques has further improved the quality of the responses produced, introducing a virtuous cycle of evaluation and correction (Ziegler et al. 2019). When such models are integrated into complex systems – for example, fleet management or warehouse automation platforms in the logistics sector – it is necessary to consider infrastructural elements (scalability of distributed computing), deployment elements (compatibility with heterogeneous environments and devices) and usability elements (intuitive interfaces and recognition of user intent). The continuous evolution of open-source versions increases the need to constantly monitor performance, since unexpected decays can compromise the quality of the service (Chen et al. 2023). Furthermore, the limits deriving from the temporal cut-off of the training data – or from the compression of the stored information (Chiang, 2023) – can be mitigated by connecting the model to external databases or real-time retrieval systems, in order to guarantee updated responses. Gen AI market reached a value of US \$ 37.87 billion in 2024 and it is expected to grow at an annual growth rate (CAGR 2025-2031) of 36.99%, resulting in a market volume of US\$ 442.07bn by 2031 (Statista, 2024). Within the next three to five years, Gen AI is expected to have an increasingly significant impact on the logistics industry, with large-scale implementation expected in this sector involving both office and operational personnel. Despite this, Gen AI is already demonstrating tangible value in logistics. Key application areas include:

- Content Creation
- Customer Experience Automation
- AI Assistants
- Transportation management
- Supply Chain Resilience

Content Creation

Gen AI enables the generation of text, images and also code scripts, opening up new opportunities in the logistics sector. For example, it can automate the drafting of product descriptions, inventory reports and customer service responses, simplifying internal communication and increasing efficiency. Additionally, Gen AI can generate visual representations of stored items or warehouse layouts, supporting inventory management. Among its applications, also packaging design is included, designed to optimize space usage and guarantee load protection. These graphical representations help accelerate the creation of

prototypes of new packaging solutions. Not only, but Gen AI can also automate the writing of data analysis scripts, refine route planning algorithms, and develop predictive models that anticipate demand. This improves the quality of data-driven decisions and operational planning (DHL, 2024). A concrete example of how Gen AI can be exploited to improve user experience and business processes comes from Amazon. Amazon uses Gen AI to enhance and personalize product recommendations and the creation of product descriptions with increasing precision, thus offering a highly personalized shopping experience that meets the customer's real needs. First of all, thanks to a vast catalog of over 300 million items, the company can count on a considerable amount of data relating to users' search, navigation and purchasing behaviours (Amazon, 2024). This information is analysed by a Large Language Model (LLM) learning model, capable of highlighting the most important attributes for each consumer, such as preferences in terms of materials, technical specifications or particular dietary needs (for example, the search for gluten-free products) . The model generates more relevant product descriptions, not limited to generic suggestions, by integrating crucial terms into texts and titles: for example, if a customer types “gluten-free cereals” after having often searched for items related to a gluten-free diet, the system makes sure to position “gluten-free” in a highly visible way in the descriptions and search results (Amazon, 2024). A similar example is shown in Figure 21, where in this case the words frequently typed in various customer searches are “for 2 people”.

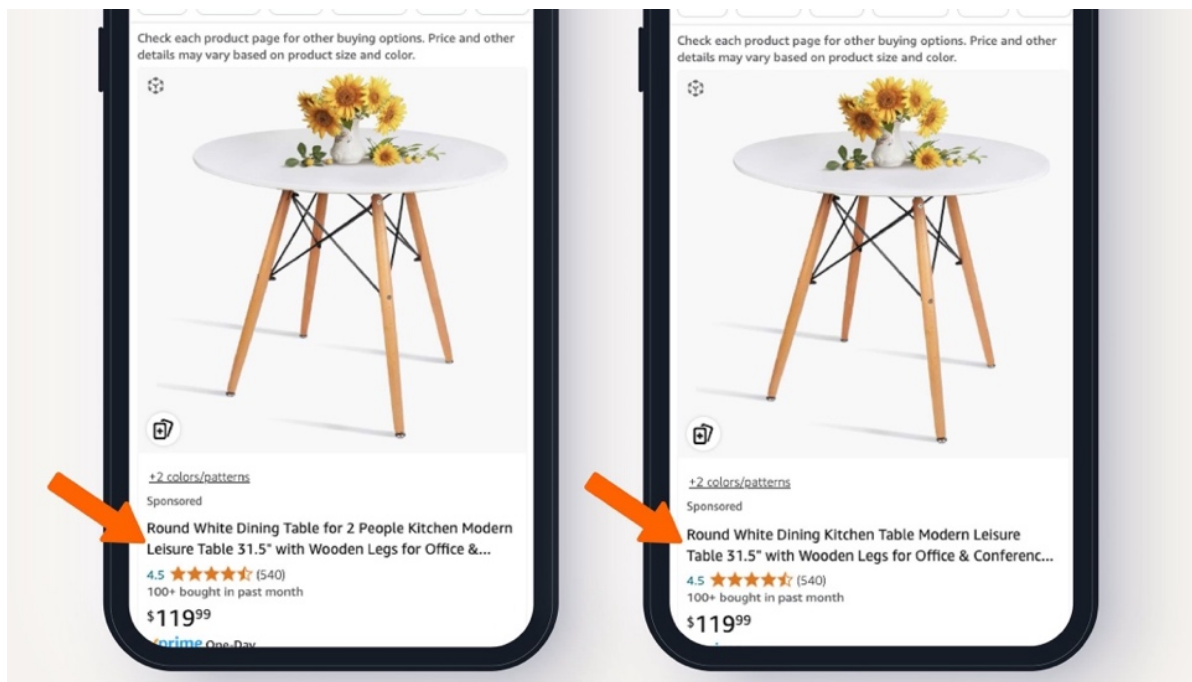


Figure 21 - AI-Powered Product Title Optimization on Amazon

Source: Amazon. (2023). Using generative AI to make product search and discovery easier for customers. *About Amazon*.

To support this process, a second model, called “LLM evaluator”, intervenes with the task of checking the generated output and providing feedback in the event of omissions or information that is not adequately personalized (Amazon, 2024). In this way, a virtuous circle of continuous correction and improvement is established, in which AI is not only able to manage a high volume of products, but is also able to “understand” what information to insert and how to present it to satisfy the needs of the individual user more immediately. Deeply personalizing the shopping experience not only speeds up the search for the desired product, but also helps to bring out potentially interesting items that might otherwise escape the consumer’s attention. On the other hand, Amazon uses the same technology to enhance its advertising tools, as demonstrated by the recent “Video generator” and “Audio generator” solutions, offered in beta to advertisers in the United States. These tools allow sellers to create high-quality videos and multimedia content starting from a single shot or a single product image, thanks to the use of image generation models, texts and even audio tracks (Amazon, 2024).

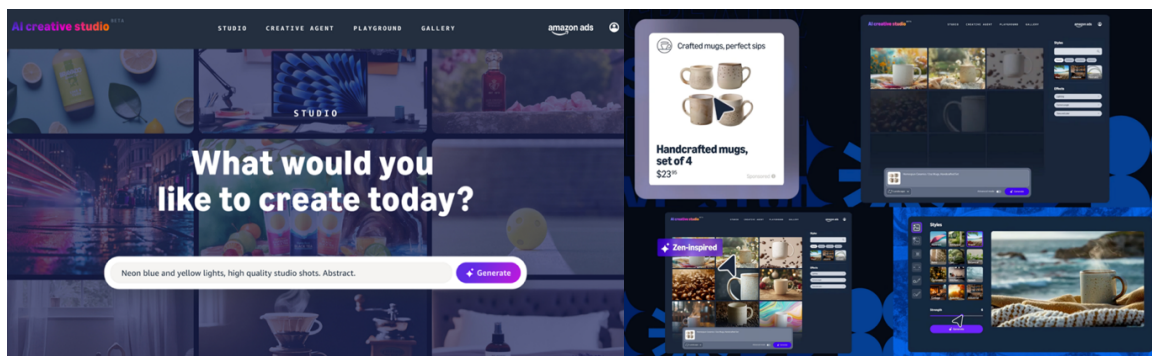


Figure 22 - Amazon Ads' AI Creative Studio

Source: Amazon. (2024). Amazon Ads unveils generative AI video generator for advertisers. *About Amazon*.

With “Video generator”, for example, the algorithm combines the image of the product with specific insights from the retail sector, creating a video in just a few minutes that emphasizes the peculiarities of the item and makes its narration more immediate and engaging. This integration between automatic analysis and AI-driven creativity offers sellers the possibility of quickly updating their advertising content at no additional cost, so as to always stay in step with market trends and consumer tastes (Amazon, 2024). Additionally, the “Live image” feature allows for the introduction of short animations (such as smoke rising from a cup of coffee) to animate campaigns, capture audience attention and improve engagement rates. This is part of a broader innovation effort that aims to break down creative barriers and support advertisers of all sizes in presenting their products in an engaging way, simplifying campaign management while ensuring a more dynamic and satisfying shopping experience for users (Amazon, 2024).

Customer Experience Automation

Chatbot interfaces powered by generative AI can be used in a variety of ways to make supply chains more customer-centric. This technology enables timely and appropriate responses to user requests, leveraging popular communication channels (DHL, 2024). For example, a single customer can receive a quick and targeted email, a phone call, or even an automatically generated text message. In this sense, Gen AI helps improve the shopping experience and increase customer satisfaction, for example offering personalized product recommendations, based on users' preferences and purchasing history as explained in the previous paragraph. In addition, Gen AI can quickly review different types of unstructured comments and ratings, such as online reviews or opinions expressed on social media. This way, when a certain number of observations about a particular product emerge, Gen AI can integrate this information into the development processes, facilitating updates and improvements in a short time (DHL, 2024). A notable example once again is Amazon and the way it uses Gen AI to simplify the decision-making process for buyers. The company offers a “review highlights” system that summarizes the main opinions expressed by users in a short paragraph (Amazon, 2024).

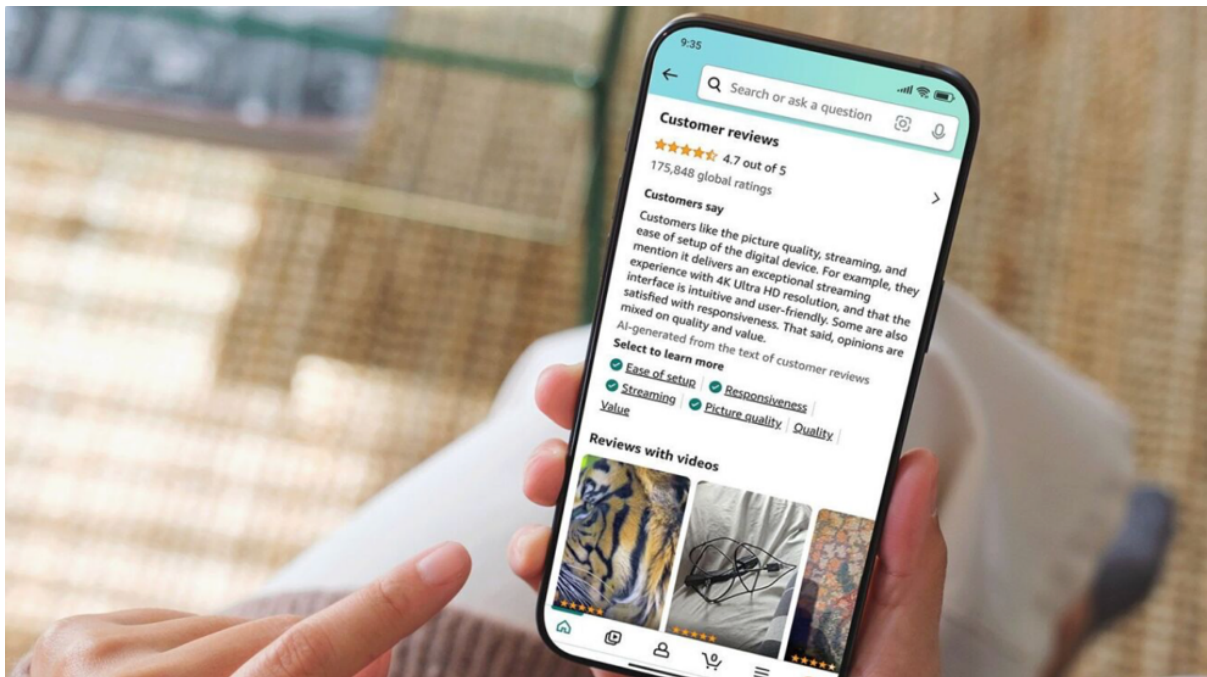


Figure 23 - AI-Generated Review Highlights on Amazon

Source: Amazon. (2024). Amazon introduces AI-generated review highlights to help customers shop with confidence. About Amazon.

In practice, the platform analyses the textual reviews of verified purchases, then it identifies the recurring themes and opinions shared by multiple customers and automatically generates a summary that highlights the strengths and weaknesses of a product. This tool, introduced in 2023, allows users to immediately view an overall overview of customer sentiment,

distinguishing between positive, negative and neutral feedback thanks to the use of graphic indicators such as the green check mark or the orange symbol (Amazon, 2024). This approach, which combines data analysis and natural language technologies, allows quick access to essential information, facilitating the choice of the product best suited to customers' needs, and helping to make the purchasing process more transparent and informed.

AI Assistants

The introduction of AI assistants (also called digital assistants or DAs) in the logistics sector is revolutionizing the management of goods and information flows, offering new opportunities to reduce the cognitive load of operators and accelerate distribution processes (Zheng et al., 2024). In particular, these systems (which can take different forms, from text-based chatbots to softbots capable of operating autonomously on information systems) foster a natural interaction between humans and digital technologies, improving efficiency along the entire supply chain (Li and Yang, 2021). For example, voice assistant platforms simplify order processing and inventory status checking, allowing operators to obtain real-time updated data simply through voice commands (Hsiao and Chang, 2019). Furthermore, thanks to the integration with data analytics algorithms, DAs provide useful predictive analytics, such as dynamic recalculation of delivery routes and optimization of inventory based on real demand. Currently, not all large-scale AI assistants are suitable for the logistics sector: in fact, in contexts such as DHL, we observe the use of assistants based on predictive analytics that, by forecasting demand, optimizing inventory levels and anticipating possible supply chain disruptions, support proactive decision-making and efficient resource allocation (DHL, 2024). At the same time, the adoption of assistants for warehouse management allows to improve stock positioning, automate picking and packing processes, monitor equipment maintenance schedules and, in the back office, facilitate administrative, legal and financial activities by screening long texts and summarizing key points. This allows, for example, faster response times for the processing of contracts, confidentiality agreements and financial reports (DHL, 2024). In short, the strategic use of these tools now appears essential for companies that want to take full advantage of the digitalization of logistics, as it allows for more agile management of complex activities and increasingly fluid and productive human-machine collaboration. A particularly innovative example is Amazon's Project Amelia. The company recently launched in beta this personal assistant based on Gen AI, specifically designed to support independent sellers. Project Amelia is configured as a true digital sales expert, capable of providing immediate and personalized answers to questions regarding product strategies, regulatory compliance, advertising campaigns, sales forecasts and supply chain management. Sellers can

interact with the assistant from any Seller Central page, obtaining updates on performance data, trend analysis and even assistance in resolving operational issues, thus simplifying the day-to-day management of their business (Amazon, 2024).

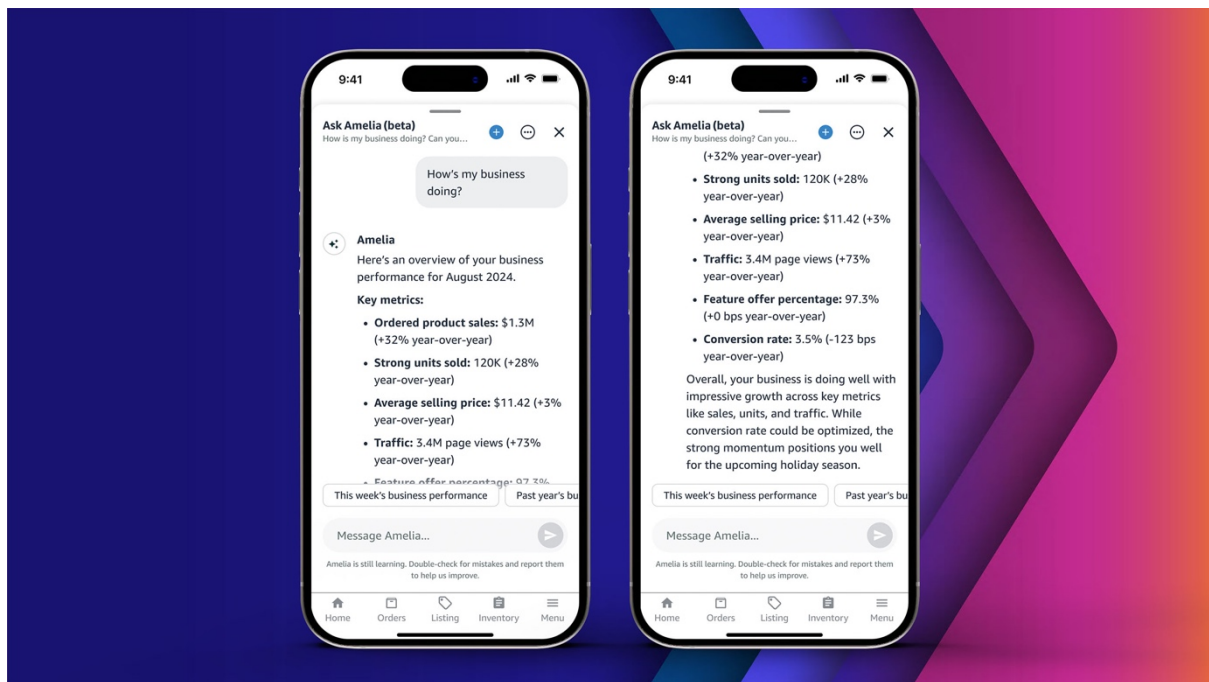


Figure 24 - Example of a conversation with Project Amelia, Amazon's AI Business Assistant

Source: Amazon. (2024). Amazon introduces Project Amelia: A new frontier in generative AI assistants. *About Amazon*.

In particular, the system allows sellers to obtain concise and easy-to-understand information from reliable sources, as well as quickly access critical metrics and reports, improving the decision-making capacity of digital entrepreneurs. Project Amelia was developed using Amazon Bedrock, a platform that offers scalable access to the latest AI models, combining global knowledge with specific skills in the world of selling on Amazon. Over time, the assistant is expected to acquire greater learning capacity, arriving not only to provide answers, but also to anticipate the needs of sellers and to autonomously solve some problems (Amazon, 2024).

Changing perspective, it is important to observe how this type of technology is also transforming the customer purchasing experience. Indeed, the introduction of conversational AI assistants like Rufus represents a significant turning point for the customer shopping experience. In this regard, Amazon developed Rufus, an AI assistant for customers (Amazon, 2024). It is a new tool designed to provide immediate and personalized answers to a wide variety of questions about products and purchasing needs. Essentially, this assistant is a virtual consultant that provides product-specific information like whether or not a coffee machine is easy to clean on the basis of information that already exists within product sheets, customer

reviews and community Q&As (Amazon, 2024). In addition, Rufus helps customers navigate the various product options by offering accurate comparisons between different features, such as the comparison between gas and wood-fired ovens or between trail and running shoes.

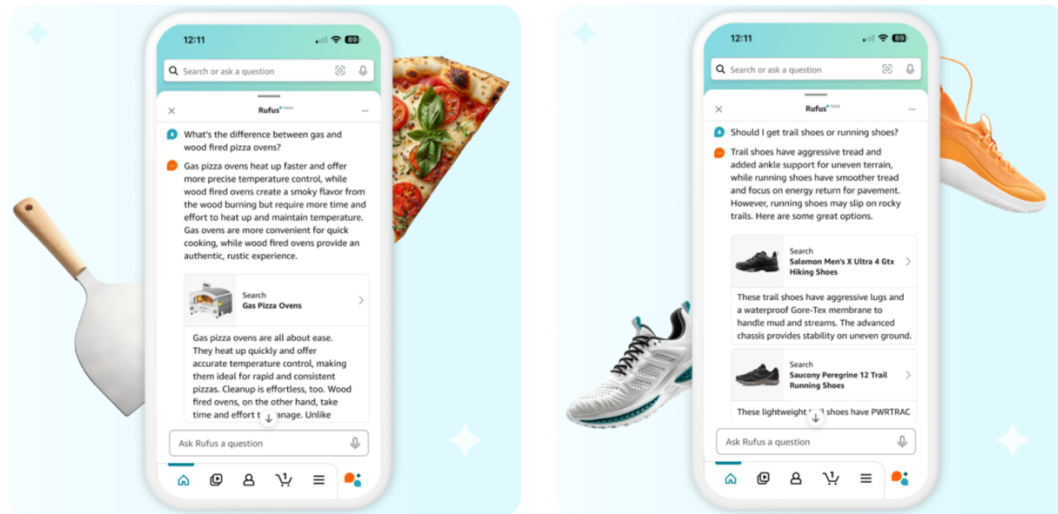


Figure 25 - Example of how Amazon Rufus helps customers compare different products to guide their purchasing decisions

Source: Amazon. (2024). How to use Amazon Rufus, your new generative AI shopping assistant. *About Amazon*.

Another important aspect concerns the ability of this assistant to provide recommendations based on contextual analysis. For instance, it is able to suggest a beach umbrella suitable for the specific weather conditions of a given region, or to present the latest news and trends. Last but not least, Rufus allows users to quickly access information relating to current and past orders, facilitating the tracking of packages and making it easier to review previous transactions, an element that can also be useful for planning future purchases (Amazon, 2024).

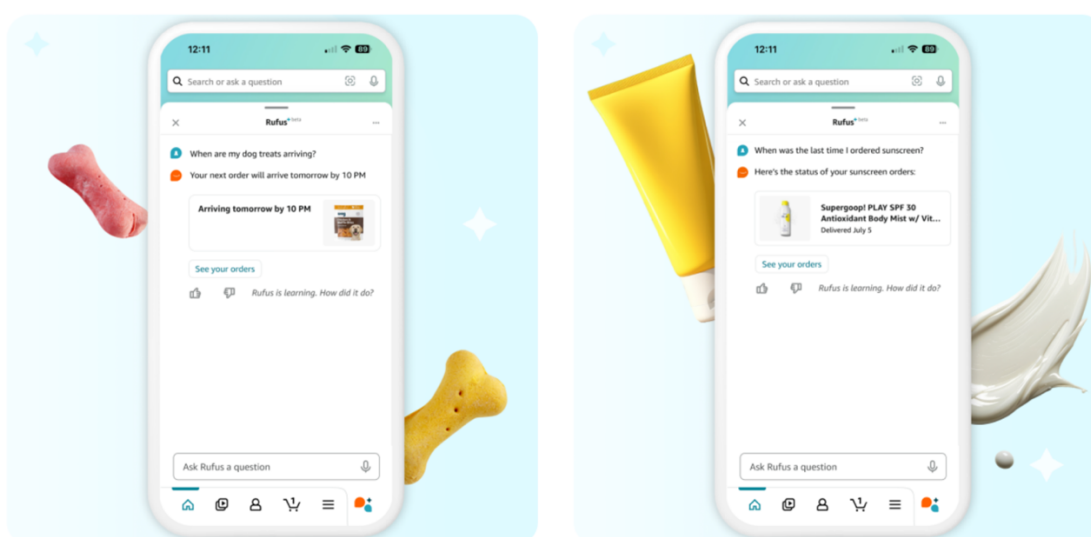


Figure 26 - Example of Amazon Rufus providing order tracking and purchase history

Source: Amazon. (2024). How to use Amazon Rufus, your new generative AI shopping assistant. *About Amazon*.

This type of assistant also has the ability to answer questions not strictly related to the purchase, such as advice on what is needed to prepare a soufflé or organize a summer party. As a result, this AI assistant offers customers an integrated support throughout the entire purchasing process, helping to simplify the decision-making process and reduce research times (Amazon, 2024).

Transportation management

The use of Gen AI tools in the logistics sector is emerging as a highly relevant strategic lever also for transport operations (Deloitte, 2024).

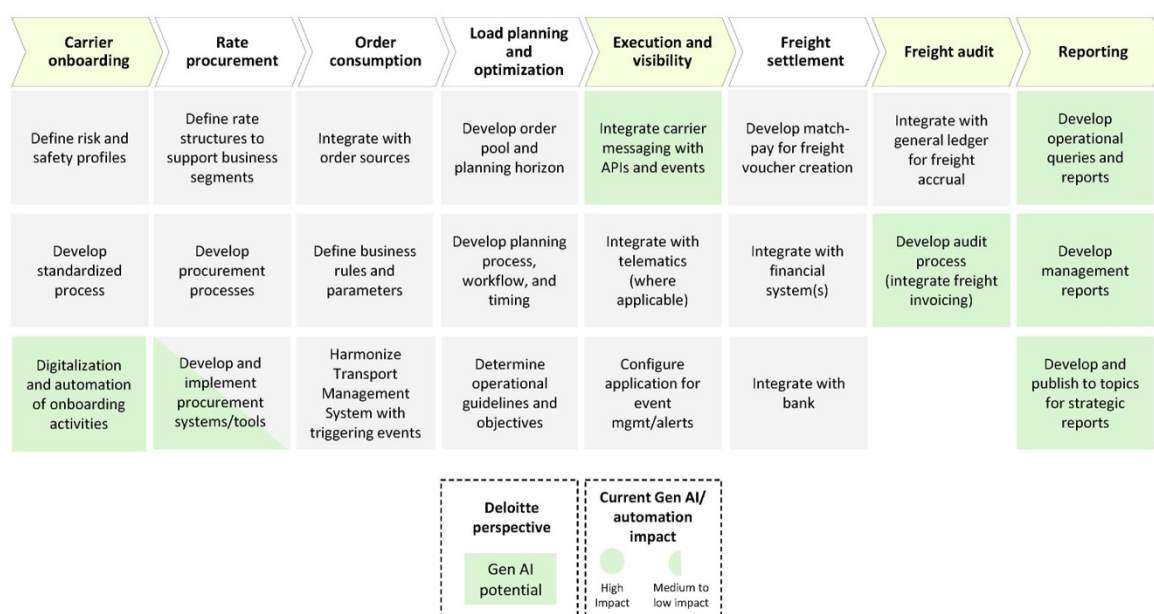


Figure 27 – Key areas where Gen AI can streamline transportation management

Source: Deloitte (2024). Generative AI in transportation management

The challenges facing the sector include, among others, the impact of macroeconomic shocks such as the COVID-19 pandemic and the need to offer a service that is always optimized in terms of costs and delivery times (Hitchcock et al., 2024). In this context, the adoption of GenAI can foster a more advanced approach to data management, allowing the collection, analysis and synthesis of large volumes of information from heterogeneous sources. This process is particularly useful for improving crucial procedures along the transport lifecycle, such as onboarding carriers, verifying their credentials and analyzing sustainability or reputation metrics in real time (Hitchcock et al., 2024). According to recent studies, Gen AI will have the biggest short- and medium-term effects on automating carrier communications, auditing transport invoices, and creating advanced reporting. These areas will provide observable advantages in terms of operational efficiency, error reduction, and improved

visibility of the entire logistics network (Deloitte, 2024). For example, Crowley (2024) highlights how the use of machine learning algorithms facilitates autonomous verification of invoices and real-time identification of anomalies, freeing up resources that can then be dedicated to innovation and continuous improvement projects. Not to mention the fact that, as already analyzed previously in this chapter, the adoption of GenAI in the transport sector is progressively extending to key functions such as demand forecasting and route optimization with a potential increase in service punctuality and a more rational use of the workforce (Deloitte, 2024). In the longer term, as reported by Hitchcock et al. (2024), a scenario is emerging in which transport fleets will evolve towards almost autonomous management, thanks to AI systems that will communicate with each other, with the consequent need to develop GenAI models designed from the outset for interoperability. Ultimately, the ability to integrate generative solutions could represent a differentiating factor for companies that will be able to develop an ecosystem based on accurate data, predictive analysis algorithms and adequate technological infrastructures, so as to reap the benefits of more flexible and reactive transport (Deloitte, 2024).

Supply Chain Resilience

In the current scenario, supply chain resilience (SCR) is still largely configured as a set of reactive practices with a high dependency on human intervention. Many companies spend numerous man-hours collecting, cleaning and analysing data, and then manually define the main corrective actions (Parrott & Natarajan, 2024).

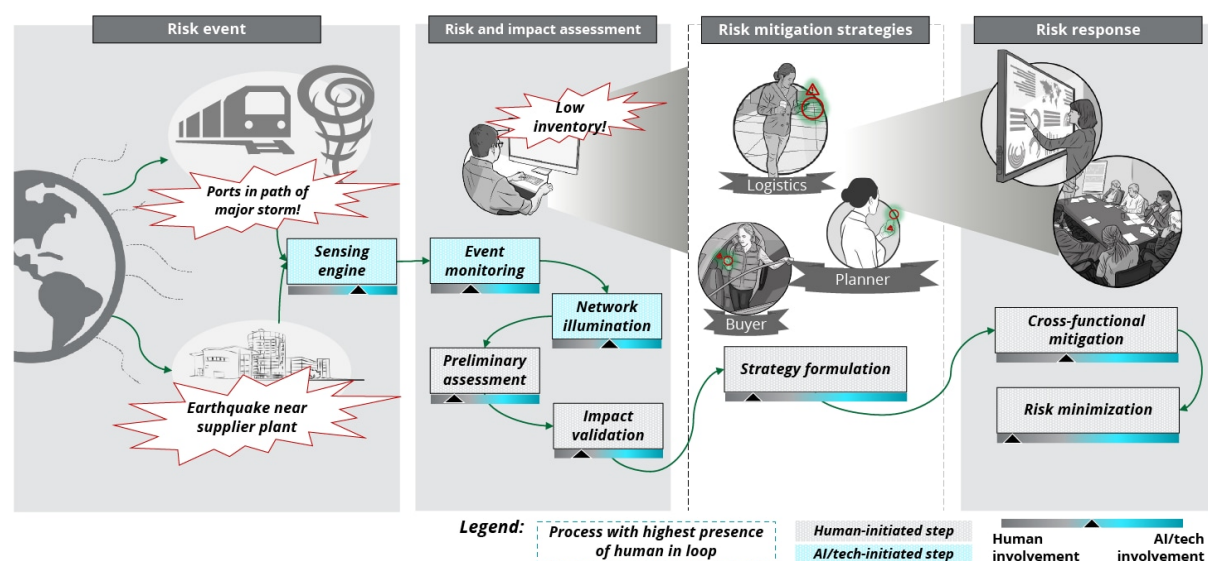


Figure 28 - Supply Chain Resilience: The Current State

Source: Deloitte. (2024). Generative AI-powered supply chain resilience. Deloitte Business Operations Room Blog.

As a result, the risk detection phase often suffers from the lack of an end-to-end vision, with response methods that are not always timely or based on integrated information, especially in complex supply chains with multiple levels of suppliers. The introduction of Gen AI tools, however, tends to shift the focus towards a more “proactive and prescribed” model (Parrott & Natarajan, 2024).

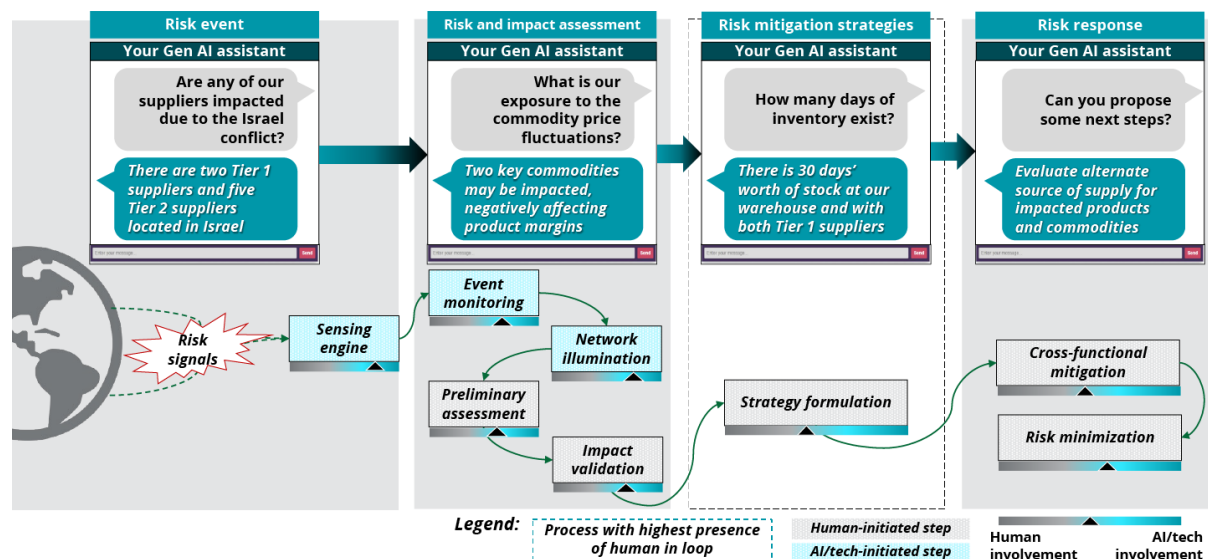


Figure 29 - Supply Chain Resilience: The Future State powered by Gen-AI

Source: Deloitte. (2024). *Generative AI-powered supply chain resilience*. Deloitte Business Operations Room Blog.

Gen AI systems, in fact, are able to continuously scan global scenarios, synthesize large amounts of data (internal and external to the company), as well as generate operational content such as risk reports, mitigation plans and suggestions for redesigning production lines. A crucial aspect is the possibility of automating a large part of the risk sensing and risk response actions, enabling a form of “guided resilience” based on libraries of already tested solutions that reduce decision-making times and dependence on individual human skills. For example, Gen AI can detect anomalies in supply flows, anticipate the scarcity of critical materials or identify possible geopolitical instabilities that impact supply chains, autonomously producing intervention scenarios that have already been prioritized (Parrott & Natarajan, 2024). In the future, these systems will have the ability to orchestrate a network of suppliers and partners more dynamically, even activating continuity plans with almost autonomous interventions (such as the diversion of shipments or alternative sourcing) in response to environmental or market triggers. In this evolution, humans will remain an element of verification and governance of processes (human-in-the-loop) but will be able to dedicate themselves more to value-added activities rather than repetitive operations, ensuring that supply chain resilience

becomes not only a short-term objective, but a real strategic factor of competitiveness (Parrott & Natarajan, 2024).

3. Internet of Things (IoT) in Logistics 4.0

Technological progress is profoundly transforming the way people use information systems both at work and in their free time. In particular, the Internet has revolutionized the consumption and exchange of information, radically changing the ways in which individuals interact. Thanks to continuous improvements in microprocessors, storage capacity, broadband networks and sensor technologies, together with increasingly efficient solutions for energy management, more and more areas of daily life are being computerized and connected to the network. Today, the use of the Internet is no longer limited to access via traditional devices such as computers or mobile phones but is progressively extending to everyday objects – such as light bulbs, refrigerators and even means of transport – which become an integral part of an interconnected ecosystem. For example, in 2023 the number of active Internet users exceeded 5 billion, corresponding to more than half of the world's population (Statista 2023a), while the number of connected devices exceeded 11 billion in 2021, with forecasts indicating an increase to approximately 30 billion by 2030 (Statista 2022a). In this scenario, the Internet of Things (IoT) emerges as a paradigm in which communication occurs not only between humans or between humans and machines, but also, and in an increasingly pervasive way, from machine to machine (Machine-to-Machine communication), paving the way for new opportunities and challenges in global interconnection.

3.1 Definition and key features

IoT Definition

IoT technology represents one of the most innovative and discussed paradigms of the latest years. Despite its growing diffusion, there is no universally accepted definition of the term.

Author	Definition
International Telecommunication Union (2012, p. 1)	“A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.”
Miorandi et al. (2012,p. 1497)	“The term “Internet-of-Things” is used as an umbrella keyword for covering various aspects related to the extension of the Internet and the Web into the physical realm, by means of the widespread deployment of spatially distributed devices with embedded identification, sensing and/or actuation capabilities.”
Xia et al. (2012,p. 1101)	“IoT refers to the networked interconnection of everyday objects, which are often equipped with ubiquitous intelligence.”
Gubbi et al. (2013,p. 1648)	“Interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless large scale sensing, data analytics and information representation using cutting edge ubiquitous sensing and cloud computing.”
McKinsey Global Institute (2015, p. 1)	“We define the Internet of Things as sensors and actuators connected by networks to computing systems. These systems can monitor or manage the health and actions of connected objects and machines. Connected sensors can also monitor the natural world, people, and

Table 2 - Selected definitions of IoT

Source: Author's personal elaboration

In general, the IoT concept refers to a set of physical objects (or “things”) equipped with sensors, actuators and connectivity capability that is able to collect data from the environment, exchange information on the network and act in a (semi)autonomous way, often with minimal or no human intervention. As previously stated in Chapter 1, when these “things” are industrial devices or systems used to support industrial operations, we are talking about Industrial Internet of Things (IIoT). Mohanraj et al. (2019) described IoT as “the set of connections of physical devices such as home appliances, vehicles and other items implanted with software, electronics, actuators, sensors and connectivity to enable communication for the transfer of data”. The term “Internet of Things” was coined by Kevin Ashton in 1999, during a presentation at Proctor & Gamble. He described it as a system of interconnection between physical world and the Internet through the use of RFID and pervasive sensor devices that observe and identify the real world (Ashton, 2011). However, the concept of interconnectivity among smart devices came into picture in early 1980s when a modified coke machine at Carnegie Mellon University, was connected to the Internet to check and report the inventory for the availability of the drinks. Ashton, founder of the Auto-ID Center at Massachusetts Institute of Technology (MIT), was one of the first to intuit the potential of using RFID tag in the field of supply chain management and to conceive a world in which everyday objects could communicate through the network.

In fact, according to some scholars, IoT is nothing more than “the next evolution of the Internet”, in which it is no longer just people who generate data online, but also things (Kosmatos, Tselikas, & Boucouvalas, 2011).

The term “internet” immediately brings back to a global system of networks based on the TCP/IP (Transmission Control Protocol/Internet Protocol) protocol, which connects billions of devices worldwide (Nunberg, 2012). “Things”, on the other hand, can indicate any physical entity, living and non-living: it ranges from electronic devices and intelligent equipment to objects that we do not normally consider “technological”, such as food, clothes, art pieces, and even monuments (Kosmatos, Tselikas, & Boucouvalas, 2011). In this context, what makes an object part of the “IoT world” is the ability to connect to the network and communicate information.

IoT is distinguished by some key characteristics:

- Pervasive connectivity: the ability to connect objects of different nature, enabling not only human-to-human but also human-to-things and, above all, things-to-things communication (Aggarwal & Lal Das, 2012).
- Unique identification: each “thing” participating in the IoT has a specific identity, often provided by RFID technologies or IP addresses, so that it can be recognized on the internet (Alavi et al., 2018).
- Data collection and analysis: smart objects, equipped with sensors, capture data in real time and transmit it to computing platforms (cloud) for advanced analysis (Graham & Haarstad, 2011).
- Automation: IoT enables processes that minimize human intervention. Devices react quickly to environmental changes and coordinates themselves in a dynamic way.
- Interoperability: to enable devices from different manufacturers to communicate, it is necessary to use common standards and open protocols, avoiding fragmentation.

These characteristics favour the birth of new application scenarios and give the IoT an extremely broad and constantly evolving nature.

IoT enabling technologies

The enabling technologies (see Figure 30) of the IoT are the set of solutions that, together with the Internet as a backbone, allow the integration of physical objects, people and systems into a single connected ecosystem.

Enabling technologies	Purposes	Examples	Standard challenges
Tagging technologies	Identify and track individual physical objects	Active/passive RFID tags	Cost of tags are still considerably higher than printed barcodes
Sensor technologies	Collect data about the real world and augment human senses	Temperature sensor, proximity sensor, GPS	Processing and making sense of the vast amounts of collected sensor data
Smart technologies	Provide processing capabilities to physical objects	Microprocessors	With improved capabilities, smart technologies require an increasing amount of energy
Miniaturization technologies	Shrink information technology such that it can fit into everyday objects	Three nanometer transistor manufacturing processes	As miniaturization continues, it becomes increasingly difficult to produce increasingly smaller things

Figure 30 - Summary of enabling technologies for the Internet of Things

Source: Sunyaev, A. (2024). *Internet computing*. Springer Nature Switzerland AG.

On the one hand, there are the so-called *tagging technologies*, which include optical identification devices (such as common barcodes) and, above all, RFID (Radio Frequency Identification). The latter uses radio waves to support computing devices in the identification, tracking and control of an object, while integrating the collection of metadata in a reliable and flexible way (Gupta & Quamara, 2020). In particular, RFID is a form of radio communication based on electromagnetic or electrostatic coupling in the radio frequency portion of the spectrum, designed to uniquely identify an object, an animal or a person (Zhu, Mukhopadhyay, & Kurata, 2012).

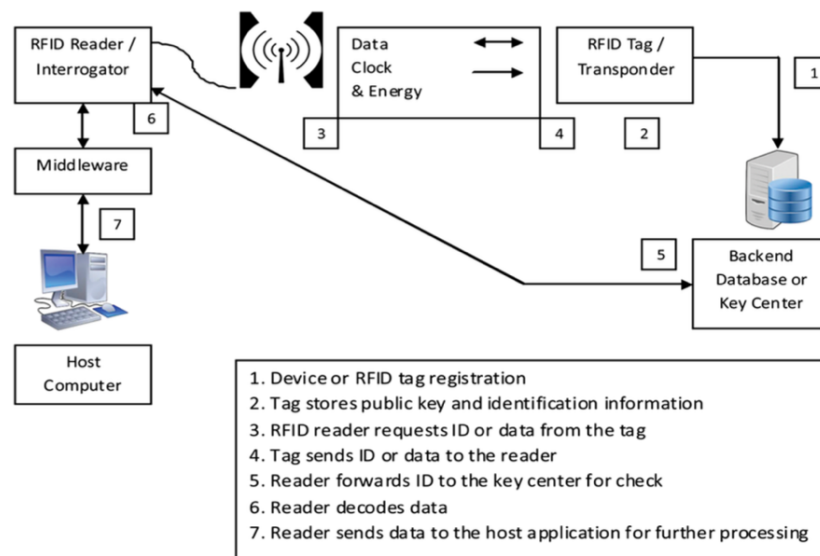


Figure 31 - A typical RFID system

Source: Gupta, B. B., & Quamara, M. (2020). *An overview of Internet of Things (IoT): Architectural aspects, challenges, and protocols*.

A typical RFID system is composed of two main components (Figure 31): the RFID Tag and the RFID Reader. The RFID Tag is a microchip connected to an antenna that stores information

and, when attached to an object, becomes its identifier. This coiled antenna transmits and receives radio waves to communicate with the reader, and the tags themselves (also known as transponders) can be active (battery-powered) or passive (powered by the reader when they are within its range) (Jia, Feng, Fan, & Lei, 2012). The RFID Reader, on the other hand, uses radio waves to communicate with the tag, obtain data and forward it to the external application, thus functioning as a transmitter and receiver (transceiver). Although it generally costs more than barcodes, RFID allows for much more granular monitoring and reading that does not require line of sight, an advantageous feature in industrial or logistics contexts.

Together with tagging systems, IoT makes extensive use of *sensor technologies*, i.e. sensors of various types (movement, brightness, temperature, etc.) which, thanks to the progressive reduction in costs and the possibility of forming wireless networks, are essential for collecting data from the real world. These sensors can be combined with actuators (for example fire-fighting systems), giving rise to WSN (Wireless Sensor and Actuator Network), in which the detected information is processed and can generate a physical reaction (Misra, 2017). Actuators are mechanical or electromechanical devices capable of providing controlled movements or positioning, using different power sources (electric, pneumatic, hydraulic) (Mouha, 2021).

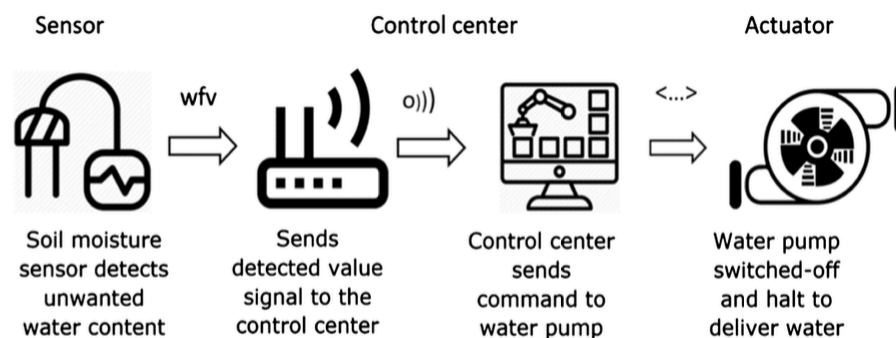


Figure 32 - Example of an actuator (pump water)

Source: Mouha, R. A. (2021). Internet of Things (IoT). *Journal of Data Analysis and Information Processing*, 9(2), 77–101. They allow, for example, linear actuation with hydraulic cylinders or electric motors, or rotary actuation with pneumatic systems, making possible applications that range from the movement of large industrial equipment to the most common household devices. The pneumatic approach, in particular, offers rapid response and great power, as demonstrated in the use of pumps and compressors (Figure 32).

The third component is *smart technologies*.

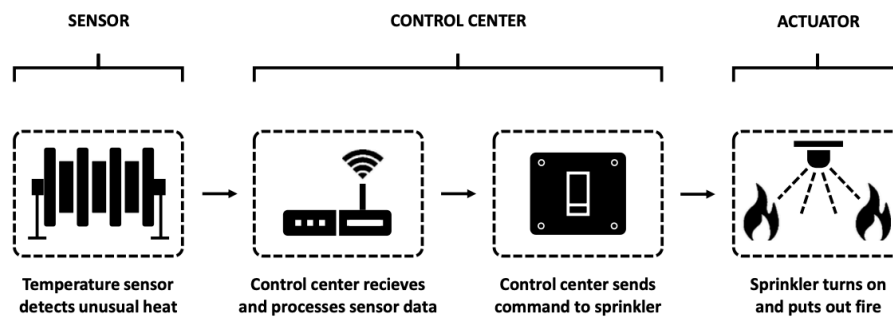


Figure 33 - Sensor to actuator flow

Source: Sunyaev, A. (2024). Internet computing. Springer Nature Switzerland AG..

They introduce intelligence on board objects, moving part of the computational processing “to the edge” (edge computing) to prevent the growing amount of data - coming from billions of connected devices – from overloading central servers (Bassi et al. 2013; International Telecommunication Union 2005).

Finally, progress in *miniaturization technologies* means that sensors, chips and batteries are so small that they can be incorporated into almost any device (International Telecommunication Union 2005). Without this miniaturization, the idea of a world in which hundreds of billions of physical objects connect, communicate and act autonomously would not be feasible.

All these components therefore work together to form the backbone of the IoT, allowing us to fully grasp the potential of an ecosystem of connected objects, capable of collecting and transmitting data, as well as interacting flexibly with the physical environment and with human users.

IoT architectures

The two simplest structures used to describe the architecture of the IoT are the three-layer and the five-layer models.

The three fundamental layers of the three-layer model are: Perception Layer, Transmission Layer and Application Layer. Each of them is organized into sublayers that reflect the different functions performed (ITU-T, 2009).

Layers	Sub-layers	Key Features	Key Technologies
Application Layer	IoT Applications	Handheld Devices, Terminals and User Interface	Cloud Computing, Middleware, M2M, Service Support Platform
	Application Support Layer		
Transmission Layer	Local & Wide Area Network	Connectivity Establishment and Information Transmission	Internet, GPRS, Wi-Fi, Ad hoc Network
	Core Network		
	Access Network		
Perception Layer	Perception Network	Sensing, Identification, Actuation and Communication Technologies	RFID, WSN, GPS, Bluetooth
	Perception Nodes		
Network Management	Physical and Information Security Management		Trust Management

Figure 34 - IoT architecture

Source: Gupta, B. B., & Quamara, M. (2018). *An overview of Internet of Things (IoT): Architectural aspects, challenges, and protocols.*

This model has gradually established itself because the IoT integrates heterogeneous technologies (such as WSN, RFID, M2M and low-power networks) and must respond to highly differentiated applications, from the healthcare sector to smart cities, up to the manufacturing industry. Below, a detailed overview of the three layers and their respective articulations.

- **Perception Layer** – Also called “Device Layer”, “Sensory layer” or “Recognition Layer”, the Perception Layer is the basis of the architecture. Its task is to detect data and perform direct actions on the surrounding environment (Suo et al., 2012; Khan et al., 2012). This area includes the perception nodes, which include physical devices such as temperature, humidity, brightness sensors, RFID readers, controllers or actuators. These elements can be organized in various topologies (mesh networks, Ad hoc environments, multi-hop networks) to ensure scalability and rapid installation (Li, Da Xu, & Zhao, 2015). Sensors, for example, monitor environmental or logistical parameters, while actuators perform mechanical actions when certain conditions occur (such as the opening or closing of a valve). Devices are often programmed to minimize energy consumption, activating only in the presence of a significant event. Nanotechnology is also used, which allows microchips to be miniaturized — in some cases embedded in objects — so that they can collect data and react in an “intelligent” way with minimal human intervention. At the same time, the Perception Network supports communication with the upper levels: it transmits the information acquired by the perception nodes to the gateways and receives, in reverse, the control commands intended for the actuators. This network can be wireless or wired and

must guarantee data security and integrity before they pass to the next level (Alaba et al., 2017).

- **Transmission Layer** – The Transmission Layer (also called “Transportation Layer” or “Network Layer”) connects the world of physical devices with the broader IT infrastructure, making the flow of data between sensors/actuators and processing or storage systems effective (Yan, Zhang, & Vasilakos, 2014). In practice, this layer acts as a bridge between “intelligent” objects and platforms that analyse information or produce response actions. Within it, further sub-layers are identified. The Access Network provides a connectivity environment for the Perception Layer: these can be 2G/3G/4G-LTE networks, Wi-Fi connections, ZigBee, Bluetooth Low Energy and even 5G solutions, which ensure higher transmission speeds. The presence (or absence) of centralized base stations then distinguishes centralized networks (such as Wi-Fi) from non-centralized environments (for example, Ad hoc networks) (Li & Chen, 2011). The Core Network (Internet), which represents the “backbone” of this architecture, transports data to end users or to other network segments, offering routing, remote access and resource management services. The Internet can be defined as a public, corporate, government, local (LAN) or geographic (WAN) network (Alaba et al., 2017). Finally, there is the area of Local and Wide Area Networks, which includes “traditional” LANs but also LPWANs (Low Power Wide Area Networks), specifically designed for low-power devices (Raza et al., 2017).
- **Application Layer** – At the top end of the IoT architecture is the Application Layer, which is responsible for providing services to end users. It is in this layer that the data coming from the Perception Layer, filtered and transmitted by the Transmission Layer, are processed, integrated and transformed into valuable actions and information. The Application Layer also governs the presentation of the results through usable interfaces (e.g. mobile apps, dashboards, web portals) (Suo et al., 2012). Within it, it is usual to distinguish between an Application Support Layer, focused on “intelligent” computing (also with data recognition and filtering techniques) and middleware functions, and a section dedicated to IoT Applications themselves (Jing et al., 2014). The middleware can include Cloud Computing platforms or service-oriented architectures (SOA), which facilitate scalability, quality of service (QoS) management and security (ITU-T, 2009). In many contexts, Machine-to-Machine (M2M) models are implemented, thanks to which devices communicate directly with each other, exchanging data on wired or wireless networks, without constant user intervention (Suo et al. 2012; Iraj et al., 2017).

The three-layer model extends to create the five-layer model, designed to respond to future evolutions of the IoT paradigm (Muntjir et al. 2017).

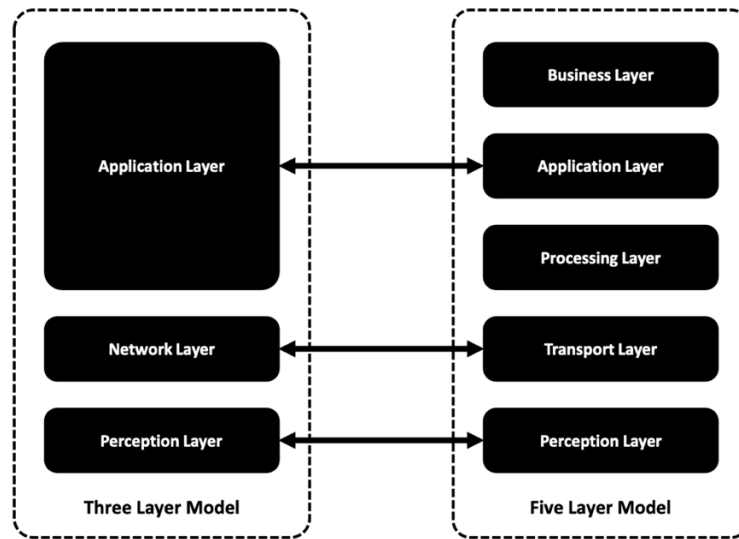


Figure 35 - Comparison of the three-layer and five-layer Internet of Things architectural models

Source: Sunyaev, A. (2024). Internet computing. Springer Nature.

This model integrates and refines the functions already highlighted in the three-layer model, introducing two additional layers and dividing some responsibilities in a more specific way. In particular, the five-layer model maintains the functions of the Perception Layer (lower layer), which continues to collect data from the environment; the Transport Layer, which is responsible for data transfer and is equivalent to the Network Layer of the three-layer model; and the Application Layer, which provides application services to users. The main innovation are the Processing Layer and Business Layer. Sometimes also called Middleware Layer, the Processing Layer is responsible for storing, processing and interpreting large amounts of data coming from the perception layer, using technologies such as databases and Cloud Computing services. While the Business Layer, located at the top of the model, is responsible for the overall management of the IoT system, including aspects such as the definition of business models and the protection of user privacy (Zhang & Zhu, 2011).

In short, if on the one hand the three-layer model compactly encloses the fundamental idea of IoT, the five-layer model allows a more detailed subdivision of the functions. This finer articulation of the layers facilitates a more efficient and scalable management, thus responding to the growing demands of complex applications and the evolution of technological scenarios.

Smart objects and smart devices

Internet-connected physical objects with embedded intelligence, often called smart things, play a key role in IoT. These smart things can be grouped into two categories: *smart devices* and

smart objects. Smart devices are portable electronic devices, usually owned and used by a single individual, that allow access to a wide range of services locally or remotely (Poslad, 2011). Typical examples are smartphones, tablets, laptops and even smartwatches or smart TVs, which are now widespread in everyday life thanks to the so-called “ubiquitous computing” described by Weiser (1991). According to his vision, in fact, the history of human-computer interaction has evolved from the time when many individuals shared a single computer to the current era in which each person owns multiple personal devices, almost always connected to the Internet. A key feature of modern smart devices, such as “tabs” (smart watches and bracelets), “pads” (smartphones and tablets) and “boards” (large interactive screens), is their ability to detect information about the surrounding environment, for example through integrated sensors, and to adapt to the user's needs, using localization functions and cloud services. This group also includes smaller and more specific solutions, such as the so-called smart dusts—small miniature devices equipped with sensors and processing functions, but without displays—that can be distributed over a large area to collect data on environmental or operating parameters. Another example is smart skins, flexible electronic “skins” integrated into fabrics, designed for applications in the medical and prosthetic fields (Benight et al. 2013). In addition to smart devices, which are distinguished by their mainly “personal” and multi-functional nature, there are also so-called smart objects. Unlike smart devices, smart objects can be objects of any type, equipped with sensors, microprocessors and communication interfaces to interact with other objects as well as with people (Kortuem et al. 2009). Consider, for example, smart light bulbs that can self-adjust brightness based on the time of day, or smart speakers such as Amazon Echo, Apple HomePod and Google Home, designed to “listen” and respond to voice commands and interact autonomously with other home systems. The central element of a smart object is its ability to collect data on the environment, process it, store it and exchange information with the outside world, thanks to network interfaces and internal sensors (Kortuem et al. 2009). Depending on the organizational context, these objects can acquire “activity-aware” functionality, recording use and work activities, “policy-aware” functionality, respecting specific business or legal rules, or “process-aware” functionality, providing support to business processes and signaling how and when to intervene in the various production or work phases (Kortuem et al. 2009). This differentiation highlights the greater conceptual “breadth” of smart objects, which do not need to be portable or have a unique owner. For this reason, the literature tends to frequently use the two terms interchangeably but also recognizes the distinction between “personal devices” and “intelligent objects” anchored to the context or to the application process of reference (Benight et al. 2013).

3.2 Internet of Things (IoT) in Logistics

The logistics sector represents one of the most promising application contexts for IoT technology (Da Xu et al., 2014; Zhou et al., 2012). The reasons for this potential reside in the very nature of logistics, where millions of shipments are moved, tracked and stored every day by a variety of actors and means (including machinery, vehicles and human operators). The IoT, by allowing the connection of these physical assets and the analysis of the data they produce, allows to optimize logistics processes in terms of efficiency, safety and quality of service (Fagnant and Kockelman, 2015). In the logistics sector, the IoT creates an ecosystem based on interconnected devices that produce and share information in real time along the entire supply chain (DHL, 2024). Using sensors, microprocessors and wireless connectivity, it is possible to constantly monitor the status of every logistics element: from containers in transit to warehouse racks, moving vehicles and simple packaging (Aamer, 2018a; Trab et al., 2015). The resulting benefits are better resource optimization, reduction of operation costs and the creation of new personalized services. Having the possibility of finding detailed information on the location of the items and their conditions, it is in fact possible to plan the physical flow in an increasingly precise manner, reducing transit times and facilitating the response to unexpected events (Mohanraj et al., 2019). Furthermore, the growing level of transparency and visibility of the logistics chain triggered by the use of IoT leads to the reduction of waste and downtime. All this contributes to the generation of a large amount of data that is collected by IoT devices. This data can be analyzed thanks to data analysis systems and AI, generating innovative services that respond in a personalized way to customer needs (PwC 2016; Akgul 2019). It is worth noting that many of the IoT devices – for example, sensors and actuators – have already been in use for some time in the logistics sector (e.g. in handheld readers for the digitalization of deliveries or in on-board sensors for monitoring truck performance). However, today's evolution of the IoT, supported by the continuous reduction in the costs of components (sensors, semiconductors), by more performing wireless networks and by increasingly powerful computing solutions, promises to revolutionize the sector even more, extending the application possibilities to previously unexplored levels (DHL, 2024).

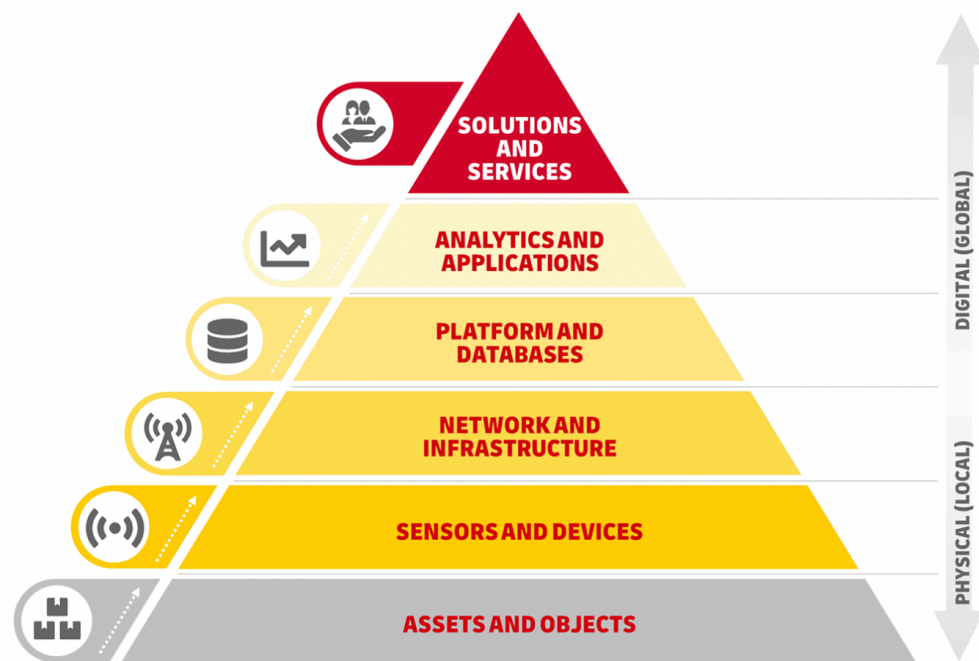


Figure 36 - The IoT Ecosystem

Source: DHL, 2024

To better illustrate the structure of IoT in logistics, it is useful to refer to Figure 36, which offers a pyramid representation of the IoT ecosystem (DHL, 2024). In this image, the lower levels (“Assets and Objects” and “Sensors and Devices”) indicate the physical elements to be connected. In this case for example we are talking about containers, pallets, shelves, vehicles and sensing devices. Going up the pyramid, we encounter the network infrastructure and data management platforms: these layers allow devices to communicate with each other and send the information collected to central analysis systems. In the upper levels (“Analytics and Applications” and “Solutions and Services”), data is processed, interpreted and transformed into concrete solutions for operators, such as real-time monitoring dashboards, decision support tools or automated services for warehouse management. This illustration highlights the need for a well-defined technological “layering” to effectively connect assets and physical objects with analysis systems and decision support tools. In other words, the process that transforms raw sensor data into a value-added service requires a solid communication infrastructure and a complex set of IT and application resources (Keller et al., 2011; Lozano-Perez, 2012).

3.2.1 Fields of applications

3.2.1.1 Smart freight transportation



Figure 37 – Example of smart freight transportation enabled by the Internet of Things (IoT)

Source: DHL & Cisco. (2015). Internet of Things in logistics: A collaborative report by DHL and Cisco on implications and use cases for the logistics industry. *DHL Trend Research*.

Freight transportation is the physical flow of goods and cargo through ships, aircraft, trains or vehicles. The industry is challenged by several issues, including wasted cargo capacity, loading and unloading errors, low operational efficiency, and issues related to transportation safety and cargo protection. In this context, the concept of “smart freight transportation” represents a framework aimed at integrating ICT technologies into transportation infrastructure and cargo itself, in order to alleviate these issues since it allows to make freight transportation not only more efficient, but also safer and traceable in real time (Hidalgo Fort et al. 2018; Liu et al. 2019). One of the key pillars of “Smart Transportation” is the adoption of IoT technologies capable of interacting with vehicles, containers and personnel involved, providing real-time data and enabling faster and more reliable decision-making processes. Transport management includes fleet supervision, vehicle condition monitoring and driver activity verification. The application of IoT in this field mainly takes the form of vehicle cloud monitoring, i.e. the integration of sensors and communication systems directly into means of transport, with the possibility of constantly collecting information and transmitting it to devices connected to the Internet (such as smartphones or tablets) (Manojlović, 2019).

Traceability, monitoring and security

One of the most significant contributions of IoT in the freight transport sector concerns the increase in traceability (track and trace). A fundamental starting point in this sense is the use of tools such as RFID, whose diffusion in freight transport allows for the precise identification and tracking of both vehicles and goods. In particular, during transportation, RFID can collect and track information about logistics resources during loading and unloading (Liu et al. 2019), locate containers (Zhang, Lu, and Wang 2014), and manage customer order data (identity, volume). Such data can then be used for vehicle configuration optimization and route planning, as well as for vehicle routing optimization. In addition, RFID tags can include the so-called Electronic Product Code (EPC), which is a code that contains product details and tracks the entire transportation process (Zhang et al. 2019). RFID technologies can be integrated with other complementary systems, such as GPS (Global Positioning System) and GIS (Geographic Information System), to provide real-time location information, optimized navigation services and constant monitoring (Liu et al. 2019; Cheung et al. 2008). GPS (based on the GNSS network, Global Navigation Satellite System) is used to locate and track the vehicle in real time, while the connection to the online application occurs via GPRS (General Packet Radio Service). GIS, on the other hand, provides the spatial distribution of roads, the related infrastructures, traffic conditions and an optimized navigation service. The data thus acquired - position, direction, time, speed, consumption - are stored in the cloud, giving the possibility of generating detailed reports on trips, management costs and load status (Manojlović, 2019). This continuous acquisition of information also allows for the creation of travel orders and real-time control over the vehicle, provided that it is connected to the Internet. All of these things are made possible, especially thanks to WSN as they allow for the real-time verification of the status of the cargo, such as temperature, humidity or any unauthorized opening of containers (Zhang et al. 2019). In particular, when transporting perishable goods, remote monitoring of the internal temperature of the products with WSN is essential (Jedermann et al., 2014). In fact, the perishability of goods is often related to the storage environment. Environmental sensors collect temperature and respiration data (oxygen and carbon dioxide), monitoring the storage environment of the goods during transport (Zhang et al. 2019). Such non-invasive measurements are of crucial importance for food supply chains, where any deviation from optimal parameters can result in deterioration of product quality and, consequently, significant economic losses.

Applications on different modes of transport

The application of IoT to “Smart Transportation” involves different modes of transport, with specific characteristics in terms of traceability, safety and route optimization (Zhang, Lu, and Wang 2014):

- Road transport: focuses on the management of the entire fleet of trucks or vans, aiming to improve route efficiency, reduce fuel consumption and intervene promptly in case of failures. The reading of RFID tags during loading and unloading phases, combined with the use of sensors and GPS, facilitates the rational allocation of vehicles, with positive effects in terms of fleet management (Cheung et al. 2008; Liu et al. 2019).
- Maritime transport: In addition to the now consolidated use of RFID for the unique identification of containers and WSN for the non-invasive monitoring of temperature, humidity and shocks, the IoT is evolving towards integrated platforms that connect the entire fleet to a shared data ecosystem. The three-level architectural model — collection node, edge gateway and cloud center — proposed by Plaza-Hernández et al. (2021) allows sensory flows (vibrations, consumption, emissions) to be processed locally and only synthetic indicators to be transmitted to the cloud, reducing decision-making latency and the use of satellite bandwidth. Route tracking, predictive maintenance and emission control applications are grafted onto this infrastructure (think of commercial solutions such as IoCurrents or Green Sea Guard), as well as telemedicine and well-being services for the crew, which are essential given the often remote areas they operate in.
- Rail transport: using WSN it can be possible to timely monitor the status of the infrastructure (tracks, bridges, switches), and consequently generate alerts in the event of abnormal vibrations or breakdowns (Fraga-Lamas et al., 2017). This significantly increases safety, as it identifies risk factors before they turn into major failures.

Despite the advantages, the literature reports the lack of studies aimed at investigating at a strategic level the impact of IoT on the design of transport networks and on the choice of modes (Zhang et al. 2019). This leaves room for possible future research aimed at exploring the dynamics of integration between road, rail and maritime transport, relating technological benefits to broader managerial decisions. A further obstacle is the fragmentation of IoT solutions, often proprietary and not interoperable with each other. To overcome this limitation and unify information from different modes of transportation in a single portal, specialized companies such as Agheera have developed open platforms that can consolidate data from

multiple telematics devices and different sensors. This way, a complete end-to-end overview of the supply chain can be achieved (DHL & Cisco, 2015).

Evolution of monitoring and predictive tools

The potential of IoT in the Smart Transportation sector goes well beyond the simple passive recording of the position and condition of the load. According to available analyses, monitoring will become progressively faster, more predictive and secure, helping to minimize losses due to theft or damage (DHL & Cisco, 2015). In fact, cargo theft continues to represent a significant problem: Overall, cargo thefts in the U.S. in Q3 2023 increased by an unprecedented 59% compared to Q3 2022, according to CargoNet. In 2024, the situation continued to worsen, with CargoNet reporting a 27% year-over-year increase in cargo thefts, reaching a record 3,625 in North America (Verisk, 2025).

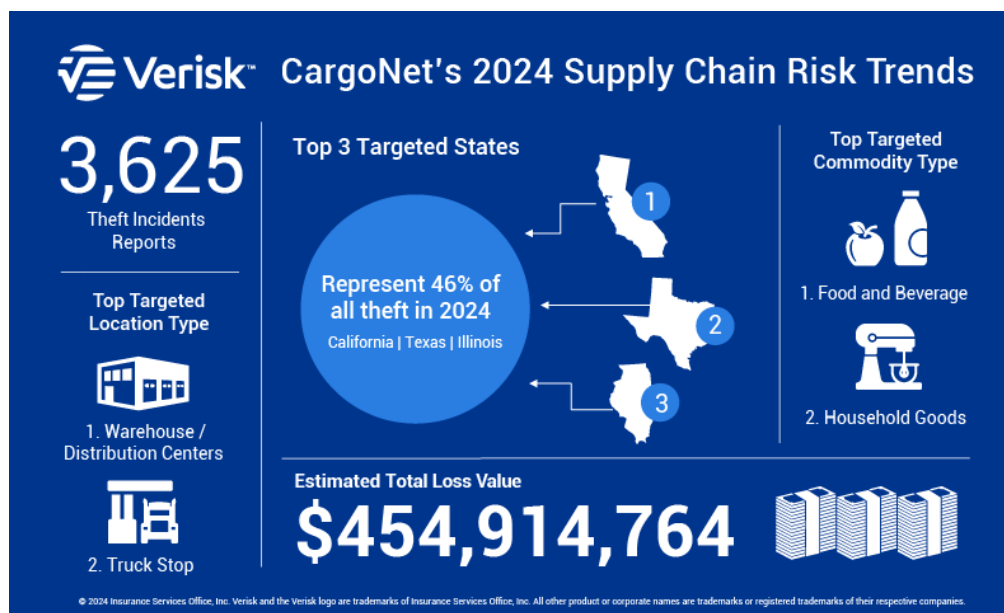


Figure 38 - CargoNet's 2024 Supply Chain Risk Trends

Source: Verisk. (2025). *Cargo theft surges to record levels in 2024, Verisk CargoNet analysis reveals.*

Such events, in addition to direct damage, lead to delays and additional costs for companies. However, IoT can provide monitoring solutions focused on the single item, thanks to multi-sensor tags that transmit information on position, environmental conditions and even the opening of the package (a possible indicator of tampering). A significant example is represented by SmartSensors, intelligent devices that detect temperature, humidity, shocks and even possible exposure to light, as this could indicate the unauthorized opening of a container. These systems then transmit everything to open platforms or clouds. These platforms integrate different devices (vehicle telematics, on-board container sensors, etc.) into a single analysis system, making real-time control possible on all goods in motion (DHL & Cisco, 2015). A

direct consequence of this evolution is the creation of centralized dashboards, where information about the position, residual load capacity, environmental data and vehicle conditions are aggregated into a single control panel. At the same time, IoT offers opportunities for optimization in fleet and asset management. Sensors installed on trucks, containers or cargo units can provide data on the frequency of use of vehicles, any long stops and levels of residual load capacity. This information feeds analytical platforms that facilitate the planning of the most efficient routes, reduce fuel consumption and limit the kilometres travelled empty by vehicles (DHL & Cisco, 2015).

Predictive maintenance and driver safety

In addition to load tracking, IoT offers great support in predictive maintenance of vehicles and in collecting information on driving conditions (Sivaraj et al., 2021). Sensors placed in critical points – such as shock absorbers, engines or refrigeration systems – allow for early identification of any wear or failures (DHL & Cisco, 2015). This data is then transmitted to analysis platforms that generate alerts and preventive maintenance requests, significantly reducing vehicle downtime and increasing delivery reliability. In this context, OBD (On-Board Diagnostics) technology collects technical parameters, for example on engine performance or safety systems, and transmits them to a cloud platform where they can be analysed in detail. The results are then sent in real time to the driver's smartphone, allowing immediate intervention in case of problems. A concrete example is the European project “MoDe” (Maintenance on Demand), which - launched in 2012 in collaboration with Volvo, DHL and other partners - led to the creation of an industrial vehicle capable of self-diagnosing and proactively deciding whether and when to intervene on damaged components (DHL & Cisco, 2015). According to the data that emerged, this approach has shown an increase in vehicle uptime of up to 30%, reducing the risk of unexpected failures that would compromise the entire delivery chain.

Risk Management Along the Supply Chain

In an increasingly globalized context, transports must also deal with exogenous factors – such as geopolitical instability, strikes, natural disasters – that can interrupt the normal circulation of goods. IoT, integrated into advanced supply chain risk management tools, promotes prevention and rapid response to such events (DHL & Cisco, 2015).

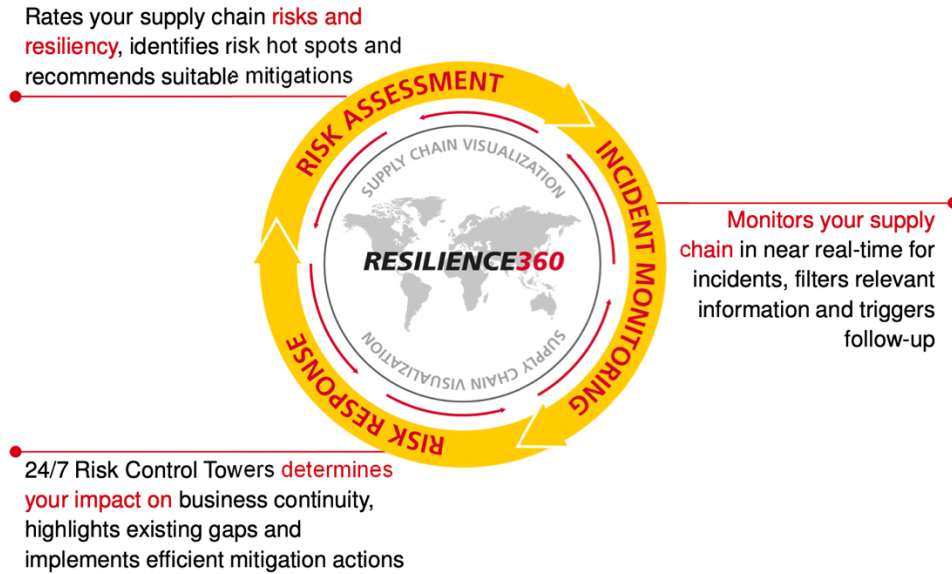


Figure 39 - Resilience360 – a holistic risk management solution

Source: DHL. (n.d.). Resilience360: Turning a potential disruption into competitive advantage [PowerPoint presentation]. DHL Corporate Solutions & Innovation.

A notable case is Resilience360, a platform which provides a real-time view of all relevant routes and infrastructures, cross-referencing alerts on strikes, port and airport closures or adverse weather conditions. If the system detects a potential impact on a specific route, then it can also suggest corrective actions like moving the load to a different carrier or redistributing stocks across other logistics hubs.

3.2.1.2 Smart warehousing

The smart warehouse is nothing more than the strategic and technological evolution of traditional warehouse. All this is made possible thanks to the integration of different technologies, among which IoT is certainly one of the most impactful. The goal of this transformation is to optimize the activities of receiving items, storage, inventory management, picking and loading, creating a more agile, efficient and safe logistics system. The warehouse becomes an “intelligent” environment in which machinery, shelves, products and operators communicate with each other, generating real-time visibility and reducing errors and delays along the supply chain. Traditionally, warehouse activities included receiving processes, allocation of goods to shelves, picking to order and loading of means of transport. Such activities, combined with a high variety of goods types and customer demands, have often led to issues such as low operational efficiency, suboptimal space utilization, and inventory management errors (Lee et al. 2018; Lim, Bahr, and Leung 2013). In this context, IoT offers effective solutions to address these issues, exploiting distributed monitoring and sensing

devices but also using automated systems that support the decision-making process. The ability to connect objects (such as shelves, forklifts, pallets) and operators via sensors and RFID tags allows the WMS (Warehouse Management System) to obtain real-time data on the status and location of each entity in the warehouse. This leads to a reduction in decision delays and facilitates rapid interventions in emergency situations such as urgent changes in picking priorities for example (Trab et al. 2017).

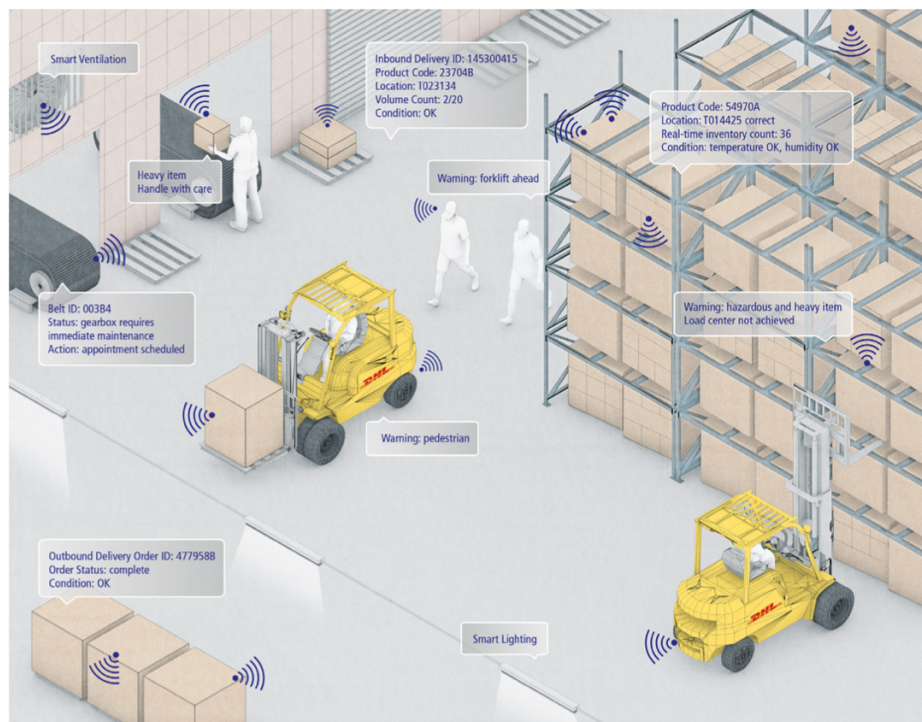


Figure 40 - Smart warehouse with integrated IoT technologies

Source: DHL & Cisco. (2015). Internet of Things in logistics: A collaborative report by DHL and Cisco on implications and use cases for the logistics industry. DHL Trend Research.

The fundamental components of IoT in the smart warehousing field are the following:

- RFID and automatic tracking
- WSN and environmental sensors
- Multi-agent systems and decentralized decision-making
- Wearable Sensors

RFID technology has been defined and explored earlier in this chapter, thus it is already known that it is considered a key technology for automatic identification and tracking of goods and warehouse assets (Garrido-Hidalgo et al. 2019). In particular, in this case RFID tags can be applied to SKUs (Stock Keeping Units), pallets, or even the warehouse floor, in order to generate data related to the type and quantity of goods, storage location, and storage conditions (Jabbar et al. 2018; Giusti et al. 2019). RFID readers, equipped with antennas, can be placed at

entrances, on shelves or on forklifts, allowing to identify in real time the status and position of each item. This approach makes the warehouse “transparent” and reduces errors due to manual input (Biswal, Jena-mani, and Kumar 2018; Giusti et al. 2019). Through precise localization, resource allocation is speeded up and the efficiency of picking and loading operations is improved (Yan et al. 2014). Furthermore, real-time tracking of forklifts and other material handling equipment (MHE) can increase safety and speed in operations (Ballestín et al. 2013). **Wireless Sensor Networks (WSN)** and **environmental sensors** also allow for the constant monitoring of warehouse conditions. They are positioned in strategic locations and then transmit data in real time to the WMS (De Venuto and Mezzina 2018). For example, sensors installed on forklifts allow for the early detection of failures or non-optimal behavior of the vehicles (Jabbar et al. 2018). If the system detects significant or anomalous variations, it sends alarms. In this way predictive maintenance is enhanced and unexpected downtime is reduced (Trab et al. 2017; Zhang, Zhao, and Qian 2017).

In parallel with the adoption of RFID and WSN technologies, the use of **Wearable Sensors** is spreading, i.e. devices equipped with sensors to be worn on the body, capable of detecting movements, physiological parameters or stress indicators (DHL, 2024).

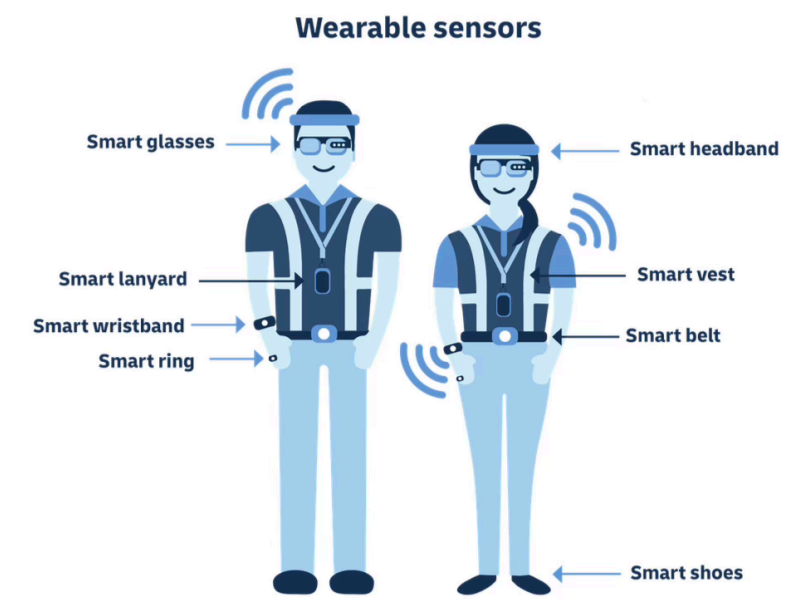


Figure 41 - Examples of wearable sensors for industry 4.0

Source: DHL. (2024). Logistics trend radar 7.0: Your guide to innovation in logistics.

These solutions range from bracelets and badges to smart glasses and smart clothing with gyroscopes, accelerometers or integrated sensors. The adoption of wearable sensors is now at the centre of security and process optimization strategies in the logistics and manufacturing sectors (DHL, 2024). Recent studies highlight how these sensors represent a fundamental piece in creating a “human-in-the-loop” paradigm, i.e. an ecosystem in which the human operator,

strengthened by sensors, collaborates closely with machines and digital systems (Kong et al., 2019).

The ecosystem of industrial wearable devices is divided into two large, often complementary, families:

- I. Human interaction devices – smart glasses, smartwatches, rugged tablets or clip-on displays. Their purpose is to convey contextualized information (pick lists, safety warnings, assembly instructions) while minimizing manual interaction (Sawyer et al. 2014).
- II. Data collection devices – ring scanners, smart gloves, RFID shoes or insoles, UWB/BLE badges, sensorized clothing with accelerometers or gyroscopes. These devices operate as distributed sensors that capture operational, biometric or localization data, sending them in real time to information systems (Schmuntzsch et al. 2014).

The same task may require the combination of both categories: for example, a picker uses the smart glasses to visualize the location of the product and at the same time the ring scanner to record the picking.

In contrast to the “all-in-one” PDA (Personal Digital Assistant) – bulky, heavy and not very ergonomic – the most effective approach in the industrial field involves a *functionally separated design*.

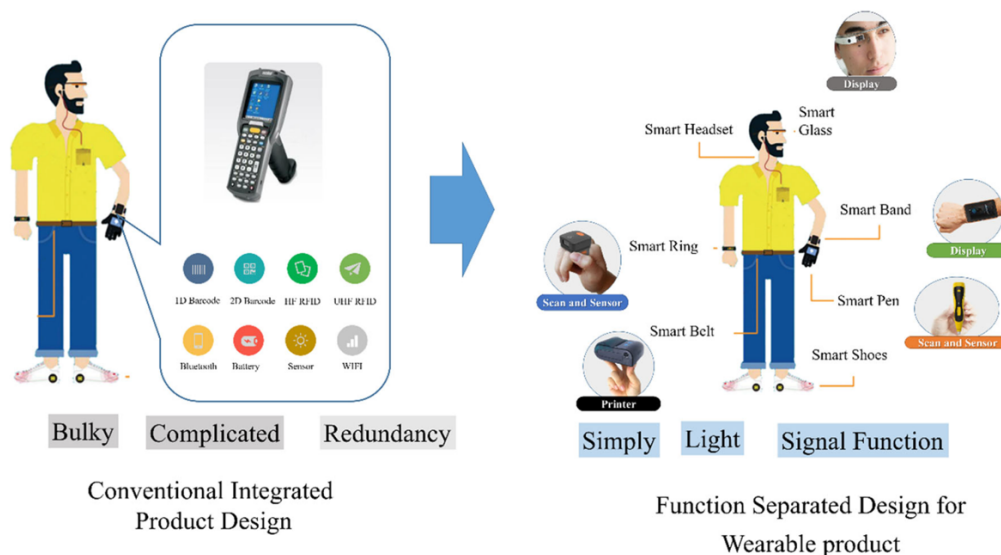


Figure 42- Functional separated design of industrial wearable system

Source: Kong, X. T. R., Luo, H., Huang, G. Q., & Yang, X. (2019). Industrial wearable system: The human-centric empowering technology in Industry 4.0. *Journal of Intelligent Manufacturing*, 30(6), 2853–2869.

This means that each device performs a specific function and is placed on the most suitable part of the body (Lukowicz et al. 2004). Thus, the scanner can be integrated into a finger, the localization module into a badge and the visual interface into a pair of glasses. The modularity

of the accessories (strap, magnetic supports, clips) that can be confined and reconfigured allows the same sensor to be adapted to different operating scenarios and different body types.



Figure 43 - Multifunctional wearable scanning device with modular accessories

Source: Kong, X. T. R., Luo, H., Huang, G. Q., & Yang, X. (2019). Industrial wearable system: The human-centric empowering technology in Industry 4.0. *Journal of Intelligent Manufacturing*, 30(6), 2853–2869.

The ring scanner illustrated in Figure 43 can, for example, transform from a barcode reader with a “touch” gesture to an RFID reader with a “grip” gesture, simply by exchanging the support (Lorenz et al. 2015).

From a human factor’s perspective, devices must:

- ensure hands-free operation during critical tasks (Lukowicz et al. 2004);
- use breathable and hypoallergenic materials in the parts in contact with the skin, respecting hygiene requirements (Lorenz et al. 2015);
- integrate forms of non-invasive feedback (light vibrations, notification LEDs, directional acoustic signals) to minimize cognitive load (Chao et al. 2016).

From operational stability point of view, these devices should have long battery life, stable wireless connection, and resistance to environmental conditions. They should interface seamlessly with ERP, MES, and WMS, and collect data directly from machinery and production systems.

The use of wearable sensors in logistics focuses mainly on three areas:

- I. Worker localization: The ability to track the position of operators in real time enables safety-related use cases, such as reporting incidents (person-down alert) or avoiding

collisions with forklifts. For high-precision localization solutions, it is necessary to invest in infrastructure such as ultra-wideband (UWB), but the choice of technology (e.g. BLE, Wi-Fi or UWB) varies based on the required accuracy and transmission speed. In some contexts, BLE (Bluetooth Low Energy) is preferable for lower costs, as in the case of the startup Sonitor, which uses BLE or ultrasound to track the position of operators and resources in real time, enabling applications such as geo-fencing and automatic reporting of working times (DHL, 2024).

- II. Process Intelligence: The analysis of data collected by wearable sensors allows obtaining Process Intelligence. For example, DHL Supply Chain uses the Motion-Mining® solution, developed by a German startup, to collect operational data (in anonymized and GDPR-compliant form) using temporary wearables. This data, free from observation bias, is processed to identify inefficiencies and improve processes. In parallel, devices such as smart glasses or wearable scanners provide real-time insights into productivity and potential bottlenecks (DHL, 2024).
- III. Ergonomic Health: Musculoskeletal disorders (MSD) are among the main problems related to the work environment in Europe. Wearable sensors can reduce risks by analysing potentially dangerous postures and movements. Solutions such as Soter Analytics or Kinetic vibrate or emit an acoustic signal when the operator makes incorrect movements (e.g. inappropriate bending or dangerous twisting), contributing to a gradual improvement in postural habits. In addition, devices such as smartwatches and smart bracelets can monitor vital parameters (stress, fatigue), sending alerts in case of anomalous values. However, these applications require maximum attention to privacy protection: the data collected (e.g. health parameters) must be anonymized and processed in compliance with data protection regulations (DHL, 2024).

The main challenges associated with the use of wearable devices in logistics therefore concern the protection of personal data, infrastructure costs and the risk of overloading operators with too many wearables. Proper technology selection and collaboration between vendors, HR managers and workplace safety figures become essential for effective adoption.

To sum up, thanks to the integration of IoT and Wearable Sensors, smart warehouses obtain numerous tangible benefits related to better inventory management, optimization of inbound and outbound flows, efficient use of machinery and predictive maintenance, worker safety and injury prevention, infrastructure monitoring and energy saving.

- Better inventory management: Real-time traceability of stock, combined with constantly updated data, prevents stock-outs and reduces the costs of overproduction or unused space.

The data generated by RFID tags or sensors installed on goods and vehicles, in fact, flow into the WMS, which precisely calculates the stock levels and their location (Biswal, Jenamani, and Kumar 2018; Giusti et al. 2019).

- Optimization of inbound and outbound flows: The ability to automatically check the contents and conditions of incoming pallets, thanks to wireless readers and cameras (to detect any damage), speeds up check-in and the assignment of a location. In the outgoing phase, each pallet is scanned and immediately compared with the order: this way the right products are always shipped, errors are avoided, and the inventory is updated in real time (Trab et al. 2017).
- Efficient use of machinery and predictive maintenance: By keeping an eye on machinery such as forklifts, conveyor belts and AGVs, it is possible to intervene immediately if a vehicle is over- or under-utilized, improving efficiency and predictive maintenance. Furthermore, by adding an analysis of parameters such as temperature, vibrations and operating cycles, predictive maintenance can easily be activated, scheduling interventions before failures occur (especially on handling machinery) or bottlenecks are created.
- Worker safety and injury prevention: installing sensors and cameras on forklifts and racks can detect hidden obstacles and dangers. Forklifts can be programmed to automatically slow down when approaching intersections or when they detect a pedestrian (Industrial Truck Association; U.S. Occupational Health and Safety Administration). In addition, the use of pressure sensors helps avoid poorly distributed or excessive loads. Some systems, such as Ravas's "smart forks", integrate scales and load centres, alerting the operator if weight limits are exceeded or if the load is unbalanced. Preventing pallets from falling or slipping can be entrusted to a set of sensors and cameras, capable of identifying imperfect storage and sending alerts before accidents occur. Whereas on the human side, as already stated, wearables monitor the physical condition of workers in real time preventing injuries and ensuring rapid interventions (Buntak, Kovačić, & Mutavdžija, 2019; Wanganoo, 2020).
- Infrastructure monitoring and energy saving: The integration of sensors also in the building infrastructure (lighting, heating system, ventilation) allows for optimizing consumption. This reduces energy costs and environmental impact (De Venuto and Mezzina 2018).

3.2.1.3 Smart Delivery

Differently from freight transportation—which involves the bulk transportation of goods between locations, often for business-to-business transactions or moving inventory—the

delivery focuses on the final stage of transportation: delivering individual packages or goods to a specific customer's address. “Smart Delivery”, instead, refers to the set of practices and technological solutions aimed at making the delivery process faster, safer and more accurate. In particular, the integration of the IoT in delivery aims to solve several problems that affect the current system, including operational inefficiencies, failed deliveries, theft of goods and the deterioration of perishable products (Shi, Zhang, and Qu 2010; Fu et al. 2015). Thanks to the connectivity and sensors typical of the IoT, tracking and monitoring of shipments become more detailed, allowing to share and make interactive the information related to the delivery status. Technologies such as RFID, environmental sensors, GPS devices, and wireless network systems support the flow and sharing of data between different actors in the logistics chain. For example, shared delivery or “joint delivery” takes advantage of the interconnection of physical logistics resources, enabling significant improvements in delivery efficiency and resource optimization (Wang et al. 2019). A crucial aspect for smart delivery is real-time traceability: by installing sensors, RFID tags, or GPS devices on vehicles and equipping personnel with mobile devices, it is possible to know the location of the courier and the goods both in outdoor environments (thanks to GPS) and in indoor environments (via RFID) (Lin, Cheng, and Wang 2011). This level of visibility allows for providing updates to customers and for any route recalculations or vehicle reassignments, for example in the event of accidents or unforeseen events (Ngai et al. 2012). Security is another pillar of smart delivery. As in the case of smart freight transport, also in the context of smart delivery, theft of goods is a crucial point to manage (Yang, Luo, and Lu 2015), as well as incorrect deliveries (Fu et al. 2015). Thanks to RFID identifiers and geofence mechanisms the control of these two phenomena becomes easier and easier (Oliveira et al. 2025), while with sensors and wireless technologies the status of the vehicle can be constantly monitored as well as the physical conditions of the driver, reporting dangerous driving situations such as drowsiness (Kido and Nakamura 2016). There is no shortage of applications for privacy protection: QR code technology, for example, allows both to authenticate the courier and to protect the privacy of the end user (Gao et al. 2018). Special attention should be paid to perishable products, as they require constant environmental controls. Real-time monitoring and collection of parameters such as temperature and humidity (Tsang et al. 2018) minimize waste and spoilage risks, with clear advantages for sectors such as the food industry or pharmaceuticals (Trebar, Lotric, and Fonda 2015; Yang, Yang, and Yang 2011). In this regard, a very important trend is that of smart packaging. Smart packaging represents the evolution of traditional packaging solutions and plays a key role in smart delivery. By integrating sensors into product packaging, it becomes possible to monitor product

quality parameters both in real time and not. In addition to protecting the intrinsic characteristics of the items, these devices collect additional information along the entire logistics chain—such as origin, route, storage conditions, and final destination—significantly enriching the available information framework (Poyatos-Racionero et al., 2018). The fact that distributors and consumers can access this evidence increases transparency and security, overcoming the limitations of traditional packaging. The result is more efficient management, capable of containing waste of resources and product along the supply chain (Kalpana et al., 2019). From an operational point of view, smart packaging solutions perform various functions—from the detection and reporting of critical conditions, to the storage, traceability, and transmission of data—laying the foundations for optimization tools that improve the overall reliability of logistics (Onwude et al., 2020).

Literature and major industry reports (DHL, 2024) distinguish three macro-categories:

- I. Active Packaging & Tracking
- II. Intelligent Packaging
- III. Modified Atmosphere Packaging (MAP)

Active packaging incorporates additives (e.g. antimicrobials or moisture absorbers) that extend the shelf life of pharmaceutical or agri-food products, but requires maintaining strict thermal control along the cold chain. The integration of IoT sensors and tracking devices allows monitoring of temperature, impacts and overturning, activating notifications when safety thresholds are exceeded. However, tracker batteries are classified as dangerous goods in air transport, a circumstance that limits their use. On the other hand, disposable Bluetooth solutions are less expensive, but generate e-waste and therefore pose sustainability issues (DHL, 2024).

Defined as “packaging that senses and informs”, Intelligent Packaging monitors the internal conditions of the product through time-temperature indicators (TTI), freshness sensors or RFID tags (Poyatos-Racionero et al., 2018; Kalpana et al., 2019). Unlike active packaging, intelligent packaging simply records and displays product information, while, as already explained above, active packaging acts directly on the product to extend its shelf life (Soltani et al., 2021). A case in point is the “Digital Shipping Label & Asset Tracker” by the startup Envio, which combines an e-ink label with detectors for opening, falling or exceeding the temperature (DHL, 2024).

Modified Atmosphere Packaging (MAP), instead, is a fundamental tool for the management of perishable or oxidation-sensitive goods. In this case, the internal atmosphere can be controlled and modified by replacing oxygen with other gases (e.g. nitrogen) to extend the shelf life. For

instance, the Covid-19 pandemic has shown how MAP is essential even in the context of the pharmaceutical industry. In fact, even in the transport of vaccines, the temperature must be strictly monitored to guarantee the preservation (DHL, 2024).

The different classifications are related to the technology used for packaging. Figure 44 shows the classification of technologies used in intelligent (smart) packaging.

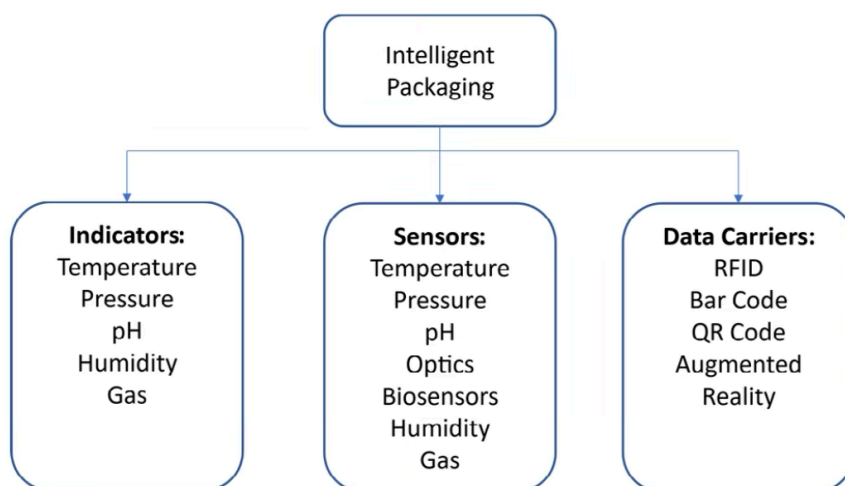


Figure 44 - Classification of smart packaging technologies

Source: Fernandez, C. M., Alves, J., Gaspar, P. D., Lima, T. M., & Silva, P. D. (2023). Innovative processes in smart packaging: A systematic review. *Journal of the Science of Food and Agriculture*, 103(3), 986–1003.

Indicators are simple devices, often similar in appearance to a label or sticker, designed to change appearance when the product is subjected to unsuitable conditions (Ahmed et al., 2018). The principle on which they are based is almost always irreversible: once the color change has occurred, the information remains “written” on the packaging and can be read at a glance by anyone, without electronic tools (Otles & Sahyar, 2016).

The following are examples of indicators:

- Time-Temperature Indicators (TTI): they are devices that can be attached to primary, secondary, and pallet packages. Inside this device there is a physical-chemical reagent which accumulates the heat received over time. If the temperature has always remained correct, the central circle remains clear; if the sum of all the small changes exceeds the threshold, the colour fades towards blue or red. In practice, a TTI translates the thermal history of an invisible risk (a change of a few degrees) into a visible signal (Müller & Schmid, 2019; Wang, Wu, & Cao, 2019).
- Freshness indicators: the focus is not on temperature but on metabolites, that is, chemicals that bacteria or the product itself release during degradation. Some examples: carbon dioxide for fruit and vegetables, biogenic amines for fish, hydrogen sulfide for meat. A freshness indicator is a label which contains a reagent that reacts with one of

these molecules to change colour so the consumer can understand if the product is still safe without opening the package (Fernandez et al., 2023).

- Variable pH films with natural colorants: The composition of gases inside a package reflects the state of conservation. Variations can depend on enzymatic or microbial activity or on micro-leaks in the packaging (Müller & Schmid, 2019). These changes can be controlled with colour-sensitive films that monitor the pH (Alizadeh-Sani et al., 2021). A natural pH-sensitive pigment, such as anthocyanins, is incorporated into a thin plastic or bioplastic base. If the food becomes more acidic or alkaline, the pigment changes colour, for example from red to blue. At that point, a glance is enough to know if the food is still good, without opening the package. Since both the support and the colorant are natural, the solution is compatible with packaging that must remain in contact with food and can be disposed of as normal organic waste (Pourjavaher et al., 2017).

The strength of the indicators lies in their immediate readability: they do not need batteries, do not require a network connection and cost a few cents. The weakness is that they provide “photographic” information: they say that the problem occurred, but not when, where or for how long. When it is necessary to accurately reconstruct environmental history or forward data in real time, **electronic sensors** come into play.

The typical architecture includes four sections:

- Receiver (or sensing part): the tip of the sensor, i.e. the material that physically comes into contact with what is to be measured (temperature, humidity, gas).
- Transducer: transforms the physical or chemical variation (e.g. an increase in °C) into an electrical signal.
- Signal processing: a small circuit that digitizes, filters and encodes the signal.
- Communication interface: the “megaphone” that sends the data outside, often via an RFID antenna or integrated NFC module. If connected to the Internet, it turns into an IoT device (Wang, Wu, & Cao, 2019).

Many sensors use button batteries because they are compact, but to reduce waste and facilitate recycling, energy harvesting solutions are becoming more widespread – for example, a tiny piezoelectric plate that converts the vibrations of the truck into micro-current sufficient to power the device for the duration of the journey. Miniaturization is made possible by printed electronics: the copper tracks of the circuits are “printed” as conductive inks on plastic films (Wang, Wu, & Cao, 2019). This cuts copper waste, avoids manual assembly of components

and reduces costs and thickness, so much so that the sensor can be inserted between two layers of packaging and remain invisible to the naked eye. The downside is even lower mechanical resistance than traditional circuits. Manufacturers must therefore calibrate film thickness and flexibility to avoid breakage during handling (Fernandez et al., 2023).

To ensure that the information collected is useful for logistics, a means of transporting the data is needed. This is where **data carriers** come in:

- Barcode and QR-code: the traditional barcode functions as a product plate but contains little information and must be read in line of sight. The QR-code, on the other hand, can store a text of several hundred characters: a warehouse worker or the consumer himself, by scanning it with a smartphone, can access the nutritional information sheet, disposal instructions or video recipes in a few seconds. If the QR is printed with thermochromic inks, it can even be “covered” at low temperatures (therefore invisible in the cold room) and “uncovered” when the package exceeds the critical threshold, acting as an additional visual warning (Djurdjevic et al., 2019).
- RFID: an RFID label contains a metal antenna and, in classic models, a microchip that stores the ID. Radio frequency allows for remote reading without line of sight, so the warehouse can inventory hundreds of packages as they pass under an automatic gate. As already discussed, passive tags work without a battery and reach only a few meters while active tags are internally powered, exceed tens of meters and support sensors, but impact costs and disposal. Between these two solutions are semi-passive tags whose battery serves only to power the internal circuit, while the transmission remains stimulated by the external field, thus offering a compromise between autonomy, range and cost (Bibi et al., 2017). Operating frequencies influence performance: LF (125 kHz) penetrates liquids well but reads at a few centimetres; HF (13.56 MHz, the same as contactless tickets) reaches about twenty centimetres; UHF (860-960 MHz) goes up to 4-8 m in optimal conditions; SHF (2.45 GHz) offers high throughput but is sensitive to water, so it is used on dry pallets or clothing.
- Chipless RFID: To reduce costs to under one euro cent, the chipless tag is being tested. Here the logic is not contained in a circuit but “drawn” in the geometric shape of the antenna, which reflects a sequence of frequency bands like a mirror that reflects different colours. The reader “sees” these bands and translates them into a unique binary code. Since there is no chip, only a plastic sheet coated with metallic ink is needed: light, flexible, potentially recyclable with less impact. The challenges are the printing

resolution (a small imperfection can change the code) and sensitivity to shocks and bends, but the first prototypes show reliable readings within 2-3 m, enough for gate controls in warehouses or depots (Fathi et al., 2020).

Bringing together indicators, sensors and data carriers means transforming the packaging into a communication node that warns if the product is deteriorating, records when and where it occurred and forwards the data to the company information system. This is explained very well by Figure 45, which shows the logistics chain diagram of a food product, based on the technology provided by the company Varcode.



Figure 45 - Schematic design of the traceability system with the use of Smart Tag

Source: Fernandez, C. M., Alves, J., Gaspar, P. D., Lima, T. M., & Silva, P. D. (2023). Innovative processes in smart packaging: A systematic review. *Journal of the Science of Food and Agriculture*, 103(3), 986–1003.

From the very beginning, the smart tag is activated and its registration takes place in real time through computer systems that store all relevant information which can be analyzed in real time. After the product is delivered, information can be obtained through interaction with the end consumer who, by scanning the QR code, can access the website and fill out a survey on the delivery conditions, such as safety, for example, and report possible problems, in addition to building customer loyalty with bonuses and loyalty incentives (Varcode, 2021).

The constant measurement of the parameters also opens the way to predictive models: the transport platforms cross-reference the sensor data with the planned route and send alerts if, for example, the temperature exceeds the threshold value for a certain period of time or if the vibrations indicate a shock that could have damaged the contents. The algorithm thus calculates

the residual useful life (RSL) of the batch and, if necessary, modifies the delivery order to reduce waste (Pal & Kant, 2020).

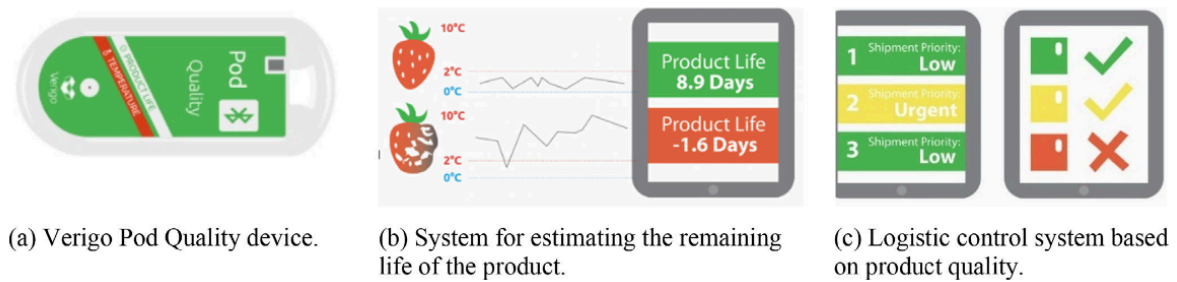


Figure 46 - Example of a smart packaging-based logistics system

Source: Verigo. (2019). POD Quality – Model PH1. Verigo.

The Verigo Pod Quality case demonstrates the practical impact: by monitoring the entire journey of strawberry crates, it was observed that, by maintaining the temperature between 0 and 2°C, the average useful life remains around 9 days, while prolonged exposure to 10°C is enough to reduce it to less than three, information that allows the fleet manager to give priority to the most at-risk packages (Verigo, 2019; Innolabel, 2022). The operational benefits are immediate: reduction in returns, optimisation of distribution routes, possibility of rapidly isolating a batch in the event of a recall and, last but not least, availability of verifiable data for environmental sustainability reports. The challenges instead concern the standardization of formats, the recycling of electronic components and compliance with regulations on the air transport of batteries, but the convergence of very low-cost passive sensors, low-power communication networks and cloud platforms for predictive analysis indicates that smart packaging will soon become an essential competitive requirement for truly transparent, safe and zero-waste delivery.

In addition to the aspects related to traceability and safety, Smart Delivery aims to improve the so-called “last mile delivery” (LMD). This is the final phase of delivery, which remains the most expensive and unpredictable part of the entire logistics chain: up to 41% of transport costs are attributable to the last kilometres that separate the distribution centre from the final recipient (Wanganoo & Patil, 2020). The widespread integration of the IoT is progressively transforming this bottleneck into a competitive advantage factor, thanks to connected devices that provide real-time visibility, capillary traceability and new operating models. GPS sensors, accelerometers, temperature and humidity detectors, placed on vehicles and packages, continuously transmit granular data on the status of the shipment. This end-to-end visibility allows to promptly identify delays, deviations or environmental conditions outside the threshold, reducing losses and disputes and improving the quality of the service (Ivankova et

al., 2020). In parallel, low-power communication networks (LPWANs), combined with edge or cloud gateways, allow the management of millions of devices with low energy consumption, an essential requirement for widespread coverage of urban territory. To address the problem of failed deliveries, smart lockers are becoming more widespread – automated lockers equipped with IoT sensors and electromechanical locks – that act as self-service collection points open 24 hours a day. The DHL Paketkasten, for example, is a container that can be installed in the home: a micro-controller registers the opening of the door, measures the internal occupancy using an ultrasound sensor and transmits the status to the central server; the courier thus receives information in advance on the availability of the compartment, avoiding empty passages and recalculating the route in real time (DHL, 2024). Parcelbox follows the same logic but uses an RFID badge instead of a digital code for unlocking, ensuring compatibility with the main delivery platforms (DHL, 2024). On the public front, many cities are experimenting with condominium lockers with refrigerated cells, in which IoT thermal probes maintain and track the temperature for sensitive food or medicines. Alongside lockers, plug-and-play devices like Postybell transform the traditional mailbox into a connected node: an infrared proximity sensor, powered by a long-life battery, recognizes the insertion of correspondence and sends a push notification to the recipient's app in a few seconds. The advantage is twofold: the courier avoids delivery attempts if the compartment is full, while the user can decide to collect the mail at the most appropriate time (DHL, 2024). IoT also enables dynamic address reprogramming. Thanks to the controlled sharing of the smartphone's location, the logistics-distribution platform suggests alternative delivery points – an office, a temporary home, an “en route” locker or even the doorman of a nearby building – calculating in real time the drop-off point that minimizes distance, time and emission impact. This paradigm, sometimes called address as a service, has already been tested by the American service Shyp, where the same network of freelance drivers offered, via app, to collect “unscheduled” packages in the immediate vicinity, transforming the last mile into a system of on-demand micro-collections and micro-deliveries (DHL, 2024). On the autonomous delivery front, IoT drone pilots further illustrate the potential of widespread connectivity. DroneTalk (Chen et al., 2022) is an experimental platform developed at the University of Hong Kong: the quadcopter integrates multi-band GPS, IMU attitude sensors, a forward-looking video camera and an LTE-M modem. These modules send flight plans, battery status and weather information every 500 ms to a ground station that processes the same data to enable micro-route adjustments and precision landings on urban micro-hubs. In Arizona, the 3D4 system (Eeshwaroju et al., 2020) focuses on “vertical” deliveries: the drone is equipped with

ultrawideband (UWB) sensors for indoor positioning and a CAN-bus-controlled winch that deposits packages up to the twentieth floor without the need to land on the roof. A LiDAR sensor monitors the distance from the balcony, while the package is “hand-shaked” via RFID tag to certify the delivery. In parallel, IoT sensors installed on electric vans, cargo bikes and ground robots monitor in real time energy consumption, battery temperature and acceleration patterns, enabling predictive maintenance and eco-driving strategies that, according to Xu et al. (2022) and Arora et al. (2017), reduce energy consumption by 10 to 20%. In regulated supply chains, the combination of IoT and blockchain seals the data collected by sensors, ensuring integrity and non-repudiation for the benefit of producers, distributors and control authorities (Markovic et al., 2020). The empirical results published so far indicate average delivery times reduced by up to 25%, a reduction in empty kilometres driven and a significant increase in customer satisfaction thanks to proactive notifications and flexible collection options (Elvas et al., 2023). However, open challenges remain: the strong growth of the cyber attack surface, the protection of personal data and the initial investment costs, particularly relevant in emerging markets (Kafle and Mbhele, 2023). The adoption of zero-trust architectures, end-to-end encryption protocols and interoperability standards therefore appears essential. Ultimately, the IoT ecosystem gives last-mile delivery unprecedented transparency, flexibility and reliability. From roadside sensors to connected lockers, from smart tags to vertical drones, each node generates and shares information that, if properly orchestrated, transforms the last mile from a critical point to a strategic element of logistics competitiveness (Fu et al. 2015; Yang, Luo, and Lu 2015).

4 The Convergence of AI and IoT in Logistics 4.0

Although the integration between AI and IoT technologies has not been explored in detail in the previous chapters, several ideas and references that emerged during the discussion have nevertheless clearly suggested a complementarity between these two technologies. This belief, deliberately disseminated throughout the thesis, will now be the subject of a specific analysis and study.

4.1 AI-IoT Integration: Enabling Smart and Adaptive Logistics

Combining AI and IoT gives rise to the so-called *Artificial Intelligence of Things* (AIoT). This is a rapidly evolving paradigm, destined to redefine the ways of managing and controlling supply chains. Indeed, when these two technologies are combined together, devices can collect and analyze data, then make decisions and act on that data autonomously (Nozari et al., 2021).

This enables companies to leverage both technologies simultaneously and achieve a state of transparent, agile and adaptable supply chain that can address even the most difficult challenges more effectively.

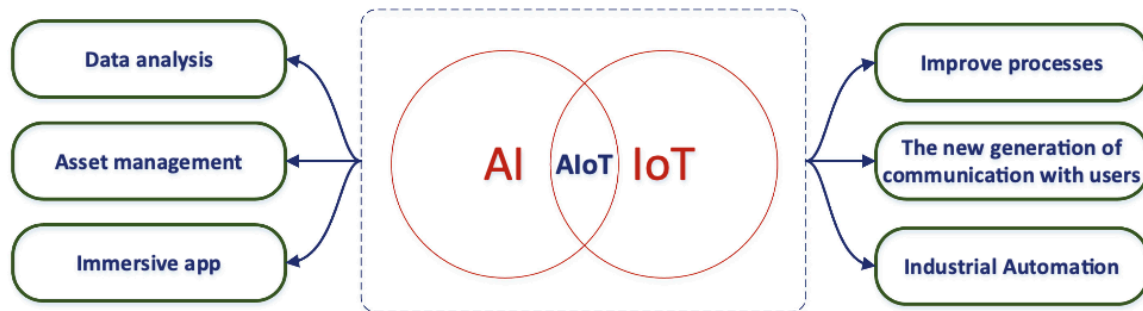


Figure 47 - AIoT Features Overview

Source: Nozari, H., Tavakkoli-Moghaddam, R., Rohaninejad, M., & Hanzalek, Z. (2023). Artificial Intelligence of Things (AIoT): Strategies for a smart sustainable-resilient supply chain (Figure 1, p. 809). Proceedings of the Czech Technical University in Prague, Industrial Informatics Department.

Figure 47 provides an effective representation of the distinctive features of AIoT. On the one hand, IoT provides one of the most valuable resources for contemporary logistics chains: the continuous and real-time flow of data on the operating conditions of vehicles, warehouses and goods in motion. As a result, the amount of data generated is significant in volume, plus it is often heterogeneous and unstructured. This clearly makes manual management and direct extraction of significant knowledge from this data, quite difficult. This is where AI comes in. To transform this “ocean” of raw data into useful insights like “in two hours machine X will need maintenance” or “demand for this product will increase by 20% in the next few days”, AI algorithms are deployed to filter the information noise and select only the variables relevant to the decision-making context. So, the two technologies not only coexist, but enhance each other. In the common area, that is AIoT, three main application areas emerge:

- Data analysis, for example the use of machine learning techniques to identify patterns and anomalies in historical data series, supporting demand planning and route optimization;
- Asset management, which uses sensors and cloud platforms to monitor the health status of vehicles and infrastructures and proactively initiate maintenance interventions;
- Immersive apps, such as the development of augmented and virtual reality interfaces that, integrated with predictive models, assist operators and managers in making decisions in the field.

On the benefits side, AIoT enables continuous process improvement (reduction of downtime, automation of workflows, dynamic reallocation of resources), introduces a new paradigm of communication with users (smart notifications, personalized dashboards, conversational

interfaces) and pushes industrial automation towards increasingly higher levels of autonomy, up to collaborative robots and self-driving vehicles used in warehouse operations and last-mile delivery (Nozari et al., 2023). In the transition from general principles to the logistics dimension, AIoT is configured as a true “digital nervous system” in which IoT sensors act as peripheral receptors, capturing continuous environmental and operational stimuli, while AI act as the “brain”, interpreting inputs, formulating predictions and orchestrating responses autonomously or in collaboration with the human operator (Sun et al., 2020). Figure 48 shows a clear representation of the process.

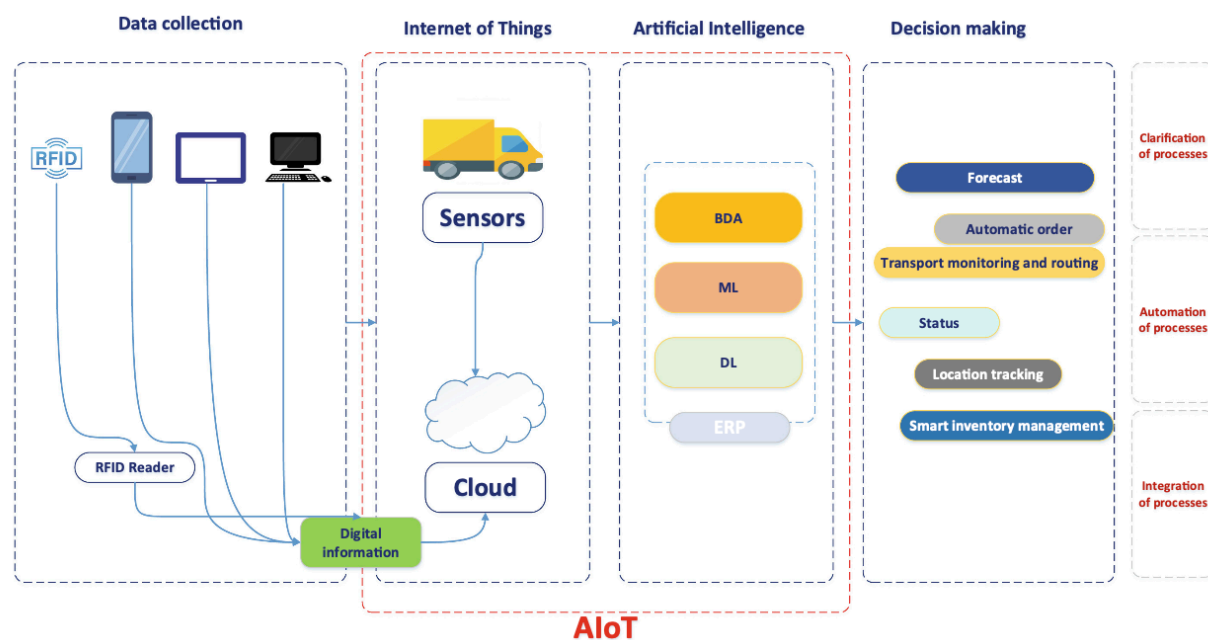


Figure 48 - AIoT Framework for Smart Supply Chain Management

Source: Nozari, H., Tavakkoli-Moghaddam, R., Rohaninejad, M., & Hanzalek, Z. (2023). *Artificial Intelligence of Things (AIoT): Strategies for a smart sustainable-resilient supply chain* (Figure 3, p. 814). *Proceedings of the Czech Technical University in Prague, Industrial Informatics Department*.

Thanks to this synergy, connected devices are no longer limited to acting as mere transmitters of data to a remote control center, but are evolving into “intelligent machines”: equipped with autonomous perception capabilities and distributed decision making, they are able to intervene directly on the field with minimal human intervention, accelerating response times and significantly reducing error margins (Xiong et al., 2021).

When this synergy is not present, sensors scattered along supply chains, vehicles and infrastructures collect heterogeneous big data and analysis remains post-event as data is directed only to central systems. The grafting of AI algorithms close to the source (edge AI) reverses the paradigm: lightweight neural networks, running on low-power microcontrollers, anticipate the time-to-failure of an engine far enough in advance to trigger the supply of spare

parts without stopping the line (Hou et al., 2023); a streaming-powered logistics digital twin continuously simulates the state of warehouses and fleets, proposes or recalculates routes based on congestion, weather and delivery constraints (Min, 2023). It is the device itself, therefore, that decides to act, no longer the control center that interrogates millions of nodes. Three new capabilities reside in this qualitative leap. First, the supply chain becomes self-synchronized: each intelligent node adapts its behavior to the global state, updates it in turn, and coordinates the entire network without going through a single direction (Nozari & Nahr, 2022). Second, learning becomes continuous in situ. The models, trained in the field with federated logics, adapt to changing layouts, volumes, or climatic conditions without interrupting operations. Finally, decision-making delegation is distributed and graduated. The architecture decides in real time which logics remain local to reduce latency, and which migrate to the cloud, transforming the supply chain from reactive to anticipatory (Najafi et al., 2023). The added value compared to the separate use of technologies emerges with particular evidence in the following table:

Dimension	IoT only	AI only	AIoT
Data temporality	Near-real-time (network latency)	Batch on historical datasets	Real-time on-device inference
Decision granularity	Centralised	Centralised or hybrid analytics	Fully distributed and autonomous
Scalability bottleneck	Limited by bandwidth	Limited by HPC clusters capacity	Elastic: edge + cloud orchestration
Sustainability impact	Environmental monitoring	Isolated optimisations	Holistic optimisation of environmental, social and economic KPIs

Table 3 - Comparative summary of IoT, AI and AIoT

Source: Author's personal elaboration

Moreover, traceability is transformed into cognitive transparency:

- I. Each package, loading bay or vehicle becomes a node capable of contextualizing information (position, temperature, delivery priority) and negotiating resources with the rest of the network;
- II. Shared ontological models allow heterogeneous devices to understand each other without centralized semantic brokers (Nozari et al., 2022);

- III. Previously invisible KPIs (such as real-time carbon footprint or packaging reuse cycles) become measurable again and have a retroactive effect on planning objectives (Bloss, 2016).

There is no shortage of critical issues:

- I. The increase in the attack surface requires zero-trust architectures and secure firmware right from the silicon;
- II. The coexistence of 5G, Wi-Fi 6/7 and mesh networks must be orchestrated to balance computing power and energy consumption;
- III. The lack of skills requires the training of hybrid figures, AIoT engineers.

However, once these issues have been addressed, the convergence between distributed perception and AI provides a logistics capable of learning, deciding and acting almost at the speed with which demand, environment and markets change.

In this context, the convergence between the IoT and AI allows to go beyond the simple automation of single processes to build a real smart warehouse, in which physical resources and computational resources operate as a single and self-adaptive system. An example of a smart warehouse architecture is shown in figure 49.

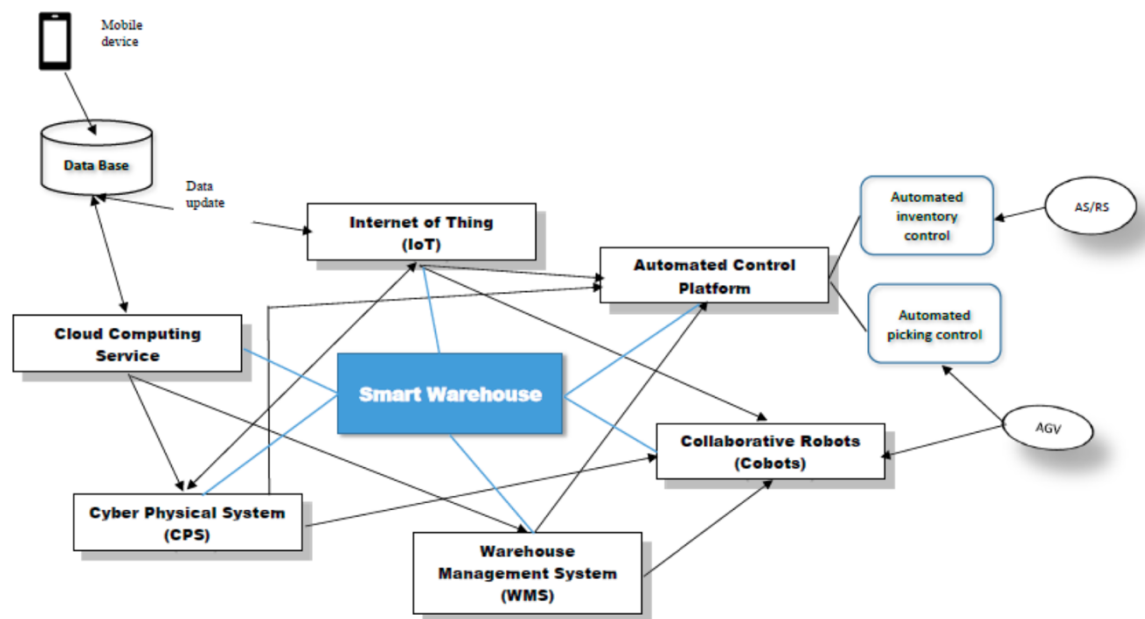


Figure 49 - Smart Warehouse Example

Source: Min, H. (2023). *Smart warehousing as a wave of the future* (Figure 1, p. 3). *Logistics*, 7(2), Article 30. MDPI.

At the core of this architecture is the Cyber-Physical System (CPS), which integrates sensors, computing capacity and network to enable autonomous decisions based on information collected from connected objects. Sensors, capable of emulating pressures, temperatures, vibrations and other “human sensory modalities”, allow to detect infrastructural anomalies and

to start predictive maintenance before failures or bottlenecks occur. The generated data are processed locally or sent to on-demand cloud computing services, which guarantee scalability and continuous software updates without downtime (Min, 2022a; Min, 2022b). Thanks to the connectivity inherent to the IoT information flows propagate at low latency between supply chain partners, improving synchronization and paving the way for extended machine-to-machine collaboration (Faulds & Raju, 2019). The operational heart of the intelligent warehouse is represented by an automated control platform composed of two complementary modules: the automated inventory control, which automates cycle counting, traceability and dynamic allocation of items by supporting AS/RS systems, and the automated picking control, which reduces costs and picking errors (traditionally the most expensive phase of warehouse activities) through voice or pick-to-light tools. Downstream, the Warehouse Management System (WMS) consolidates all information in a single interface, offering end-to-end visibility on flows and accelerating order processing. On the physical level, handling is managed by cobots that can safely collaborate with operators and by AGVs that follow digital paths, increasing accuracy and productivity without compromising flexibility. From the point of view of value drivers, the literature identifies five main levers: internal IoT sensors that provide real-time data, CPS integration that enhances M2M connectivity, edge computing that ensures operational continuity even in remote sites, AI-based “servitization” strategies to customize flows, and intelligent automation capable of autonomously diagnosing and correcting process inefficiencies. These elements produce concrete benefits: reduction of inventory thanks to greater visibility, prompt identification of bottlenecks and therefore shorter response time to customers; increase in labor productivity through human-robot cooperation and seasonal peak-shaving; higher return on assets for full use of equipment; better quality of service thanks to continuous monitoring of performance and operating conditions (Min, 2023).

This conceptual framework prepares the ground for the analysis of the main application fields in which the emerging properties of AIoT find their most concrete manifestation: Digital Twins and AIoT-driven robotics.

4.1.1 Digital Twins in Logistics

In light of the power that comes from the integration between IoT and AI, it is almost inevitable to introduce the concept of Digital Twin (DT), as it represents one of the most advanced and concrete expressions of this technological integration. DTs, in fact, represent a perfect meeting point between the pervasive acquisition of data enabled by IoT and the analytical and predictive capabilities of AI. A definition that captures well this convergence is offered by Negri,

Fumagalli and Macchi (2017) who describe the DT as “*a form of cyber-physical device that uses numerous IoT sensors and produces a high-fidelity visual image of a physical asset. The abundance of data obtained by the Digital Twins is then aggregated and analyzed using machine learning algorithms to promote strategic and organizational decision-making*”. Another relevant definition is the one proposed by IBM (2022): “*A digital twin is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning, and reasoning to help decision-making*”.

DTs are based on a structure divided into three fundamental levels, each of which plays a crucial role in ensuring the effective functioning and fidelity of the virtual model compared to the physical counterpart. The first level is the ***physical level***, which includes all the real information relating to the object or system represented. In this level, concrete data, operational decisions, actions performed and any other element that characterizes the behavior and state of the physical entity are collected. It is in this phase that reality is recorded as it is, laying the foundations for an accurate and updated digital reproduction over time. The second level is represented by the ***communication level***, which has the task of ensuring that the information collected in the physical world is transmitted, translated and made usable in the digital domain. In this dimension, data transmission tools are placed, such as IoT networks, communication protocols, information encoding and decoding systems. Through these tools, real data is converted into machine-readable formats and, at the same time, the results processed in the digital model can be converted back into operational actions to be implemented in the physical system. Here quality and efficiency are essential to ensure synchrony and coherence between the DT and the reality it represents. The third component is the ***digital layer***, which combines the simulation and computation techniques required to interpret the data provided, conduct analysis and develop projections. The core of the DT’s intelligence is represented by this layer, as it enables not only the replication of the physical object’s behaviour but also the prediction of its future evolutions (Far & Rad, 2022; Lv, Qiao, Li, Yuan and Wang, 2022; Zheng, Lu and Kiritsis, 2022). Figure 50 illustrates a conceptual model of how DTs interact with logistics and supply chain systems across these three layers.

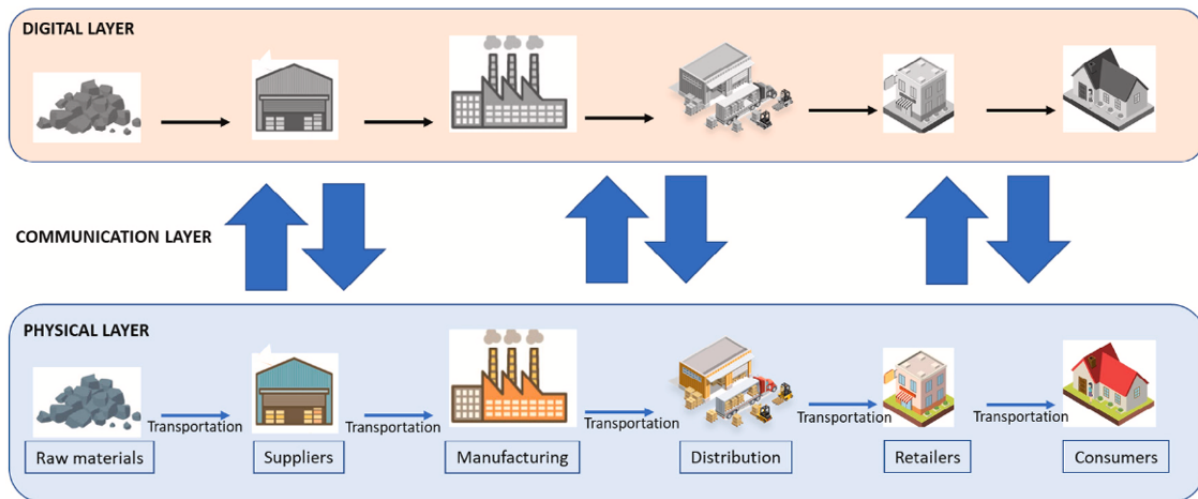


Figure 50 - Conceptual model of Digital Twin integration in logistics and supply chain systems

Source: Le, T. V., & Fan, R. (2024). Digital twins for logistics and supply chain systems: Literature review, conceptual framework, research potential, and practical challenges (Figure 6, p. 9). Computers & Industrial Engineering, 187, 109768.

The key features of DTs are:

1. **Accurate mapping:** DTs create a direct link between physical objects and their digital counterparts, synchronising real-time and historical data for accurate representation
2. **Real-time synchronization:** Unlike traditional simulations, DTs are constantly updated with real-time data from physical objects.
3. **Networked and Distributed Modeling:** They can represent multiple physical entities across networks, including sensors, IoT devices and larger systems.
4. **Intelligence:** They use AI algorithms to be able to analyse and process large amounts of data, thus optimising, predicting and supporting decision-making for physical systems.
5. **Bidirectionality:** DTs exchange real-time data with their corresponding physical objects, providing feedback and optimisation.

The high complexity that characterizes DTs is largely compensated by the tangible advantages that this technology makes possible. Thanks to a DT, it is in fact possible to supervise and manage physical assets remotely, optimizing their use, reducing operating costs and automating repetitive tasks subject to human error. In this way, resources – economic and personnel – are freed up to be reallocated to activities with higher added value (Blomkvist & Ullemar Loenbom, 2020). Pioneers who have implemented DTs in real contexts report substantial benefits in three key areas:

- Higher quality of decisions, thanks to more complete and reliable data;
- Streamlining of daily processes, made possible by the real-time integration between the physical and digital worlds;

- Opening up to new business models, such as servitization or product-as-a-service formulas, which were previously difficult to implement (Blomkvist & Ulleamar Loenbom, 2020; Uhlemann et al., 2017).

On an analytical level, a DT is able to collect information that eludes traditional methods. This data, processed with advanced algorithms, feeds recommendations aimed at improving the performance not only of the current asset, but also of its future design evolutions. The descriptive value is expressed instead in the possibility of remotely viewing and monitoring physical assets. For example this is very useful for visualizing the status of an asset in dangerous or difficult-to-reach environments, such as offshore construction sites or remote plants. This allows continuous monitoring even during extraordinary missions like long-range transport (Blomkvist & Ulleamar Loenbom, 2020). The predictive value emerges when historical and operating data are analyzed in large volumes: DTs not only estimate the future status of an asset, but proactively suggest corrective interventions or optimization opportunities (Uhlemann et al., 2017). Looking ahead, this capability will fuel increasingly autonomous systems, capable of making design and production decisions with a positive impact for both internal staff and external stakeholders. Finally, the diagnostic value allows to quickly trace the causes of an anomaly: the intersection of real-time data and historical series, analyzed with machine learning techniques, facilitates the early diagnosis of malfunctions and the planning of targeted interventions (Blomkvist & Ulleamar Loenbom, 2020; Uhlemann et al., 2017). Although DTs are not yet widespread in the logistics sector, many enabling technologies are already mature (see Figure 51). In recent years, for example, the widespread adoption of sensors has significantly increased the availability of real-time data, an essential prerequisite for the future evolution of DTs (Haße et al., 2019). In parallel, the sector has started a progressive process of modernizing its digital infrastructures. In fact, there is a growing adoption of open Application Programming Interfaces ¹⁰ (APIs) strategies, which facilitate the interoperability between different information systems and improve the exchange of data along the entire value chain (Blomkvist & Ulleamar Loenbom, 2020). In addition, many logistics companies are migrating to cloud-based IT solutions, which lead to greater scalability and flexibility. Another crucial element regards the adoption of machine learning techniques and advanced data analysis, increasingly used by logistics companies to optimize their supply chains and improve operational efficiency. Predictive data processing can, for example, help

¹⁰ APIs are building blocks designed to be reused by developers (eliminating the need to redo the programming from scratch) that enable interaction between applications such as databases, networks, and IoT devices.

anticipate bottlenecks, reduce equipment downtime and improve inventory management, all of which are perfectly compatible with future DT integration (Camerer, 2018).

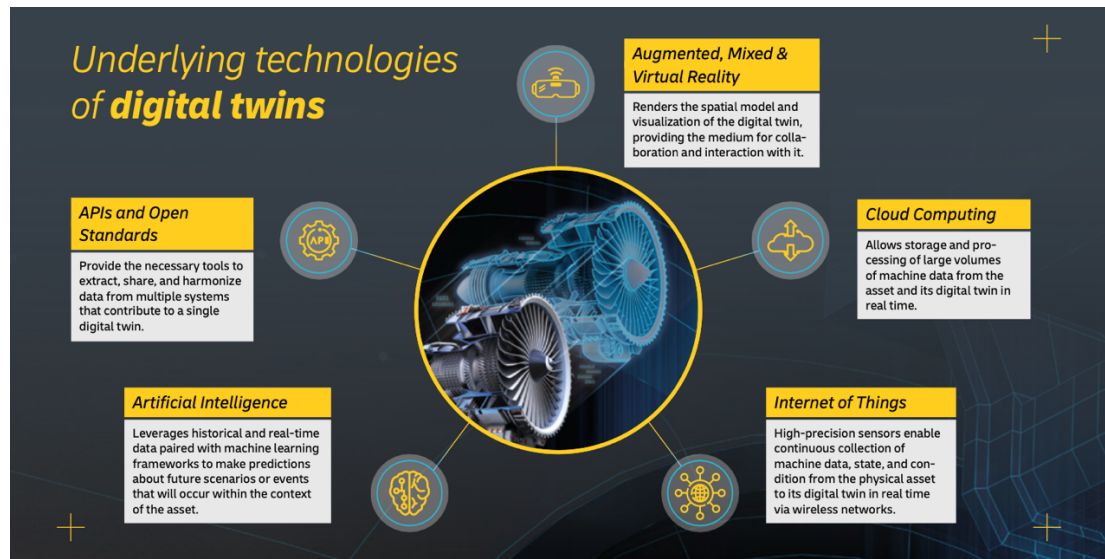


Figure 51 - Technologies behind Digital Twins

Source: DHL Trend Research. (2019). Digital twins in logistics: A DHL perspective on the impact of digital twins on the logistics industry (Figure 4, p. 7). DHL Customer Solutions & Innovation.

Finally, other technologies that can contribute to enriching the information assets needed to build accurate and dynamic DTs are augmented reality, mixed reality, and virtual reality, for which there is currently a growing interest in logistics processes. While IoT, cloud computing, APIs, and AI provide the fundamental sensing and processing infrastructure required to construct a DT, immersive technologies (augmented, mixed, and virtual reality) are used for visualisation, either on a screen (2D) or in a physical space (3D), to make DTs real for users (Yang, 2019; Omollo, 2019). In essence, although the large-scale use of DTs in logistics is still in its early stages, the necessary technological infrastructure is already at an advanced stage of development, paving the way for the full integration into industry operating models in the coming years (DHL Trend Research, 2019). In order to provide a comprehensive overview of their application, an analysis will now follow on how DTs manifest themselves and bring value in several crucial areas of logistics, including:

- warehouse management
- transport operations
- across the entire supply chain

Digital Twins in the warehouse management

Warehouses and distribution centers are ideal environments to implement DTs, due to the complexity of their structure and the high-intensity of the operations. The application of a DT

allows to realistically simulate the movement of products, personnel and equipment within the facility. By creating a virtual 3D model of the plant and integrating it with data from IoT-connected warehouse platforms, in addition to inventory and operations data, it is possible to reproduce the facility's daily operations (DHL Trend Research, 2019). Looking at Figure 52, the left side illustrates a DT of a warehouse, while, the right side shows a heat map generated through the DT which highlights the areas of high worker and forklift intensity.

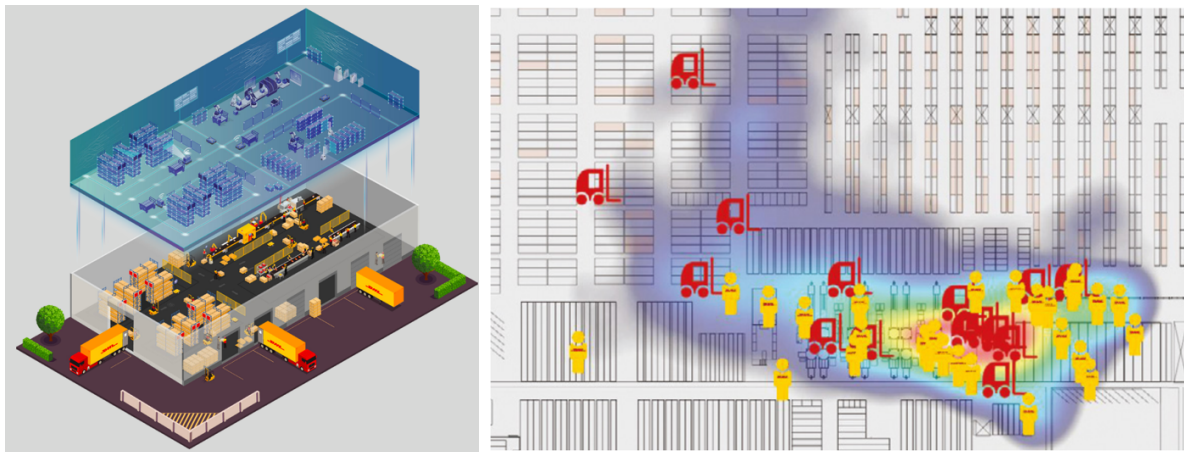


Figure 52 - Application of Digital Twins in Warehouse Logistics

Source: DHL Trend Research. (2019). Digital twins in logistics: A DHL perspective on the impact of digital twins on the logistics industry (Figure 21, p. 23). DHL Customer Solutions & Innovation.

This approach brings several benefits: greater visibility into processes, more effective planning, better use of space, more efficient management of operations and a reduction in energy consumption and waste. In this sense, as already mentioned, DTs are proving to be extremely effective tools for implementing predictive maintenance strategies. In an industrial context where the costs due to unplanned downtime are particularly high, the ability to monitor the status of assets in real time is essential. For instance, companies like Kraft Heinz, in collaboration with Microsoft, have created DTs of their production sites with the aim of reducing mechanical stops. Similarly, major logistics operators are developing digital replicas of specific assets such as robots, forklifts and trucks, monitoring their wear and tear to prevent failures. The adoption of DTs for predictive maintenance allows logistics service providers to reduce up to 40% of reactive maintenance activities in a year, increasing productivity and reducing costs (DHL, 2024). In spite of this, the potential of DTs is not limited to simple monitoring: they can also have a significant impact on the design, management and optimization of logistics facilities. During the design phase, DTs can support the definition of the layout of new facilities, allowing companies to simulate the flows of goods, people and handling equipment, thus optimising the spatial configuration according to specific operational needs. During daily operations, DTs are continuously updated thanks to data collected by

automation systems that are becoming increasingly widespread in modern warehouses. These tools include inventory counting systems using drones, automated guided vehicles (AGVs), goods-to-person systems for automated picking and automatic storage and retrieval equipment. The interaction between DTs and these automated systems enables further optimisation of operational performance (DHL Trend Research, 2019). Additionally, having detailed, 3D data across the entire plant offers significant opportunities to improve workers' productivity: companies can develop virtual reality training tools that provide a safe, immersive environment for learning operations, or introduce augmented reality picking systems based on wearable devices. However, the ability of DTs to drive continuous improvement may be the most convincing reason to use them. Thanks to the systematic data collection, identifying inefficiencies and waste in warehouse operations becomes very easy and before introducing operational changes, managers can exploit simulation through the DTs to assess the potential impact of the change (DHL Trend Research, 2019). Simulation is now one of the most effective tools for the analysis and design of complex logistics systems. It allows testing the behavior of the value chain in relation to multiple variables: throughput, costs, delivery reliability, variability and risks. The main advantage lies in the possibility of evaluating future scenarios and design options without having to intervene on the real physical system, thus avoiding operational discontinuities or errors that are difficult to reverse. In particular, the use of simulation models is crucial when dealing with large organizations, for which structural or strategic changes imply high complexity and multiple interdependencies (Tannock et al., 2007). Traditionally, the construction and application of simulation models follow discrete approaches (discrete-event simulation), characterized by an iterative process, articulated in multiple phases. However, in recent years, scientific literature has begun to pay increasing attention to the automation of modeling processes, through the use of integrated and data-driven models. In these approaches, the information describing the characteristics of the model is stored in a structured way, often in relational databases such as SQL, or conveyed via XML schemas, to be used directly by simulation software. When the necessary data comes from existing sources, such as company ERP systems, the degree of automation increases further. Information such as bills of materials (BOM), production capacities, processing times and details relating to customers and suppliers can be extracted automatically, validating and updating the simulation model in real time (Krenczyk & Bocewicz, 2015). Data-driven modelling and simulation thus take on the role of decision-making tools, capable of supporting the redesign of the supply chain according to real operating conditions. Data can be stored locally or shared through collaborative portals ("collaboration hubs"), which encourage

interaction between the different partners of an extended network. Through these systems, ERP data are converted into formats compatible with simulation software, contributing to the automatic creation of models. However, it is still necessary to provide for a continuous data validation phase, in order to guarantee the reliability and consistency of the simulations (Cozmiuc & Petrisor, 2018). From an operational point of view, there are two main methodologies for building simulations: modular and data-driven. Modular simulations are based on reusable templates, which represent generic elements of the system (e.g. a production line, a warehouse, a loading point), managed through user-friendly graphical interfaces. Recent studies have explored the integration of parameters related to reverse logistics and lean manufacturing, in order to further specialize these models (Abideen et al., 2021).

The models that underpin data-driven simulations are completely parameterised and fed by data that production departments gather on a daily basis, such as through MES (Manufacturing Execution Systems) systems. The analysis of historical series allows to accurately estimate process times, decision probabilities and variability of results, so as to build models in an almost automatic way thanks to modular software components, programmable in SQL or Python and easily reusable in different contexts (Goodall et al., 2019; Abideen et al., 2020). Based on a solid literature review, some authors propose a framework that integrates real-time data flows in the creation of digital twins: these twins reproduce the plant as it operates, continuously updating themselves and maintaining a satisfactory level of accuracy (Rožanec et al., 2021). In practice, the digital model does not limit itself to replicating the failures or anomalies that may occur, but also incorporates the countermeasures adopted by human operators. The observed behavior is recorded and becomes raw material for training machine learning algorithms, to create a reinforced learning environment capable of proposing increasingly effective decisions. Consequently, the digital twin evolves from a descriptive or predictive tool to a prescriptive system: not only does it show “what is happening” or “what could happen”, but it also suggests “what is best to do”, transforming operational choices from reactive to proactive and opening up particularly promising prospects for logistics and for all activities that depend on complex, dynamic and interconnected processes.

Digital twin in transport operations

In the field of logistics transport, DTs are built on the basis of continuous data collection made possible by an extensive network of sensors installed on vehicles that monitor fundamental variables (e.g. GPS position, acceleration, angular velocity, battery state of charge, environmental conditions, component wear and specific operating parameters). When this data is fed into a virtual model that is updated in real time, it is possible to reproduce the behavior

of the vehicle in a simulated environment with high precision. A prominent example is that of Li and Wang (2025), who created a platform to monitor, predict, and improve the operation of autonomous vehicles used for the movement of goods.

The first step was to equip the real vehicles with a dense network of sensors – positioned on the chassis, guidance systems and load units – capable of providing a detailed picture of the operating conditions in real time. Based on the data collected, the authors divided the mission cycle into four macro-states, each representing a specific moment in the logistics process:

- Waiting: the vehicle is stationary, for example queuing for loading or awaiting instructions;
- Loading: the vehicle is loading or unloading goods;
- Slowing: the vehicle slows down due to obstacles, traffic or particular operating conditions;
- Driving: the vehicle is moving towards the destination following a planned route.

To collect data useful for building the predictive model, the researchers had real vehicles run numerous cycles of transport missions in a test environment.

During each mission, the vehicle acceleration was continuously detected along the three Cartesian axes (X, Y, Z) and used to recognize and classify the four operational states identified by Li and Wang (2025). The signals thus collected fed a LSTM (Long Short-Term Memory) neural network model, particularly suitable for analyzing time series because it “memorizes” the past evolution and improves the prediction of future behavior. To ensure the robustness of the model, the authors applied cross-validation on data samples not seen in training and carefully optimized the hyperparameters, reducing the risk of overfitting and favoring the generalization capacity. After nine iterative cycles the network achieved an accuracy of 100% in correctly identifying the four behavioral states and a Weighted Efficiency (WE) index also equal to 100%. The result demonstrates how the integration between digital twins and advanced deep learning, if rigorously designed, constitutes a very powerful tool for the predictive management of autonomous fleets and for logistics optimization. On the operational level, a DT allows to estimate in advance travel times, operating conditions and anomalous behaviors, improving in real time the planning of routes, the assignment of loads and the use of resources. It also offers the possibility of exploring “what-if” scenarios without taking risks (Mohamed et al., 2017). A significant example is the work of Martínez-Gutiérrez et al. (2021), who simulated and managed the behavior of autonomous vehicles (AGVs) in real industrial contexts by modeling both the vehicles and the surrounding environment (walls, barriers and surfaces) with

the ROS (Robot Operating System) ¹¹ framework and the Gazebo¹² simulator, obtaining extremely realistic reproductions validated on a physical AGV equipped with advanced sensors both in a small laboratory and in a larger production area. In parallel, a complete DT of the vehicle and the surrounding environment was built, simulated in Gazebo, in order to faithfully replicate physical reality. Six distinct missions were planned for each scenario, in which the AGV had to move between predefined points representing workstations, following specific routes and completing movement sequences. To confirm the simulation's accuracy, the actual execution time for each mission was measured and compared to the one projected by the DT. The data showed a correspondence of over 97%, with peaks of 98.82% in the second scenario, demonstrating that the virtual model is able to reproduce with high precision the behaviors of the AGV in different operating environments.

Furthermore, DTs enable the coordinated management of multiple autonomous vehicles. In practice, virtual models of different AGVs can be connected, thus allowing their movements to be synchronized within the facility. This leads to an optimization of lane usage, the elimination of the risk of collisions and more efficient traffic management. Such multi-vehicle coordination would be very difficult to manage manually, which is why the adoption of interconnected DTs is crucial in this respect (Martínez-Gutiérrez et al., 2021).

In terms of information management, integrating DTs with Manufacturing Execution Systems (MES) creates a direct connection between operational data collected from vehicles and production management systems, thus obtaining an integrated view of the material flow. As a consequence, this helps to optimize the synchronization between transport and production processes and improve the traceability of shipments in real time (Negri et al., 2020). Furthermore, the contribution of DTs in the areas of operational safety and environmental sustainability is also significant. Thanks to continuous monitoring of vehicles, simulation of routes and early identification of anomalies, it is possible to reduce the risk of accidents, energy consumption and CO2 emissions. This protects not only the vehicles and goods, but above all the personnel involved, making the entire supply chain more efficient and in line with the environmental objectives of Industry 5.0 (Xu, Xu, & Li, 2018).

¹¹ ROS is an open-source framework for robotics software development. It provides tools, libraries, and conventions for creating complex programs in a modular and scalable way.

¹² Gazebo is an open-source simulator that allows you to create realistic 3D environments to test robots and autonomous systems, replicating physical dynamics, sensors and interactions with the environment.

Digital twin across the supply chain

DTs applied to supply chains represent one of the most promising innovations in the field of contemporary logistics. They allow the entire flow of goods, from source to final destination, to be digitally modelled, integrating transport systems, information systems, order management and, last but not least, human intervention. If we consider that warehouses and distribution centres represent only a small part of the global logistics infrastructure, it is clear that the success of a system depends on the effective synchronization of ships, trucks, planes, IT systems and human interactions. This systemic dimension is clearly evident in large logistics hubs, such as cargo airports and container ports, where the multiplicity of actors involved makes operational efficiency particularly complex. Such structures often suffer from poor integration between information exchange systems, with offline processes that increase the risk of errors, delays and inefficiencies (DHL Trend Research, 2019). A concrete example is the project currently underway in Singapore, where the Maritime and Port Authority (MPA), in collaboration with the National University of Singapore (NUS), launched the first Maritime Digital Twin of the Port of Singapore on 24 March 2025. At the beginning, the scientific leadership of the project was entrusted to Professor Lee Loo Hay, who highlighted how the maturation of the technology is now made possible by the convergence of several factors: simulation-based optimization, Industry 4.0 technologies, and the IoT, which in recent years have found new impetus thanks to AI and its predictive capabilities. The ultimate ambition in the field of logistics would be the creation of a DT of the entire network, capable of including not only logistics resources, but also geophysical and infrastructural elements such as oceans,

railways, highways, urban streets and, ideally, even final destinations represented by homes, offices and industrial plants.



Figure 53 - A visionary example of the elements involved in a digital twin of an entire supply chain network

Source: DHL Trend Research. (2019). *Digital twins in logistics: A DHL perspective on the impact of digital twins on the logistics industry* (Figure 23, p. 24). DHL Customer Solutions & Innovation.

Although such a model remains for the moment more of a vision than a concretely realizable reality, it is essential to understand the evolutionary directions of the technology to fully grasp its transformative potential. Within this context, one of the most relevant areas that benefits from the introduction of DTs is supply chain visibility. Visibility is not only a matter of sharing information, but a real strategic outcome of well-coordinated organizational practices, involving people, processes and technologies. The ability to obtain, share and process in real time reliable and updated information on the internal and external supply chain improves planning, forecasting, coordination and implementation of orders (Lohmer et al., 2020).

Busse et al. (2017) show that digital twins can enhance four pillars of corporate visibility: sensing, learning, coordination, and integration. Perception-based visibility concerns the ability of the company to quickly and accurately obtain information on internal processes and the external environment. In this field, DT is crucial: a widespread network of intelligent sensors distributed along the logistics chain generates unprecedented data flows and, thanks to real-time synchronization, interprets operational variations and promptly triggers reports to management. This allows to promptly adjust supplies to actual demand, refine order planning, and identify potential bottlenecks in the packaging and shipping phases in advance (Srinivasan

& Swink, 2018; Fan et al., 2020). The second dimension, visibility through learning, concerns the acquisition and absorption of knowledge from internal and external sources. DTs, thanks to the ability to accumulate experiences, codify knowledge and articulate it in a shareable form, can act as continuous learning platforms. They offer opportunities to better understand the behaviour of suppliers, logistics carriers, and even critical phases of the product life cycle revealing gaps or inefficiencies that would otherwise be invisible (Xu et al., 2019; Elmo & Stead, 2020; Wang & Luo, 2021). Coordination-oriented visibility concerns the ability to efficiently orchestrate supply chain activities, promoting operational alignment between the various partners. In this context, digital twins become key decision-making tools: they allow for the advance estimation of needs, testing alternative logistics routes, and discovering latent vulnerabilities in current models. Their use therefore allows for the precise measurement of the benefits of any reconfigurations and for the prevention of risks, strengthening the decision-making readiness of the organization (Barricelli et al., 2020; Park, Son & Noh, 2020). Finally, integration-oriented visibility focuses on the company's ability to accommodate and harmonize new technologies and management methodologies, a process that digital twins facilitate by acting as a bridge between heterogeneous systems and accelerating the adoption of innovative solutions along the entire logistics network. The introduction of DTs favours the creation of a shared identity within the supply chain, enabling an alignment mindset between actors and processes. They enable in-depth analysis of vital processes, promoting transparency and sharing of critical information. However, to achieve these results, it is necessary to ensure data accuracy and minimize human errors, as well as strictly monitor access to information, to avoid the unauthorized dissemination of sensitive data (Shahat et al., 2021, Guo et al., 2020).

Indeed, although DTs represent one of the most promising technologies for the digital transformation of supply chains, their large-scale implementation is far from being without difficulties. While on the one hand they enable unprecedented visibility, traceability and predictive capabilities, on the other hand they pose numerous technical, organizational and economic challenges. It is therefore essential to understand in detail the main barriers that hinder their effective adoption, in order to address the required transformations in a strategic and conscious way. One of the first critical issues lies in the need for training and cultural change within organizations. Like any profound technological transformation, the introduction of DTs requires workers to acquire new skills, not only technical, but also managerial. The problem, however, does not only concern training, but a broader change in mentality and operating practices. This includes fully comprehending the causes and motives for the change. To fully exploit the advantages offered by DTs, it is necessary to redefine organizational

models, decision-making processes and internal communication structures. The success of the transformation therefore depends on the company's ability to effectively manage change management, inspiring its employees and ensuring a consistent and motivated transfer of knowledge (Uhlemann et al., 2017). A second obstacle is linked to the accurate representation of the physical system. Developing a DT that is a faithful and functional replica of the real asset is particularly complex, especially in contexts in which the objects or processes to be modeled are highly complex and subject to numerous variables (Modoni et al., 2019). In many projects, technological and, above all, budget limitations require reducing the complexity of the digital twin, with the risk of sacrificing part of the accuracy or functionality. The real objective therefore becomes balancing the desired level of detail with the economic and operational sustainability of the initiative (Blomkvist & Ullevar Loenbom, 2020). This challenge is accompanied by the closely related challenge of data quality: a DT in fact relies on continuous flows of data from distributed IoT networks, but severe operating conditions, network latencies or unstable communications can generate incomplete, inconsistent or even incorrect data. It is therefore essential to have reliable mechanisms for filtering, validating and correcting data, in order to ensure that the digital twin can formulate reliable representations and predictions (Uhlemann et al., 2017). A further significant limitation is represented by implementation costs. Starting a digital twin platform requires a significant initial investment, including software development, sensors, infrastructure for data collection and management, as well as integration with systems already in use. If not carefully monitored, these expenses can grow rapidly (Kritzinger et al., 2018). A rigorous cost-benefit analysis is therefore required: in many cases, it is preferable to start with a "lean" DT, focused on a few strategic parameters, rather than immediately aiming for a complete replication. From the early stages, it is also necessary to carefully define which data to acquire, to reduce development and operating costs in the long term. Another issue concerns the protection of intellectual property: the effectiveness of a DT depends on the exchange of information between supply chain partners, but when the data touches distinctive skills or critical processes, issues of ownership, security and access control inevitably arise. Robust procedures for managing digital identity and usage rights that balance operational transparency and confidentiality are therefore needed (Modoni et al., 2019). Related to this is the issue of cybersecurity: digital twins, custodians of detailed and sensitive information, are potential targets of cyber attacks and require protected architectures, constant monitoring and adequate mitigation plans. A compromised DT not only risks exposing confidential data, but could also generate damaging consequences on an operational level, especially if connected in real time with physical assets. The protection of

data and digital infrastructures, therefore, cannot be considered an accessory aspect, but must be designed as a central element of the system architecture (Blomkvist et al., 2020). Furthermore, the issue of interoperability deserves particular attention. Many companies, especially small and medium-sized ones, do not have the necessary skills to develop advanced DTs internally and are therefore forced to turn to external suppliers (Uhlemann et al., 2017). This can lead to a strong dependence on technology vendors, with future difficulties in replacing or updating the solutions adopted. The lack of universal standards for modelling and data exchange exacerbates the problem by limiting scalability and integration across systems (Blomkvist & Ullemar Loenbom, 2020).

In a nutshell the use of DTs in supply chains has significant potential benefits, but it also brings an array of structural barriers that should not be overlooked. Companies interested in taking this route must not only invest in technology, but also have clear strategies for change management, security, data governance, and employee training. The full potential of DTs can be realised only by addressing these difficulties in a systematic way.

4.1.2 AIoT-driven Robotics

Another area that is experiencing unprecedented acceleration thanks to the integration of IoT and AI is robotics. Although the importance of AI in the robotics has already been covered in Chapter 2, the analysis proposed there has been intentionally kept on a general level. This is because, in the current technological scenario, robotics can no longer be considered in isolation as mere intelligent automation: today, it is increasingly configured as a connected ecosystem, in which IoT plays a structural and essential role. The integration between AI and IoT therefore does not represent a simple functional enrichment, but constitutes the very foundation of the new generation of robotic systems used in the logistics sector. In fact, modern logistics robots are no longer limited to “moving” or “manipulating” objects, but, thanks to this combination, act as real intelligent agents within the supply chain. IoT allows them to perceive the environment and maintain a constant connection with other devices, systems and digital infrastructures. AI, on the other hand, allows robots to understand and interpret data on their own, create predictive models, optimize paths, recognize objects and situations, and adapt their actions accordingly (Grover & Ashraf, 2023; Dabic-Miletic, 2024). This phenomenon, called “cognitive and connected robotics”, manifests itself in different solutions, each of which combines AI and IoT in a particular way.

In warehouse operations, robots are mostly employed in order processing, inventory management, picking and dispatch operations. Starting from order processing, which is the first crucial stage in warehouse operations, robots support activities such as checking the correspondence between orders and invoices, verifying quantities, and picking items from shelves for the subsequent packing phase. Sensors, cameras, and machine learning algorithms allow them to move autonomously between the aisles, identify items, and handle them with precision. Regarding the inventory management, robotics has established itself as an effective response to the growing need to optimize spaces and reduce goods handling times. Internal material transportation is typically handled using mobile robots such as Automated Guided Vehicles (AGVs) and Autonomous Mobile Robots (AMRs). However, there are also more complex systems such as automated storage and retrieval systems (AS/RS), which enable complete automation of item storage and retrieval operations.

Finally, in the field of pickup and dispatch operations, robots help speed up and make the process of picking and shipping items more reliable: being able to quickly identify items on the shelves, they can pick them accurately and, in some cases, also take care of packing and preparing them for shipping. Robotic sorting systems also organize items based on criteria like the final destination or size, improving speed and accuracy in the dispatch phase (Sainath, 2025). In all these areas, the use of AI- and IoT-supported robots brings numerous benefits: increased operational efficiency, reduced labor costs, greater accuracy in order management and the possibility of operating 24 hours a day. In order to have safe and efficient operations, however, the implementation of these solutions requires careful planning, integration with pre-existing information systems, and frequent monitoring.

The analysis will focus on the following types of robots:

- Automated Guided Vehicles (AGVs)
- Autonomous Mobile Robots (AMRs)
- Automated Storage and Retrieval Systems (AS/RS)
- Robotic Arms
- Collaborative Robots (Cobots)
- Drones

Automated Guided Vehicles (AGVs)

When talking about robotics applied to logistics, the first example that comes to mind is AGV (Automated Guided Vehicle), autonomous vehicles that are now at home in warehouses and factories but are far from “mature technology”: they continue to evolve in step with sensors, artificial intelligence and increasingly refined navigation techniques. AGVs move without a driver thanks to a mix of lasers, cameras, lidars, magnetic tape or floor markers and, above all, control software that decides trajectories and maneuvers in real time (Sodiya et al., 2024). Their history goes back a long way: the first prototypes, little more than towed carts that followed an underground wire, were developed by Barrett Electronics in the mid-1950s (Dhaliwal, 2023). Since then, technology has made great strides: we have gone from invisible UV markers to laser navigation and, today, to three-dimensional vision, capable of “reading” the environment with great accuracy (DHL, 2024). In the meantime, more compact and cost-effective models, Automated Guided Carts or SmartCarts¹³, have emerged, which extend the range of action of AGVs in small and medium-sized companies. A crucial question is how to assign transport missions. The classic “first come, first served” (FIFO) only works in simple scenarios; in dynamic plants, however, algorithms inspired by well-known problems such as the Traveling Salesman Problem or the Vehicle Routing Problem reduce downtime, limit empty trips and make internal logistics more fluid (Oliveira et al., 2025). Techniques such as insertion algorithms¹⁴ or the sweep method¹⁵ have proven to be particularly effective when demand is constantly changing or production priorities are overturned from one moment to the next. The “new generation” of AGVs communicates in real time with Warehouse Management Systems (WMS): it receives orders, sends feedback on the status of missions, coordinates its path with that of other robots and, thanks to the incorporated AI modules, recalculates routes, intervention times and task assignments in a few milliseconds, cutting waste and errors (Sodiya et al., 2024). This qualitative leap has paved the way for AMRs (Autonomous Mobile Robots),

¹³ AGCs are a cheaper version of AGV, particularly suitable for small and medium-sized companies that manage small-scale material handling. They are based on magnetic tapes for guidance, which is a simpler and faster technology to install than laser systems. They are ideal for point-to-point transport of loads between picking stations or within production plants (Dhaliwal, 2023).

¹⁴ An insertion algorithm is a generic term for any procedure that aims to insert a new element into a data structure while keeping its properties intact (order, balance, unique key constraints, etc.).

¹⁵ The sweep method is a technique that “slides” an imaginary line over the data: as the line advances, it maintains and updates only the elements it touches, allowing you to solve geometry problems (such as finding intersections or closest pairs) in an orderly and efficient way.

direct heirs of AGVs, which add an extra dose of intelligence and freedom of movement, confirming the centrality and continuous evolution of these systems in the future of logistics. In highly dynamic environments, predictive algorithms help anticipate congestion, adjust logistics priorities, or balance workloads across different operating units. Furthermore, AGVs aren't just used for moving goods horizontally: they also handle tasks like automatically loading and unloading racks and managing company waste (Liu, Tsang, & Lee, 2024). A significant application is the use of autonomous pallet movers in high-intensity warehouses, as in DHL's warehouse automation program, where fleets of high-capacity AGVs are used to move pallets up to 11 meters high, performing double-stacking and heavy-load handling tasks (DHL, 2024).

Another key area of development is the use of AGVs in yard logistics, that in other words is the automated movement of materials even in outdoor and more challenging environments. Research has shown that AGVs can operate beyond indoor warehouses by being connected to advanced Fleet Management Systems (FMS), which help them adapt to changing conditions like weather and infrastructure limits (Ritzinger et al., 2025). In these outdoor settings, planning the best routes and managing potential conflicts between vehicles becomes even more important. To tackle these challenges, algorithms like Large Neighborhood Search are used to solve pickup and delivery tasks while taking into account time constraints caused by traffic or weather. This approach has proven effective during industrial tests carried out in large logistics hubs. These outdoor applications open new perspectives for the adoption of AGVs on a large scale in supporting integrated and resilient supply chains. Another important aspect concerns the contribution of AGVs to the optimization of space inside warehouses. Precise handling makes it possible to reduce the safety spaces normally needed for manual maneuvers, which means more goods can be stored without compromising safety (Liu, Tsang, & Lee, 2024). In addition, using electric AGVs with regenerative braking systems and energy-saving features helps lower environmental impact by cutting harmful emissions and improving air quality inside warehouses (DHL, 2024).

Even though AGVs offer clear benefits, their adoption comes with some important challenges. The upfront costs (including not only vehicles but also management systems, infrastructure adaptation and staff training) can be quite high (Dabic-Miletic, 2024). In addition, integrating AGVs with existing systems needs careful planning to avoid compatibility problems. One risk that is often overlooked is technological dependency: software failures, cyberattacks, or coordination errors can bring logistics operations to a halt, making it essential to have strong backup strategies in place (Dabic-Miletic, 2024). Then there are operational limitations that are

strictly linked to the very nature of AGVs: while they excel at repetitive and well-structured tasks, they are less adaptable in contexts where flexibility or complex decision-making capabilities are required. Furthermore, not all AGVs can handle specific loads or adapt easily to existing logistics infrastructures, making hybrid solutions or ad hoc customizations necessary.

Autonomous Mobile Robots (AMRs)

In recent years, the integration of Autonomous Mobile Robots (AMRs) in industrial logistics has seen significant development, driven by the need of manufacturing companies to increase productivity and efficiency, also in response to the pressures of globalization and the objectives of digital and environmental sustainability (Raamets et al., 2024). The use of AMRs is no longer limited to production, but it is increasingly expanding into the warehouse sector, radically changing traditional intralogistics models. Unlike AGVs, which follow fixed routes or tracks, AMRs can make decisions on their own and don't need fixed infrastructure to navigate (Sodiya et al., 2024). AMRs have made a quantum leap: more sensitive sensors, more powerful hardware, and smarter AI algorithms allow them to move around crowded warehouses and work side by side with people in complete safety, relieving them of repetitive and tiring movements (Keith & La, 2024). When these AMRs are integrated with an advanced WMS and optimized route strategies, the result is a leaner workflow: the robots cut out unnecessary movements – the so-called “motion waste” of Lean thinking – and leave operators time to focus on higher value-added activities.

AMRs play a key role in building reconfigurable factories, a concept closely connected to the shift toward Industry 5.0 and, in the future, Industry 6.0. These systems make it possible to quickly reassign logistics resources, adjusting transport capacity and functions based on changes in demand or production setup (Raamets et al., 2024). The difference between modern AMRs and traditional AGVs lies in the way they make decisions: unlike AGVs, AMRs do not rely on a rigid centralized control but autonomously plan their tasks and routes. This feature makes the whole system more elastic and resilient, able to promptly react to unforeseen events like congested areas, machinery breakdowns or changes in priorities (Raamets et al., 2024). In traditional structures, material handling involved large margins of inefficiency: operators had to walk long distances, resulting in increased fatigue and reduced productivity. The use of AMRs in collaboration with human personnel instead allows for a redistribution of tasks, with robots taking care of transport, while operators focus on higher value-added

activities, such as picking difficult-to-handle or particularly delicate objects (Keith & La, 2024).

From a technological perspective, AMRs are integrated with a heterogeneous set of sensors (2D/3D cameras, accelerometers, gyroscopes and LiDAR), which, fused together through sensor fusion techniques, allows robots to build detailed maps of the space and to localize themselves precisely, moving autonomously within the warehouse (De Silva et al., 2018). Navigation systems such as Simultaneous Localization and Mapping (SLAM) are now a standard practice to allow AMRs to operate in unknown and changing environments (Singandhupe & La, 2019). In parallel, advances in computational hardware have made edge processing of navigation data and real-time fleet management possible (Keith & La, 2024). Efficient management of AMRs cannot ignore a close integration with corporate information systems, as shown in Figure 54.

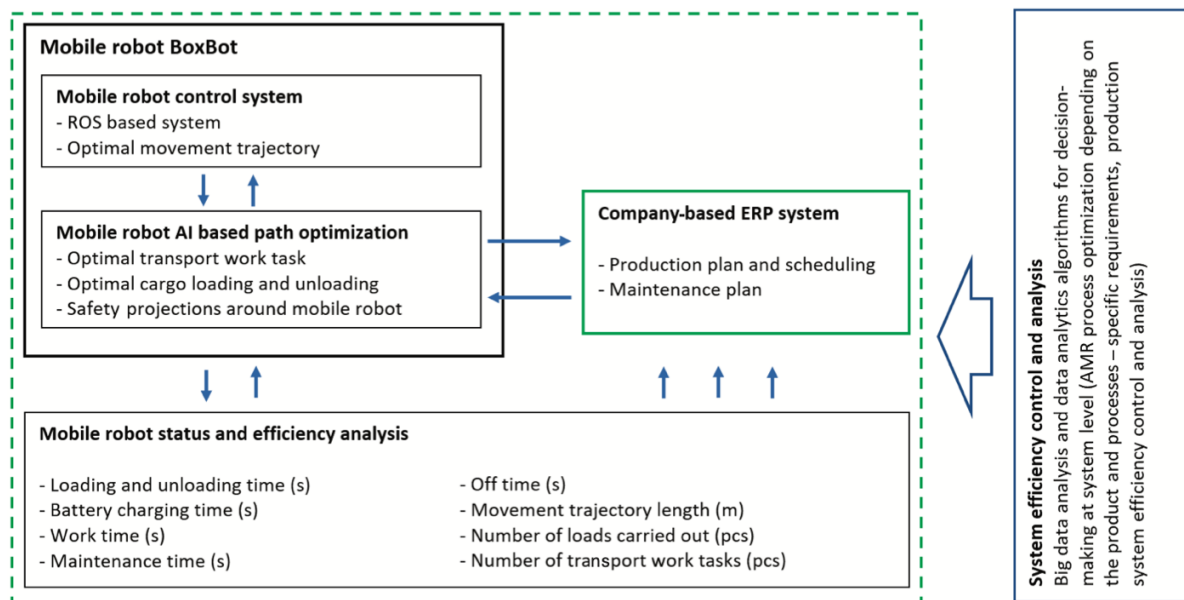


Figure 54 - General framework of the AMR data exchange

Source: Raamets, T., Majak, J., Karjust, K., Mahmood, K., & Hermaste, A. (2024). Autonomous mobile robots for production logistics: A process optimization model modification (Figure 4, p. 138). *Proceedings of the Estonian Academy of Sciences*, 73(2), 134–141.

The overall data exchange framework between AMRs and corporate ERP consists of three main layers: the mobile robot control system, AI-based path optimization, and operational status analysis. The ERP system supplies essential information like production planning and maintenance schedules, while the robot sends back detailed data on loading and unloading times, battery charging times, operating times, completed routes, and the number of missions

carried out. This information feeds into system-level efficiency analysis algorithms, supporting continuous performance optimization and better decision-making.

Energy efficiency has also benefited from technological evolution: modern lithium-ion batteries allow AMRs to have significant operating autonomy and short charging times, although questions remain about the environmental impact of disposing of such batteries (Keith & La, 2024). Innovative charging systems, such as wireless power transfer and intelligent charge cycle management, allow AMRs to maintain high operational availability, even during multi-shift operations.

Moving around safely is a big challenge for AMRs. In dynamic contexts like warehouses, they have to keep updating their paths to avoid collisions with moving obstacles like carts, other robots, or people. To do this, different methods have been created: from simple ones like bug algorithms and vector field histograms, to newer ones that use AI techniques like deep reinforcement learning, genetic algorithms, and swarm intelligence. Furthermore, hierarchical models can be integrated into the decision-making process of AMRs: at the top level, the mission is established (which nodes should be visited), while at the bottom level, the optimal path to perform the mission efficiently is calculated.

In the management of robotic fleets, there is an increasing shift from centralized control architectures to decentralized solutions. The first approaches, while offering an overview that allows global optimization, suffer from two obvious limitations: a single malfunction can paralyze the entire system and, as the number of units grows, scalability becomes problematic. In decentralized models, however, each robot takes part in the decision-making process, distributing the computational load, increasing resilience to unexpected events and adapting more quickly to changes in flow or operational priorities. This evolution is accompanied by the issue of human-robot collaboration. AMRs do not aim to replace operators, but to work alongside them, combining the precision and strength of the robot with the human ability to manage exceptions and complex judgments. Examples such as the Collaborative Human-Robot Order Picking System (CHR-OPS) demonstrate this: by integrating batching, sequencing and routing algorithms, these systems reduce waiting times, redistribute workloads in real time and raise the bar of overall efficiency, making the most of the skills of both actors. The physical design of the warehouse also plays a decisive role: unconventional layout solutions, such as the fishbone layout, allow to reduce the distances traveled by 10–15% compared to traditional rectilinear layouts, further improving the performance of the AMR system. The design of spaces must therefore take into account the specific modes of movement and interaction of the robots, favoring configurations that minimize congestion and non-optimal paths. Despite

significant progress, several areas remain open for future research. In particular, there is a need to deepen the decentralized management of order scheduling, the dynamic definition of intervention zones to avoid congestion, and the integration of human factors in human-robot collaboration models, aspects that are still little explored in the literature (Keith & La, 2024).

Automated Storage and Retrieval Systems (AS/RS)

Automated Storage and Retrieval Systems (AS/RS) consist of a variety of computer-controlled systems designed to automate the loading, positioning and retrieval of goods from specific areas within a warehouse. This automation is particularly useful in contexts characterized by high volume turnover or by stringent needs to optimize the available space.



Figure 55 - Step-by-step operation of an automated storage and retrieval system (AS/RS)

Source: Adapted by the author from *Automated Storage and Retrieval Systems - How it works [Video]*, RINAC Engineering Evolution, (2021).

Through robotic processes, AS/RS allow to reduce management costs, improve warehouse organization, increase storage density (thanks to narrower aisles and higher racks) without requiring physical expansions, and significantly reduce labor costs (Turner, 2020). From the point of view of the economic sustainability of warehouse management systems (WMS), AS/RS play a key role, improving the accuracy of inventory control, reducing errors and promoting a faster rotation of high-moving products (Tostani et al., 2020; Fragapane et al., 2021). They are particularly suited to the management of sensitive items, such as refrigerated products for the food and pharmaceutical sectors, which require rigorous storage conditions.

The AS/RS system is composed of cranes and automatic shuttles that run along predefined aisles and vertical levels to deposit or retrieve load units, drastically reducing order fulfillment times and improving inventory control (Banur et al., 2024). A relevant contribution is that of Manzini, Gamberi and Regattieri (2006), who propose a multi-parametric dynamic model, supported by interactive visual simulations, to evaluate the effect of different design and operational choices on performance. Through thousands of “what-if” scenarios, the authors demonstrate that class-based storage policies based on the Cube-per-Order Index (COI) cut picking times and boost productivity: the right balance between storage location assignment, order batching and mission routing is crucial to shorten the distances traveled by the shuttles and reduce the average lead time. The design of an AS/RS, they emphasize, must take into account parameters such as available area, aisle layout, vehicle capacity and parceling strategy, to be analyzed with Design of Experiments techniques: among the most influential drivers emerge the COI curve and the shuttle load capacity. Although the initial investment is substantial and requires careful engineering, the benefits in terms of efficiency, precision, operational flexibility and sustainability make the AS/RS a pillar of future intelligent and resilient supply chains.

Robotic Arms

Robotic arms, thanks to their ability to perform repetitive tasks with extreme precision and speed, are today one of the most promising technologies for the transformation of logistics activities. They are provided with multiple degrees of freedom and can be equipped with different types of end-effectors (such as grippers, suction cups or magnets) that allow them to manipulate products, packaging and loads of various kinds with great dexterity (Sodiya et al., 2024). In more complex contexts, where the position of objects is not predetermined, robotic arms combine sensors and artificial vision systems supported by AI, thus allowing real-time visual recognition and more intelligent manipulation of objects (Dhaliwal, 2021).

From a mechanical point of view, robotic arms are divided into four main categories:

- I. Cartesian (or gantry) robots, which operate on three linear axes X-Y-Z;
- II. Cylindrical arms, based on movements around a cylindrical axis;
- III. Spherical (or polar) arms, which allow complete rotation movements in space;
- IV. SCARA robots, particularly suitable for pick-and-place operations on a plane (Dhaliwal, 2021).

This classification highlights the great variety of possible applications, from the simple movement of items to the management of more complex tasks such as assembly. Recently, a

specific trend called Stationary Robotics has developed, which includes all those robots, often in the shape of an arm, that operate from a fixed position: anchored to floors, ceilings or other structures (DHL, 2024). Fixed robotic arms applications fall into two main categories: collaborative applications, which involve direct interaction with human operators and require additional risk assessments, and industrial applications, which involve heavy loads, long operating distances, and high speeds, typically taking place in segregated and protected areas. With the continued development of machine learning and perception technologies, an ever-increasing integration between mobile and fixed robotic systems is expected, which is particularly useful in an environment marked by labor shortages and volatile demand.

Robotic arms are being increasingly used in logistics to automate several key processes, including shipment sorting, picking and placing, palletizing and depalletizing. The process of sorting shipments is a highly repetitive task, thus it is very easy for human operators to lose focus and make mistakes. This makes it particularly suitable for automation through robotic arms. They use cameras and AI to classify packages based on predefined characteristics. This reduces errors and rework costs.

Regarding the picking and placing process, manually separating and arranging packages is a tedious and labour-intensive activity. Robotic arms coupled with advanced vision systems can automate the induction of items onto conveyor belts, enhancing throughput and decreasing reliance on the labour market. Palletizing and depalletizing operations benefit greatly from the use of robotic arms. While uniform pallet handling has already been extensively automated, mixed pallet solutions, which require more sophisticated AI to handle loads of various shapes and weights, are rapidly maturing and are projected to gain broad implementation in the coming years.

Despite the benefits brought by the use of robotic arms related to increased productivity, reduced errors and greater operational safety, they also have some limitations that should not be ignored. In particular, they usually are designed to handle packages of specific shapes and may have difficulties in handling certain kinds of items. Furthermore, performance achieved in the laboratory is not always successfully replicated in real-world operating conditions, due to the complexity of warehouse flows. Furthermore, even with an increasing level of automation, human supervision will still be required to manage robotic applications, making full automation without human intervention unlikely in the near future (DHL, 2024).

Collaborative Robots (Cobots)

A key element in the evolution of smart logistics is represented by cobots (collaborative robots), robotic devices designed to work side by side with human operators in shared

environments. Cobots are profoundly different from traditional industrial robots: while the latter usually operate in segregated spaces and perform repetitive tasks autonomously, cobots are designed for safe and direct interaction with humans, thanks to advanced sensor systems and AI (Abdullayev et al., 2024). Unlike traditional industrial robots, cobots perceive the environment, interpret it in fractions of a second and continuously adapt their behavior. The credit goes to the set of force sensors, high-resolution cameras and machine learning algorithms that, by processing the collected data in real time, allow the cobot to deviate when it encounters an obstacle, dose the force on delicate materials and minimize the risk of collisions (Bagnoli et al., 2022). However, this contextual intelligence would be sterile without an interface that is truly accessible to those who use it: intuitive graphic dashboards and guided procedures allow even operators without specialist skills to reconfigure the system in a few minutes, with almost no impact on downtime. For small and medium-sized enterprises – which cannot count on dedicated teams of engineers – this ease of use represents a decisive competitive advantage (Abdullayev et al., 2024).

In the logistics sector, cobots find application in many processes, such as automatic picking, package selection and warehouse management. They are able to move safely even in complex and constantly evolving environments. From the point of view of safety, which is a fundamental aspect in human-robot interaction (HRI), cobots adopt advanced strategies to avoid or limit accidental contacts.

Computational vision systems, force-torque sensors and predictive algorithms allow to anticipate and prevent accidental collisions. When contact is unavoidable, mitigation techniques are applied to reduce the impact energy and protect the physical integrity of the operator. In addition, the growing attention to ergonomics in the workplace has prompted the development of cobots designed not only to increase productivity, but also to reduce biomechanical load and cognitive stress on operators. Human-robot collaboration, in fact, allows the transfer of physically more demanding or repetitive tasks to cobots, freeing up human resources for tasks with higher added value (Patil, Vasu, & Srinadh, 2023). However, the presence of cobots also implies new challenges in terms of cognitive safety, since the unpredictability of some robotic movements can generate mental stress in operators. For this reason, the design of cobot interfaces and behaviors must take into account not only physical risks, but also psychological and social aspects of the interaction. An important distinction among cobots is based on the ways in which they collaborate with humans. We can distinguish independent cobots, which operate in parallel with operators on distinct tasks but in the same environment; simultaneous, in which cobots and operators work simultaneously on the same

activity without time dependence; sequential, where activities are organized in a temporal manner (first the robot, then the human, or vice versa); and finally supportive, where the completion of a given task requires synergistic cooperation between cobot and operator (Patil, Vasu, & Srinadh, 2023).

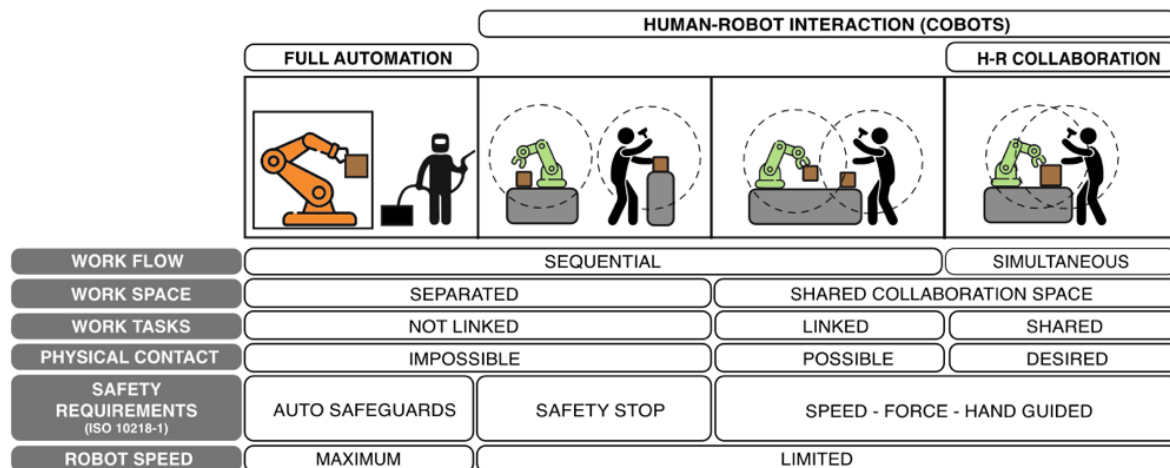


Figure 56 - Types of human-robot relationship

Source: Burden, A. G., Amayo Caldwell, G., & Guertler, M. R. (2022). *Towards human-robot collaboration in construction: Current cobot trends and forecasts* (Figure 1, p. 211). *Construction Robotics*, 6, 209–220. Springer Nature Switzerland AG.

The potential of cobots in logistics is not limited to warehouse management: they can increase efficiency in loading and unloading operations, optimize packing and picking processes, manage just-in-time workflows, support predictive maintenance thanks to the collection and analysis of IoT data and also collaborate in the creation of highly customized solutions for last-mile deliveries. The challenges associated with the implementation of cobots undoubtedly include the need to develop increasingly intuitive and reliable interaction systems, capable of adjusting to complex and constantly evolving operational situations. At the same time, the relationship of trust between operators and robots is of fundamental importance, and it is a point on which much work needs to be done, also supported by the definition of clear regulatory standards that guarantee the safety and effectiveness of collaboration. The integration of technologies such as edge computing, distributed machine learning and Industrial IoT opens up very promising prospects: the cobots of the future will be increasingly autonomous, intelligent and safe, ready to contribute to the creation of collaborative and resilient work environments, in line with the principles of Industry 5.0.

Drones

Drones, also called unmanned aerial vehicles (UAVs), are vehicles that operate autonomously, or under remote control of a human operator, without a pilot or crew on board. They were born mainly for military purposes, but then progressively extended their scope of application to multiple civil sectors, including: environmental monitoring, emergency management, logistical support, aerial photography and, more recently, warehouse and distribution operations (Barmounakis et al., 2016). The turning point in the commercial adoption of drones occurred in 2016, when Amazon announced its first UAV delivery to a customer in England, paving the way for a new era of logistics in which rapid and autonomous transport of goods becomes a concrete possibility. Technological advances played a key role in making drones effective and versatile tools in this field. Among the most significant recent advances are the integration of advanced sensors, autonomous navigation systems based on GPS, LiDAR, radar and computer vision algorithms, as well as new generations of solid-state batteries and hydrogen fuel cells that improve autonomy and flight times. Modern drones are able to navigate even in environments with signal interference, processing data from multiple sensory sources in real time thanks to sensor fusion techniques developed by companies such as Teledyne Geospatial (DHL, 2024). The combined use of AI and ML algorithms turned drones into autonomous platforms capable of not only “seeing” the environment, but also of interpreting it, recognizing and avoiding obstacles without the need for human intervention. At the same time, the emergence of new technologies is opening up new operational scenarios. One example is swarm intelligence, which is based on decentralized and self-organizing networks in which fleets of drones cooperate in a coordinated manner. In logistics, these devices find application in four key areas: inventory management, intralogistics, deliveries, and inspection or surveillance missions. In inventory control, drones overcome the limitations of manual methods—slow, expensive, and sometimes risky—by performing audits, cycle counts, package localization, and buffer management in drastically reduced times. Companik et al. (2018) underline how drones are now able to perform inventory audits, cycle counts, item localization and reserve stock management much faster than traditional methods, while Varmus and Bosko (2022) estimate a barcode scanning speed up to 119 times higher than a human operator. A concrete example is represented by the study by Culus et al. (2018), which analyzes the case of the NHS terminal in the port of Antwerp, where the use of pre-programmed drones enabled the automation of the inventory process of steel bars, increasing both the efficiency and the precision of the operations. Among the most recent developments are the adoption of QR codes for product identification (Cristiani et al., 2020; Ali et al., 2021) and the use of advanced

computer vision techniques for barcode extraction, based on algorithms such as the Harris Corner Detector¹⁶ and the Hough Transform¹⁷. As demonstrated by Jhunjhunwala et al. (2019), these approaches have achieved satisfactory results even in complex contexts such as large warehouses. A further development concerns the integration of RFID scanners with UAV systems, which has allowed obtaining good performances in automatic inventory detection.

In the intralogistics field, drones started to emerge as an effective solution to speed up deliveries within industrial plants as they facilitate the direct transportation of components, tools and consumables to the production lines (Benarbia and Kyamakya, 2021). To mention some studies, Cavalcante et al. (2017) developed a mission planning system specifically designed to coordinate material picking and delivery activities between warehouses and production areas. Other practical examples are the authorized flights of the DPD Group in France or the tests conducted by Walmart in collaboration with Flytrex. All these examples demonstrate drones potential to optimize internal material handling.

The so-called Drone Deliveries represent one of the most innovative frontiers in modern logistics. Delivery drones are designed to cover different stages of transportation, from the first mile to the middle mile, up to the last mile, with the aim of reducing delivery times and improving the overall efficiency of the supply chain. Although the collective imagination focuses mainly on the use of drones in the last mile, in current operational practice, implementations are mainly focused on rural or poorly served areas, where the benefits in terms of speed and accessibility are more evident (DHL, 2024). Among the most significant developments is the design of cargo drones capable of carrying heavy loads, such as those made by Sabrewing, Dronamics and Elroy Air which can move up to 376 kilograms. However, despite recent regulatory advances, such as the Federal Aviation Administration (FAA) authorizations for Beyond Visual Line of Sight (BVLOS) flights, the full adoption of drone deliveries in urban settings remains, at least for now, limited by stringent regulations and difficulties related to integration into existing airspace (DHL, 2024). We can expect that in the coming years the growth of drone deliveries will be mainly limited to niche use cases, such as the transport of critical medical supplies to remote areas, the movement of urgent materials within large industrial complexes, or the management of deliveries in private contexts such as campuses or isolated production plants. Despite technological advances, widespread adoption

¹⁶ The Harris Corner Detector is a computer vision algorithm that analyzes intensity variations in a small window of the image: if these variations are high in all directions, the point is classified as a “corner”.

¹⁷ The Hough Transform is a feature extraction technique used in image analysis, computer vision, pattern recognition, and digital image processing.

of drones in urban areas continues to be hampered by safety concerns, complex management of shared airspace, and population perception of risk (DHL, 2024). In spite of this, delivery drones are emerging as a strategic solution to the growing pressure on logistics networks, driven by the expansion of e-commerce and the need to rethink distribution models for greater efficiency and sustainability.

Also for inspection and surveillance activities, the use of drones is proving to be particularly useful. Silvagni et al. (2016) and Ali and Kaur (2022) report that they allow to safely inspect roofs, shelves, walls and ceilings, reducing risks for personnel and improving the overall efficiency of operations. The application of SLAM technology with 3D sensors and optical scanners, such as the one developed by Virus and documented by Wawrla, Maghazei and Netland (2019), allows to create high-precision three-dimensional maps and to localize the drone inside the warehouse. This technology, which processes millions of pixels per second, paves the way for continuous surveillance operations, structural monitoring and early detection of damage or anomalies. Even in high-risk sectors such as the petrochemical sector or in the surveillance of maritime infrastructures, drones are proving to be irreplaceable tools for reducing operational risks (C-S Yang, 2019).

Despite the many advantages, the implementation of drones in logistics contexts still presents significant critical issues. From a technological point of view, limitations persist in payload capacity, battery life and autonomous navigation accuracy, especially in indoor environments without GPS signal. Although the introduction of advanced technologies has contributed to improving localization accuracy, the autonomy of drones used in indoor environments remains generally limited to less than 30 minutes. Wired solutions can extend operating times, but at the cost of reduced freedom of movement. From a regulatory point of view, as highlighted by DHL (2024) and other recent studies, the still very restrictive regulations on the use of drones, particularly in civil and urban environments, continue to represent a significant obstacle to their diffusion. In addition to these critical issues, there are further challenges related to privacy protection, security in the management of collected data and insurance issues related to possible accidents, which contribute to slowing down large-scale adoption.

4.2 Challenges in AI and IoT Integration

4.2.1 Data privacy, security, and ethical concerns

In the logistics context, the widespread adoption of sensors, actuators and cloud-based platforms transforms every package, means of transport or shelving into a continuous source of data. This “connected pervasiveness” is the heart of the IoT, but, in parallel with the benefits

of efficiency and operational transparency, it introduces a complex range of issues relating to confidentiality, security and ethics. Already within information and communication technologies (ICT) it has been highlighted that the critical issues revolve around accessibility, ownership and integrity of information. The IoT amplifies these critical issues because it puts into circulation data generated autonomously by objects that, by their nature, are difficult for the end user to monitor (Popescul & Georgescu, 2013). On the privacy side, the end-to-end traceability of goods, essential to guarantee visibility of the supply chain, involves the collection of metadata that allow inferring not only the position of a pallet, but also the work shifts of operators, waiting times at customs or the reliability of a sub-carrier. Automatic identification mechanisms, such as RFID, NFC or image recognition cameras, can trace apparently innocuous events (for example, scanning a label at the warehouse gate) to specific personal identities (Ziegeldorf et al., 2014). If such datasets are integrated with external registers – such as drivers' personal data or professional social networks – the risk of linkage increases exponentially, compromising the subject's ability to control their information. Furthermore, distributed storage on edge gateways, mobile devices and cloud servers makes it difficult to guarantee the definitive deletion of data when a device changes ownership, configuring the problem of lifecycle transitions: a resold or decommissioned sensor may still contain mission logs, GPS coordinates and environmental parameters related to previous shipments. From a security point of view, the logistics ecosystem is a tempting target for cyber attacks motivated both economically and geopolitically. The NotPetya incident that hit Maersk in 2017, paralyzing port terminals and booking systems for several days, showed how malware that can rapidly propagate between heterogeneous hosts can block global supply chains and generate multi-million dollar losses. At the micro level, interference with a single actuator – for example, the unauthorized opening of a refrigerated container – can deteriorate perishable goods and affect the food safety of end consumers. The problem is exacerbated by the convergence of IT and OT (Operational Technology)¹⁸: late patches, never-changed default passwords and unencrypted industrial protocols are the Achilles heel of many automated warehouses. The ethical implications do not only concern data protection, but also the dignity and autonomy of workers and customers. Real-time location systems (RTLS) promise to

¹⁸ Operational Technology is the set of hardware and software that directly monitor and control physical processes within industrial plants, automated warehouses, transportation systems, energy distribution networks and, in general, all those infrastructures where it is necessary to intervene “on the field” (for example with sensors and actuators). Unlike IT (Information Technology), which focuses on data and business applications, OT governs valves, motors, robots, conveyor belts and other operational equipment.

optimize picker routes, but, if used without adequate protection, they can turn into tools of micro-surveillance and psychological pressure. Similarly, behavioral profiling enabled by the analysis of sensor and camera logs could influence performance evaluation or assignment granting, generating implicit discrimination. The literature recalls that, in the IoT field, what seem to be “purely” technical problems (authentication, encryption, key management) always have an ethical-social dimension, because they determine who controls what, when and how (NIST, 2018; Allhoff & Henschke, 2018). To address these challenges, privacy-by-design and security-by-design practices must be integrated from the early stages of designing logistics architectures. From a regulatory point of view, Regulation (EU) 2016/679 (GDPR) provides a rigorous framework for the protection of personal data, imposing the principle of minimization and the right to be forgotten also in machine-to-machine flows. On a technical level, the adoption of standards such as ISO/IEC 27001, combined with threat modeling methodologies specific to IoT, allows identifying exposure points and defining countermeasures proportionate to the risk. End-to-end encryption, mutual authentication between nodes, secure firmware updates and network segmentation are now essential best practices. Finally, emerging approaches such as multilevel trust frameworks are added, which associate each device with a dynamic reliability score based on tests of compliance and operating behavior (Sato et al., 2016).

Further challenges concern the use of AI. Ethics applied to AI in the logistics sector can no longer be considered a simple technological corollary. In light of the most recent sector studies, it constitutes an enabling condition for any truly sustainable digital transformation project. The adoption of machine learning algorithms, predictive analysis systems and autonomous robotics allows, on the one hand, to generate measurable efficiencies but, on the other, opens up a field of action full of critical issues related to data privacy, cybersecurity, decision-making transparency and socio-occupational impacts. In terms of confidentiality, the concentration of sensitive information makes AI platforms a privileged target for malicious actors. The privacy-preserving techniques, such as federated learning and homomorphic encryption show good results in preserving information sovereignty, but they do not completely eliminate the risk of data poisoning or exfiltration of model parameters, which are among the most cited threats in international incident reports today (Adewale et al., 2025). European legislation adds a further level of complexity: the combined provisions of GDPR and AI Act require periodic audits, reference datasets without significant biases and human supervision for all applications classified as “high risk” (European Commission, 2024). Algorithmic bias is the primary ethical concern. Adewale et al. (2025) have shown that models trained on unbalanced datasets can

penalize entire supply basins, worsening pre-existing inequalities and, in fact, reducing the diversity of the supply-chain network. The European guidelines on trustworthy AI invite to integrate explainability mechanisms right from the design phase, so as to clarify the logical connection between inputs, intermediate features and the final decision. Such transparency is not only a regulatory requirement, but also a lever of trust towards customers and partners: without a shared understanding of the routing or inventory allocation logics, any operational anomaly risks being read as “algorithm arbitrariness”. On the security side, the extension of the attack surfaces caused by the interconnection of AI, IoT and cloud has already emerged in various news stories: from ransomware attacks that paralyze warehouse management systems to sensor manipulations that divert automated vehicles onto unwanted routes. It must be highlighted also the growing danger of adversarial attacks, in which imperceptible perturbations in input data induce catastrophic errors in computer vision models (Adewale et al., 2025). Mitigation requires a mix of secure-by-design, continuous robustness testing and the implementation of end-to-end encryption protocols, as well as multifactorial access controls and real-time monitoring based on AI-driven threat intelligence. Thus, AI requires multi-level governance that integrates ethical guidelines, technical standards and clear legal responsibilities along the entire supply chain. Experience shows that regulatory compliance alone is not enough: a corporate culture of responsible innovation is needed, based on independent audits, internal ethics committees and feedback platforms open to employees and external stakeholders.

4.2.2 Technological and infrastructural barriers

The implementation of AI and IoT solutions the logistics context faces a series of technological and infrastructural barriers that, if not recognized and managed in time, risk significantly reducing the return on investment and compromising the operational continuity of the systems. First of all, AI critically depends on the availability of large amounts of accurate, timely and semantically uniform data; however, in warehouses and transport nodes, datasets are often fragmented between heterogeneous management systems (ERP, WMS, TMS) and proprietary IoT devices, generating inconsistencies that limit the accuracy of the models and impose a theoretical performance threshold that rarely exceeds 75% accuracy (Gudivada et al., 2017). Secondly, the high computational requirements of deep neural networks entail the need for hardware infrastructures that cannot always be hosted on-premises for reasons of space, energy consumption and cooling: the use of the cloud reduces the barrier to entry, but introduces further critical issues related to network latency, scaling costs and data sovereignty, particularly

relevant when (almost) real-time analyses are required for route optimization or inventory rebalancing. A third barrier is represented by integration with legacy systems: many platforms used in logistics have been designed according to monolithic logics and do not expose modern APIs, forcing companies to develop ad hoc middleware that not only increase architectural complexity, but also become points of failure in the event of uncoordinated updates (Shrivastav, 2022). Added to this is the management of “model drift”: consumer demand, delivery times and fuel costs represent dynamic variables that alter the distribution of input data. Without automatic monitoring and retraining (MLOps) pipelines, models progressively degrade, generating suboptimal decisions and undermining operator confidence (Nelson et al., 2015).

Also in this sense, the critical issues of AI are intertwined with those of IoT. The first obstacle concerns the hardware-software heterogeneity of the ecosystem: RFID sensors, NFC tags, environmental data-loggers, edge gateways and cloud platforms come from different vendors and speak distinct protocols. The absence of mature standards for data serialization and automatic device discovery produces information silos that are difficult to integrate, with inevitable costs of customization of APIs and development of translation middleware (Garrido-Hidalgo et al., 2019; Cortés et al., 2015). This fragmentation is amplified when trying to connect the new “smart” nodes to legacy systems (ERP, WMS, TMS) designed for intermittent data flows and not for real-time streaming: the need for adapters and backward-compatibility interfaces introduces latencies, points of failure and recurring maintenance costs (Samaranayake et al., 2022). On the infrastructural level, network coverage is not homogeneous nor guaranteed in all segments of the supply chain: warehouses located in remote industrial areas, road sections in rural areas or ocean crossings suffer from discontinuous connectivity. Consequently, devices must switch between low-power technologies (LPWAN) and cellular networks with significant impacts on energy expenditure and battery life, already limited by the miniaturization required for smart pallets and containers (Li & Li, 2017). The cost of replacing or recharging devices, especially when we are talking about thousands of units dispersed in multiple countries, has a heavy impact on TCO (Total Cost of Ownership) and slows down the return on the initial investment, as highlighted by studies on post-pandemic economic drivers (Ali et al., 2023). Data quality and continuity represent another critical bottleneck. Sensors exposed to vibrations, thermal shocks or extreme humidity record calibration drifts that compromise the fidelity of readings. This requires periodic recalibration procedures and self-diagnostic systems that, if absent, degrade the reliability of decision-making dashboards and trigger false alarms along the cold chain (Tsang et al., 2018). In

parallel, the explosion of information volumes (high-velocity and high-variety) generates data management challenges: robust pipelines are needed for edge filtering, packet compression and encryption, as well as scalable data lakes that guarantee consistent metadata and versioning. In the absence of a solid governance framework, the risk is a flood of non-contextualized “dark data” that weighs on storage costs and complicates predictive analyses (Mashayekhy et al., 2022; Hu, Al-Barakati, & Rani, 2022). Finally, the issue of infrastructural sustainability should not be overlooked. The high turnover of low-cost sensors, often not designed for recovery or recycling, generates e-waste flows that conflict with environmental responsibility policies and circular supply chain objectives (Ding et al., 2023). The lack of operational guidelines on end-of-life and disposal, combined with the difficulty of tracking components and materials throughout the entire life cycle, undermines the coherence between the “green” narrative of IoT and the daily practice of warehouses.

In summary, AI and IoT share four critical nodes that feed each other: data quality, interoperability, and governance; computational capacity and network resilience; legacy integration and lifecycle management of models and devices; total costs, cybersecurity, and environmental impact. Removing these obstacles requires synergistic interventions: definition of open standards and common semantics, investments in highly reliable 5G and LPWAN networks, cloud-edge architectures that minimize latency and decentralize the computational load, MLOps pipelines that automate model retraining and versioning, secure-by-design devices with over-the-air firmware updates, and finally eco-design strategies that include takeback, recycling, and extended producer responsibility from the outset. Only a holistic approach, capable of holding these dimensions together, will allow companies to move from pilot experiments to scaled implementations, transforming the promise of predictive, transparent and sustainable logistics into a concrete operational reality.

4.2.3 Workforce transition and reskilling

The progressive adoption of AI and IoT solutions in logistics is profoundly reshaping the professional profiles of the sector, making a systematic process of reskilling and upskilling essential. On an individual level, literature highlights how the perception of self-efficacy and the balance between work demands and resources outlined by the Job Demands-Resources Model influence workers’ willingness to learn data analytics, basic programming and maintenance of AI systems. However, the introduction of intelligent technologies does not only involve new technical skills: the constant flow of real-time data requires critical judgment skills and a renewed digital literacy to interpret often opaque algorithmic outputs, avoiding both

automation blindness and distrust towards systems. At the team level, human-machine collaboration transforms shifts and coordination mechanisms: operators must communicate with decision-support interfaces and, at the same time, develop relational skills to manage more interconnected and transparent processes, in which individual performances are continuously monitored. From an organizational point of view, AI allows to outsource or automate repetitive tasks, but generates demand for hybrid roles, like algorithm maintainers and data-driven warehouse supervisors, which require flexible and modular training paths often based on micro-credentialing and e-learning platforms. In this context, a strategic approach to change management becomes crucial: job crafting programs and personalized career plans can mitigate resistance to change, supporting intrinsic motivation and the perception of autonomy, key elements for well-being and productivity in digitalized contexts (Klumpp & Ruiner, 2022).

The World Economic Forum's Future of Jobs Report 2025 overturns the apocalyptic narrative that has often accompanied automation: the percentage of "job disruption" will be significant (22% of current roles will be redefined by 2030), but the net effect will be positive, with 170 million new jobs and 92 million positions moved, for a balance of +78 million job opportunities. In terms of skills, however, the picture remains challenging: almost 40% of the skills currently required will change and 59 out of 100 workers will need requalification or updating courses by 2030; of these, 11 risk not receiving them, exposing over 120 million people to potential layoffs. Employers are sensing the problem: 63% identify the skills gap as the main obstacle to business transformation, while 77% plan upskilling programs, but 41% predict headcount reductions due to automation (World Economic Forum, 2025). The fastest growing skills profile confirms the two-faced nature of demand: on the one hand, technological skills – AI, big data, cybersecurity, OT/IT networks –, on the other, cognitively intensive human skills – analytical-creative thinking, collaboration, resilience, flexibility. The hybridization of the two areas becomes the new currency of exchange on the labor market. Logistics companies experience it on a daily basis: surveys conducted in mature economies (UK, Germany, USA) indicate structural deficiencies in data science, industrial safety and predictive maintenance, but also in soft skills such as complex problem solving and intercultural communication. Similar evidence emerges from emerging countries: a survey of logistics companies in Oman finds pronounced shortages in data analytics (68%), digital marketing (52%), the ability to learn continuously and creativity/innovation (48%), programming/coding (44%) and industrial cyber-security (48%). The same companies indicate the reskilling of internal staff as their primary strategy (45%), followed by the outsourcing of specialist functions (21%), while they recognize that the main obstacles are the lack of adequate

training courses (40%) and the misalignment between academic curricula and industrial needs (32%) (Benayoune et al., 2022).

In light of this evidence, a synergic action between companies, universities and policy-makers is essential. On the academic side, it is necessary to rethink teaching in a modular and “blended” way, integrating simulation laboratories, micro-credentials oriented to specific technologies (e.g. IoT API management, logistics data modeling, predictive maintenance) and internships co-designed with companies, so as to reduce the time-to-skill reported by studies (Benayoune et al., 2022). Companies, for their part, must invest in knowledge-sharing platforms and apprenticeship programs that allow workers to acquire medium-high level skills without interrupting production activity – a need particularly felt in emerging contexts where the availability of low-cost foreign labor can slow down technological adoption, but at the same time limit the career paths of local workers. Finally, public policies must promote the creation of national skill frameworks that dynamically map skills needs and incentivize experimentation with new training models, reducing the “digital divide” which, if not addressed, risks widening employment inequalities.

4.3 Cross-cutting applications of the AIoT approach beyond logistics

IoT and AI are not simply an overlapping of technologies: rather, they represent the backbone of a cybernetic ecosystem that transversally permeates a variety of sectors. The unifying element is a continuous cycle – perception, connection, analysis, action – that allows previously inert objects to transform into intelligent nodes, capable of generating data, learning hidden correlations and intervening in the physical world. Below is an organic and in-depth discussion of the main application areas, showing how the models developed in logistics constitute only a small part of a much broader phenomenon.

4.3.1 Energy sector

The energy sector, characterized by capital-intensive assets with multi-decade life cycles and a growing weight of intermittent renewable sources, is reconfiguring itself around the convergence of IoT and AI, a synergy often referred to as the Energy Internet of Things (EIoT). Distributed sensors (smart meters, substation RTUs, accelerometers, thermocouples and in-line optical fibres) generate a continuous flow of data that, conveyed by NB-IoT, LTE-M or 5G networks and pre-processed at the edge, feeds predictive machine-learning models running in the cloud. These models, trained on meteorological variables, SCADA signals and historical consumption series, enable a proactive balancing between supply and demand (DHL & Cisco, 2015). The experiment conducted by DeepMind with National Grid in the United Kingdom

showed that forecasting demand 48 hours in advance and with an error margin of less than 10% allows a 10% reduction in the need for rotating reserves, with consequent savings in fossil fuel and lower emissions (Kreutzer & Sirrenberg, 2020). In parallel, the digital twin paradigm extends the first-time-right approach already used in logistics to the world of generation and transmission: hybrid thermo-fluid dynamic models with recurrent neural networks simulate the wear of bearings and wind turbine blades in real time, scheduling maintenance only when the risk indicator exceeds the optimal economic threshold. On the network front, line digital twins (built by integrating LIDAR data, IR images and climate measurements) enable dynamic line rating, allowing controlled overloads of up to 15% without violating thermal limits and postponing investments in new transport capacity. In the distribution sector, domestic gateways communicate with neighborhood aggregators through open protocols, enabling demand response strategies based on deep-reinforcement-learning that modulate heat pumps and electric vehicle charging. The same sensor-cloud infrastructure supports advanced predictive maintenance practices in midstream plants: in the compressors of the Trans-Anatolian Pipeline, anomaly-detection models, built with auto-encoders and LSTM networks, have cut unexpected downtime and gas consumption (Nagaty, 2023). On the market level, the real-time availability of granular data paves the way for Energy-as-a-Service models, peer-to-peer trading on distributed ledgers and dynamic pricing based on smart contracts, with kilowatt hours becoming tradable information flows (Perwej et al., 2019). Crucial challenges remain: cybersecurity, made more complex by the enormous attack surface of millions of devices; interoperability, which requires the adoption of open semantic schemes; the computational sustainability of AI models, mitigated by hybrid cloud-edge architectures and serverless techniques; finally, human capital, to be updated with cross-sector skills in data science, electrical engineering and data governance (Khanna & Kaur, 2020).

4.3.2 Residential context

In the residential context, the IoT-AI combination is transforming the home into a cyber-physical platform capable of learning habits, autonomously managing critical resources and offering value-added services, overcoming the traditional home automation vision based on static scenarios and proprietary protocols (Kreutzer & Sirrenberg, 2020). The core of the smart home ecosystem is represented by a local gateway that coordinates the various devices present in the home (sensors, actuators, connected appliances) and harmonizes their different communication methods, channeling data towards management applications residing locally or in the cloud (Perwej et al., 2019). Lightweight machine-learning models (TinyML) are run

on these streams for on-device recognition of behavioral patterns: for example, the neural network trained on the absorption profile of an oven distinguishes domestic cooking from a potential fire, generating a local alert in less than 50 ms and reducing the perceived latency compared to full-cloud solutions by about 80% (Nagaty, 2023). In many advanced domestic solutions, where the home is modeled as a digital twin to track consumption, system configuration and usage profile of household appliances in real time, the same flow of electrical data, broken down with non-intrusive load monitoring techniques, allows the home's digital twin to estimate the health status of household appliances and trigger smart replenishment logics: the washing machine, when it recognizes an anomalous consumption of detergent, sends an automatic order to the integrated e-retailer, inaugurating “consumable-as-a-service” models already tested in industrial pay-per-use contracts (Khanna & Kaur, 2020). On the energy side, the reinforcement learning algorithm incorporated in the smart thermostat optimizes the set-point curve taking into account weather forecasts, TOU (Time-Of-Use) rates and heat pump response times. In “prosumer” environments equipped with photovoltaics and batteries, the digital twin calculates in real time the best charge/discharge strategy to maximize self-consumption or provide balancing services to the local energy community through smart contracts on the Energy Web blockchain. Artificial vision models, borrowed from logistics for pallet recognition, power cashier-less functionality in condominium micro-markets: wide-angle cameras cross-reference user IDs, postures and barcodes, assigning picks to a virtual cart. On the shelf, computer vision identifies out-of-stock and compliance planograms, suggesting predictive replenishments that reduced cart abandonment by 25% in pilot tests by a European retailer (Dohrmann, Pitcher, & Kamdar, 2024). Similar CNN networks analyze the behavior of lonely elderly people in real time: deviations in the walking pattern, detected by solid-state lidars or millimeter-wave FMCW radars, activate a tele-assistance protocol that forwards end-to-end encrypted video clips to caregivers, in compliance with the GDPR thanks to an anonymization pipeline at the edge. From a socio-economic point of view, the introduction of these solutions fuels new business models: “domestic well-being” subscription packages that include sensors, predictive maintenance and pay-how-you-live insurance services; condominium community clouds that sell flex-capacity to the DSO (Distribution System Operator); data platforms that monetize anonymous insights for demand-side marketing. However, widespread adoption depends on change management initiatives and the digital maturity of users: longitudinal studies show that the learning curve of home automation systems stabilizes after about six weeks, but that energy efficiency degrades if the algorithms are not periodically recalibrated on lifestyle changes (Balta-Ozkan et al., 2013).

4.3.3 *Healthcare sector*

In the healthcare domain, the integration between the IoT and AI is progressively redefining the entire continuum of care (from prevention to diagnosis, from therapy to follow-up) thanks to an ecosystem of wearable sensors, connected medical devices, edge-cloud platforms and machine learning models trained on unprecedented amounts of data. Already today, real-time monitoring of vital parameters through electrocardiographic patches, pulse oximeters or smart-watches allows the translation of raw physiological signals into clinically relevant alerts. AI, applied to these streams, identifies warning patterns of heart failure or hypoglycemia and triggers proactive interventions that reduce rehospitalizations and visits to the emergency room. The same “sense–think–act” paradigm enabled by edge computing finds application in high-intensity care departments: local low-latency gateways aggregate endoscopic videos, high-frequency EEG traces and data from infusion pumps, performing on-device inferences to detect arrhythmias or hemodynamic drifts millisecond by millisecond, before the event degenerates. The experience of Streams at the Royal Free London NHS Foundation Trust, where a mobile app notifies critical changes in kidney function in a few seconds, has demonstrated the possibility of compressing decision-making latencies and anticipating life-saving treatments (Kreutzer & Sirrenberg, 2020). On the diagnostic side, convolutional neural networks trained on millions of CT and MRI images achieve sensitivity superior to the human eye in identifying breast micro-calcifications or lymph node metastases. The challenge is no longer computing power, but the quality of the training data – to be ensured with multi-expert annotation pipelines and bias mitigation techniques – and the regulatory certification of the models. Similarly, NLP algorithms extract predictive insights from electronic clinical diaries, bridging the traditional gap between structured data and narrative notes: in oncology settings, AI synthesizes guidelines, clinical trials, and the patient’s molecular profile into personalized therapeutic recommendations, replicating the function of the tumor board on a scale (Kreutzer & Sirrenberg, 2020). At home, networks of environmental sensors integrated with telemedicine extend care beyond the hospital walls. The IBM Elderly Care project, in partnership with Malteser International, equips over 150 homes with motion sensors, water flow meters, and thermal detectors capable of learning the elderly person’s daily “rhythm”: deviations in bathroom visits or night-time openings of the front door generate yellow or red notifications, grading the urgency of the intervention (Bauer et al., 2018). In parallel, computer vision-based tele-rehabilitation systems guide the execution of post-operative exercises and automatically measure joint angles, reducing in-person sessions without compromising adherence to the program. A line of research that has gained particular momentum in recent years concerns the

use of digital twins to model selected portions – or the entire – human organism, with the aim of placing a virtual counterpart alongside the physical patient, continuously updated by real-world clinical data. Studies conducted by Siemens Healthineers have already demonstrated the feasibility of a digital twin of the heart: starting from radiological images and electrocardiographic tracings, a machine learning algorithm reconstructs the anatomy and reproduces the electro-mechanical behavior of the myocardium, allowing the simulation of failure scenarios and the *in silico* testing of the effectiveness of different therapeutic regimens. The project, at the end of a six-year trial on one hundred patients with heart failure, has shown that the model's predictions tend to converge with the observed clinical outcomes, paving the way for future applications in diagnosis and intervention planning (DHL Trend Research, 2023). Philips is following a similar path, developing its own cardiac twin and using the same twin logic for devices: a single CT scanner can generate up to 800,000 log messages per day, aggregated in the cloud and analyzed with predictive algorithms that anticipate failures and enable proactive maintenance. On the biomedical research front, the European consortium DigiTwins (118 academic centers and companies) is aiming for an even more ambitious goal: creating a personalized digital twin for every citizen of the Union, so as to minimize prognosis errors and off-target toxicity, which today are worth approximately 280 billion euros per year, equal to 20% of European healthcare spending (DHL Trend Research, 2023).

4.3.4 Smart city context

Finally, the “smart city” paradigm arises from the need to govern urban complexity – demographic, energetic, environmental – through a digital ecosystem that grafts sensor networks, pervasive connectivity and AI algorithms onto infrastructures often designed for an analogue world. In the consolidated vision, the smart city is divided into three macro-layers:

- (i) a physical level, consisting of low-power IoT devices (air quality sensors, artificial vision cameras, smart meters) located throughout the territory;
- (ii) a communication level, which combines low-consumption wireless networks for short distances with the latest generation mobile band, thus channeling data towards processing points distributed within the urban fabric;
- (iii) a cognitive level, where cloud-native platforms apply machine learning and digital twin techniques to transform information flows into operational decisions (Nagaty, 2023).

An emblematic case comes from Darmstadt, where 272 intersections have been equipped with high-definition cameras and over 2,000 traffic lights transmit more than a billion records to a centralized data lake every day. Deep learning models analyze queues, average speeds and

accident probabilities in (almost) real time, automatically adjusting traffic light plans and sending predictive alarms to the traffic control center (Darmstadt, 2019). The result is a documented reduction of 15% in travel times and emissions from congestion, with benefits comparable to much more expensive infrastructure interventions. Smart-lighting systems integrate LED lamps, motion sensors and edge gateways capable of varying light intensity based on pedestrian traffic, weather conditions and the presence of events. The streetlight network, powered by reinforcement learning algorithms, achieves energy savings of over 60% compared to static regulation scenarios and acts as a backbone for the installation of additional environmental sensors (noise, NO₂, PM 2.5), generating new revenue streams for the municipal administration. Low-power micro-sensory networks (LPWAN) continuously detect temperature, humidity, concentration of fine dust and volatile organic compounds. The data, geolocalized and enriched with meteorological information, feed spatial models that relate urban morphology to the distribution of pollutants, allowing the impact of traffic calming or urban forestry interventions to be assessed in advance. A smartphone application allows citizens to view, in real time, maps indicating the air quality along the streets and to receive suggestions on healthier alternative routes. Each user, by automatically or voluntarily sending the environmental data collected by their device, thus becomes an active part of a widespread detection network (crowdsensing). The principle is the same as that tested by ZenCity, where reports from social media, phone calls to switchboards and information from urban sensors flow into analytical dashboards that support the decisions of administrations (ZenCity, 2019). Smart bins equipped with ultrasonic sensors measure the filling level and, via NB-IoT networks, send the volumetric estimate to an optimization engine that recalculates the routes of the collection vehicles on a daily basis: experiments in the EU show cuts in kilometers traveled of up to 25% and a significant decrease in emissions (Perweij et al., 2019). A similar scheme for the water network: pressure switches and acoustic meters correlate micro-drops in pressure and vibration patterns, automatically identifying hidden leaks and scheduling maintenance interventions according to risk-based asset management logics. The natural evolution of these vertical subsystems is the construction of a digital twin of the city or individual districts, i.e. a numerical model that integrates road topology, energy constraints, building heritage and mobility flows. These platforms, born in the logistics sector to orchestrate fleets of vehicles in real time, now allow policy makers to test “what-if” scenarios – from the introduction of low-emission zones to the planning of mass events or the management of blackouts – without repercussions on the physical world. Pilot projects in Scandinavia show that traffic-energy co-simulation allows to reduce the peak electricity demand from vehicle

charging by up to 18%, thanks to demand-response strategies coordinated with intelligent traffic lights (DHL Trend Research, 2023).

Conclusion

The analysis carried out in this thesis demonstrated, first of all, that AI and the IoT today represent the two technological cornerstones on which the transformation of logistics towards the 4.0 paradigm rests. By examining first their separate contributions and then their potential convergence, the literature highlights concrete benefits but also an evident fragmentation of studies, a symptom of a maturity that is still uneven between application domains, industrial sectors and geographical areas.

Four key results emerge from the systematization of the sources.

First, machine-learning algorithms already offer tangible advantages in activities with high information content—multi-stage demand forecasts, dynamic route optimization, computer vision for automated package management—provided they are fed by quality datasets and decision-making processes capable of integrating their outputs.

Second, widespread sensors and LPWAN/5G networks have proven indispensable to generate the necessary database: without granular tracking of assets, vehicles and environments, AI remains deprived of the “information oxygen” that allows it to detect patterns and anomalies.

Third, the literature confirms that the two domains do not produce the maximum value when operating in isolation: the real competitive lever lies in their integration (AIoT) which allows to orchestrate physical and digital flows in real time, enabling digital twin logics, predictive maintenance and adaptive automation.

Fourth, despite the growing interest in AIoT, transversal barriers persist: fragmentation of interoperability standards, cybersecurity concerns, lack of clear data governance models and a widespread skills gap involving analysts, network engineers and operations personnel.

On a theoretical level, this thesis provides an organic framework that fills the gap in knowledge identified at the beginning: it compares, with homogeneous criteria, the evidence on AI and IoT, positioning them along a continuum that goes from specific applications to the systemic perspective of AIoT. This synthesis, based on a systematic and interdisciplinary review of the sources, allows us to overcome the overly rigid classifications that have so far limited the dialogue between the two research communities and offers a coherent taxonomy of benefits, constraints and open challenges.

From a methodological point of view, the work claims its exploratory and theoretical-analytical nature: the absence of original empirical data reduces the risk of overlapping with case studies already present in the literature but, at the same time, limits the scope of the conclusions to a

level of abstraction that requires field verification. It is therefore appropriate that future research focuses on three complementary directions:

- (i) longitudinal empirical studies in companies that have started AIoT projects, to measure their real impact on costs, emissions and service levels;
- (ii) comparative analyses between different sectors and regulatory contexts, useful for identifying replicable best practices and enabling policies;
- (iii) investigations on human capital, aimed at understanding how skills and forms of human-machine collaboration evolve in intelligent warehouses and distribution centers.

Ultimately, the joint examination of AI and IoT provides the image of logistics in transition: still far from full digital maturity, but already oriented towards ecosystems capable of self-adapting, anticipating disruptions and minimizing environmental impact.

List of Tables

Table 1. Digital Transformation definitions

Table 2. Selected definitions of IoT

Table 3. Comparative summary of IoT, AI and AIoT

List of Figures

Figure 1. Phases of Change

Figure 2. Key drivers for transformation

Figure 3. An Overview of the Four Industrial Revolutions

Figure 4. Schematic of smart factories with general properties required in Industry 4.0

Figure 5. Fundamental Technologies of Industry 4.0

Figure 6. SCOR Model

Figure 7. Inbound and Outbound Logistics Activities

Figure 8. Development Process of Logistics

Figure 9. The evolution of AI Generations from AI 1.0 to AI 4.0

Figure 10. AI components

Figure 11. Building blocks of AI

Figure 12. Difference between machine learning and deep learning

Figure 13. Major classification of artificial neural networks

Figure 14. Use of the AI system in different parts of logistics

Figure 15. Computer Vision Market Size Worldwide (in billion USD)

Figure 16. Classification & segmentation of Computer Vision

Figure 17. Image Processing Stages in Computer Vision

Figure 18. Pallet AI: Defect Detection System for High-Speed Pallet Inspection

Figure 19. Sentspec Load Optimization Workflow

Figure 20. From Raw Footage to Real Insights With Kibsi

Figure 21. AI-Powered Product Title Optimization on Amazon

Figure 22. Amazon Ads' AI Creative Studio

Figure 23. AI-Generated Review Highlights on Amazon

Figure 24. Example of a conversation with Project Amelia, Amazon's AI Business Assistant

Figure 25. Example of how Amazon Rufus helps customers compare different products to guide their purchasing decisions

Figure 26. Example of Amazon Rufus providing order tracking and purchase history

Figure 27. Key areas where Gen AI can streamline transportation management

Figure 28. Supply Chain Resilience: The Current State

Figure 29. Supply Chain Resilience: The Future State powered by Gen-AI

Figure 30. Summary of enabling technologies for the Internet of Things

Figure 31. A typical RFID system

Figure 32. Example of an actuator (pump water)

Figure 33. Sensor to actuator flow

Figure 34. IoT architecture

Figure 35. Comparison of the three-layer and five-layer Internet of Things architectural models

Figure 36. The IoT Ecosystem

Figure 37. Example of smart freight transportation enabled by the Internet of Things (IoT)

Figure 38. CargoNet's 2024 Supply Chain Risk Trends

Figure 39. Resilience360 – a holistic risk management solution

Figure 40. Smart warehouse with integrated IoT technologies

Figure 41. Examples of wearable sensors for Industry 4.0

Figure 42. Functional separated design of industrial wearable system

Figure 43. Multifunctional wearable scanning device with modular accessories

Figure 44. Classification of smart packaging technologies

Figure 45. Schematic design of the traceability system with the use of Smart Tag

Figure 46. Example of a smart packaging–based logistics system

Figure 47. AIoT Features Overview

Figure 48. AIoT Framework for Smart Supply Chain Management

Figure 49. Smart Warehouse Example

Figure 50. Conceptual model of Digital Twin integration in logistics and supply chain systems

Figure 51. Technologies behind Digital Twins

Figure 52. Application of Digital Twins in Warehouse Logistics

Figure 53. A visionary example of the elements involved in a Digital Twin of an entire supply chain network

Figure 54. General framework of the AMR data exchange

Figure 55. Step-by-step operation of an automated storage and retrieval system (AS/RS)

Figure 56. Types of human–robot relationship

References

- Aamer, A. M. (2018a). Outsourcing in non-developed supplier markets: A lean thinking approach. *International Journal of Production Research*, 56(18), 6048–6065.
- Abdirad, M., & Krishnan, K. (2020). Industry 4.0 in logistics and supply chain management: A systematic literature review. *Engineering Management Journal*.
- Abdullayev, V., Faizal, A., Seyidova, I., Mikayilov, S., Mammadova, R., Pirverdiyeva, L., & Guliyev, E. (2024). Integration of artificial intelligence and robotics into the industrial sector. *Data and Metadata*, 3, Article 209.
- Abideen, A. Z., Mohamad, F. B., & Fernando, Y. (2020). Lean simulations in production and operations management—A systematic literature review and bibliometric analysis. *Journal of Modeling in Management*, 16(2), 623–650.
- Abideen, A. Z., Sundram, V. P. K., Pyeman, J., Othman, A. K., & Sorooshian, S. (2021). Digital twin integrated reinforced learning in supply chain and logistics. *Logistics*, 5(4), 84.
- Abolghasemi, M., Khodakarami, V., & Tehranifard, H. (2015). A new approach for supply chain risk management: Mapping SCOR into Bayesian network. *Journal of Industrial Engineering and Management*, 8(1), 280–302.
- Adamik, A. (2019). Creating a competitive advantage in the age of Industry 4.0. *Problemy Zarządzania*, 2(82), 13–31.
- Adewale, T., & coautori. (2025). The ethical and security challenges of AI adoption in logistics. *ResearchGate*.
- Aggarwal, R., & Lal Das, M. (2012). RFID security in the context of “Internet of Things”. In *Proceedings of the First International Conference on Security of Internet of Things* (pp. 51–56). ACM. <https://doi.org/10.1145/2490428.2490435>
- Ahmed, I., Lin, H., Zou, L., Li, Z., Brody, A. L., Qazi, I. M., et al. (2018). An overview of smart packaging technologies for monitoring safety and quality of meat and meat products. *Packaging Technology and Science*, 31, 449–471.
- Akgul, A. (2019). Soon, most logistics companies may go out of business due to technology. *More Than Shipping*.
- Alaba, F. A., Othman, M., Hashem, I. A. T., & Alotaibi, F. (2017). Internet of Things security: A survey. *Journal of Network and Computer Applications*, 88, 10–28.
- Alavi, A. H., Jiao, P., Buttlar, W. G., & Lajnef, N. (2018). Internet of Things-enabled smart cities: State-of-the-art and future trends. *Measurement*, 129, 589–606.

- Albergaria, M., & Jabbour, C. J. C. (2020). The role of big data analytics capabilities (BDAC) in understanding the challenges of service information and operations management in the sharing economy: Evidence of peer effects in libraries. *International Journal of Information Management*, 51, 102023.
- Ali, S. M., Ashraf, M. A., Taqi, H. M. M., Ahmed, S., Rob, S. M. A., Kabir, G., & Paul, S. K. (2023). Drivers for Internet of Things (IoT) adoption in supply chains: Implications for sustainability in the post-pandemic era. *Computers & Industrial Engineering*, 183, 109515.
- Ali, S. S., & Kaur, R. (2022). Exploring the impact of technology 4.0 driven practice on warehousing performance: A hybrid approach. *Mathematics*, 10(8), 1252. <https://doi.org/10.3390/math10081252>
- Ali, S. S., Kaur, R., Gupta, H., Ahmad, Z., & Elnaggar, G. (2021). Determinants of an organization's readiness for drone technologies adoption. *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2021.3083138>
- Alizadeh-Sani, M., Tavassoli, M., Mohammadian, E., Ehsani, A., Khaniki, G. J., Priyadarshi, R., et al. (2021). pH-responsive color indicator films based on methylcellulose/chitosan nanofiber and barberry anthocyanins for real-time monitoring of meat freshness. *International Journal of Biological Macromolecules*, 166, 741–750.
- Allhoff, F., & Henschke, A. (2018). The Internet of Things: Foundational ethical issues. *Internet of Things*, 1–2, 55–66.
- Amazon. (2023). How Amazon is using generative AI to help sellers grow and improve the shopping experience. About Amazon.
- Amazon. (2024). Amazon Ads unveils generative AI video generator for advertisers. About Amazon.
- Amazon. (2024). Amazon introduces AI-generated review highlights to help customers shop with confidence. About Amazon
- Amazon. (2024). Amazon introduces Project Amelia: A new frontier in generative AI assistants. About Amazon.
- Amazon. (2024). How to use Amazon Rufus, your new generative AI shopping assistant. About Amazon.
- Amazon. (2024). Using generative AI to make product search and discovery easier for customers. About Amazon.

- Ammari, D., Ergün, E., Görener, A., & Özüdoğru, A. G. (2018). How Industry 4.0 changes business: A commercial perspective. *International Journal of Commerce and Finance*, 4(1), 84–95.
- Anastasiadis, T., Lampropoulos, G., & Siakas, K. (2019). Internet of Things in the context of Industry 4.0: An overview. *International Journal of Enterprise Knowledge*, 7(1), 4–19.
- and Challenging Problems. 2011 IEEE ICCSAE, Shanghai, 10-12 June 2011, 3-12.
- Arnold, C., & Kiel, D. (2016). How Industry 4.0 changes business models in different manufacturing industries. *ISPIM Innovation Conference*, June.
- Arora, P., Srivastava, S., & Majumder, S. (2017). Using automation technology and IoT-based data capturing to ensure high quality last-mile logistics. In *Proceedings of the 3rd World Conference on Supply Chain Management* (pp. 5755–5756), Colombo, Sri Lanka, 17–19 May 2017.
- Ashton, K. (2011). That ‘Internet of Things’ thing. *RFID Journal*. Retrieved from <https://www.rfidjournal.com/articles/view?4986>
- Ayala, N. F., Benitez, G. B., Dalenogare, L. S., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics*, 204(August), 383–394.
- Azuma, R., Baillot, Y., Behringer, R., Feiner, S., Julier, S., & MacIntyre, B. (2001). Recent advances in augmented reality. *IEEE Computer Graphics and Applications*, 21(6), 34–47.
- Bagnoli, C., Albarelli, A., Biazzo, S., Biotto, G., Marseglia, G. R., Massaro, M., Messina, M., Muraro, A., & Troiano, L. (2022). *Digital business models for Industry 4.0: How innovation and technology shape the future of companies*. Springer.
- Ballestín, F., Pérez, Á., Lino, P., Quintanilla, S., & Valls, V. (2013). Scheduling of retrieval and storage warehouse operations: Static and dynamic policies with RFID. *Computers and Industrial Engineering*, 66(4), 696–709.
- Ballou, R. H. (2007). The evolution and future of logistics and supply chain management. *European Business Review*, 19(4), 332–348.
- Balta-Ozkan, N., Davidson, R., Bicket, M., & Whitmarsh, L. (2013). Social barriers to the adoption of smart homes. *Energy Policy*, 63, 363–374.
- Banur, O. M., Patle, B. K., & Pawar, S. (2024). Integration of robotics and automation in supply chain: A comprehensive review. *Robotic Systems and Applications*, 4(1), 1–19.
- Barata, J. (2021). The fourth industrial revolution of supply chains: A tertiary study. *Journal of Engineering and Technology Management*, 60, 101624.

- Barmounakis, E. N., Vlahogianni, E. I., & Golias, J. C. (2016). Unmanned aerial aircraft systems for transportation engineering: Current practice and future challenges. *International Journal of Transportation Science and Technology*, 5(3), 111–122.
- Barreto, L., Amaral, A., & Pereira, T. (2017). Industry 4.0 implications in logistics: An overview. *Procedia Manufacturing*, 13, 1245–1252.
- Barrett, M., Davidson, E., Prabhu, J., & Vargo, S. L. (2015). Service innovation in the digital age. *MIS Quarterly*, 39(1), 135–154. <https://doi.org/10.25300/MISQ/2015/39:1.03>
- Barricelli, B. R., Casiraghi, E., Gliozzo, J., Petrini, A., & Valtolina, S. (2020). Human digital twins for fitness management. *IEEE Access*, 8, 26637–26664.
- Bartodziej, C. J. (2017). The concept Industry 4.0.
- Bassi A, Bauer M, Fiedler M, van Kranenburg R, Kramp T, Lange S, Meissner S (2013) Enabling things to talk: designing IoT solutions with the IoT architectural reference model. Springer, Heidelberg, Germany
- Bauer, A., Hüfner, O., & Ruemping, T. (2018). Why you need to know about IBM's elderly care solution. IBM.
- Begum, S., Akash, M. A. S., Khan, M. S., & Bhuiyan, M. R. (2024). A framework for lean manufacturing implementation in the textile industry: A research study. *International Journal of Science and Engineering*, 1(4), 17–31.
- Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2024). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. *Annals of Operations Research*, 333, 627–652.
- Benarbia, T., & Kyamakya, K. (2021). A literature review of drone-based package delivery logistics systems and their implementation feasibility. *Sustainability*, 14(1), Article 360. <https://doi.org/10.3390/su14010360>
- Benayoune, A., Hamid, A. A., Abdul Rahman, N. S. F., Al Kalbani, K., & Slimi, Z. (2022). Logistics 4.0 skills requirements: Evidence from a developing country. *Canadian Journal of Business and Information Studies*, 4(2), 24–36.
- Benight SJ, Wang C, Tok JBH, Bao Z (2013) Stretchable and self-healing polymers and devices for electronic skin. *Prog Polym Sci* 38(12):1961–1977
- Berman, S., & Marshall, A. (2014). The next digital transformation: From an individual-centered to an everyone-to-everyone economy. *Strategy & Leadership*, 42(5), 9–17.

- Bharadwaj, A., El Sawy, O., Pavlou, P., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly*, 37(2), 471–482.
- Bibi, F., Guillaume, C., Gontard, N., & Sorli, B. (2017). A review: RFID technology having sensing aptitudes for food industry and their contribution to tracking and monitoring of food products. *Trends in Food Science & Technology*, 62, 91–103.
- Biswal, A. K., Jenamani, M., & Kumar, S. K. (2018). Warehouse efficiency improvement using RFID in a humanitarian supply chain: Implications for Indian food security system. *Transportation Research Part E: Logistics and Transportation Review*, 109, 205–224.
- Blomkvist, Y., & Ullemar Loenbom, L. (2020). Improving supply chain visibility within logistics by implementing a digital twin: A case study at Scania Logistics. KTH Royal Institute of Technology.
- Bloss, R. (2016). Collaborative robots are rapidly providing major improvements in productivity, safety, programming ease, portability, and cost while addressing many new applications. *Industrial Robot*, 43, 463–468.
- Boorová, B., Mijušković, V. M., Aćimović, S., & Đurđić, D. (2024). Application of artificial intelligence in Logistics 4.0: DHL case study analysis. *Economics of Enterprise*, 29, 292–304.
- Boudoin, D., Morel, C., & Gardat, M. (2014). Supply Chains and Urban Logistics Platforms. In J. Gonzalez-Feliu, F. Semet, & J. L. Routhier (Eds.), *Sustainable Urban Logistics: Concepts, Methods and Information Systems. Environmental Issues in Logistics and Manufacturing*. Berlin, Germany: Springer; doi:10.1007/978-3-642-31788-0_1
- Boute, R. N., & Udenio, M. (2021). AI in logistics and supply chain management. In R. Merkert & K. Hoberg (Eds.), *Global logistics and supply chain strategies for the 2020s: Vital skills for the next generation*. Springer Series in Supply Chain Management. (In press)
- Brachman, R. J., & Henig, F. H. (1988). The emergence of artificial intelligence technology. *AT&T Technical Journal*, 67(1), 3–6.
- Broberg, O., Kadir, B. A., & Souza da Conceição, C. (2019). Current research and future perspectives on human factors and ergonomics in Industry 4.0. *Computers & Industrial Engineering*, 137, 106004.
- Brylka, R., Bierwirth, B., & Schwanecke, U. (2021, December). AI-based recognition of dangerous goods labels and metric package features. In *Proceedings of the Hamburg International Conference of Logistics (HICL)* (pp. 245–272). epubli.

- Buliga, O., Müller, J. M., & Voigt, K. I. (2018). Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0. *Technology Forecasting & Social Change*, 132, 2–17.
- Buntak, K., Kovačić, M., & Mutavdžija, M. (2019). Internet of things and smart warehouses as the future of logistics. *Tehnički glasnik*, 13(3), 249.
- Busse, C., Schleper, M. C., Weilenmann, J., & Wagner, S. M. (2017). Extending the supply chain visibility boundary: Utilizing stakeholders for identifying supply chain sustainability risks. *International Journal of Physical Distribution & Logistics Management*.
- Çağlar, M. B. (2014). The relationship between the use of information technologies in logistics enterprises, customer satisfaction, and business performance: A research. *Selçuk University Social Sciences Institute Magazine*, Issue 32, pp. 41–55.
- Camerer, C. F. (2018). Artificial intelligence and behavioural economics. In *The economics of artificial intelligence: An agenda* (pp. 587–608). University of Chicago Press.
- Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable chain management: Moving toward new theory. *International Journal of Physical Distribution & Logistics Management*, 38(5), 360–387.
- Casadio Strozzi, M., & Sala, L. (2024). *Gestione dei sistemi produttivi e della logistica: Guida agli approcci, metodologie e tecniche per la pianificazione ed il controllo del sistema produttivo e logistico*. Società Editrice Esculapio. ISBN: 978-88-9385-432-0
- Cavalcante, T. R. F., Bessa, I. V. D., & Cordeiro, L. C. (2017). Planning and evaluation of UAV mission planner for intralogistics problems. In *2017 VII Brazilian Symposium on Computing Systems Engineering (SBESC)* (pp. 9–16). <https://doi.org/10.1109/SBESC.2017.8>
- Ceyhun, G. Ç. (2020). Recent developments of artificial intelligence in business logistics: A maritime industry case. In *Digital Business Strategies in Blockchain Ecosystems: Transformational Design and Future of Global Business* (pp. 343–353). Springer.
- CFI. (2015). CFI, Roadmap per la ricerca e l'innovazione - Research and Innovation Roadmap.
- Chao, H.-C., Zeadally, S., & Hu, B. (2016). Wearable computing for health care. *Journal of Medical Systems*, 40(4), 87.
- Chaowai, K., & Chutima, P. (2024). Demand forecasting and ordering policy of fast-moving consumer goods with promotional sales in a small trading firm. *Engineering Journal*, 28(4), 21–40.

- Chen, F., Deng, P., Wan, J., Zhang, D., Vasilakos, A. V., & Rong, X. (2015). Data mining for the Internet of Things: Literature review and challenges. *International Journal of Distributed Sensor Networks*, 2015(12), 1–12.
- Chen, K. W., Xie, M. R., Chen, Y. M., Chu, T. T., & Lin, Y. B. (2022). DroneTalk: An Internet-of-Things-based drone system for last-mile drone delivery. *IEEE Transactions on Intelligent Transportation Systems*, 23, 15204–15217.
- Chen, L., Zaharia, M., & Zou, J. (2023). How is ChatGPT’s behavior changing over time? *arXiv:2307.09009*.
- Chen, T. L., Chang, C. Y., Yao, Y. C., & Chung, K. C. (2021). Constructional cyber-physical system: An integrated model. *Intelligent Automation and Soft Computing*, 28(1), 73–82.
- Cheung, B. K. S., Choy, K. L., Li, C. L., Shi, W., & Tang, J. (2008). Dynamic routing model and solution methods for fleet management with mobile technologies. *International Journal of Production Economics*, 113(2), 694–705.
- Chiang, T. (2023). ChatGPT is a blurry JPEG of the web. *The New Yorker*. Accessed 25 August 2023.
- Chukalov, K. (2017). Horizontal and vertical integration as a requirement for cyber-physical systems in the context of Industry 4.0. *International Scientific Journal Industry 4.0*, 157(4), 155–157.
- Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A., & De Felice, F. (2020). Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. *Sustainability*, 12(2), 492.
- Companik, E., Gravier, M., & Farris, M. T. (2018). Feasibility of warehouse drone adoption and implementation. *Journal of Transportation Management*, 29(1), Article 4.
- Confartigianato. (2017). *Industria 4.0 e manifattura digitale*.
- Confidex. (2023). *Smart industries*. Confidex.
- Cooper, J., & James, A. (2009). Challenges for database management in the Internet of Things. *IETE Technical Review*, 26, 320–329. <https://doi.org/10.4103/0256-4602.55275>
- Cortés, B., Boza, A., Pérez, D., & Cuenca, L. (2015). Internet of Things applications on supply chain management. *International Journal of Computer and Information Engineering*, 9(12), 2486–2491.
- Cozmiuc, D., & Petrisor, I. (2018). Industrie 4.0 by Siemens: Steps made today. *Journal of Cases on Information Technology*, 20(2), 30–48.

- Cristiani, D., Bottonelli, F., Trotta, A., & Di Felice, M. (2020). Inventory management through mini-drones: Architecture and proof-of-concept implementation. (Informazione incompleta, mancano rivista e DOI)
- Csik, M., Frankenberger, K., & Gassmann, O. (2016). *St. Gallen Business Model Navigator*. St. Gallen University Press.
- Curi, J. T., & Casquino, Y. S. (2022). Digital transformation in the distribution and exhibition channels of auteur cinema. In R. J. Howlett & L. C. Jain (Eds.), *Marketing and smart technologies* (pp. 273–274). Springer Nature.
- Da Xu, L., He, W., & Li, S. (2014). Internet of Things in industries: A survey. *IEEE Transactions on Industrial Informatics*, 10(4), 2233–2243.
- Dabic-Miletic, S. (2024). The challenges of integrating AI and robotics in sustainable WMS to improve supply chain economic resilience. *Journal of Industrial Intelligence*, 2(2), 119–131.
- Darmstadt. (2019, 26 aprile). Bundesweit einzigartig: Verkehrssteuerung in Echtzeit speist Open-Data-Plattform.
- Dash, C. S. K., Behera, A. K., Dehuri, S., & Cho, S. B. (2016). Radial basis function neural networks: A topical state-of-the-art survey. *Open Computer Science*, 6(1), 33–63.
- Daugherty, P. J., Bolumole, Y., & Grawe, S. J. (2019). The new age of customer impatience: An agenda for reawakening logistics customer service research. *International Journal of Physical Distribution and Logistics Management*, 49(1), 4–32. *International Journal of Logistics Management*, 29(4), 1255–1278.
- De Silva, V., Roche, J., & Kondo, A. (2018). Robust fusion of LiDAR and wide-angle camera data for autonomous mobile robots. *Sensors*, 18(8), 2730.
- De Venuto, D., & Mezzina, G. (2018). Spatio-temporal optimization of perishable goods shelf life by a pro-active WSN-based architecture. *Sensors*, 18(7), 2126.
- Deloitte. (2024). Generative AI in transportation management: AI's impact on supply chain logistics. Deloitte Business Operations Room Blog.
- Derakhti, A., Santibanez Gonzalez, E. D. R., & Mardani, A. (2023). Industry 4.0 and beyond: A review of the literature on the challenges and barriers facing the agri-food supply chain. *Sustainability*, 15(6), 5078.
- Dhaliwal, A. (2021). Reinventing logistics: Use of AI & robotics technologies. In D. Chanda, A. Sengupta, & D. Mohanti (Eds.), *Proceedings of the International Conference*

on Business Research and Innovation (ICBRI 2021) (pp. 147–157). Excel India Publishers. ISBN: 978-81-952843-7-5.

- DHL & Cisco. (2015). Internet of Things in logistics: A collaborative report by DHL and Cisco on implications and use cases for the logistics industry. DHL Trend Research.
- DHL Trend Research. (2019). Digital twins in logistics: A DHL perspective on the impact of digital twins on the logistics industry. DHL Customer Solutions & Innovation.
- DHL. (2024). Logistics trend radar 7.0: Your guide to innovation in logistics. AI & sustainability in focus. DHL Group.
- Diabat, A., & Deskoors, R. (2016). A hybrid genetic algorithm based heuristic for an integrated supply chain problem. *Journal of Manufacturing Systems*, 38, 172–180.
- Dietterich, T. G. (1997). Machine-learning research. *AI Magazine*, 18(4), 97–136.
- Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., & Dolen, M. (2017). The role of additive manufacturing in the era of Industry 4.0. *Procedia Manufacturing*, 11, 545–554.
- Ding, S., Ward, H., Cucurachi, S., & Tukker, A. (2023). Revealing the hidden potentials of Internet of Things (IoT): An integrated approach using agent-based modelling and system dynamics to assess sustainable supply chain performance. *Journal of Cleaner Production*, 421, 138558.
- Djurdjevic, S., Novakovic, D., Dedijer, S., Kasikovic, N., & Zeljkovic, Z. (2019). Development of augmented reality application for interactive smart materials. *MATEC Web of Conferences*, 290, 01002.
- Dohrmann, K., Pitcher, E., & Kamdar, M. (2024). AI-driven computer vision: A DHL perspective on the impact of computer vision in logistics. DHL Customer Solutions & Innovation.
- Donald, J., Olabiyi, W., & Owen, E. (2024). Understanding Industry 4.0. ResearchGate.
- Dörr, L., Brandt, F., Pouls, M., & Naumann, A. (2020, August). Fully-automated packaging structure recognition in logistics environments. *Proceedings of the International Conference on Emerging Technologies and Factory Automation*.
- DP-DHL. (2018). Logistics trend radar 2018.
- Drath, R., & Horch, A. (2014). Industrie 4.0: Hit or hype? [Industry forum]. *IEEE Industrial Electronics Magazine*, 8(2), 56–58.
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – Evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63–71.

- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., ... Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994.
- Eeshwaraju, S., Jakkula, P., & Abdellatif, I. (2020). An IoT based three-dimensional dynamic drone delivery (3D4) system. In *Proceedings of the 2020 IEEE Cloud Summit* (pp. 119–123), Harrisburg, PA, USA, 21–22 October 2020.
- Ejjami, R., & Boussalham, K. (2024). Resilient supply chains in Industry 5.0: Leveraging AI for predictive maintenance and risk mitigation. *International Journal for Multidisciplinary Research*, 6(4), 1–32.
- Elmo, D., & Stead, D. (2020). Disrupting rock engineering concepts: Is there such a thing as a rock mass digital twin and are machines capable of learning rock mechanics? In *Proceedings of the 2020 International Symposium on Slope Stability in Open Pit Mining and Civil Engineering* (pp. 565–576). Perth, Australia.
- Elvas, L. B., Tokkozhina, U., Martins, A. L., & Ferreira, J. C. (2023). Implementation of disruptive technologies for the last mile delivery efficiency achievement. *Transportation Research Procedia*, 72, 32–39.
- Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of Manufacturing Systems*, 39, 79–100.
- European Commission. (2024). Regulatory framework on artificial intelligence. Shaping Europe's digital future. Retrieved May 11, 2025
- Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, 77, 167–181.
- Fan, C., Jiang, Y., & Mostafavi, A. (2020). Social sensing in disaster city digital twin: Integrated textual–visual–geo framework for situational awareness during built environment disruptions. *Journal of Management in Engineering*, 36, 04020002.
- Far, S. B., & Rad, A. I. (2022). Applying digital twins in metaverse: User interface, security and privacy challenges. *Journal of Metaverse*, 2(1), 8–15.
- Fathi, P., Karmakar, N. C., Bhattacharya, M., & Bhattacharya, S. (2020). Potential chipless RFID sensors for food packaging applications: A review. *IEEE Sensors Journal*, 20, 9618–9636.

- Faulds, D. J., & Raju, P. S. (2019). An interview with Chuck Martin on the Internet of Things. *Business Horizons*, 62, 27–33.
- Fernández-Caramés, T. M., Blanco-Novoa, O., Froiz-Míguez, I., & Fraga-Lamas, P. (2019). Towards an autonomous Industry 4.0 warehouse: A UAV and blockchain-based system for inventory and traceability applications in big data-driven supply chain management. *Sensors*, 19(10), 2394.
- Fernández-Villacañás, M. A. (2019a). Desarrollo e Implementación de Plataformas Logísticas de Carga 4.0 [Development and Implementation of Logistics Cargo Platforms 4.0]. *Proceedings of Primer Congreso Internacional de Tecnología e Innovación en Logística 4.0*.
- Fernández-Villacañás, M. A. (2019b). Strategies for the Digital Transformation for the In-Service Support Phase of the Aerospace Weapon Systems. *Proceedings of the Third International Joint Conference of Logistics by EPFAC & UMNG*.
- Fernández-Villacañás, M.A. (2018) Las plataformas logística 4.0 y la mejora del comercio global: Creando ventaja competitiva logística y desarrollo sostenible [Logistics 4.0 platforms and the improvement of global trade: Creating competitive logistics advantage and sustainable development]. *VI Simposio Internacional Online de Logística y Competitividad, High Logistics Simposios, Medellín, Colombia*.
- Fernandez, C. M., Alves, J., Gaspar, P. D., Lima, T. M. & Silva, P. D. (2023). Innovative processes in smart packaging: A systematic review. *Journal of the Science of Food and Agriculture*, 103(3), 986–1003.
- Filho, B. D. B. F., Cabral, E. L. L., & Soares, A. J. (1998). A new approach to artificial neural networks. *IEEE Transactions on Neural Networks*, 9(6), 1167–1179.
- Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2014). Embracing digital technology: A new strategic imperative. *MIT Sloan Management Review*, 55(2), 1–16.
- Fraga-Lamas, P., Fernández-Caramés, T. M., & Castedo, L. (2017). Towards the internet of smart trains: A review on industrial IoT-connected railways. *Sensors*, 17(6), 1457.
- Fragapane, G., de Koster, R., Sgarbossa, F., & Strandhagen, J. O. (2021). Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda. *European Journal of Operational Research*, 294(2), 405–426.
- Fu, H. P., Chang, T. H., Lin, A., Du, Z. J., & Hsu, K. Y. (2015). Key factors for the adoption of RFID in the logistics industry in Taiwan. *International Journal of Logistics Management*, 26(1), 61–81.

- Gajšek, B., & Grzybowska, K. (2016) Supply Chain Logistics Platform as a Supply Chain Coordination Support. Highlights of Practical Applications of Scalable Multi-Agent Systems. Proceedings of Collection International Workshops of PAAMS 2016. Doi:10.1007/978-3-319-39387-2_6
- Galindo, L. D. (2016). The challenges of Logistics 4.0 for supply chain management and information technology (Master's thesis). Norwegian University of Science and Technology, Department of Production and Quality Engineering
- Ganzarain, J., Ibarra, D., & Igartua, J. I. (2018). Business model innovation through Industry 4.0: A review. *Procedia Manufacturing*, 22, 4–10.
- Gao, Q., Zhang, J., Ma, J., Yang, C., Guo, J., & Miao, Y. (2018). LIP-PA: A logistics information privacy protection scheme with position and attribute-based access control on mobile devices. *Wireless Communications and Mobile Computing*, 2018, 1–14.
- Garrido-Hidalgo, C., Olivares, T., Ramirez, F. J., & Roda-Sanchez, L. (2019). An end-to-end Internet of Things solution for reverse supply chain management in Industry 4.0. *Computers in Industry*, 112, 103127.
- Ghobakhloo, M., Fathi, M., Iranmanesh, M., Maroufkhani, P., & Morales, M. E. (2021). Industry 4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants. *Journal of Cleaner Production*, 302, 127052.
- Giusti, I., Cepolina, E. M., Cangialosi, E., Aquaro, D., Caroti, G., & Piemonte, A. (2019). Mitigation of human error consequences in general cargo handler logistics: Impact of RFID implementation. *Computers & Industrial Engineering*, 137, 106038.
- Göçmen E, Erol R (2018) The transition to industry 4.0 in one of the Turkish logistics company. *Int J 3D Print Technol Digit Ind* 2(1):76–85
- Goodall, P., Sharpe, R., & West, A. (2019). A data-driven simulation to support remanufacturing operations. *Computers in Industry*, 105, 48–60.
- Graham, M., & Haarstad, H. (2011). Transparency and development: Ethical consumption through Web 2.0 and the Internet of Things. *Journal of Development Studies*^[1]_[SEP]
- Grosvenor, R., Liu, Y., & Qin, J. (2016). A categorical framework of manufacturing for Industry 4.0 and beyond. *Elsevier*, 52, 173–178.
- Grover, A. K., & Ashraf, M. H. (2023). Leveraging autonomous mobile robots for Industry 4.0 warehouses: A multiple case study analysis. *The International Journal of Logistics Management*.

- Gruchmann, T., & Seuring, S. (2018). Explaining logistics social responsibility from a dynamic capabilities perspective.
- Gudivada, V., Apon, A., & Ding, J. (2017). Data quality considerations for big data and machine learning: Going beyond data cleaning and transformations. *International Journal on Advances in Software*, 10(1), 1–20.
- Gunasekaran, A., Subramanian, N., & Papadopoulos, T. (2017). Information technology for competitive advantage within logistics and supply chains: A review. *Transportation Research Part E: Logistics and Transportation Review*, 99, 14–33.
- Guo, D., Zhong, R. Y., Lin, P., Lyu, Z., Rong, Y., & Huang, G. Q. (2020). Digital twin-enabled Graduation Intelligent Manufacturing System for fixed-position assembly islands. *Robotics and Computer-Integrated Manufacturing*, 63, 101917.
- Gupta, B. B., & Quamara, M. (2020). An overview of Internet of Things (IoT): Architectural aspects, challenges, and protocols. *Concurrency and Computation: Practice and Experience*, 32(21), e4946. <https://doi.org/10.1002/cpe.4946>
- Haanpaa, D., Beach, G., & Cohen, C. J. (2016, October). Machine vision algorithms for robust pallet engagement and stacking. In *2016 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)* (pp. 1–8). IEEE.
- Haße, H., Li, B., Weißenberg, N., Cirullies, J., & Otto, B. (2019). Digital twin for real-time data processing in logistics. In *Artificial intelligence and digital transformation in supply chain management: Innovative approaches for supply chains. Proceedings of the Hamburg International Conference of Logistics (HICL)* (pp. 4–28). Technische Universität Hamburg.
- Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for Industrie 4.0 scenarios. In *2016 49th Hawaii International Conference on System Sciences (HICSS)* (pp. 3928–3937). IEEE.
- Hidalgo Fort, E., Garcia Oya, J. R., Munoz Chavero, F., & Gonzalez Carvajal, R. (2018). Intelligent containers based on a low-power sensor network and a non-invasive acquisition system for management and tracking of goods. *IEEE Transactions on Intelligent Transportation Systems*, 19(8), 2734–2738. <https://doi.org/10.1109/TITS.2017.2769179>
- Hirt, M., & Willmott, P. (2014). Strategic principles for competing in the digital age. *McKinsey Quarterly*, 5(1), 1–13.
- Hitchcock, L., Crowley, E., Rauch, M., Garza Benavides, M., & Ferrara, K. (2024). Gen AI transforming transportation: Lessons from the frontier of an emerging technology. Deloitte Development LLC.

- Hofmann E, Rüsch M (2017) Industry 4.0 and the current status as well as future prospects on logistics. *Comput Ind* 89:23–34
- Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences*, 79(8), 2554–2558.
- Horenberg D (2017) Application within logistics 4.0. 9th IBA Bachelor thesis conference. University of Twente, The Faculty of Behavioural, Management and Social Sciences.
- Hou, K. M., Diao, X., Shi, H., Ding, H., Zhou, H., & de Vaulx, C. (2023). Trends and challenges in AIoT/IIoT/IoT implementation. *Sensors*, 23(11), 5074.
- Hsiao, W.-H., & Chang, T.-S. (2019). Exploring the opportunity of digital voice assistants in the logistics and transportation industry. *Journal of Enterprise Information Management*, 32(6), 1034–1050.
- Hu, Y., Al-Barakati, A., & Rani, P. (2022). Investigating the Internet-of-Things (IoT) risks for supply chain management using q-Rung orthopair fuzzy-SWARA-ARAS framework. *Technological and Economic Development of Economy*, 1–26.
- Huang, S.-J., Lee, T.-S., Li, W.-H., & Chen, R.-Y. (2019). Modular on-road AGV wireless charging systems via interoperable power adjustment. *IEEE Transactions on Industrial Electronics*, 66(8), 5918–5928.
- IBM. (2022). What is digital twin?. IBM.
- Ilin, V., Simić, D., & Saulić, N. (2019). Logistics Industry 4.0: Challenges and opportunities. Faculty of Technical Sciences, University of Novi Sad.
- Innolabel. (2022). Innolabel – Verigo Bluetooth logger.
- International Telecommunication Union (2005) ITU internet reports 2005: the internet of things. <https://www.itu.int/net/wsis/tunis/newsroom/stats/The-Internet-of-Things2005.pdf>. Accessed 10 July 2023
- Iraj, S., Mogensen, P., & Ratasuk, R. (2017). Recent advances in M2M communications and Internet of Things (IoT). *International Journal of Wireless and Information Networks*, 24(3), 240–242. <https://doi.org/10.1007/s10776-017-0331-0>
- ITU-T. (2009). Overview of ubiquitous networking and of its support in NGN (ITU-T Recommendation Y). ITU-T.
- Ivankova, G. V., Mochalina, E. P., & Goncharova, N. L. (2020). Internet of Things (IoT) in logistics. *IOP Conference Series: Materials Science and Engineering*, 940, 012033.
- IVISYS. (2024). PalletAI – Automated pallet inspection system. IVISYS.

- İyigün, İ., & Görçün, Ö. F. (Eds.). (2022). *Logistics 4.0 and future of supply chains*. Springer Nature Singapore. <https://doi.org/10.1007/978-981-16-5644-6>
- Jabbar, S., Khan, M., Silva, B. N., & Han, K. (2018). A REST-based industrial web of things framework for smart warehousing. *Journal of Supercomputing*, 74(9), 4419–4433.
- Jack, F., & Bommu, R. (2024). Unveiling the potential: AI-powered dynamic inventory management in the USA. *International Journal of Advanced Engineering Technologies and Innovations*, 1(3), 241–261.
- Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, 31(3), 685–695.
- Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management*, 7(1), 83–111.
- Jedermann, R., Pötsch, T., & Lloyd, C. (2014). Communication techniques and challenges for wireless food quality monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 372(20130304), 1–22.
- Jhunjhunwala, P., S., M., & Rufus, E. (2019). Development of hardware based inventory management system using UAV and RFID. In *International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*.
- Jia, X., Feng, Q., Fan, T., & Lei, Q. (2012). RFID technology and its applications in Internet of Things (IoT). In *Proceedings of the 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet)*, Yichang, China.
- Jing, Q., Vasilakos, A. V., Wan, J., Lu, J., & Qiu, D. (2014). Security of the Internet of Things: Perspectives and challenges. *Wireless Networks*, 20(8), 2481–2501.
- Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospectives. *Science*, 349(6245), 255–260.
- Juan-Verdejo, A., & Surajbali, B. (2016). XaaS multi-cloud marketplace architecture enacting the Industry 4.0 concepts. In *International Federation for Information Processing* (pp. 11–23). Springer.
- Kafiye, M., & Mbhele, T. P. (2023). Improving last mile distribution systems through the Internet of Things: A South African case. *Acta Logistica*, 10, 597–603.
- Kagermann, H. (2015). Change through digitization: Value creation in the age of Industry 4.0. In *Management of Permanent Change* (pp. 23–45). Springer.

- Kalpana, S., Priyadarshini, S. R., Maria Leena, M., Moses, J. A., & Anandharamakrishnan, C. (2019). Intelligent packaging: Trends and applications in food systems. *Trends in Food Science & Technology*, 93, 145–157.
- Kamnardsiri, T., Charoenkwan, P., Malang, C., & Wudhikarn, R. (2022, November). 1D barcode detection: Novel benchmark datasets and comprehensive comparison of deep convolutional neural network approaches. *Sensors*, 22(22), 8788.
- Kane, G. (2019). The technology fallacy: People are the real key to digital transformation. *Research-Technology Management*, 62(6), 44–49.
- Kasarda, J. D. (2019). Aerotropolis. In A. Orum (Ed.), *The Wiley Black well Encyclopedia of Urban and Regional Studies*. John Wiley & Sons Ltd.; doi:10.1002/9781118568446.eurs0436
- Keith, R., & La, H. M. (2024). Review of autonomous mobile robots for the warehouse environment. *arXiv preprint arXiv:2406.08333*.
- Keller, C. G., Dang, T., Fritz, H., Joos, A., Rabe, C., & Gavrila, D. M. (2011). Active pedestrian safety by automatic braking and evasive steering. *IEEE Transactions on Intelligent Transportation Systems*, 12(4), 1292–1304. <https://doi.org/10.1109/TITS.2011.2160627>
- Khan, R., Khan, S. U., Zaheer, R., & Khan, S. (2012). Future internet: The Internet of Things architecture, possible applications and key challenges. Paper presented at the 10th International Conference on Frontiers of Information Technology (FIT), Islamabad, Pakistan.
- Khan, S., Singh, R., Sá, J. C., Santos, G., & Ferreira, L. P. (2022). Modelling of determinants of Logistics 4.0 adoption: Insights from developing countries. *Machines*, 10(12), 1242.
- Khanna, A., & Kaur, S. (2020). Internet of things (IoT), applications and challenges: A comprehensive review. *Wireless Personal Communications*, 114, 1687–1762.
- Khang, A., Hajimahmud, V. A., Alyar, A. V., Etibar, M. K., Soltanaga, V. A., & Niu, Y. (2024). Application of industrial robotics in manufacturing. In *Machine Vision and Industrial Robotics in Manufacturing*. CRC Press.
- Kiangala, K. S., & Wang, Z. (2022). An experimental safety response mechanism for an autonomous moving robot in a smart manufacturing environment using g-learning algorithm and speech recognition. *Sensors*, 22, 941.
- Kibsi. (2024). Computer vision solutions for smart operations. Kibsi.

- Kido, T., & Nakamura, M. (2016). New SaaS-based operations management system to realize safe driving support and improve transport quality: Logit TM-NexTR. *Fujitsu Scientific and Technical Journal*, 52(4), 92–97.
- Kim, T. Y. (2020). Improving warehouse responsiveness by job priority management: A European distribution centre field study. *Computers & Industrial Engineering*, 139, 105564.
- Klumpp, M., & Ruiner, C. (2022). Artificial intelligence, robotics, and logistics employment: The human factor in digital logistics. *Journal of Business Logistics*, 43(3), 297–301.
- Kocaoglu, B. (2024). *Logistics information systems: Digital transformation and supply chain applications in the 4.0 era*. Springer.
- Kong, X. T. R., Luo, H., Huang, G. Q., & Yang, X. (2019). Industrial wearable system: The human-centric empowering technology in Industry 4.0. *Journal of Intelligent Manufacturing*, 30(6), 2853–286
- Kortuem G, Kawsar F, Sundramoorthy V, Fitton D (2009) Smart objects as building blocks for the internet of things. *IEEE Internet Comput* 14(1):44–51
- Kosmatos, E. A., Tselikas, N. D., & Boucouvalas, A. C. (2011). Integrating RFIDs and smart objects into a unified Internet of Things architecture. *Advances in Internet of Things*, 1(1), 5–12. <https://doi.org/10.4236/ait.2011.11002>
- Kovalcik, J., & Villalobos, M. (2019). Automated storage & retrieval system: From storage to service. *Information Technology and Libraries*, 38(4), 114–124.
- Kraus, M., Feuerriegel, S., & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research*, 281(3), 628–641.
- Krenczyk, D., & Bocewicz, G. (2015). Data-driven simulation model generation for ERP and DES systems integration. In K. Jackowski, R. Burduk, K. Walkowiak, M. Wozniak, & H. Yin (Eds.), *Intelligent Data Engineering and Automated Learning – IDEAL 2015* (pp. 264–272). Springer International Publishing.
- Kreutzer, R. T., & Sirrenberg, M. (2020). *Understanding artificial intelligence: Fundamentals, use cases and methods for a corporate AI journey*. Springer Nature Switzerland AG.
- Kristian, K. (2018). Machine learning and artificial intelligence: Two fellow travelers on the quest for intelligent behavior in machines. *Frontiers in Big Data*, 1, Article 6.

- Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11), 1016–1022.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25.
- Kryvinska, N., & Bickel, L. (2020). Scenario-based analysis of IT enterprises' servitization as a part of digital transformation of the modern economy. *Applied Sciences*, 10(3), 1076.
- Kückelhaus, M. (2013). DHL – Low-cost sensor technology. *DHL Customer Solutions & Innovation*.
- Kucuk, H., Al Muallim, M. T., Yilmaz, F., & Kahraman, M. (2019, March). Development of a dimensions measurement system based on depth camera for logistic applications. In D. P. Nikolaev, P. Radeva, A. Verikas, & J. Zhou (Eds.), *Eleventh International Conference on Machine Vision (ICMV 2018)* (p. 93). Munich, Germany: SPIE.
- Kucukaltan, B., Saatcioglu, O. Y., Irani, Z., & Tuna, O. (2022). Gaining strategic insights into Logistics 4.0: Expectations and impacts. *Production Planning & Control*, 33(2–3), 211–227.
- Kuzlu, M., Catak, F. O., Cali, U., Catak, E., & Guler, O. (2022). Adversarial security mitigations of mmWave beamforming prediction models using defensive distillation and adversarial retraining. *International Journal of Information Security*.
- Lagorio, A., Pinto, R., & Golini, R. (2016). Research in urban logistics: A systematic literature review. *International Journal of Physical Distribution Management*, 46(10). doi:10.1108/IJPDLM-01-2016-0008
- Laotrakunchai, S., Wongkaew, A., & Patanukhom, K. (2013, December). Measurement of size and distance of objects using mobile devices. In *2013 International Conference on Signal-Image Technology & Internet-Based Systems* (pp. 156–161).
- Le, T. V., & Fan, R. (2024). Digital twins for logistics and supply chain systems: Literature review, conceptual framework, research potential, and practical challenges. *Computers & Industrial Engineering*, 187, 109768.
- LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., & Jackel, L. D. (1989). Backpropagation applied to handwritten zip code recognition. *Neural Computation*, 1(4), 541–551.

- Lee, C. K. M., Lv, Y., Ng, K. K. H., Ho, W., & Choy, K. L. (2018). Design and application of Internet of Things-based warehouse management system for smart logistics. *International Journal of Production Research*, 56(8), 2753–2768.
- Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23.
- Lee, M. Y., & Edmondson, A. C. (2017). Self-managing organizations: Exploring the limits of less-hierarchical organizing. *Research in Organizational Behavior*, 37, 35–58. <https://doi.org/10.1016/j.riob.2017.10.002>
- Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International Journal of Robotics Research*, 37(4–5), 421–436.
- Li, A., Zhuang, S., Yang, T., Lu, W., & Xu, J. (2024). Optimization of logistics cargo tracking and transportation efficiency based on data science deep learning models. In *Proceedings of the 6th International Conference on Computing and Data Science* (pp. 71–77).
- Li, B., & Li, Y. (2017). Internet of Things drives supply chain innovation: A research framework. *International Journal of Organizational Innovation*, 9(3), 71–92.
- Li, C., & Chen, C. L. (2011). A multi-stage control method application in the fight against phishing attacks. In *Proceedings of the 26th Computer Security Academic Communication Across the Country*.
- Li, C., & Yang, H. J. (2021). Bot-X: An AI-based virtual assistant for intelligent manufacturing. *Multiagent and Grid Systems*, 17(1), 1–14.
- Li, D., Wan, J., Wang, S., & Zhang, C. (2016). Implementing smart factory of Industrie 4.0: An outlook. *International Journal of Distributed Sensor Networks*, 2016(1), 1–23.
- Li, J., & Wang, J. (2025). Digital twin-driven management strategies for logistics transportation systems. *Scientific Reports*, 15, 12186.
- Li, S., Da Xu, L., & Zhao, S. (2015). The Internet of Things: A survey. *Information Systems Frontiers*, 17(2), 243–259.
- Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2021). A survey of convolutional neural networks: Analysis, applications, and prospects. *IEEE Transactions on Neural Networks and Learning Systems*.

- Lim, M. K., Bahr, W., & Leung, S. C. H. (2013). RFID in the warehouse: A literature analysis (1995–2010) of its applications, benefits, challenges and future trends. *International Journal of Production Economics*, 145(1), 409–430.
- Lima, F., et al. (2019). Digital manufacturing tools in the simulation of collaborative robots: Towards Industry 4.0. *Brazilian Journal of Operations Production Management*, 16(2), 261–280.
- Lin, C. Y., Cheng, W. T., & Wang, S. C. (2011). An end-to-end logistics management application over heterogeneous location systems. *Wireless Personal Communications*, 59(1), 5–16.
- Linde, L., Frishammar, J., & Parida, V. (2021). Revenue models for digital servitization: A value capture framework for designing, developing, and scaling digital services. *IEEE Transactions on Engineering Management*, 1–16.
- Liu, H., Tsang, Y. P., & Lee, C. K. M. (2024). A cyber-physical social system for autonomous drone trajectory planning in last-mile superchilling delivery. *Transportation Research Part C: Emerging Technologies*, 158, 104448.
- Liu, S., Zhang, Y., Liu, Y., Wang, L., & Wang, X. V. (2019). An Internet of Things enabled dynamic optimization method for smart vehicles and logistics tasks. *Journal of Cleaner Production*, 215, 806–820.
- Lohmer, J., Bugert, N., & Lasch, R. (2020). Analysis of resilience strategies and ripple effect in blockchain-coordinated supply chains: An agent-based simulation study. *International Journal of Production Economics*, 228, 107882.
- Lorenz, M., Ruessmann, M., Strack, R., Lueth, K., & Bolle, M. (2015). *Man and machine in Industry 4.0: How will technology transform the industrial workforce through 2025?* Boston: Boston Consulting Group.
- Lozano-Perez, T. (2012). *Autonomous robot vehicles*. Springer Science & Business Media.
- Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. *Journal of Industrial Information Integration*, 6, 1–10.
- Lukowicz, P., Kirstein, T., & Tröster, G. (2004). Wearable systems for health care applications. *Methods of Information in Medicine – Methodik der Information in der Medizin*, 43(3), 232–238.
- Lv, Z., Qiao, L., Li, Y., Yuan, Y., & Wang, F.-Y. (2022). Blocknet: Beyond reliable spatial digital twins to parallel metaverse. *Patterns*, 3(5).

- Maltaverne, B. (2017). Digital transformation of procurement: A good abuse of language? *The Digital Transformation People*.
- Mangalaraj, G., Nerur, S., & Dwivedi, R. (2021). Digital transformation for agility and resilience: An exploratory study. *Journal of Computer Information Systems*, 1–13.
- Mani, V., Delgado, C., Hazen, B. T., & Patel, P. (2017). Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain. *Sustainability*, 9(4), 608.
- Manojlović, M. (2019). Analiza usluga mrežnih operatora temeljenih na IoT konceptu (Završni rad, Sveučilište u Zagrebu, Fakultet prometnih znanosti).
- Manzini, R., Gamberi, M., & Regattieri, A. (2006). Design and control of an AS/RS. *International Journal of Advanced Manufacturing Technology*, 28, 766–774.
- Markovic, M., Jacobs, N., Dryja, K., Edwards, P., & Strachan, N. J. C. (2020). Integrating Internet of Things, provenance, and blockchain to enhance trust in last mile food deliveries. *Frontiers in Sustainable Food Systems*, 4, 563424.
- Martinelli, A., Mina, A., & Moggi, M. (2021). The enabling technologies of Industry 4.0: Examining the seeds of the fourth industrial revolution. Oxford University Press. <https://doi.org/10.1093/icc/dtaa060>
- Martínez-Gutiérrez, A., Díez-González, J., Ferrero-Guillén, R., Verde, P., Álvarez, R., & Perez, H. (2021). Digital twin for automatic transportation in Industry 4.0. *Sensors*, 21(10), 3344.
- Mashayekhy, Y., Babaei, A., Yuan, X.-M., & Xue, A. (2022). Impact of Internet of Things (IoT) on inventory management: A literature survey. *Logistics*, 6(2), 33.
- Mathauer, M., & Hofmann, E. (2019). Technology adoption by logistics service providers. *International Journal of Physical Distribution and Logistics Management*, 49(4), 416–434.
- McKinsey & Company. (2021). Succeeding in the AI supply chain revolution. McKinsey & Company.
- Meindl, B., Ayala, N. F., Mendonça, J., & Frank, A. G. (2021). The four smarts of Industry 4.0: Evolution of ten years of research and future perspectives. *Technological Forecasting and Social Change*, 168, 120784.
- Merkert, R., & Hoberg, K. (Eds.). (2023). Global logistics and supply chain strategies for the 2020s: Vital skills for the next generation. Springer.
- Min, H. (2022). Developing a smart port architecture and essential elements in the era of Industry 4.0. *Maritime Economics & Logistics*, 24, 189–207.

- Min, H. (2022). Smart factory: A game changer or another fad in the era of the fourth industrial revolution. *International Journal of Technology Management*, 89, 26–45.
- Min, H. (2023). Smart warehousing as a wave of the future. *Logistics*, 7(2), 30.
- Mindas, M., & Bednar, S. (2016). Mass customization in the context of Industry 4.0: Implications of variety-induced complexity. *Industry 4.0*, 21–39.
- Mishra, V., Kapadia, H. K., Zaveri, T. H., & Pinnamaneni, B. P. (2019). Development of low-cost embedded vision system with a case study on 1D barcode detection. In *Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018* (Vol. 1, pp. 505–513). Springer.
- Misra J (2017) IoT system | Sensors and actuators. Accessed 10 July 2023^[1]_{SEP}
- Mladenow, A., Bauer, C., & Strauss, C. (2016). “Crowd logistics”: The contribution of social crowds in logistics activities. *International Journal of Web Information Systems*, 12(3), 379–396.
- Modoni, G. E., Caldarola, E. G., Sacco, M., & Terkaj, W. (2019). Synchronizing physical and digital factory: Benefits and technical challenges. *Procedia CIRP*, 79, 472–477.
- Mohamed, E., Jafari, P., Siu, M.-F. F., & AbouRizk, S. (2017). Data-driven simulation-based model for planning roadway operation and maintenance projects. In V. Chan, A. D'Ambrogio, G. Zacharewicz, & N. Mustafee (Eds.), *Proceedings of the 2017 Winter Simulation Conference (WSC)* (pp. 3323–3334). IEEE.
- Mohamed, I. S., Capitanelli, A., Mastrogiovanni, F., Rovetta, S., & Zaccaria, R. (2020, July). Detection, localisation and tracking of pallets using machine learning techniques and 2D range data. *Neural Computing and Applications*, 32(13), 8811–8828.
- Mohanraj, K., Vijayalakshmi, S., Balaji, N., Chithrakkannan, R. and Karthikeyan, R. (2019), “Smart warehouse monitoring using IoT”, *International Journal of Engineering and Advanced Technology*, Vol. 8 No. 6, pp. 3597-3600.
- Molter, B., & Fottner, J. (2018, July). Real-time pallet localization with 3D camera technology for forklifts in logistic environments. In *2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI)* (pp. 297–302). IEEE.
- Molter, B., & Fottner, J. (2019, October). Semi-automatic pallet pick-up as an advanced driver assistance system for forklifts. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)* (pp. 4464–4469). IEEE.

- Montreuil, B., Meller, R. D., & Ballot, E. (2010). Towards a physical internet: the impact on logistics facilities and material handling systems design and innovation. In K. Gue (Ed.), *Progress in material handling research*. Material Handling Industry of America.
- Morakanyane, R., Grace, A. A., & O'Reilly, P. (2017). Conceptualizing digital transformation in business organizations: A systematic review of literature. In *Bled eConference* (pp. 427–443).
- Mouha, R. A. (2021). Internet of Things (IoT). *Journal of Data Analysis and Information Processing*, 9(2), 77–101. <https://doi.org/10.4236/jdaip.2021.92006>
- Muango, C. O., Abrokwah, E., & Shaojian, Q. (2021). Revisiting the link between information technology and supply chain management practices among manufacturing firms. *European Journal of International Management*, 16(4), 647–667.
- Müller, P., & Schmid, M. (2019). Intelligent packaging in the food sector: A brief overview. *Foods*, 8, 16.
- Muntjir M, Rahul M, Alhumiany H (2017) An analysis of internet of things (IoT): novel architectures, modern applications, security aspects and future scope with latest case studies. *Build Serv Eng Res Technol* 6(6):422–448
- Nagaty, K. A. (2023). IoT commercial and industrial applications and AI-powered IoT. In A. Iranmanesh (Ed.), *Frontiers of Quality Electronic Design (QED): AI, IoT and hardware security* (pp. 465–500). Springer Nature Switzerland.
- Najafi, S. E., Nozari, H., & Edalatpanah, S. A. (2023). Artificial Intelligence of Things (AIoT) and Industry 4.0–Based Supply Chain (FMCG Industry). In J. M. Chatterjee, H. Garg, & R. N. Thakur (Eds.), *A roadmap for enabling Industry 4.0 by artificial intelligence* (pp. 31–42). Scrivener Publishing.
- National Institute of Standards and Technology (NIST). (2018). Internet of Things (IoT) trust concerns (NIST Cybersecurity White Paper, October 2018).
- Naumann, A., Dörr, L., Salscheider, N. O., & Furmans, K. (2020, March). Refined plane segmentation for cuboid-shaped objects by leveraging edge detection. *Proceedings of the International Conference on Machine Learning and Applications*.
- Negri, E., Berardi, S., Fumagalli, L., & Macchi, M. (2020). MES-integrated digital twin frameworks. *Journal of Manufacturing Systems*, 56, 58–71.
- Negri, E., Fumagalli, L., & Macchi, M. (2017). A review of the roles of digital twins in CPS-based production systems. *Procedia Manufacturing*, 11, 939–948.

- Nelson, K., Corbin, G., Anania, M., Kovacs, M., Tobias, J., & Blowers, M. (2015, May). Evaluating model drift in machine learning algorithms. In 2015 IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA) (pp. 1–8). IEEE.
- Ng, A. (2021). A chat with Andrew on MLOps: From model-centric to data-centric AI [Video]. YouTube.
- Ngai, E. W. T., Leung, T. K. P., Wong, Y. H., Lee, M. C. M., Chai, P. Y. F., & Choi, Y. S. (2012). Design and development of a context-aware decision support system for real-time accident handling in logistics. *Decision Support Systems*, 52(4), 816–827.
- Noceti, N., Zini, L., & Odone, F. (2018, February). A multi-camera system for damage and tampering detection in a postal security framework. *EURASIP Journal on Image and Video Processing*, 2018(1), 11.
- Nozari, H., & Nahr, J. G. (2022). The impact of blockchain technology and the internet of things on the agile and sustainable supply chain. *International Journal of Innovation in Engineering*, 2(2), 33–41.
- Nozari, H., Fallah, M., Kazemipoor, H., & Najafi, S. E. (2021). Big data analysis of IoT-based supply chain management considering FMCG industries. *Business Informatics*, 15, 78–96.
- Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the challenges of Artificial Intelligence of Things (AIoT) for the smart supply chain (case study: FMCG industries). *Sensors*, 22(8), 2931.
- Nozari, H., Tavakkoli-Moghaddam, R., Rohaninejad, M., & Hanzalek, Z. (2023). Artificial Intelligence of Things (AIoT): Strategies for a smart sustainable-resilient supply chain. *Proceedings of the Czech Technical University in Prague, Industrial Informatics Department*.
- Nunberg, G. (2012). The advent of the Internet: 12th April, Courses.
- Nuñez, D., Fernández, G., & Luna, J. (2017). Cloud system. *Procedia Computer Engineering*, 62, 149–164.
- Oliff, H., Liu, Y., Kumar, M., Williams, M., & Ryan, M. (2020). Reinforcement learning for facilitating human-robot interaction in manufacturing. *Journal of Manufacturing Systems*, 56, 326–340.
- Oliveira, J., Fernandes, B., & Henriques, M. (2025). Optimizing internal logistics using automated guided vehicles: An evaluation of heuristic approaches. In M. Dassisti et al.

(Eds.), *Proceedings of the International Conference on Industry 4.0 and Logistics (IN4PL 2024)* (pp. 42–55). Springer.

- Omollo, C. A. (2019). *Disruptive technologies in the logistics and supply chain industry: A study on blockchain*. United States International University Africa.
- Onwude, D. I., Chen, G., Eke-Emezie, N., Kabutey, A., Khaled, A. Y., & Sturm, B. (2020). Recent advances in reducing food losses in the supply chain of fresh agricultural produce. *Processes*, 8, 1–31.
- Otles, S., & Sahyar, B. Y. (2016). Intelligent food packaging. In *Comprehensive Analytical Chemistry*, 74, 377–387.
- Özgür, Ç., Alias, C., & Noche, B. (2016). Comparing sensor-based and camera-based approaches to recognizing the occupancy status of the load handling device of forklift trucks. *Logistics Journal: Proceedings*, 2016(05).
- Padmakumar, M. (2022). Influence of powder characteristics on properties of parts manufactured by metal additive manufacturing. *Lasers in Manufacturing and Materials Processing*, 9(3), 312–337.
- Paelke, V. (2014). Augmented reality in the smart factory: Supporting workers in an Industry 4.0 environment. In *Emerging Technology and Factory Automation (ETFA)*, IEEE (pp. 1–4).
- Paksoy, T., Koçhan, Ç., & Ali, S. S. (Eds.). (2021). *Logistics 4.0: Digital Transformation of Supply Chain Management*. CRC Press.
- Pal, A., & Kant, K. (2020). Smart sensing, communication, and control in perishable food supply chain. *ACM Transactions on Sensor Networks*, 16, 1–41.
- Park, K. T., Son, Y. H., & Noh, S. D. (2020). The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *International Journal of Production Research*, 1–22.
- Parrott, A., & Natarajan, V. (2024). Generative AI-powered supply chain resilience. *The Business Operations Room [Blog]*. Deloitte US.
- Partners, S., et al. (2015, January). Industrial Internet of Things: Unleashing the potential of connected products and services committed to improving the state of the world. *World Economic Forum*.
- Patil, S., Vasu, V., & Srinadh, K. V. S. (2023). Advances and perspectives in collaborative robotics: A review of key technologies and emerging trends. *Discover Mechanical Engineering*. Published online 29 August 2023.

- Payne, L. M., Peltier, J. W., & Barger, V. A. (2017). Omni-channel marketing, integrated marketing communications and consumer engagement: A research agenda. *Journal of Research in Interactive Marketing*, 11(2). doi:10.1108/JRIM-08-2016-0091
- Perera, H. N., Fahimnia, B., & Tokar, T. (2020). Inventory and ordering decisions: A systematic review on research driven through behavioral experiments. *International Journal of Operations & Production Management*, 40(7/8), 997–1039.
- Perera, H. N., Hurley, J., Fahimnia, B., & Reisi, M. (2019). The human factor in supply chain forecasting: A systematic review. *European Journal of Operational Research*, 274(2), 574–600.
- Perwej, Y., Haq, K., Parwej, F., & Mohamed Hassan, M. M. (2019). The Internet of Things (IoT) and its application domains. *International Journal of Computer Applications*, 182(49), 36–49.
- Peters, J. F., Baumann, M., Zimmermann, B., Braun, J., & Weil, M. (2017). The environmental impact of Li-ion batteries and the role of key parameters – A review. *Renewable and Sustainable Energy Reviews*, 67, 491–506.
- Ping, G., Zhu, M., Ling, Z., & Niu, K. (2024). Research on optimizing logistics transportation routes using AI large models. *Spectrum of Research*, 4(1), 1–22.
- Plaza-Hernández, M., Gil-González, A. B., Rodríguez-González, S., Prieto-Tejedor, J., & Corchado-Rodríguez, J. M. (2021). Integration of IoT technologies in the maritime industry. In S. Rodríguez-González et al. (Eds.), *Advances in intelligent systems and computing: Vol. 1242. 16th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS 2020)* (pp. 107–115). Springer.
- Popescu, D., & Georgescu, M. (2013). Internet of Things – Some ethical issues. *The USV Annals of Economics and Public Administration*, 13, 210–216.
- Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. The Free Press.
- Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., De Amicis, R., Pinto, E. B., Eisert, P., Döllner, J., & Vallarino, I. (2015). Visual computing as a key enabling technology for Industrie 4.0 and industrial internet. *IEEE Computer Graphics and Applications*, 35(6), 26–40.
- Poslad S (2011) *Ubiquitous computing: smart devices, environments and interactions*. Wiley, West Sussex, Chichester, UK

- Pourjavaher, S., Almasi, H., Meshkini, S., Pirs, S., & Parandi, E. (2017). Development of a colorimetric pH indicator based on bacterial cellulose nanofibers and red cabbage (*Brassica oleracea*) extract. *Carbohydrate Polymers*, 156, 193–201.
- Poyatos-Racionero, E., Ros-Lis, J. V., Vivancos, J. L., & Martínez-Máñez, R. (2018). Recent advances on intelligent packaging as tools to reduce food waste. *Journal of Cleaner Production*, 172, 3398–3409.
- PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft (PwC), (2024). Transportation and logistics sector report: 2024 mid-year analysis.
- Priore, P., Ponte, B., Rosillo, R., & de la Fuente, D. (2018). Applying machine learning to the dynamic selection of replenishment policies in fast-changing supply chain environments. *International Journal of Production Research*, 57(11), 3663–3677.
- Przegalińska, A. (2019). State of the art and future of artificial intelligence. Policy Department for Economic, Scientific, and Quality of Life Policies (European Parliament), PE 631.051.
- Purnamasari, D. I., Permadi, V. A., Saefudin, A., & Agusdin, R. P. (2023). Demand forecasting for improved inventory management in small and medium-sized businesses. *JANAPATI*, 12(1), 56–66.
- PwC. (2016). The future of the logistics industry.
- Qi, M., Li, X., Yan, X., & Zhang, C. (2018). On the evaluation of AGVS-based warehouse operation performance. *Simulation Modelling Practice and Theory*, 87, 379–394.
- Raamets, T., Majak, J., Karjust, K., Mahmood, K., & Hermaste, A. (2024). Autonomous mobile robots for production logistics: A process optimization model modification. *Proceedings of the Estonian Academy of Sciences*, 73(2), 134–141.
- Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems*, 2(1), 3.
- Raj, R., & Kos, A. (2022a). A comprehensive study of optical character recognition. In 29th International Conference on Mixed Design of Integrated Circuits and System (MIXDES) (pp. 151–154).
- Raj, R., & Kos, A. (2022b). Different techniques for human activity recognition. In 29th International Conference on Mixed Design of Integrated Circuits and System (MIXDES) (pp. 171–176).
- Ramirez-Asis, E., Bhanot, A., Jagota, V., Chandra, B., Hossain, M. S., Pant, K. & Almashaqbeh, H. A. (2022). Smart logistic system for enhancing the farmer-customer

corridor in the smart agriculture sector using artificial intelligence. *Journal of Food Quality*, 2022, Article ID 7486974.

- Rathore, H. (2016). Artificial neural network. In *Mapping Biological Systems to Network Systems* (pp. 79–96). Springer International Publishing.
- Raza, U., Kulkarni, P., & Sooriyabandara, M. (2017). Low power wide area networks: An overview. *IEEE Communications Surveys & Tutorials*, 19(2), 855–873.
- Ritzinger, U., Hu, B., & Reinthaler, M. (2025). Automated guided vehicles in yard logistics: A time-dependent approach. In A. Quesada-Arencibia et al. (Eds.), *EUROCAST 2024: Computer Aided Systems Theory* (pp. 131–139). Springer, *Lecture Notes in Computer Science*, 15172.
- Rodrigue, J. P., & Dablanc, L. (2020) What is City Logistics? In *City Logistics: Concepts, Policy and Practice*. MetroFreight Consortium, Dept. of Global Studies & Geography, Hofstra University. <https://globalcitylogistics.org/>
- Romare, M., & Dahllöf, L. (2017). The life cycle energy consumption and greenhouse gas emissions from lithium-ion batteries. IVL Swedish Environmental Research Institute.
- Rosário, A. T., & Dias, J. C. (2023). How Industry 4.0 and sensors can leverage product design: Opportunities and challenges. *Sensors*, 23(3), 1165.
- Roshid, M. M., Waaje, A., Meem, T. N., & Sarkar, A. (2024). Logistics 4.0: A comprehensive literature review of technological integration, challenges, and future prospects of implementation of Industry 4.0 technologies. *The International Journal of Technology, Knowledge, and Society*, 20(1), 65–85.
- Ross, J. W., Sebastian, I. M., Beath, C., Scantlebury, S., Mocker, M., Fonstad, N., Kagan, M., & Krusell, S. G. (2016). *Designing digital organisations*. Centre for Information Systems Research, 406, 1–19.
- Rožanec, J. M., Kažič, B., Škrjanc, M., Fortuna, B., & Mladenić, D. (2021). Automotive OEM demand forecasting: A comparative study of forecasting algorithms and strategies. *Applied Sciences*, 11(15), 6787.
- Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323(6088), 533–536.
- Rushton, A., Croucher, P., & Baker, P. (2022). *The handbook of logistics and distribution management: Understanding the supply chain* (6th ed.). Kogan Page.
- Russell, S. (2019). *Human compatible: AI and the problem of control*. Penguin UK.

- Rutkofsky, M., & Banu, G.-O. (2018). The additive journey. In *Smartech Markets Publishing* (Issue 22).
- Sahay, N., & Ierapetritou, M. (2013). Supply chain management using an optimization driven simulation approach. *AIChE Journal*, 59, 4612–4626.
- Sainath, K. L. (2025). Robots in logistics: Apprehension of current status and future trends in Indian warehouses. In A. Kumar et al. (Eds.), *ICDSMLA 2023*, LNEE 1273 (pp. 201–211). Springer Nature Singapore.
- Samaranayake, P., Laosirihongthong, T., Adebajo, D., & Boon-itt, S. (2022). Prioritising enabling factors of Internet of Things (IoT) adoption in digital supply chain. *International Journal of Productivity and Performance Management*.
- Sato, H., Kanai, A., Tanimoto, S., & Kobayashi, T. (2016, May). Establishing trust in the emerging era of IoT. In *2016 IEEE Symposium on Service-Oriented System Engineering (SOSE)* (pp. 398–406). IEEE. <https://doi.org/10.1109/SOSE.2016.50>
- Sawyer, B. D., Finomore, V. S., Calvo, A. A., & Hancock, P. A. (2014). Google Glass. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 56, 1307–1321
- Schmuntzsch, U., Sturm, C., & Roetting, M. (2014). The warning glove—Development and evaluation of a multimodal action-specific warning prototype. *Applied Ergonomics*, 45(5), 1297.
- Schwartz, E. I. (2001). *Digital Darwinism: 7 breakthrough business strategies for surviving in the cutthroat web economy*. Broadway.
- Sentspec. (2024). Smart logistics solutions powered by AI and computer vision. Sentspec.
- Shahat, E., Hyun, C. T., & Yeom, C. (2021). City digital twin potentials: A review and research agenda. *Sustainability*, 13, 3386.
- Shi, J., Zhang, J., & Qu, X. (2010). Optimizing distribution strategy for perishable foods using RFID and sensor technologies. *Journal of Business and Industrial Marketing*, 25(8), 596–606.
- Shrivastav, M. (2022). Barriers related to AI implementation in supply chain management. *Journal of Global Information Management*, 30(8), 1–19. <https://doi.org/10.4018/JGIM.296725>
- Siagri, R. (2021). *La servitizzazione: Per un futuro senza limiti di crescita*. Edizioni Angelo Guerini e Associati.

- Silvagni, M., Tonoli, A., Zenerino, E., & Chiaberge, M. (2016). Multipurpose UAV for search and rescue operations in mountain avalanche events. *Geomatics, Natural Hazards and Risk*, 8(1), 18–33. <https://doi.org/10.1080/19475705.2016.1238852>
- Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., ... & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587), 484–489.
- Simic, V., Dabic-Miletic, S., Tirkolaee, E. B., Stević, Z., Ala, A., & Amirteimoori, A. (2023). Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems. *Applied Soft Computing*, 143, 110400.
- Singandhupe, A., & La, H. M. (2019). A review of SLAM techniques and security in autonomous driving. In *Proceedings of the 2019 Third IEEE International Conference on Robotic Computing (IRC)* (pp. 602–607). IEEE.
- Singh, A., Klärner, P., & Hess, T. (2020). How do chief digital officers pursue digital transformation activities? The role of organization design parameters. *Long Range Planning*, 53(3), 101890. <https://doi.org/10.1016/j.lrp.2019.07.001>
- Singh, J., & Banerjee, R. (2019). A study on single and multi-layer perceptron neural network. In *3rd International Conference on Computing Methodologies and Communication (ICCMC)* (pp. 35–40).
- Singh, P. K. (2023). Digital transformation in supply chain management: Artificial intelligence (AI) and machine learning (ML) as catalysts for value creation. *International Journal of Supply Chain Management*, 12(6), 57–63.
- Sivaraj, D., Kumar, S. H., Jogarao, D. V. S., Dutta, S., Ezhumalai, K., & Rabjor, E. (2021). Analysis of driving behaviour for improved safety in commercial fleet management using onboard diagnostics (OBD-II). In *Proceedings of the 2021 IEEE International Conference on Smart Technologies, Communication and Robotics (STCR)* (pp. 1–5). IEEE.
- Smagulova, K., & James, A. P. (2019). A survey on LSTM memristive neural network architectures and applications. *The European Physical Journal Special Topics*, 228, 2313–2324.
- Sodiya, E. O., Umoga, U. J., Amoo, O. O., & Atadoga, A. (2024). AI-driven warehouse automation: A comprehensive review of systems. *GSC Advanced Research and Reviews*, 18(2), 272–282.

- Soltani Firouz, M., Mohi-Alden, K., & Omid, M. (2021). A critical review on intelligent and active packaging in the food industry: Research and development. *Food Research International*, 141, 110113.
- Sözen, M., & Mescioğlu, T. (2019). Driving forces of Industry 4.0 and their impact on Turkey and China. *International Journal of Social Inquiry*, 12(1), 287–315.
- Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective. *Production and Operations Management*, 27, 1849–1867.
- Statista (2022a) Number of Internet of Things (IoT) connected devices worldwide from 2019 to 2021, with forecasts from 2022 to 2030. <https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/>. Accessed 15 June 2023
- Statista (2023a) Number of Internet and social media users worldwide as of April 2023. <https://www.statista.com/statistics/617136/digital-population-worldwide/>. Accessed 15 June 2023
- Statista. (2024). Computer Vision – Worldwide Market Outlook. Statista Market Insights.
- Statista. (2024). Generative AI – Worldwide Market Outlook. Statista Market Insights.
- Stindt, D. (2017). A generic planning approach for sustainable supply chain management—How to integrate concepts and methods to address the issues of sustainability? *Journal of Cleaner Production*, 153, 1. doi:10.1016/j.jclepro.2017.03.126
- Sudharshan, D. (2020). *Marketing in customer technology environments: Prospective customers and magical worlds*. Emerald Group Publishing.
- Sukolkit, N., Arunyanart, S., & Apichottanakul, A. (2024). An open innovative inventory management based demand forecasting approach for the steel industry. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(4), 100407.
- Sun, H., Chen, L., Hao, X., Liu, C., & Ni, M. (2020). An energy-efficient and fast scheme for hybrid storage class memory in an AIoT terminal system. *Electronics*, 9(6), 1013.
- Sun, Y., Liu, Z. X., Li, M., Zeng, Z. T., Zong, Z. X., & Ji, C. L. (2020, November). An object recognition and volume calculation method based on YOLOv3 and depth vision. *Journal of Physics: Conference Series*, 1684(1), 012009.
- Sunyaev, A. (2024). *Internet computing*. Springer Nature Switzerland AG. <https://doi.org/10.1007/978-3-031-61014-1>

- Suo, H., Wan, J., Zou, C., & Liu, J. (2012). Security in the Internet of Things: A review. Paper presented at the 2012 Computer Science and Electronics Engineering (ICCSEE), Hangzhou, China.
- Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*(pp. 1–9). Boston, MA, USA.
- Szymańska, O., M. Adamczak and P. Cyplik. 2017. Logistics 4.0-a new paradigm or set of known solutions? *Research in Logistics & Production*, 7.
- Tang, J., & Hai, L. (2021). Construction and exploration of an intelligent evaluation system for educational APP through artificial intelligence technology. *International Journal of Emerging Technologies in Learning (iJET)*, 16(05), 17–31.
- Tannock, J., Cao, B., Farr, R., & Byrne, M. (2007). Data-driven simulation of the supply chain—Insights from the aerospace sector. *International Journal of Production Economics*, 110(1–2), 70–84.
- The Boston Consulting Group. (2015). *Industry 4.0: The future of productivity and growth in manufacturing industries*.
- Timm, I. J., & Lorig, F. (2015). Logistics 4.0—A challenge for simulation. In Yilmaz, L., Chan, W. K. V., Moon, I., Roeder, T. M. K., Macal, C., & Rossetti, M. D. (Eds.), *Winter Simulation Conference*. IEEE.
- Tom Dieck, M. C., & Jung, T. (2018). A theoretical model of mobile augmented reality acceptance in urban heritage tourism. *Current Issues in Tourism*, 21(2), 154–174.
- Tostani, H. H., Haleh, H., Molana, S. M. H., & Sobhani, F. M. (2020). A bi-level bi-objective optimization model for the integrated storage classes and dual shuttle cranes scheduling in AS/RS with energy consumption, workload balance and time windows. *Journal of Cleaner Production*, 257, 120409.
- Trab, S., Bajic, E., Zouinkhi, A., Abdelkrim, M. N., Chekir, H., & Ltaief, R. H. (2015). Product allocation planning with safety compatibility constraints in IoT-based warehouse. *Procedia Computer Science*, 73, 290–297.
- Trab, S., Bajic, E., Zouinkhi, A., Thomas, A., Abdelkrim, M. N., Chekir, H., & Ltaief, R. H. (2017). A communicating objects approach for smart logistics and safety issues in warehouses. *Concurrent Engineering: Research and Applications*, 25(1), 53–67.

- Trebar, M., Lotrič, M., & Fonda, I. (2015). Use of RFID temperature monitoring to test and improve fish packing methods in Styrofoam boxes. *Journal of Food Engineering*, 159, 66–75.
- Tsang, Y. P., Choy, K. L., Wu, C. H., Ho, G. T. S., Lam, H. Y., & Tang, V. (2018). An intelligent model for assuring food quality in managing a multi-temperature food distribution centre. *Food Control*, 90, 81–97.
- Tsang, Y. P., Choy, K. L., Wu, C.-H., Ho, G. T. S., Lam, C. H. Y., & Koo, P. S. (2018). An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks. *Industrial Management & Data Systems*, 118(7), 1432–1462.
- Turner, A. (2020). Evaluation of automated storage and retrieval in a distribution center (Doctoral dissertation, Massachusetts Institute of Technology).
- Uhlemann, T. H.-J., Lehmann, C., & Steinhilper, R. (2017). The digital twin: Realizing the cyber-physical production system for Industry 4.0. *Procedia CIRP*, 61, 335–340.
- Ukko, J., Saunila, M., Nasiri, M., Rantala, T., & Holopainen, M. (2022). Digital twins' impact on organizational control: Perspectives on formal vs social control. *Information Technology & People*, 35(8), 253–272.
- Unruh, G., & Kiron, D. (2017). Digital transformation on purpose. *MIT Sloan Management Review*.
- Vairagade, N., Logofatu, D., Leon, F., & Muharemi, F. (2019). Demand forecasting using random forest and artificial neural network for supply chain management. In *Computational Collective Intelligence: 11th International Conference, ICCCI 2019, Proceedings, Part I* (Vol. 11, pp. 328–339). Springer.
- Vaka, D. K. (2024). From complexity to simplicity: AI's route optimization in supply chain management. *Journal of Artificial Intelligence, Machine Learning and Data Science*, 2(1), 386–389.
- Varcode. (2021). Temperature monitoring solutions company. Varcode.
- Varga, R., Costea, A., & Nedevschi, S. (2015, September). Improved autonomous load handling with stereo cameras. In *2015 IEEE International Conference on Intelligent Computer Communication and Processing (ICCP)* (pp. 251–256). IEEE.
- Varmus, M., & Bosko, P. (2022). UAVs in practice: Benefits, concerns, examples, and managerial implications. *Journal of Innovation and Business Best Practice*, 2022, Article 496714.

- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*.
- Verigo. (2019). POD Quality – Model PH1. Verigo.
- Verisk. (2025, January 21). Cargo theft surges to record levels in 2024, Verisk CargoNet analysis reveals.
- Wang S, Wang J, Zhang D, Li D, Zhang C (2016). Towards smart factory for industry 4.0: A self organized multiagent system with big data based feedback and coordination. *Comput Netw* <https://www.elsevier.com/locate/comnet>
- Wang, K., & Wang, Y. (2018). How AI affects the future predictive maintenance: A primer of deep learning. In *Advanced Manufacturing and Automation* (Vol. 7, pp. 1–9). Springer.
- Wang, L., Wu, Z., & Cao, C. (2019). Technologies and fabrication of intelligent packaging for perishable products. *Applied Sciences*, 9, 4858.
- Wang, P., & Luo, M. (2021). A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing. *Journal of Manufacturing Systems*, 58, 16–32.
- Wanganoo, L. (2020). Streamlining reverse logistics through IoT driven warehouse management system. In *Proceedings of the 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions), (ICRITO)* (pp. 854–858). IEEE.
- Wanganoo, L., & Patil, A. (2020). Preparing for the smart cities: IoT enabled last-mile delivery. In *Proceedings of the 2020 Advances in Science and Engineering Technology International Conferences (ASET)*, Dubai, United Arab Emirates, 4 February–9 April 2020.
- Wawrla, L., Maghazei, O., & Netland, T. (2019). Applications of drones in warehouse operations. *ETH Zurich, D-MTEC, Chair of Production and Operations Management*. www.pom.ethz.ch
- Wirtz, B. W. (2024). *Digital business and electronic commerce: Strategy, business models and technology* (2nd ed.). Springer.
- World Economic Forum. (2025). *The Future of Jobs Report 2025*. World Economic Forum.
- Woschank, M., Rauch, E., & Zsifkovits, H. (2020). A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics. *Sustainability*, 12(9), 3760.

- Wu, J., You, H., & Du, J. (2024). AI generations: From AI 1.0 to AI 4.0. AI Generations: From AI 1.0 to AI 4.0, University of Florida.
- Wurst, C., & Graf, L. (Eds.). (2021). Disrupting logistics: Startups, technologies, and investors building future supply chains. Springer Nature Switzerland AG. <https://doi.org/10.1007/978-3-030-61093-7>
- Xia, W. H., Zhou, D., Xia, Q. Y., & Zhang, L. R. (2020). Design and implementation path of intelligent transportation information system based on artificial intelligence technology. *The Journal of Engineering*, 13, 482–485.
- Xiao, J., Lu, H., Zhang, L., & Zhang, J. (2017, November). Pallet recognition and localization using an RGB-D camera. *International Journal of Advanced Robotic Systems*, 14(6), 172988141773779.
- Xiong, Z., Cai, Z., Takabi, D., & Li, W. (2021). Privacy threat and defense for federated learning with non-i.i.d. data in AIoT. *IEEE Transactions on Industrial Informatics*, 18, 1310–1321.
- Xu, J., Liu, X., Li, X., Zhang, L., Jin, J., & Yang, Y. (2022). Energy-aware computation management strategy for smart logistic system with MEC. *IEEE Internet of Things Journal*, 9, 8544–8559.
- Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: State of the art and future trends. *International Journal of Production Research*, 56(8), 2941–2962.
- Xu, Y., Sun, Y., Liu, X., & Zheng, Y. (2019). A digital-twin-assisted fault diagnosis using deep transfer learning. *IEEE Access*, 7, 19990–19999.
- Yadav, A. B. (2024). Machine minds, mechanical might: The pinnacle of AI-driven robotics.
- Yadav, B. R. (2024). Machine learning algorithms: Optimizing efficiency in AI applications. *International Journal of Engineering and Management Research*, 14(5), 49–57.
- Yan, J., Xin, S., Liu, Q., Xu, W., Yang, L., Fan, L., Chen, B., & Wang, Q. (2014). Intelligent supply chain integration and management based on Cloud of Things. *International Journal of Distributed Sensor Networks*, 10(3), 1–15.
- Yan, Z., Zhang, P., & Vasilakos, A. V. (2014). A survey on trust management for Internet of Things. *Journal of Network and Computer Applications*, 42, 120–134.
- Yang, C.-S. (2019). Investigating UAVs applications and intention to use in the maritime shipping in Taiwan. *Maritime Policy and Management*, 46(8), 982–994.

- Yang, C.-S. (2019). Maritime shipping digitalization: Blockchain-based technology applications, future improvements, and intention to use. *Transportation Research Part E: Logistics and Transportation Review*, 131, 108–117.
- Yang, H., Yang, L., & Yang, S. H. (2011). Hybrid Zigbee RFID sensor network for humanitarian logistics centre management. *Journal of Network and Computer Applications*, 34(3), 938–948.
- Yang, M. (2008, December). Using data driven simulation to build inventory model. In *Proceedings of the 2008 Winter Simulation Conference* (pp. 2595–2599). Miami, FL, USA.
- Yang, M. H., Luo, J. N., & Lu, S. Y. (2015). A novel multilayered RFID tagged cargo integrity assurance scheme. *Sensors*, 15(10), 27087–27115.
- Yarlagadda, V. K. (2024). Cutting-edge developments in robotics for smart warehousing and logistics optimization. *Robotics Xplore: USA Automation Digest*, 1(1), 61–79.
- Ye, S. J., Xiao, Z., & Zhu, G. (2014). Identification of supply chain disruptions with economic performance of firms using multi-category support vector machines. *International Journal of Production Research*, 53(10), 3086–3103.
- Yılmaz Ü, Duman B (2019) Lojistik 4.0 kavramına genel bir bakış: Geçmişten bugüne gelişim ve değişimi. *Bilecik , Seyh Edebali Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 4(1):186–200.
- ZenCity. (2019). Listen to your city. ZenCity.
- Zhang, C., Chen, Y., Chen, H., & Chong, D. (2021). Industry 4.0 and its implementation: A review. *Information Systems Frontiers*, 1–11.
- Zhang, G., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. *Journal of Industrial Information Integration*, 23, 1–9.
- Zhang, H.D. and Zhu, L. (2011) *Internet of Things: Key Technology, Architecture*
- Zhang, J., Chen, M., Sun, H., Li, D., & Wang, Z. (2020). Object semantics sentiment correlation analysis enhanced image sentiment classification. *Knowledge-Based Systems*, 191, 105245.
- Zhang, R., Lu, J. C., & Wang, D. (2014). Container drayage problem with flexible orders and its near real-time solution strategies. *Transportation Research Part E: Logistics and Transportation Review*, 61, 235–251.
- Zhang, Y. (2024). *Digital twin: Architectures, networks, and applications* (p. 126). Springer Nature.

- Zhang, Y., Wang, W., Yan, L., Glamuzina, B., & Zhang, X. (2019). Development and evaluation of an intelligent traceability system for waterless live fish transportation. *Food Control*, 95, 283–297.
- Zhang, Y., Zhao, L., & Qian, C. (2017). Modeling of an IoT-enabled supply chain for perishable food with two-echelon supply hubs. *Industrial Management and Data Systems*, 117(9), 1890–1905.
- Zheng, T., Grosse, E. H., Morana, S., & Glock, C. H. (2024). A review of digital assistants in production and logistics: Applications, benefits, and challenges. *International Journal of Production Research*, 62(21), 8022–8048.
- Zheng, X., Lu, J., & Kiritsis, D. (2022). The emergence of cognitive digital twin: Vision, challenges and opportunities. *International Journal of Production Research*, 60(24), 7610–7632.
- Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. *Heliyon*, 9(4).
- Zhou, H., Liu, B., & Wang, D. (2012). Design and research of urban intelligent transportation system based on the Internet of Things. In Y. Wang & X. Zhang (Eds.), *Internet of Things* (pp. 572–580). Springer.
- Zhu, X., Mukhopadhyay, S.K. and Kurata, H. (2012) A Review of RFID Technology and Its Managerial Applications in Different Industries. *Journal of Engineering and Technology Management* , 29, 152-167.
- Ziegeldorf, J., Morchon, O., & Wehrle, K. (2014). Privacy in the Internet of Things: Threats and challenges. *Security and Communication Networks*, 7, 2728–2742.
- Ziegler, D. M., Stiennon, N., Wu, J., Brown, T. B., Radford, A., Amodei, D., Christiano, P., & Irving, G. (2019). Fine-tuning language models from human preferences. *arXiv:1909.08593*.